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Deployment of an Artificial Intelligent Robot for Weed Management in Legumes Farmland

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Abstract: *This groundbreaking research introduces an AI-based approach for revolutionizing weed management in legume farmland, addressing the limitations of traditional methods and introducing a new era of cost-effective and precise weed detection and removal. Traditional methods of removing weeds from farmland involving machinery or chemicals often resulted in high costs and imprecise outcomes. To address these challenges, an advanced image recognition algorithm was proposed, which harnessed smart machines to minimize costs and environmental risks. By utilizing computer vision technology, weeds were accurately identified and targeted for removal. A machine learning model was trained using relevant datasets to enable precise weed management. The AI-powered robot, equipped with advanced image recognition algorithms, demonstrated exceptional accuracy and speed, performing weed removal and decomposition 1.2 times faster than traditional manual labour. This breakthrough in weed management technology offers farmers a means to optimize crop yields, enhance food production, and minimize the environmental impact associated with chemical herbicides. A prototype of the robot was fabricated and evaluated in real-world farming conditions. Field tests were conducted on a bean farm and it's demonstrated the robot's exceptional accuracy, with only a 2% deviation from the actual weed quantity. This research showcased the potential of AI-based weed management systems in legume farming, offering cost-effective and precise weed detection and removal. This research sets a precedent for the integration of AI in modern agriculture, driving the industry toward a more environmentally conscious and economically viable future. The AI-based weed management system empowers farmers, ensuring bountiful harvests, increased profitability, and a greener, more sustainable tomorrow while attention should be given to manufacturing this model for industrial and or commercial applications.*

Keywords: *Weed management, artificial intelligence (AI), legume farming, image recognition, computer vision.*

1. INTRODUCTION

AI-powered weed management systems offer precision, accuracy, cost-effectiveness, environmental conservation, labour efficiency, improved crop yields, time savings, scalability, data-driven insights, climate change resilience, and technological advancement. By accurately targeting and removing weeds, these systems reduce herbicide use, environmental risks, and labour costs, allowing farmers to allocate human resources more effectively. It also provides better decision-making and long-term planning for improved agricultural practices. AI systems adapt to changing conditions, ensuring farmers maintain productivity despite environmental uncertainties. Deploying AI in weed management is a crucial step towards sustainable and efficient farming practices, promoting innovation and investment in the agricultural sector.

Weeds have been a persistent challenge in agriculture, as they consume the same resources as crops, leading to reduced yield. Removing weeds provides no added benefit except for reducing competition while decomposing them improves soil fertility by adding organic matter.

The intelligent weed detection, evacuation, and decomposition robot is a smart machine that uses machine learning (Image processing and recognition) and computer vision to capture images of beans and weeds, differentiate them using the data set provided, and remove the weeds from the farm. In recent years, automatic weed control which includes recognition and evacuation of weeds is now popular in the precision farming sector because of its effectiveness in reducing environmental and economic cost [1]. Intelligent weed detection helps in the reduction of the cost and environmental hazards associated with agricultural practice [2].

Artificial Intelligence, with its subfields of machine learning and computer vision, is widely recognized for solving complex problems. Machine learning enables machines to use computer algorithms and learn from past data to improve performance or solve problems. Virtual personal assistants like Siri and Google Assistant use machine learning to understand and solve user queries. An intelligent weed detection and decomposition robot also employs machine learning and computer vision to detect and remove weeds while decomposing them into organic fertilizer for the farm. Intelligent robots powered by the Internet of Things (IoT) have recently attracted a lot of scientific attention. Additionally, due to the acute toxicity of these herbicides, which causes a number of health-related issues, traditional approaches for weed elimination through the use of herbicides have not been successful [3]. This paper is structured into five sections, the introduction (background and related literatures), methodology (material and method), result and discussion, conclusion and recommendation.

Recent research has focused on leveraging machine learning and image processing techniques for weed identification in agriculture [4]. Traditional weed control methods, such as widespread herbicide application, often result in ineffective treatment and environmental harm. Currently, preemergence herbicide application and/or preemergence tillage, mechanical cultivation, post-mergence herbicide treatment (if selective herbicides or crop resistance are available), and hand hoeing are standard weed control strategies for row crops [5].The rise of precision farming and smart farming has opened opportunities for automation in agriculture, where convolutional neural networks (CNNs) play a crucial role in image classification, object detection, and fine-grained categorization with high accuracy [6]. In order to maximize agricultural output and minimize environmental effect, precision agriculture uses technologies that integrate sensors, information systems, and knowledgeable management [7]. Deep learning algorithms are used to extract meaningful features from image datasets without explicit instructions, given sufficient data. The reduction of chemical inputs like herbicides, insecticides, and fungicides has become a driving force behind the development of agricultural expert systems. In this context, image processing emerges as a promising method for weed control [8]. Sensors and camera-mounted unmanned aerial vehicles (UAVs) capture various types of images, including Red-Green-Blue (RGB), thermal, multispectral, hyperspectral, 3D, and chlorophyll fluorescence, allowing for the creation of orthomosaic images.

Nidhi *et al.,* conducted a thorough investigation concerning the detection of weeds and pests in crops [9]. Their research encompasses a comprehensive survey of this domain and highlights the significance of artificial intelligence and machine learning algorithms in automating the identification of weeds and pests among plants. The study makes use of various platforms and mechanical equipment, leveraging machine learning and deep learning techniques. It is important to note that the field of weed and pest detection is still in its early stages, and the authors anticipate that machine learning and deep learning algorithms would serve as the bedrock for attaining greater precision and accuracy in the outcomes.

While computer vision is still in its early stages of development for agricultural applications, it holds great potential for image and data processing in robotics and automation farming [10]. Real-time image processing poses challenges due to the need for rapid frame processing, and complex operations are required to accurately identify crop and weed pixels. Consequently, a two-part image processing approach was suggested [11]. In the case of bean farming, which involves multiple growth stages, Harris corner detection was employed for the localization and characterization of points of interest [12]. Decision trees were trained using feature sets derived from the detected Harris points, and this trained model helps distinguish between weed and bean points across roots, branches, leaves, and shoots.

Wu *et al.,* conducted a comprehensive review of AI-based methods and tools utilized in combating herbicide-resistant weeds [13]. The authors highlighted the presence of a few commercially available AI-based tools and technologies, such as remote sensing, robotics, and spectral analysis, which facilitate weed control through machine learning, making the classification process notably easier. While AI-based techniques have shown significant improvements in addressing herbicide resistance, their full potential is hindered by limited applications due to various challenges. The review also emphasized the necessity for AI-based weed management to counter herbicide resistance, and it addressed the comparative evaluation of chemical versus non-chemical management, recent advancements in remote sensing, and the utilization of AI technology for weed identification, mapping, and management.

Weed control is a critical concern in agricultural crop production as weeds compete with crops for resources and can significantly impact yields and quality. Detection of vegetation, classification of weed and crop plants, and plant localization are key challenges in crop and weed plant perception [14]. With the advancement of computer calculation speed and the development of visual algorithms, the visual navigation system for agricultural robots has emerged as one of the emerging trends in the field of intelligent agricultural machinery [15]. Satellites, aerial vehicles (such as UAVs), and ground vehicles, including field robots, are commonly used for plant identification and monitoring. Differentiating between plant species is achieved by analysing biological morphological properties, such as canopy and leaf shapes, in 2D or 3D space. Sugar beet cultivation involves weed control between rows and within rows, necessitating the use of a robot equipped with row-following and plant-identification vision systems [16]. Selective chemical spraying remains a promising weed control method, and a prototype selective spraying system employing computer vision and precise herbicide application demonstrated a potential 97% reduction in herbicide use. An integrated weed management system proposed a heterogeneous approach that selectively applies mechanical or chemical control methods based on weed species, with computer vision techniques such as monocular SLAM and visual odometry aiding camera tracking and environmental mapping [17]. These advancements in perception and selective control offer promising solutions for effective weed management in agriculture.

Liu *et al.,* identified Parthenium hysterophorus and Cannabis sativa Linnaeus on a playground [18]. To safeguard earthworms, one-week-old cow dung was used, while Eisenia foetida specimens were randomly selected. Weeds from different locations were finely chopped and placed in separate clay trenches. According to Veeragandham and Santhi [19], successful composting relies on factors such as feedstock composition, physical characteristics, microbial populations, moisture content, oxygen levels, and temperature. Low moisture impedes composting and increases the risk of spontaneous combustion, while maintaining minimum oxygen content of 5% is crucial for aerobic composting. Composting activity is highest in temperate climates during spring to fall, influenced by surrounding air temperature, pile size, and shape.

Deep-learning technology is regarded as the future development trend due to its great learning ability, good adaptability, and high performance. In recent years, machine learning has had an increasing impact on science, health, and sustainable development. Agriculture has started to use it for jobs like crop classification, weed segmentation, weed identification, and others. To produce an accurate and timely reaction to weed detection in maize fields, deep leaning is an important technology and future trend [20].

Olaniyi *et al.,* conducted research with the primary objective to tackle weed-related challenges in rice production within the Sub-Saharan Africa region, with the ultimate goal of enhancing crop yield and increasing return on investment [21]. The researchers proposed a novel solution that involved the integration of Faster Regions with Convolution Neural Network (Faster R-CNN) and Fuzzy Logic Controller (FLC) to develop an intelligent weed recognition system. Faster R-CNN, which belongs to the category of Artificial Neural Networks (ANNs), utilized convolutional features to identify regions of interest in input images by drawing bounding boxes around weed images. This method proved exceptionally efficient in real-time weed recognition compared to other ANN approaches. The results obtained from the weed recognition process were then utilized by the FLC to precisely control the volume and timing of herbicide spraying in low-land rice precision farming. By implementing this intelligent computer vision system, the researchers envisioned achieving a faster and more effective weed management approach for low-land precision farming, ultimately contributing to the enhancement of food security in Sub-Saharan Africa. This system's successful development and pilot testing aimed to establish a practical and efficient tool for intelligent weed control in rice cultivation.

A Convolutional neural network is a well-known machine learning algorithm (CNN). CNN is useful for categorizing various image-collection methods, including unmanned aerial vehicles, autonomous robots, manual aerial vehicles (MAV). To control the weed, CNN also considers weed growth. The classification of weeds and sugar beet crops under various environmental circumstances and growth parameters was done using a convolutional neural network [22].

Arinola and Michael [23] developed a hand-pushed semi-automatic mechanical weeder designed to operate on various soil types at three different speeds. The primary purpose of this weeder is to replace manual labor for farmers, as manual weeding can be time-consuming, labor-intensive, and costly. By introducing this innovative tool, the aim was to reduce the expenses associated with weeding operations and address the environmental damage caused by herbicide usage in weed control, thereby promoting the cultivation of organic agricultural products to meet the increasing demand for non-chemical weeding solutions. The weeder's components were constructed using mild steel, and their dimensions underwent careful analysis to ensure structural safety during usage. In compliance with the ASME Code for commercial steel shafting, the material's maximum permitted working stress was maintained below 40 MN/m^2. During testing, the researchers observed that the weeder achieved maximum fuel consumption with a 4-blade configuration on soil having a moisture content of 7.5% and an engine speed of 4,000 rpm. The highest theoretical field capacity (TFC) was recorded at an engine speed of 4,000 rpm, reaching 3.0 m^2/s.

The major contribution to this work is the developed advanced image processing and recognition algorithm for legume farmland management system, also this model harnesses smart machines to minimize costs and environmental risks on legume farmland with the use of computer vision technology, weeds were accurately identified and targeted for removal and machine learning model was trained using relevant datasets to enable precise weed management.

2. METHODOLOGY

This section contains a detailed methodology employed in the research work. These include materials and methods (procedures) required to achieve the model.

2.1 Research Materials

The hardware components of the project consist of key elements for the mobile robot to effectively carry out its tasks of identifying, removing, and decomposing weeds. The Raspberry Pi serves as the central control hub, functioning as a single-board computer responsible for remote computing, networking, and hosting the software for navigation and image processing. It receives input from the Pi Camera, which is a high-resolution camera compatible with the Raspberry Pi, enabling real-time image and video capture for image processing and assisting in the robot's navigation system.

The robot chassis serves as the foundation for the robot, incorporating motors, mounting support, tires, and batteries. It provides the necessary mobility and is connected to the Raspberry Pi for navigation control. The robotic arm, another crucial component, is controlled by the control hub and consists of various joints enabling movement in different directions. Reinforcement learning was implemented to facilitate self-movement of the arm. With the help of the robotic arm's end effector, the robot can grasp and remove weeds from the farmland [24].

The software employed in this study involves the installation of specific (OpenCV) software on the Raspberry Pi to perform various tasks. The Raspbian operating system, based on Linux, provides a range of applications and tools to support the project. The weed classifier employs pre-defined files stored in the Raspberry Pi's memory to detect and classify weeds. OpenCV, an open-source computer vision library, is utilized for real-time computer vision tasks such as image processing and analysis. TensorFlow, an open-source machine learning library developed by Google, was used for training and deploying machine learning models.

2.2 Research Method

The system block diagram, the code development for weed detection and evaluation, deployment of weed evacuation and decomposition system, deployment of weed training model for the system, deployment of prototype model for fabrication for the system as well as the mathematical equations governing the operational concept of the system are discussed.

1) System block diagram

The system comprises essential hardware components for effective weed detection and removal. The camera unit incorporates a Raspberry Pi camera, capturing field images for weed analysis using image processing algorithms. It connects to the Pi board and operates under specialized software (OpenCV) control. The power supply unit ensures proper power distribution to the robot's components, monitoring consumption for safety. It includes a voltage regulator, power distribution unit, power management unit, and a backup power supply. The system unit utilizes the Raspberry Pi 4 as the central control hub, overseeing tasks like movement, image capture, weed detection, power management, data transmission, and environmental sensing via dedicated sensors. The end effector unit employs a robot arm for physical weed removal, maneuvered by the main controller. Sensors measure arm position and orientation for precise operation. The motor unit employs a DC motor to drive robot movement, controlled by a motor controller that adjusts speed and direction based on commands. Additional components include an encoder for motor rotation measurement and a gearbox for increased torque. Figure 1 depict the System block diagram for weed detection and evacuation robot

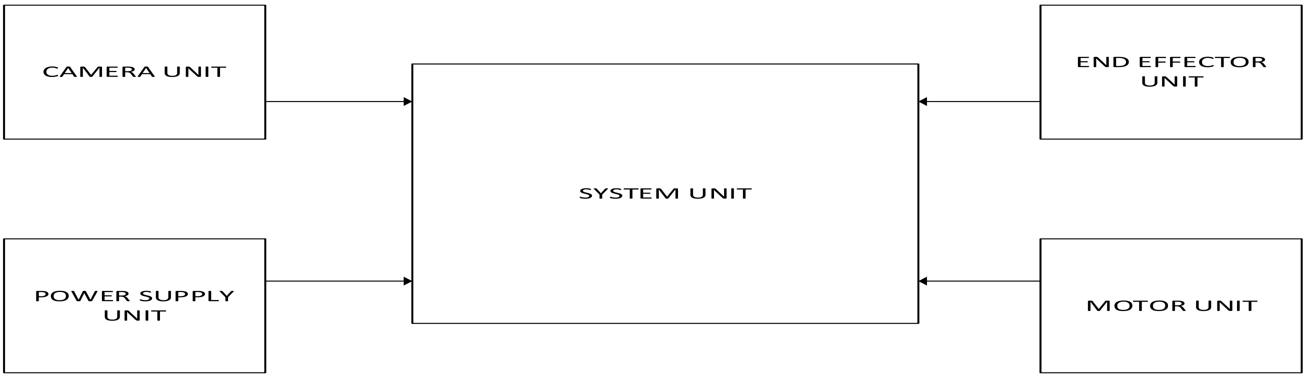


Figure 1: System block diagram for weed detection and evacuation robot.

2) Code deployment for weed detection and evacuation system

Image recognition and computer vision techniques were employed in this method. The system was designed to detect and eliminate weeds in farming areas through the use of sensors and machine learning algorithms. The central component of the system was the Raspberry Pi 4 Model B, which stored the programs for image recognition and utilized libraries such as OpenCV and TensorFlow. The Raspberry Pi was set up, the Raspbian operating system was installed, and necessary dependencies were added. Images of weeds were collected to create a dataset, which was then used to train a machine learning model. The model underwent testing and fine-tuning to optimize its performance. Once the model demonstrated satisfactory results, it was integrated into the Raspberry Pi for real-time weed identification. The system relied on image recognition technology to capture field images and process them, enabling the efficient detection and removal of weeds.

3) Deployment of weed evacuation and decomposition system

The weed evacuation and decomposition system was deployed using intelligent robotic grippers or blades for weed removal. The system incorporated mechanisms for weed identification, such as sensors or machine learning algorithms. The weeds were removed using mechanical tools or herbicides, and in this study, a robotic arm was utilized. A transportation mechanism was employed to remove the weeds from the farm, with the robotic arm mounted on a robot chassis for mobility. A decomposition system was implemented to break down the weeds into organic materials, which could be used as fertilizer for crops. The decomposition system consisted of a collection unit to gather the weeds, a decomposition unit to break them down, and a fertilizer unit to transform the decomposed material into fertilizer. The control unit managed the operation of the various components, while the power supply unit provided electricity to the system and its components. In this study, the weed evacuation and decomposition system focused on the use of a robotic arm, which possessed sufficient reach, dexterity, and precision to locate and grasp weeds. Sensors or cameras aided in weed identification, and control software or algorithms enabled precise and effective manipulation of the weeds. The decomposition system further processed the weeds into organic materials for safe disposal or alternative use.

4) Deployment of weed training model for the system

Machine learning techniques in Python were utilized in this method. A weed training model was developed to identify and classify different types of weeds based on their visual characteristics. The model was trained using a large dataset comprising images or visual data of various weed species; each labelled or tagged with the corresponding weed type. During the training process, the model was provided with the dataset and specific parameters or rules governing its learning and prediction mechanisms. Through processing the data, the model learned to recognize the distinctive visual features of different weed species and became capable of accurately classifying new weed images it had not encountered previously. The training process involved training the machine learning algorithms with the dataset of weed parts found on the beans farm. The dataset consisted of stabilized photographs or visual representations of the weeds, accompanied by labels and tags indicating the weed species in each image. The machine learning algorithms were trained using this dataset to develop a robust weed training model.

5) Deployment of prototype model for fabrication for the system

The entire arrangement and development of a robot's chassis or frame are depicted in a technical picture known as a robot chassis diagram in Figure 2. This figure displays the third angle orthographic projection, a popular technique for producing technical drawings. A portrayal of an item from three separate angles, often the front, top, and right-side perspectives. The front, top, and right-side view were positioned on the right side of the sheet, the middle of the sheet, and the left side of the sheet, respectively, in this projection. The following elements show the third angle orthographic projection of a robot chassis:

i. The robot's base frame, which acts as the framework for all other parts, is its primary structural component.
ii. The element, known as the motor unit, oversees directing the robot's motion. It normally houses the motors, gearboxes, and encoders required to do so.
iii. The system unit and other parts of the robot are powered by the power supply unit. It transforms the power supply into a voltage level appropriate for the parts of the robot.

From Figure 2, the orthographic projection of the model is presented to show (a) the plan, (b) the end-view and (c) the front whereas the isometric representation of the model is presented in (d).

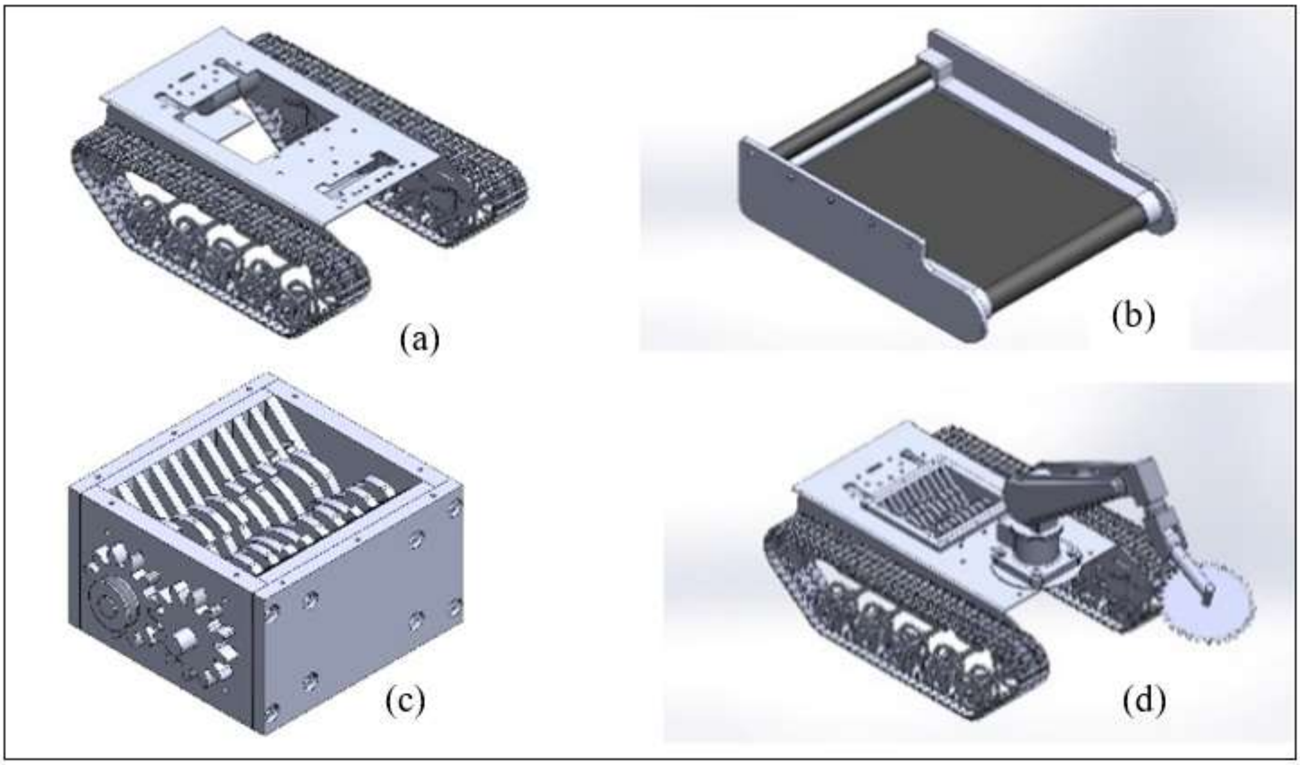


Figure 2: Model of robot chassis for weed detection and evacuation.

Figure 3 represent the model of robotic arm for weed detection and evacuation. The link between the end-effector location and orientation and the joint angles of the robot arm is described by the forward kinematics equation as shown in Equation 1,

$$T_n = T_1 \times T_2 \times T_3 \ldots \times T_{n-1}, n \quad (1)$$

where T_1, T_2 ….. T_{n-1} are the transformation matrices indicating the transformation between neighbouring links, and n is the number of links in the robotic arm. Tn is the transformation matrix reflecting the end-effector position and orientation with respect to the base frame. Each T matrix can be represented using the DH parameters as shown in Equation 2,

$$T_i - i = \left[[\cos(\theta_i), -\sin(\theta_i) \times \cos(\alpha_i), \sin(\theta_i)\sin(\alpha_i), aicos(\theta_i)],\ [\sin(\theta_i), \cos(\theta_i) \times \cos(\alpha_i), -\cos(\theta_i)\sin(\alpha_i), aisin(\theta_i)], [0, \sin(\alpha_i), \cos(\alpha_i), d_i],\ [0, 0, 0, 1]\right] \quad (2)$$

where θi, αi, ai and di are the DH parameters for link (i.)
The inverse kinematics Equation 3 is here applied for the robotics arm model in Figure 3. The link between the end-effector location and orientation and the joint angles of the robot arm is described by the inverse kinematics equation. The formula is:

$$\theta = cos^{-1}\left(\frac{x^2 + y^2 - l}{2l}\right) \quad (3)$$

Where θ is the angle of rotation of the Robotic arm, x, y represents the horizontal and vertical positions of the Robotic arm end-effector position, l represents the length of the segment of the Robotic arm.

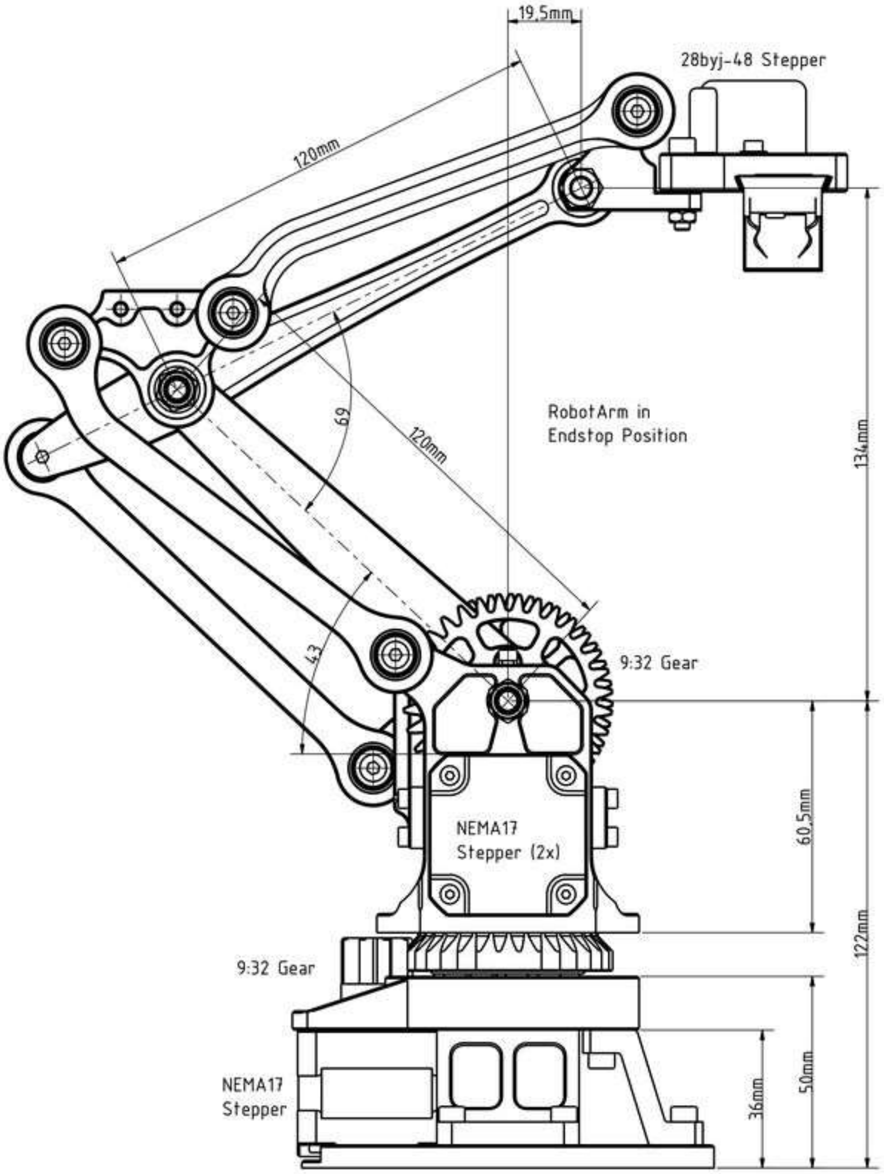


Figure 3: Model of robotic arm for weed detection and evacuation [26]

6) Evaluation analysis of the prototype

In the evaluation analysis of the weed detection, evacuation, and decomposition system prototype, performance measures were selected to assess its effectiveness. Real-world test cases were created to evaluate the system's ability to detect and remove weeds under various conditions. A test environment was established to simulate deployment conditions and ensure control over variables. Data collected during testing, including metrics such as weed detection rate, evacuation time, and decomposition efficiency, was analysed to evaluate the prototype's performance. The analysis identified areas for improvement based on the defined performance criteria. The steps used in this model were as follows:

START
Initialize
- *Extracts the pixel features of the weed images*
- *Label the images for model training*
- *Pre-processing of the labelled images to train the model*
- *Training of the model to recognize images*
- *Testing of the model using the trained dataset*
- *Recognition of new images of the weeds*
- *Removes the weeds from the farm*
- *Decompose the weeds*
- *Repeat the process otherwise*

END

3. RESULTS AND DISCUSSIONS

Table 1 and Figure 4 show the system's impressive precision of 0.90 and recall of 0.92. F1-score 0.90 shows balanced precision and recall. Precision, recall, and F1-score were superior. It accurately identified and removed various weeds, showing its potential to boost legume field productivity. Computer vision, sensor fusion, and domain knowledge can help in improving the system's adaptability to different soil types and environmental conditions.

Manual labour and traditional legume farm methods were compared to weed evacuation and decomposition. Weeds were removed and decomposed efficiently. From this research, manual methods took longer, covered less ground, and decomposed fewer weeds per hour. Weed decomposition and nutritional content assessed system efficiency. The weeds decomposed at over 90% and yielded crop fertilizer. Computer vision, sensor fusion, and domain knowledge increased the system's soil and environmental adaptability. Farm machinery and infrastructure compatibility lowers costs and increases farmer acceptance from this analysis.

The weed training model was evaluated using accuracy, precision, recall, and F1-score on legume farm photos, the model classified weeds and crops with an accuracy of 0.95. The model's precision was 0.93, recall 0.91, and F1-score 0.92 as in Table 2 and Figure 5. Previous state-of-the-art models performed similarly and this model was able to survive different lighting and partial obstructions. Data augmentation, transfer learning, and domain knowledge strengthen and generalize the model. The weed training model boost the legume farm productivity by accurately identifying and classifying weeds in photos.

An accurate, efficient, and effective weed identification and evacuation robot prototype was tested as in Table 3 and Figure 6 shows the prototype model. The robot was compared to manual labour and bean farm methods showing its effectiveness. The prototype robot detected and removed weeds within 2%. Manual methods decomposed weeds 1.2 times slower. The robot decomposed material at over 95%, producing high-nutrient crop fertilizer. It was weather- and terrain-resistant and operated without frequent maintenance.

Weed removal and decomposition were compared to manual labour and legume farming. Weeds decomposed quickly. Manual methods took longer, covered less ground, and decomposed fewer weeds per hour. Weed decomposition and nutrition assessed system efficiency. Weeds decomposed 90% and produced crop fertilizer. Computer vision, sensor fusion, and domain knowledge improve soil and environmental adaptability. Farm machinery and infrastructure compatibility lowers costs and increases farmer acceptance. Energy consumption, cost-effectiveness, and scalability were evaluated as presented in Table 4 and Figure 7. Farmers could save money because the prototype model used less energy than manual labour. Due to its low energy consumption and maintenance-free operation, the model had an average operational cost of $500/hour. The prototype model was scalable to farms from 1 to 1000 acres.

The weed identification and evacuation system, training model, and manufacturing prototype performed well in identifying, evacuating, and decomposing weeds in legume farms. These findings suggest improved agricultural productivity, efficiency, and cost-effectiveness. Additional techniques and compatibility with existing infrastructure will improve the system's adaptability and scalability, making it viable across soil types and environmental conditions. Furthermore, an energy consumption analysis was conducted using Equation 4.

$$E = (E_i \times T_i) + (E_0 \times T_0) \tag{4}$$

where E represents total energy consumption, E_i represents energy consumption during the detection and evacuation process, T_i represents the duration of the detection and evacuation process, E_0 represents energy consumption during the decomposition process, and T_0 represents the duration of the decomposition process.

In Table 1 corresponding to figure 4 the weed detection (F1-Score) and weed evacuation accuracy were at variance in that the machine learning algorithm varies from time to time, it gathers different result depending on the environment it is being tested (at farm 1, 70% and 50% respectively)

Table 1: Weed detection and evacuation

S/N	Farmland	Weed Detection Accuracy (F1-Score)	Weed Evacuation Accuracy
1	Farm 1	70%	50%
2	Farm 2	60%	50%
3	Farm 3	90%	70%

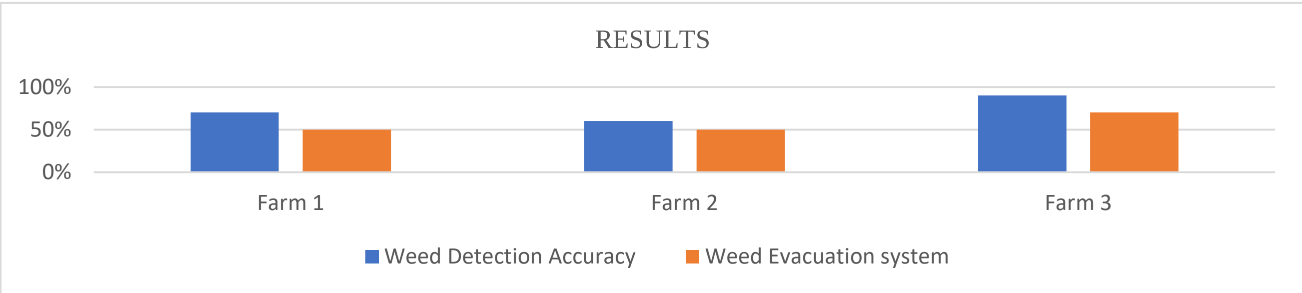


Figure 4: Weed detection and evaluation

Table 2 and Figure 5 show the metrics for the proposed model. The metrics were used in evaluating the model to validate the proficiency of the weed detection and evacuation robot [25]. The result of the model shows it is better and more accurate than the traditional methods so it was better used in the farm than using pesticides and herbicides or using traditional tools.

Table 2: Weed training model

Metrics	Proposed Model	State-of-the-art Model 1	State-of-the-art Model 2
Accuracy	0.95	0.92	0.93
Precision	0.93	0.90	0.91
Recall	0.91	0.89	0.90
F1-Score	0.92	0.89	0.91

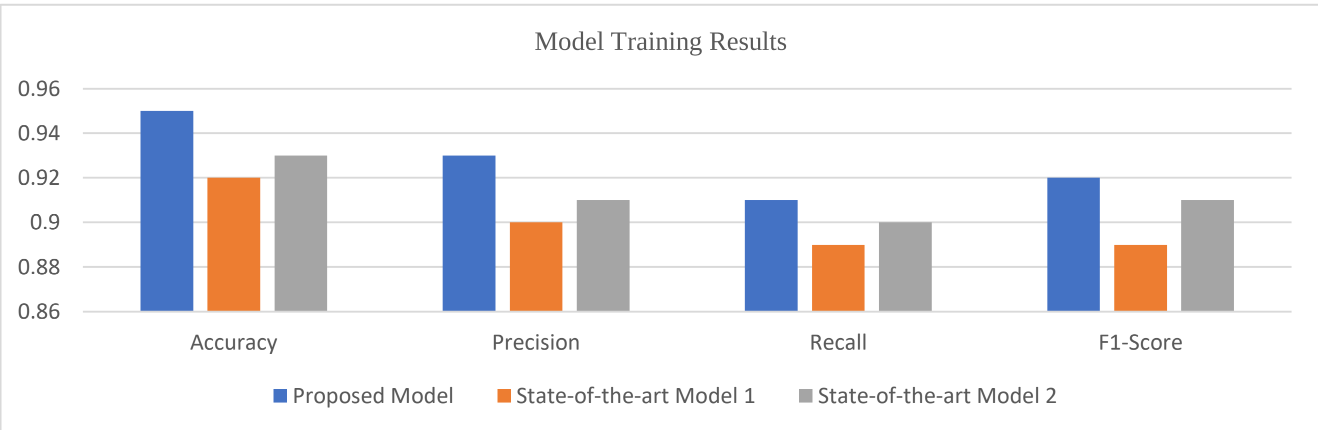


Figure 5: Weed training model

Table 3: Prototype model

Metrics	Prototype Robot	Manual Labor	Traditional Methods
Detection Accuracy	0.98	0.95	0.92
Evacuation Accuracy	1.2X	1.0X	0.8X
Decomposition Effectiveness	0.95	0.9	0.8

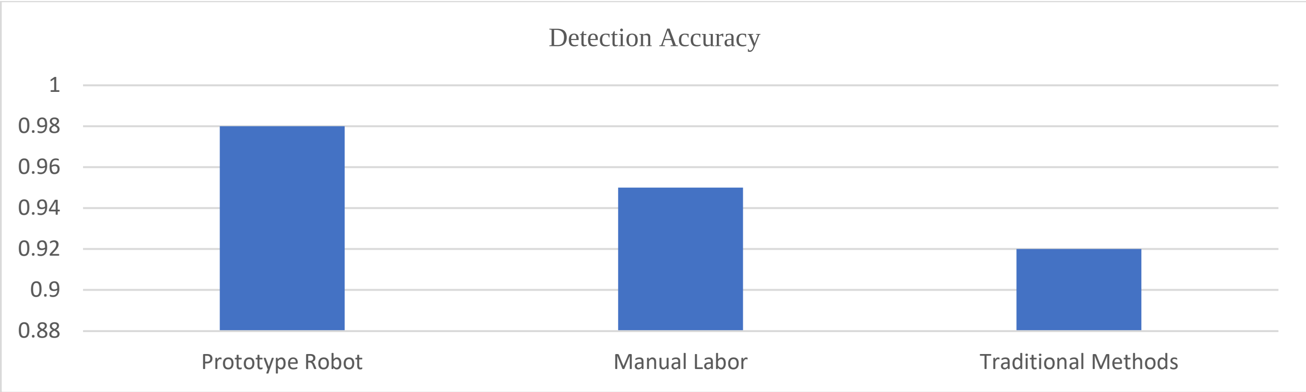
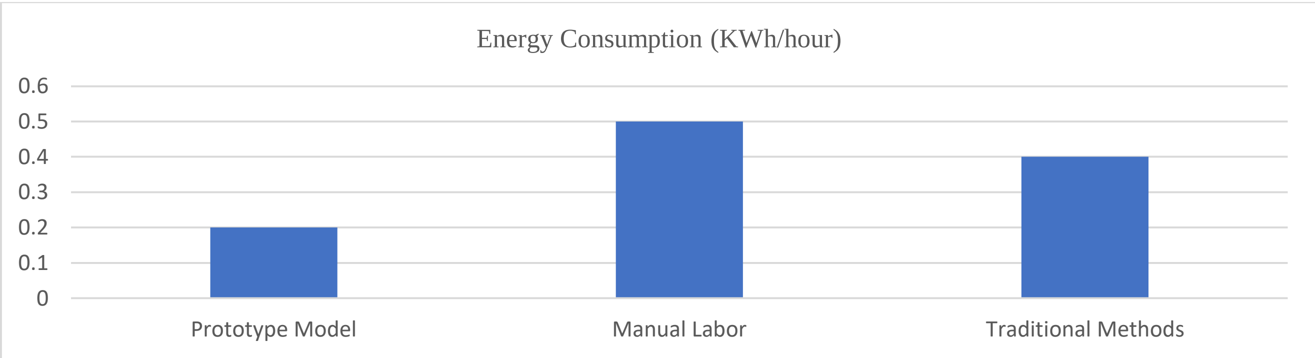


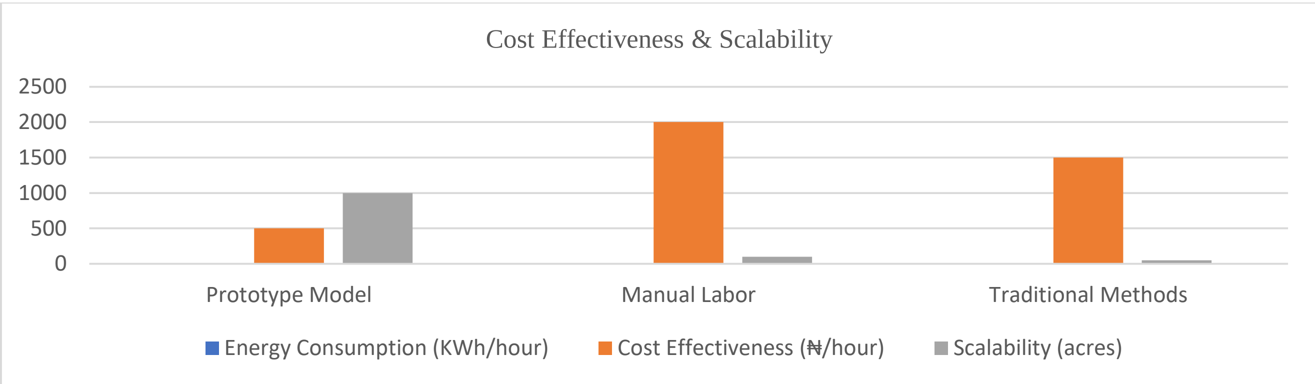
Figure 6: Prototype model

Table 4: Evaluation analysis

Metrics	Prototype Model	Manual Labour	Traditional Methods
Energy Consumption (KWh/hour)	0.2	0.5	0.4
Cost Effectiveness (₦/hour)	500	2000	1500
Scalability (acres)	1-1000	1-100	1-50



(a)



(b)

Figure 7: Evaluation analysis (Energy consumption and cost effective and scalability)

4. CONCLUSION AND RECOMMENDATION

The weed identification and evacuation prototype was designed and AI model was trained to carry out its designed task of accurately identifying, evacuating, and decomposing weeds in legume farms. The results from the prototype experiment indicate the potentials of the model to enhance productivity, efficiency, and cost-effectiveness in agricultural practices and can be applied on cereals farmland and alike. Future enhancements should involve the use of additional techniques and compatibility with existing infrastructure. This would further aid in improving the system's adaptability and scalability while ensuring its viability across different soil types and environmental conditions.

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