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AI-Powered Subterranean Crop Harvesting Stage Detection and Automation

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Highlights

- This paper focuses on detection of harvesting stage of subterranean crop.
- A deep Learning technique ResNet-50 is applied to classify the harvesting stage of subterranean crop.
- A robotic arm is trigged to carry out the harvesting operation.

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Abstract

This work introduces a system that combines deep learning with robotics to automate the detection and harvesting of beetroot crops. The system utilizes a convolutional neural network (CNN) based on the ResNet-50 architecture for image classification and is trained to identify beetroot plants at their ideal harvesting stage. With an accuracy of 99.08% and a precision of 98.39%, the model ensures dependable detection. A robotic platform, equipped with a camera, captures images in the field, which are processed by the ResNet-50 model to assess the readiness of the beetroots. Once a beetroot is confirmed ready for harvest, a robotic arm is triggered to carry out the harvesting operation. This system tackles the difficulty of timely and accurate crop identification, automating a critical aspect of the harvesting process. By leveraging deep learning for detection and robotics for execution, the system aims to minimize manual oversight and improve the effectiveness of beetroot harvesting operations.

1. INTRODUCTION

Agriculture is facing a pressing need for automation due to widespread labor shortages and the growing global demand for efficient food production [1,2]. Traditional farming methods, which mainly rely on manual labor, are becoming increasingly unsustainable [3]. To address this challenge, automation technologies, particularly in the area of harvesting, have become essential [4,5]. This work focuses on automating the harvesting process for selective subterranean crops, such as beetroot, by utilizing advanced artificial intelligence and computer vision systems [6].

The core objective of this initiative is to detect the optimal harvesting stage for subterranean crop like beetroot, a crop that requires precise timing to maximize yield and quality [7,8]. By replacing subjective human judgment with a data-driven system, this approach ensures automation with classification accuracy in harvesting [9-12]. This method addresses the challenge of labor shortages in agricultural farming [13,14]. This work underscores the critical role of automation in modern agriculture [15,16], offering a practical solution for farmers to reduce reliance on manual labor, minimize crop waste, and boost overall productivity. In doing so, it paves the way for more sustainable agricultural practices, while improving economic outcomes for farmers [17-19]. Once the harvesting stage is identified, a robotic arm is activated to pluck the beetroot crop [20,21].

2. NOVELTY AND CONTRIBUTION

The primary novelty of this work lies in the integration of AI-driven detection with robotic automation for harvesting subterranean crops. Specifically, Specifically, we have built a robotic vehicle that is built indigenously and that autonomously identifies beetroot crops at the ideal harvesting stage using a CNN

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(ResNet-50) and physically plucks them using a robotic arm. While ResNet-50 is a well-established model, its adaptation and deployment in a real-time agricultural environment combined with a mobile robotic platform form the practical innovation of this work. Initial field trials validated the feasibility of the complete system under real farm conditions, confirming its operational capability in detecting and harvesting beetroot crops.

3. RELATED WORK

In light of expanding populations, early disease identification in crops is crucial for ensuring food security, as highlighted by recent developments in agricultural technology. Plant disease detection, especially in tomato plants, has been successfully achieved by machine learning and image processing techniques, providing farmers with timely information on crop health. Recent work has merged computer vision and machine learning methods to identify plant leaf diseases. To detect illnesses in the leaves of plants, Harakannanavar et al. [1] used machine learning techniques, demonstrating how computer vision may be used to automate the diagnostic process for early crop intervention. The introduction of "DeepCrop" by Islam et al. [4] is an example of a deep learning-based crop disease prediction model that is combined with an online application. This model facilitates the use of modern technology for disease detection by users. These uses highlight the potential of automated systems to detect plant illnesses and lessen the need for human inspection.

Particularly, Convolutional Neural Networks (CNNs) are deep learning techniques that have become more and more prominent in the field of plant identification due to their ability to extract information automatically. Zhu et al. [2] developed an improved deep CNN model for plant leaf recognition that increased the accuracy of classifying different plant species. Following improvements to deep neural network transfer learning parameters by Ghazia et al. [3], plant identification models outperformed others.

According to Bansal et al. [11], who used a deep convolutional neural network to identify illnesses in apple leaves, CNNs are essential for disease detection as well. The model effectively recognized patterns linked to illness, facilitating quicker diagnosis in agricultural settings. In another study, Hassan and Maji [7] demonstrated the effectiveness of CNNs in high-dimensional data extraction by using deep learning approaches to identify plant species based on leaf photographs.

In order to fine-tune models pre-trained on a big dataset for a particular task, transfer learning has been widely implemented in the field of plant species recognition. Because features learnt from large datasets can be reused, Karahan and Nabiyev [5] used transfer learning to CNNs for plant identification and achieved superior classification results. In a similar vein, [6] investigated how deep learning networks can extract leaf data for the purpose of classifying plants, proving that CNNs are successful in detecting minute differences between species.

Plant leaf recognition systems have been improved by a number of advances [12]. A multiscale fusion CNN model was presented by Hu et al. [13]; it fuses various image data scales to increase classification accuracy. When leaves have different sizes and shapes, these models are essential. The model's performance in plant identification tasks was improved by their usage of very deep CNNs, which exploit deeper layers for more sophisticated feature extraction [8-10].

Moreover, robotic systems for agricultural applications have included deep learning. A CNN was used in an Internet of Things robotic system by Xenakis et al. [14] to automatically diagnose plant problems. An important first step toward completely automated agricultural monitoring systems is this IoT and deep learning integration. Likewise, Buenconsejo and Linsangan [15] used CNN to categorize leaves as healthy or unhealthy, illustrating the use of deep learning in real-time plant health monitoring.

On a Raspberry Pi, Paul Shekonya et al. [16] looked at the usage of deep learning-based object detectors for melon leaf anomalies identification. The affordability of implementing deep learning on embedded systems such as Raspberry Pi underscores the technology's suitability for small-scale farming. Deep learning model optimization for embedded and mobile systems is becoming more and more popular as a

way to provide plant disease diagnosis in resource-constrained settings. Furthermore, another area of ongoing research is the integration of robotic arms and AI for automated crop monitoring and harvesting [20, 21]. For instance, Dhananjay et al. [17] investigated the use of CNNs with IoT systems for accurate agricultural detection and classification.

In agriculture, the use of convolutional neural networks (CNNs) has greatly improved crop monitoring and disease detection accuracy. Numerous studies have shown how well these cutting-edge machine learning approaches work for identifying plant illnesses [18] and analyzing the various stages of crop growth. A CNN-based method was provided by M. S. Arya et al. [19], who emphasized the usefulness of CNNs for extensive agricultural monitoring and the significance of big datasets for enhancing model performance.

One important addition was made by Huu Quan Cap [22], who suggested a CNN-based system for categorizing illnesses that harm crops. With an astounding accuracy of 96.3%, this model highlights how flexible CNNs are at diagnosing illnesses from visual cues in plant photos [23,24]. In agriculture, sorghum crop detection is becoming more and more significant, especially because of its potential for medicinal use. Recent developments in deep learning have improved the accuracy of image recognition and classification considerably, meeting the urgent demand for efficient techniques for automatic crop identification. Using a deep learning model and K-fold cross-validation, this study shows enhanced detection and classification performance on a dataset of about 50,000 photos of sorghum leaves [25-28].

Although plant diseases can cause significant losses and a decline in biodiversity, the agricultural industry is essential for both economic growth and the quality of food. Mitigating economic effects and enhancing food production depend on early diagnosis using automated methods. Plant disease detection and identification have undergone a substantial transformation thanks to recent developments in machine learning and deep learning [29-31]. They developed a framework that emphasizes feature extraction and classification for precise disease identification. It uses computer vision in conjunction with a variety of machine learning methods.

The potential of machine learning (ML) and deep learning (DL) techniques to improve accuracy and efficiency over manual methods in the identification of plant diseases [32]. This procedure can be streamlined by using automated disease detection techniques, which will save human labor and enable faster identification of damaged leaves. By improving plant disease classification accuracy over current methods, the suggested algorithm seeks to enable more efficient plant health monitoring and management [33].

Crops are susceptible to diseases brought on by things like pests and climate change [34], which can cause serious harm. Even though several systems have been created for the early diagnosis of disease, traditional techniques frequently need laborious, prone to error manual feature extraction and segmentation [35-37].

Plucking point localization, motion planning, and efficient tea shot recognition are critical to the robotic harvesting of premium tea. To improve efficiency and accuracy, this robotic harvesting system combines point cloud analysis, deep learning, and spatial path planning [20]. In response to the growing need for smart farming technologies that use AI for pattern recognition, this research introduces a novel continuum robot arm for cherry tomato harvesting. In order to do the task in the shortest amount of time possible, this study investigates the optimization of task partitioning for kiwifruit harvesting using several robot arms. Since it is assumed that every robot arm is capable of harvesting fruits, it is possible to assign duties among the robots in a flexible manner, increasing the speed and efficiency of the harvesting process [21].

Aforementioned groups have experimented with different deep learning methods; among them, ResNet50 has been quite successful at identifying crops, including ones other than root vegetables. We particularly concentrated on underground vegetables, such as beetroot, in our work. The beetroot was harvested using a robotic arm that turned on when the crop was ready to be harvested.

4. MATERIAL METHOD

In this work, Initially the images captured by the camera are transmitted to a microcontroller for further image processing utilizing the ResNet-50 architecture. The system analyzes the images to determine if the beetroot is at the appropriate harvesting stage. If the harvesting stage is detected, the robotic arm is activated to pluck the beetroot. If not, the system proceeds to capture and analyze the next image. In this process, real-time coordinates from the images are not communicated to the robot; the focus is solely on detecting the harvesting stage and triggering the arm's activation and the proposed diagram is shown in Figure 1.

Table 1. *Requirements*

SlNo.	Particulars
1.	Raspberry Pi 4, 8GB RAM
2.	Arduino UNO
3.	Logitech Camera Module 720p
4.	16X2 LCD
5.	Chassis, BO Motor & Wheels
6.	3.7V Battery

TensorFlow and OpenCV are essential software libraries installed on Raspberry Pi OS, enabling efficient deep learning and computer vision applications for real-time image processing and analysis.

Table 1 outlines the essential hardware and software components required for the robotic harvesting system, including a Raspberry Pi 4, Arduino UNO, camera module, motors, batteries, and TensorFlow with OpenCV for machine learning and computer vision tasks.

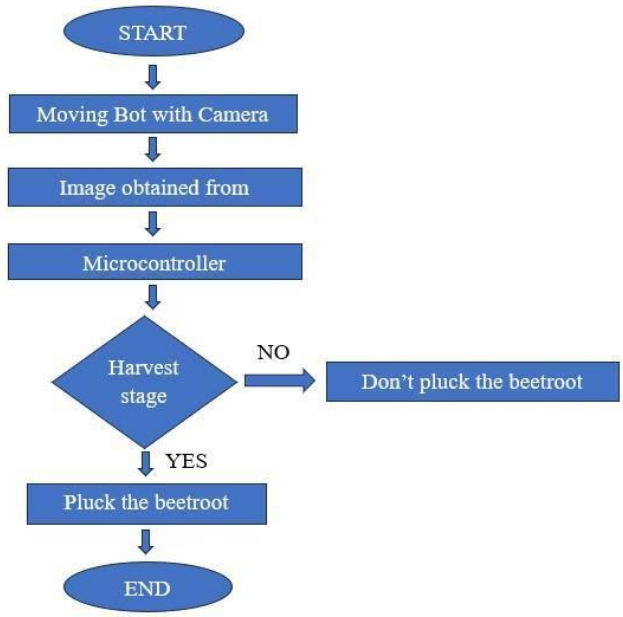


Figure 1. *Proposed Flow Diagram*

4.1. Image Processing Using CNN

The ResNet-50 architecture, a particular kind of Convolutional Neural Network (CNN) well-known for its effectiveness in image detection and classification applications, is the foundation of our AI-powered beetroot harvesting system. ResNet-50 is a 50-layer network that makes use of residual connections to help with training deep networks while reducing the issue of vanishing gradients. This property is essential for facilitating efficient learning in extremely deep networks. Built on the ResNet50 architecture and employing transfer learning with pre-trained weights from ImageNet, the ResNet50 model is a variation of

the ResNet family. Table 2 shows the detailed architecture breakdown of the ResNet-50 model, highlighting the number of layers in each block along with corresponding filter sizes.

Table 2. *Resnet 50 Architecture*

Layer Type	Number of Layers	Filter Size/Units
Convolutional Layer	1	64 filters
Residual Block 1	3	64 filters
Residual Block 2	4	128 filters
Residual Block 3	6	256 filters
Residual Block 4	3	512 filters
Global Average Pooling	1	-
Global Average Pooling	1	-
Total	**50**	**-**

A batch normalization layer, a max pooling layer, and an initial convolutional layer usually make up ResNet50's 50 layers. There are 45 convolutional layers in total after that, ending with a single fully linked layer and a final average pooling layer. ResNet-50 is commonly employed in transfer learning, having been pre-trained on large datasets such as ImageNet. This pre-training allows it to acquire general features that can be tuned for specific applications, such as detecting when beetroots are ready for harvest. The model excels in extracting features for object localization and classification, serving as a backbone network for various object detection methods.

With an impressive top-5 error rate of less than 5% on ImageNet, ResNet-50 processes input images through its multi-layer structure, generating output predictions for class labels with remarkable accuracy. The architecture includes convolutional, batch normalization, activation, and pooling layers, each playing a vital role in enhancing the network's performance. The residual connections within ResNet-50 enable the effective training of deep networks, allowing it to recognize intricate details in images.

We applied transfer learning by using the ResNet-50 model pre-trained on the ImageNet dataset. This allowed us to utilize general image features the model had already learned such as edges, textures, and shapes which are useful across many visual tasks. To adapt the model to our beetroot detection application, we retained the earlier convolutional layers to preserve these foundational features and replaced the original classification head with a fully connected (dense) layer containing a single neuron and a sigmoid activation function. This enabled binary classification, identifying whether a beetroot is harvest-ready or not. We trained the model using the Binary Cross-Entropy (BCE) loss function and the Adam optimizer with a learning rate of 0.0001. For evaluation, we used various performance metrics including Accuracy, F1 Score, and Matthews Correlation Coefficient (MCC) to assess the quality of binary predictions.

We processed about 1,500 images from different parts of Karnataka for our application, evenly resizing them to 224 × 224 pixels. We used approaches for data augmentation to improve the diversity of the dataset. After then, the dataset was divided in a 70:20:10 ratio into training, testing, and validation sets. By utilizing the ResNet-50 architecture, this configuration represents a substantial breakthrough in agricultural technology and a potent instrument for precise, data-driven decision-making in our beetroot harvesting system and it is shown in Figure 2.

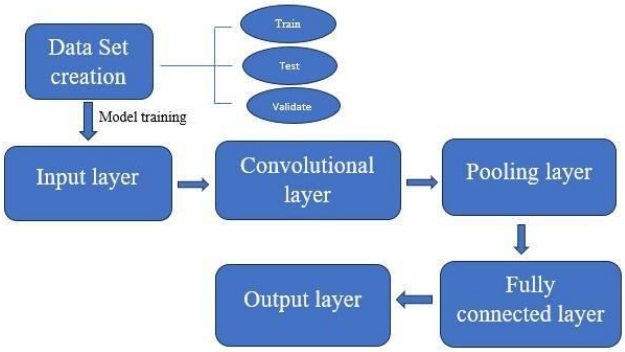


Figure 2. *Block Diagram of Image Processing using CNN*

4.2. Image Capturing Using Moving Bot

Figure 3 shows the integrated Raspberry Pi 4 with camera module, chassis, DC motors, LCD, batteries, and wheels, utilizing the outputs from our software development. This critical step ensured seamless functionality by aligning the physical setup with our software's image detection capabilities. Assembling these components marks a significant milestone in the completion of our image detection system, This makes use of the ResNet-50 design. Every component is necessary for the system to function as a whole. The LCD display gives the user feedback and real-time information, while the camera module takes pictures for processing and analysis. The Raspberry Pi 4 serves as the system's central processing unit, coordinating all of its functions. The battery supplies power to all components, ensuring mobility and functionality. The DC motors and wheels enable movement, allowing the system to navigate its environment, and the chassis offers structural support and stability for the assembled components. This integration not only enhances the system's adaptability but also significantly increases its utility in various applications. The hardware model receives input from the trained ResNet-50 model, facilitating effective image detection and analysis.

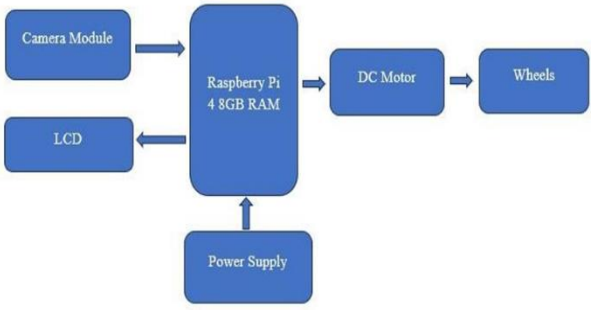


Figure 3. Block diagram of moving bot for capturing images

4.3. Equations

The following equations define key performance metrics used to evaluate the model's effectiveness in binary classification tasks. True Positive Rate (TPR) (1), also known as sensitivity or recall, measures the proportion of actual positives that are correctly identified. Specificity (SPC) (2) assesses the proportion of actual negatives that are correctly identified. Precision or Positive Predictive Value (PPV) (3) indicates the accuracy of positive predictions. Negative Predictive Value (NPV) (4) measures the accuracy of negative predictions. The False Positive Rate (FPR) (5) represents the proportion of negatives incorrectly classified as positives, while the False Discovery Rate (FDR) (6) is the ratio of false positives to the total positive predictions. False Negative Rate (FNR) (7) shows the proportion of actual positives that were missed. Accuracy (ACC) (8) calculates the proportion of correctly classified instances out of the total. The F1 Score (9) is a harmonic mean of precision and recall, balancing the two metrics.(10) refers to binary cross entropy.Finally, the Matthews Correlation Coefficient (MCC) (11) assesses the overall quality of binary classifications, accounting for true and false positives and negatives, providing a balanced measure even for imbalanced datasets

$$\text{TPR} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{SPC} = \frac{TN}{FP + TN} \tag{2}$$

$$\text{PPV} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{NPV} = \frac{TN}{TN + FN} \tag{4}$$

$$\text{FPR} = \frac{FP}{FP + TN} \tag{5}$$

$$\text{FDR} = \frac{FP}{FP + TP} \tag{6}$$

$$\text{FNR} = \frac{FN}{FN + TP} \tag{7}$$

$$\text{ACC} = \frac{(TP + TN)}{(P + N)} \tag{8}$$

$$\text{F1} = \frac{2TP}{(2TP + FP + FN)} \tag{9}$$

$$\text{BCE} = -(1 / N) \sum_{(i=1)}^{n} [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)] \tag{10}$$

$$\text{MCC} = ((\text{TP} \times \text{TN}) - (\text{FP} \times \text{FN})) / \sqrt{((\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN}))} . \tag{11}$$

5. RESULTS

We initially tested our image detection system by capturing images and processing them through the Raspberry Pi to evaluate its capability in detecting the harvesting stages of crops. The system performed well in a controlled environment, achieving good accuracy with the ResNet-50 architecture. However, during subsequent field tests in actual agricultural settings, the system demonstrated its adaptability by successfully identifying and classifying the harvesting stage under real-world conditions.



Figure 4. *Camera Module capturing live video of the crop*



Figure 5. *Prediction being displayed on LCD*

Figure 4 illustrates the camera module capturing live video of the crop, a critical component for detecting the readiness of the beetroot for harvesting. Initially, this system was tested on a Raspberry Pi equipped with the camera module to ensure accurate image processing and model performance. Figure 5 shows the prediction being displayed on the LCD, providing real-time updates on the crop's readiness for harvest. This feature allows farmers to easily monitor the system's decision-making process.



Figure 6. Non harvesting stage



Figure 7. *Harvesting stage*

Figure 6 demonstrates the detection of a non-harvesting stage, where the beetroot is not yet ready for harvest. In contrast, Figure 7 illustrates the detection of the harvesting stage, where the system determines that the beetroot is ready to be plucked by the robotic manipulator.



Figure 8. *Arm plucking the beetroot*

Figure 8 illustrates the robotic arm plucking the beetroot from the ground after the harvesting stage has been detected. Upon confirming that the beetroot is ready for harvest, the robotic arm is activated to perform the operation of removing the beetroot from its soil, demonstrating the integration of technology in modern agricultural practices.



Figure 9. *Harvested beetroot*

After the arm successfully plucks the beetroot from the soil, the harvested beetroot is displayed in Figure 9, showcasing the automated harvesting system in agricultural field.

TARGET / OUTPUT	Harvest	Non Harvest	SUM
Harvest	61 55.96%	1 0.92%	62 98.39% 1.61%
Non Harvest	0 0.00%	47 43.12%	47 100.00% 0.00%
SUM	61 100.00% 0.00%	48 97.92% 2.08%	108 / 109 99.08% 0.92%

Figure 10. *Confusion Matrix*

Figure 10 presents the confusion matrix, where an accuracy of 99.08% and a precision of 98.39% were achieved. This high level of performance underscores the effectiveness of the implemented model in accurately classifying the harvesting stage of the beetroots.

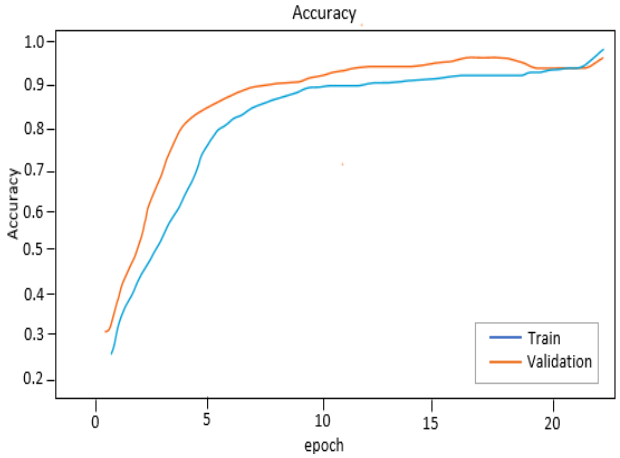


Figure 11. *Accuracy Curve*

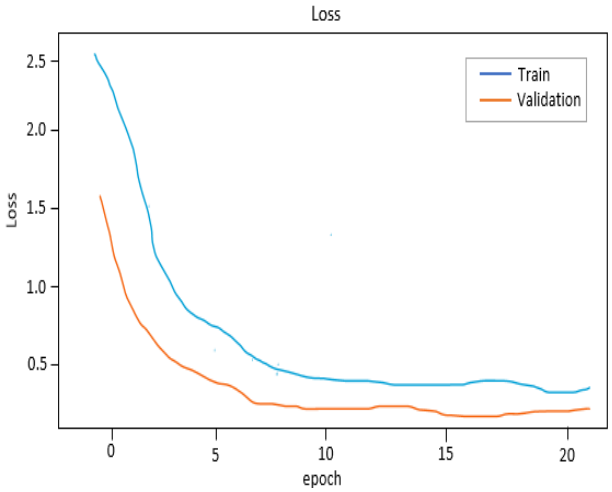


Figure 12. *Loss Curve*

Figure 11 shows the accuracy curve of the ResNet50 model, which starts with a gradual increase from 0.4 and rises steadily to 0.9. After reaching this level, the accuracy stabilizes, maintaining consistency between 0.9 and 0.9908 across different epochs. Similarly, Figure 12 illustrates the loss curve, which begins at 2.75 and decreases steadily until it reaches 0.0092.

Table 3. Performance metrics

Measure	Value
Sensitivity	1.0000
Specificity	0.9792
Precision	0.9839
Negative Predictive Value	1.0000
False Positive Rate	0.0208
False Discovery Rate	0.0161
False Negative Rate	0.0000
Accuracy	0.9908
F1 Score	0.9919

Table 3 highlights key performance metrics of the model, including a sensitivity of 1.0000, specificity of 0.9792, precision of 0.9839, and an accuracy of 0.9908, demonstrating the model's high effectiveness and reliability. Further refinements in model training and additional field trials are expected to enhance accuracy and reliability across diverse agricultural settings.

5.1. Field Testing and Environmental Observations

The system was field-tested at three locations across Karnataka, India: Mullur in H.D. Kote Taluk, Mysuru District; Devarahalli in Gundlupet Taluk, Chamarajanagar District; and a test site in Chikmagalur District.Tests were conducted during daytime under normal sunlight in moist, fertile soil conditions. In these settings, the ResNet-50 model performed as expected, accurately detecting harvest-ready beetroots, and the robotic arm successfully plucked the crops. However, under cloudy conditions with reduced lighting, the model exhibited misclassifications due to poor contrast between the crop and background. Additionally, the robotic gripper was optimized for loose soil and faced difficulty in hardened soil, where more power is required for effective harvesting.

5.2. Comparison with Existing Literature

Unlike previous studies that mainly focus on detecting surface or above-ground crops using traditional machine learning or standard CNN models, our approach specifically addresses the challenges of identifying subterranean crops like beetroot. As detailed in Table 4, our system achieves not only higher detection accuracy and improved performance under real-field conditions, but also integrates harvesting-stage recognition with a robotic arm for automated beetroot collection. This complete end-to-end solution highlights the practical potential of automation in underground crop harvesting.

Table 4. *Comparison table of our work with existing literature*

Paper	Technique Used	Crop Type	Detection Accuracy	Field Testing	Automation Level	Key Limitations
Sunil S. Harakannanavar et al., 2022	Computer Vision + ML	Multiple (General leaves)	~94%	No	Semi-automated	Lacks real-time deployment
Md. Manowarul Islam et al., 2023	CNN + Web App	Tomato, Potato, Corn	98%	Yes (Web interface)	Fully automated	Limited to certain crops
Sue Han Lee et al., 2019	Deep Learning (CNN)	44 Plant species	High (Over 97% in many cases)	No	Semi-automated	High dependence on dataset quality
Paul Shekonya Kanda et al., 2021	Deep Learning	Leaf datasets (General)	99.6%	No	Semi-automated	Model tested on controlled data only
Jing Hu et al., 2018	Multiscale Fusion CNN	32-class leaf DB	96.3%	No	Semi-automated	No real-world validation
Apostolos Xenakis et al., 2020	CNN in IoT Robotic System	Tomato, Grape	~95%	Yes (IoT + Robotics)	Automated	Computational overhead in real-time IoT
Dhananjay Bisen, 2020	Deep CNN	Leaf images	~96%	No	Semi-automated	Model accuracy drops under poor lighting
S. P. Mohanty et	Deep	14 crop	99.35%	No	Semi-	No real-time app

al., 2016	CNN (Transfer Learning)	species	(top-5)		automated	integration
Kalpana P. et al., 2024	Swin Transformer + Residual CNN	Multiple (ImageNet/ PlantVillage)	Up to 99.2%	No	Semi-automated	High training complexity
J., A. et al., 2022 (Agronomy)	Deep Learning (CNN variants)	Tomato, Potato	~97%	No	Semi-automated	Needs cloud or high compute for inference
Our Work	ResNet-50 + Robotic Arm	Beetroot	99.08%	Yes (Real Farms)	End-to-End: Detection + Harvesting	Performs well in moist soil; challenges in low light

While previous groups have explored different deep learning techniques for crop detection, their focus has largely remained on surface-level crops. In contrast, our work uniquely targets subterranean crops specifically beetroot by combining harvesting-stage detection via ResNet-50 with a robotic arm that autonomously plucks the crop when identified as ready to harvest. This integration was successfully tested in real-world conditions across three distinct regions in south Karnataka, India.

6. CONCLUSION

This work offers a ground-breaking approach to modernizing agricultural techniques, specifically transforming the traditional method of beetroot harvesting through the use of advanced technologies like Raspberry Pi hardware and the ResNet-50 architecture. By capturing images from a camera, the system processes them to determine whether the beetroot is ready for harvest. If deemed ready, a robotic manipulator is triggered to pluck the beetroot from the ground, fully automating the harvesting process. The ResNet-50 architecture, known for its deep learning capabilities, played a crucial role in training the model to accurately identify the ideal stage for beetroot harvesting. This model was integrated into a robotic system controlled by Raspberry Pi, further enhancing automation. One of the project's standout achievements was the successful integration of an LCD, which provided real-time information about the condition and readiness of the beetroot. This allowed farmers to remotely monitor the harvesting process and make informed decisions, greatly enhancing system usability and productivity. The precision in identifying the optimal harvesting stage significantly reduced crop waste while increasing overall production, promoting a more sustainable farming approach.

In addressing real-world challenges faced by farmers, such as labor shortages and cost-effectiveness, the work automated the harvesting process, thereby reducing reliance on manual labor, easing the workload, and improving efficiency. Additionally, the incorporation of cutting-edge technologies like robotics and AI optimized resource use, leading to more economical farming methods. In summary, this work demonstrated the immense potential of artificial intelligence and robotics to revolutionize agriculture, paving the way for a more efficient, productive, and sustainable future in subterranean crop farming and beyond.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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