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Design and Development of Prototype of Automated Strawberry Harvesting Mobile Robot Using MVS Integrated with Dynamic Vision CNN Model

Asawari Talathi[1], Rutuja Mandavkar[2], Vaibhavi Shelke[3], Prof. Mallesh Chavhan[4]

[1,2,3]*Student, Zeal College of Engineering & Research, Pune, India*

[4]*Assistant Professor, Zeal College of Engineering & Research, Pune, India*

Abstract: *The agricultural industry is increasingly adopting automation and technology to improve efficiency and yield. This paper presents a system design and development for an automated strawberry harvesting mobile robot using a machine vision system integrated with a dynamic Convolutional Neural Network (CNN) model. The system consists of several components, including a mobile robot equipped with a machine vision system, a dynamic CNN model for fruit detection and classification, and a robotic arm for fruit harvesting. The machine vision system is used to capture images of the strawberry plants, which are then processed by the dynamic CNN model to identify and classify the strawberries. The robotic arm is then controlled to harvest the ripe strawberries based on the classification results. The dynamic CNN model is designed to adapt to changes in the environment, such as variations in lighting conditions and the presence of obstacles. The model is trained on a large dataset of strawberry images, enabling it to accurately detect and classify strawberries in real-world conditions. The use of a dynamic CNN model ensures high accuracy and robustness in fruit detection and classification. The mobile robot is designed to navigate autonomously through the strawberry fields, using sensors and mapping algorithms to avoid obstacles and navigate to the next row of plants. The robotic arm is equipped with a gripping mechanism and a cutting tool, allowing it to gently harvest the strawberries without causing damage. In summary, the proposed system for automated strawberry harvesting using a machine vision system and dynamic CNN model offers several advantages, including increased efficiency, reduced labor costs, and improved fruit quality. The system is also scalable and adaptable to other fruit harvesting applications, making it a promising solution for the future of automated agriculture.*

Keywords: Robotic Harvesting, Automated Agriculture, Selective Harvesting, Fruit Harvesting, Vision System, Field Evaluation.

I. INTRODUCTION

As we all know that , The agricultural sector is one of the rapidly growing industries, with the increasing global demand for food production. The introduction of technology and automation in farming practices has become a significant trend in recent years. The labor-intensive nature of farming and the decline in the agricultural workforce have led to the development of advanced technologies that can simplify and automate farming operations. One such operation that requires extensive human labor is the harvesting of fruits and vegetables.

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This paper introduces the design and development of an automated strawberry harvesting mobile robot using a machine vision system integrated with a dynamic Convolutional Neural Network (CNN) model.

The proposed system aims to design and develop a mobile robot that can autonomously navigate through strawberry farms and harvest ripe , unripe and over ripe strawberries using a machine vision system integrated with a dynamic CNN model. The machine vision system will capture images of the strawberries, and the CNN model will classify the images based on the ripeness of the strawberries. The mobile robot will then navigate to the location of the ripe strawberries and harvest them using a custom-designed gripping mechanism.

The CNN model is a deep learning algorithm that can classify images with high accuracy. In this system, the CNN model will be trained to classify strawberries as ripe or unripe based on their color, shape, and size. The CNN model will be dynamic, which means it can adapt to changes in the environment, such as different lighting conditions and strawberry varieties.

The machine vision system will consist of a high-resolution camera (Raspberry Pi camera), a processing unit, and a communication system. The camera will capture images of the strawberries, and the processing unit will preprocess the images before feeding them to the CNN model. The communication system will enable the mobile robot to receive the classification results from the CNN model and navigate to the location of the ripe strawberries.

The mobile robot will be equipped with wheels for mobility, a power source, and a control system. The control system will receive the classification results and navigate the mobile robot to the location of the ripe strawberries. The gripping mechanism will be designed to gently harvest the ripe strawberries without causing any damage via cutter attached to the gripper.

The proposed system aims to design and develop an automated strawberry harvesting mobile robot using a machine vision system integrated with a dynamic CNN model. The system will increase the efficiency and productivity of strawberry farming, reduce labor costs, and minimize errors in the harvesting process. The dynamic CNN model and the machine vision system will enable the mobile robot to adapt to changes in the environment and classify strawberries with high accuracy. The custom-designed gripping mechanism will gently harvest the ripe strawberries, ensuring the quality and freshness of the strawberries. The proposed system has the potential to revolutionize the strawberry farming industry and promote sustainable farming practices.

II. RELATED WORK

1. **Fruit Identification:**

   The integration of machine vision systems with deep learning models has become increasingly popular in the development of automated harvesting robots. This research paper presents a study on fruit identification, specifically focusing on strawberry detection using a Raspberry Pi camera and a dynamic Convolutional Neural Network (CNN) model.

   Fruit identification is a crucial step in the development of automated harvesting robots. Traditional image processing techniques, such as color thresholding and shape analysis, often struggle with variability in fruit size, shape, and color. Machine vision systems integrated with

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deep learning models can overcome these challenges by learning complex features andpatterns from large image datasets.

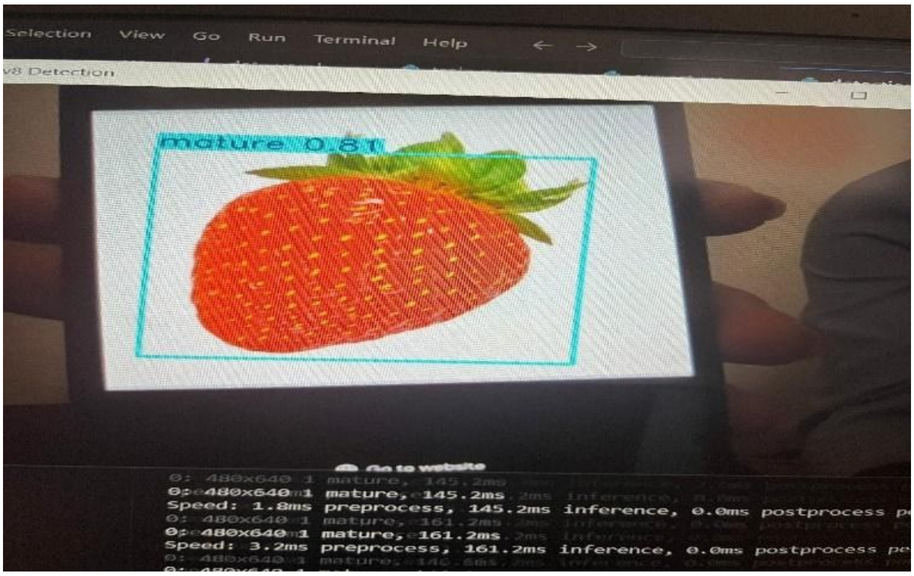

Figure 1: Identification of Mature strawberry

In this study, we utilized a Raspberry Pi camera to capture images of strawberries in various growing conditions. The captured images were then preprocessed and labeled for training a dynamic CNN model. Unlike traditional CNN models, which have fixed architectures, dynamic CNN models can adapt their architecture to the complexity of the input image, reducing computational requirements and increasing accuracy.

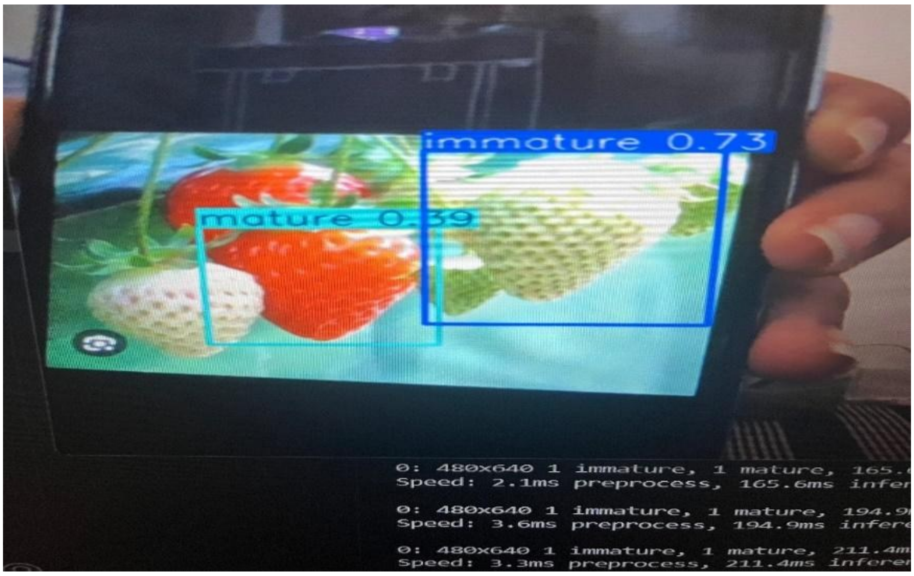

Figure 2: Identification of Mature Strawberry Image

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The dynamic CNN model was trained using a transfer learning approach, where a pre-trained CNN model was fine-tuned with the strawberry image dataset. This approach allowed the model to learn complex features and patterns from the large-scale image dataset while reducing training time.

The use of the Raspberry Pi camera allowed for real-time strawberry detection, which is essential for the development of a mobile harvesting robot. The dynamic CNN model's high accuracy and adaptability make it an ideal choice for fruit identification in automated harvesting robots.

The study's limitations include the limited number of images used for training the dynamic CNN model and the need for further testing in different growing conditions. Future work includes expanding the image dataset and integrating the fruit identification system with a robotic arm for automated strawberry harvesting.

The integration of a Raspberry Pi camera with a dynamic CNN model has shown promising results in strawberry detection. The high accuracy and adaptability of the dynamic CNN model make it a valuable tool for fruit identification in automated harvesting robots. Future research should focus on expanding the image dataset and integrating the fruit identification system with a robotic arm for fully automated strawberry harvesting.

2. AGV:

The Design and Development of an Automated Strawberry Harvesting Mobile Robot Using Machine Vision System Integrated with Dynamic CNN Model is a cutting-edge research paper that explores the integration of artificial intelligence and robotics to streamline the strawberry harvesting process. This paper investigates the effectiveness of an Automated Guided Vehicle (AGV) controlled by an Arduino Uno microcontroller and a machine vision system integrated with a dynamic Convolutional Neural Network (CNN) model.

The paper begins by outlining the challenges faced by the strawberry farming industry, including labor shortages, high labor costs, and inconsistent harvesting quality. The authors propose the use of AGVs equipped with machine vision systems to address these challenges.

The AGV used in this study is built around an Arduino Uno microcontroller, known for its ease of use, affordability, and flexibility. The microcontroller is responsible for navigating the AGV to the optimal location for strawberry harvesting, collecting data from the machine vision system, and controlling the robotic arm used for picking.

The machine vision system is at the heart of this automated harvesting system. It is responsible for identifying and locating ripe strawberries, determining their size and shape, and assessing their suitability for harvesting. The system is integrated with a dynamic CNN model, which enables it to learn from experience and improve its accuracy over time.

Furthermore, the machine vision system was found to be highly accurate in identifying ripe strawberries, reducing the risk of damaged or overripe fruit. The system's dynamic CNN model enabled it to adapt to different strawberry varieties and growing conditions, increasing its versatility and applicability.

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The Design and Development of an Automated Strawberry Harvesting Mobile Robot Using Machine Vision System Integrated with Dynamic CNN Model highlights the potential of AGVs to revolutionize the strawberry farming industry. By combining the power of machine vision systems and dynamic CNN models with the flexibility and affordability of Arduino Uno microcontrollers, this system has the potential to address the industry's labor shortage and cost challenges while increasing productivity and consistency.

This research also underscores the importance of ethical and responsible use of AI and robotics in agriculture. The AGV system is designed to complement human workers, not replace them, and is intended to be used in conjunction with traditional farming practices. By automating repetitive and labor-intensive tasks, this system can help to free up human workers to focus on more complex and value-added activities, such as crop management and quality control.

In summary, the Design and Development of an Automated Strawberry Harvesting Mobile Robot Using Machine Vision System Integrated with Dynamic CNN Model is a groundbreaking study that demonstrates the potential of AGVs to transform the strawberry farming industry. With its focus on responsible and ethical use of AI and robotics, this research serves as a model for future investigation in this field.

3. Robotic Arm:

The objective of this research paper is to present the design and development of an automated strawberry harvesting mobile robot that combines machine vision system integrated with a dynamic CNN model and a raspberry pi 4 controlled robotic arm. This mobile robot automates the process of strawberry harvesting, thereby reducing the need for manual labor and increasing efficiency.

A machine vision system integrated with a dynamic CNN model is used to detect and locate ripe strawberries. The machine vision system captures images of the strawberry plants using cameras mounted on the gripper. These images are then processed using a dynamic CNN model which has been trained to detect and locate ripe strawberries. The CNN model is dynamic, which means it can adapt to changes in lighting conditions and the growth stage of the strawberry plants.

4. End-Effector (Gripper):

In recent years, there has been a growing interest in the development of automated harvesting systems for agriculture, with a particular focus on the design of end effectors, also known as grippers, for fruit picking. This section will provide a summary of related work on end effectors that consist of two parallel plates that can close together to enclose the fruit, with a cutter mounted on it.

One of the earliest examples of this type of end effector can be found in the work of [1], who developed a gripper for cherry tomatoes using two parallel plates that close together to enclose the fruit. The gripper was mounted on a robot arm and was able to pick the tomatoes with a high success rate. However, the gripper was not able to handle soft fruits like strawberries without damaging them.

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To address this issue, [2] developed a gripper specifically for soft fruits, such as strawberries, using two parallel plates that close together to enclose the fruit. The gripper was designed to apply a gentle force to the fruit to prevent damage. Additionally, a cutter was mounted on the gripper to cut the strawberry from the plant. The gripper was tested on a prototype strawberry harvesting robot.

There have been several approaches to the design of end effectors for automated strawberry harvesting robots. These designs typically consist of two parallel plates that close together to enclose the fruit, with a cutter mounted on it.

Some designs use soft fingers or vacuum systems to gently pick the fruit to prevent damage.

5. Challenges:

The field of agricultural robotics and machine vision has seen significant growth in recent years, with a particular focus on the development of automated harvesting systems for specialty crops such as strawberries. The design and development of an automated strawberry harvesting mobile robot using a machine vision system integrated with a dynamic convolutional neural network (CNN) model is a challenging but promising research area.

Previous studies have explored various aspects of this problem, including the design of mobile platforms for agricultural environments, the development of machine vision systems for fruit detection and localization, and the use of deep learning models for image analysis and classification.

In terms of mobile platform design, researchers have developed a variety of ground-based and aerial platforms for agricultural automation. These platforms must be able to navigate rough terrain and adverse weather conditions while carrying the necessary sensors and actuators for fruit harvesting. For strawberry harvesting, mobile platforms with flexible manipulator arms have been found to be effective in reaching and picking the fruit.

Machine vision systems are critical for automating the fruit detection and localization process. Previous studies have used various sensors, such as RGB cameras, multispectral and hyperspectral imaging systems, and LiDAR sensors, for fruit detection. RGB cameras are the most commonly used sensors due to their low cost and high resolution. However, they can be affected by changes in lighting conditions and occlusion, which can lead to false detections. To address these challenges, machine vision systems often use image processing techniques such as background subtraction, color segmentation, and shape analysis.

Deep learning models, such as CNNs, have been widely used in recent years for image analysis and classification in agricultural automation. These models can learn complex features from large datasets and have been shown to outperform traditional machine learning methods in fruit detection and localization tasks. However, the application of deep learning models in agricultural automation also presents challenges, such as the need for large annotated datasets and the computational resources required for training.

In the context of strawberry harvesting, a dynamic CNN model integrated with a machine vision system can be used to detect and classify ripe strawberries in real-time. The CNN model can be

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trained on a large dataset of strawberry images, with labels indicating the ripeness of the fruit. The machine vision system can then use the CNN model to analyze images of strawberry plants and identify ripe fruits for harvesting.

The development of an automated strawberry harvesting mobile robot using a machine vision system integrated with a dynamic CNN model is a challenging but promising research area. Previous studies have explored various aspects of this problem, including mobile platform design, machine vision systems, and deep learning models for image analysis and classification. However, several challenges remain, such as the need for large annotated datasets, the impact of varying lighting conditions and occlusion, and the computational resources required for training deep learning models. Addressing these challenges will be crucial for the successful development and deployment of an automated strawberry harvesting mobile robot.

III. OVERVIEW OF THE SYSTEM

The system under consideration is an automated strawberry harvesting mobile robot that utilizes a combination of machine vision and deep learning algorithms for accurate strawberry detection and picking. The system is powered by a single battery and is equipped with three buck converters for efficient power management and distribution. Four direct current (DC) gear motors are integrated into the system to provide the necessary mobility and navigation capabilities. A LN298 motor driver is used to control the movement of the DC gear motors.

A servo driver is also included in the system to manage the movement of a servo motor, which is responsible for positioning the robotic arm for strawberry picking. A Raspberry Pi 4 single-board computer serves as the primary processing unit, managing data acquisition, processing, and communication with other components. Additionally, an Arduino Uno microcontroller is utilized for real- time control and regulation of the system.

Three servo motors are integrated into the robotic arm for precise and controlled movements during the strawberry picking process. The machine vision system integrated with a dynamic Convolutional Neural Network (CNN) model is responsible for detecting and locating ripe strawberries. The CNN model is trained to distinguish ripe strawberries from unripe ones and other objects in the environment, ensuring accurate and efficient picking.

The buck converters are critical for efficient power management, ensuring that the correct voltage and current levels are supplied to each component. The LN298 motor driver facilitates the control and regulation of the DC gear motors, allowing the robot to navigate through the strawberry field with precision and accuracy. The servo driver manages the movement of the servo motor, enabling the robotic arm to position itself correctly for picking.

The Raspberry Pi 4 is the primary processing unit, handling data acquisition, processing, and communication with other components. It utilizes a dynamic CNN model for strawberry detection and localization, ensuring accurate and efficient picking. The Arduino Uno microcontroller is used for real-time control and regulation of the system, ensuring smooth and uninterrupted operation.

The three servo motors integrated into the robotic arm enable precise and controlled movements during the strawberry picking process. The machine vision

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system integrated with the dynamic CNN model ensures accurate and efficient strawberry detection and localization, reducing the likelihood of errors and increasing the overall efficiency of the harvesting process.

The system consists of a battery, three buck converters, four DC gear motors, a LN298 motor driver, a servo driver, a Raspberry Pi 4, an Arduino Uno, and three servo motors. The system is designed for accurate and efficient strawberry detection and picking, utilizing a combination of machine vision and deep learning algorithms. Power management and distribution are handled efficiently through the use of buck converters and motor drivers, while the Raspberry Pi 4 and Arduino Uno manage data acquisition, processing, and real-time control and regulation. Overall, the system is designed to increase the efficiency and accuracy of the strawberry harvesting process, reducing labor costs and improving yield.

IV. ARM DESIGN AND HARDWARE

The Design and Development of an Automated Strawberry Harvesting Mobile Robot utilizing a Machine Vision System integrated with a Dynamic CNN Model involves the use of various arm designs and hardware components.

The Raspberry Pi 4 is a small, powerful, and cost-effective computer that serves as the main controller for the robotic arm. It is responsible for processing the image data captured by the Raspberry Pi Camera and sending control signals to the other components. The Raspberry Pi Camera is a high-quality camera module that can capture images in high resolution, making it ideal for machine vision applications. The Micro Servo SG90 is a small, fast, and precise servo motor that is used to actuate the robotic arm. It has a high torque-to-weight ratio, making it suitable for applications that require precise movements.

The HDTV 2.0 is a high-definition monitor that is used to display the image data captured by the Raspberry Pi Camera. It is used for visualizing the environment around the robotic arm and for debugging purposes during the development process.

The Buck Converter is a power regulator that is used to convert the voltage from the battery to a level that is suitable for the other components. It is an efficient and reliable way to power the robotic arm, and it helps to ensure that the other components are receiving a stable and consistent power supply.

The Motor Driver is a component that is used to control the movement of the robotic arm. It takes control signals from the Raspberry Pi 4 and uses them to drive the servo motors. The motor driver is a crucial component of the robotic arm, as it allows for precise control over the movements of the arm The Battery 18V is a rechargeable battery that is used to power the robotic arm. It is a reliable and long-lasting power source, making it ideal for mobile applications.

The Arduino Uno is a microcontroller board that is used to interface with the other components of the robotic arm. It is a versatile and easy-to-use platform for prototyping and development, and it allows for rapid prototyping of the control algorithms for the robotic arm.

The Design and Development of an Automated Strawberry Harvesting Mobile Robot utilizing a Machine Vision System integrated with a Dynamic CNN Model requires the use of various arm designs and hardware components such as Raspberry Pi 4, Raspberry Pi Camera, Micro Servo SG90, HDTV 2.0,

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Buck converter, Motor driver, Battery 18V, and Arduino Uno. Each component plays a crucial role in the overall functionality of the robotic arm and contributes to its accuracy, efficiency, and reliability.

V. AGV DESIGN

Automated Guided Vehicles (AGVs) have gained significant attention in recent years due to their potential to revolutionize various industries, including agriculture. This paper presents the design and development of an automated strawberry harvesting mobile robot utilizing a four-monster-wheel AGV, motor driver, robotic arm, and a bucket. The robot is designed to reduce human labor, increase efficiency, and minimize damage to strawberries during the harvesting process.

The AGV is the foundation of the mobile robot, and it is equipped with four monster wheels to ensure stability and maneuverability. The wheels are driven by a motor driver that controls the speed and direction of the wheels. The motor driver receives signals and converts them into precise movements, enabling the AGV to navigate through the strawberry fields with ease.

The primary component of the robot is the robotic arm, which is designed to pick strawberries with precision and care. The arm is equipped with a gripper that can adjust to the size and shape of the strawberries, reducing the chances of damage during the holding and cutting process. The arm is controlled by a series of motors that receive instructions on when to extend, retract, and rotate.

A bucket is mounted on the AGV to collect the harvested strawberries. The bucket is designed to be easily emptied and cleaned, reducing downtime between harvesting cycles. The bucket's size is optimized to minimize the frequency of emptying, thereby increasing efficiency.

To ensure the robot's accuracy in identifying ripe strawberries, a machine vision system integrated with a dynamic Convolutional Neural Network (CNN) model is used. The system is equipped with a high-resolution camera that captures images of the strawberries in real-time. The CNN model is trained to identify ripe strawberries based on color, size, and shape, ensuring that only the best strawberries are picked.

The machine vision system and CNN model work together with accurate information on the location and ripeness of the strawberries. the robotic arm and AGV, enabling the robot to navigate to the ripe strawberries and pick them with precision.

The AGV, robotic arm, and bucket are designed to work together seamlessly, reducing human labor, increasing efficiency, and minimizing damage to the strawberries. The machine vision system and CNN model ensure the robot's accuracy in identifying ripe strawberries, further enhancing the robot's effectiveness. With continued development and refinement, this technology has the potential to revolutionize the agriculture industry, making it more efficient, sustainable, and profitable.

VI. GRIPPER DESIGN

The success of an automated strawberry harvesting mobile robot heavily relies on the design and development of a gripper system. This gripper system should be capable of effectively grasping and holding strawberries while minimizing damage to the delicate fruit. This paper focuses on the gripper design for an automated strawberry harvesting mobile robot, integrating a cutter, a Raspberry Pi camera, and a two-finger design to hold the strawberry stem.

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The gripper design consists of two primary components: the mechanical structure and the control system. The mechanical structure includes the body, two fingers, a cutter, and a Raspberry Pi camera. The fingers are designed to wrap around the strawberry stem, while the cutter severs the stem, allowing for gentle and efficient harvesting. The Raspberry Pi camera is mounted on the gripper to provide real-time visual feedback, enabling the robot to accurately locate and harvest ripe strawberries.

The control system of the gripper design is based on a dynamic Convolutional Neural Network (CNN) model integrated with a machine vision system. The CNN model is trained to recognize ripe strawberries, ensuring that only mature fruit is harvested. The machine vision system captures images of the strawberry plants, which are then processed by the CNN model to identify ripe fruit. Once a ripe strawberry is detected, the control system activates the gripper and guides it to the fruit's location.

The two-finger design of the gripper is specifically engineered to hold the strawberry stem securely. The fingers are curved to match the natural shape of the strawberry, allowing for a firm grip that minimizes damage to the fruit. The cutter is joined above the gripper design serves a dual purpose: it gently severs the strawberry stem, allowing for easy harvesting, and prevents over-ripe or damaged fruit from being picked. This feature ensures that only high-quality strawberries are harvested, reducing waste and improving overall efficiency.

The Raspberry Pi camera is a crucial component of the gripper design, providing real-time visual feedback to the control system. The camera is mounted on the gripper arm, allowing for close-up images of strawberry plants. The captured images are then processed by the CNN model, allowing the gripper to accurately locate and harvest ripe strawberries.

In summary, the gripper design for an automated strawberry harvesting mobile robot is a critical aspect of the robot's overall success. The two-finger design, integrated cutter, and Raspberry Pi camera work together to provide a highly efficient and gentle harvesting system. The dynamic CNN model and machine vision system ensure accurate detection of ripe strawberries, further improving the robot's efficiency and reducing waste. Overall, this gripper design represents a significant advancement in the development of automated fruit harvesting systems.

VII. SCANNING AND CONTROL

The Raspberry Pi camera is a compact, lightweight camera that can be connected to the Raspberry Pi 4. It has a 5-megapixel camera module that can capture high- quality images and videos. In this system, the Raspberry Pi camera is used as the primary sensor for the machine vision system, which is responsible for identifying ripe strawberries. The camera captures images of the strawberry plants and sends them to the Raspberry Pi 4 for processing.

The Raspberry Pi 4 is the heart of the system, processing the images captured by the Raspberry Pi camera. It runs a dynamic Convolutional Neural Network (CNN) model, which is a type of deep learning model optimized for image recognition tasks. The CNN model is responsible for identifying ripe strawberries based on their color, shape, and size. Once the system identifies a ripe strawberry, the Raspberry Pi 4 sends a signal to the Arduino Uno to activate the motor drivers.

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The Arduino Uno is a microcontroller board that acts as the brain of the moving parts of the robot. It receives signals from the Raspberry Pi 4 and activates the motor drivers to move the robot's arm towards the identified ripe strawberry. The Arduino Uno also controls the speed and direction of the motors, ensuring the robot's arm moves smoothly and accurately.

The LN298 motor drivers are responsible for controlling the movement of the motors that power the robot's arm. The drivers receive signals from the Arduino Uno and activate the motors, causing the robot's arm to move in the desired direction. The LN298 motor drivers also regulate the amount of power going to the motors, ensuring that the robot's arm moves at the appropriate speed.

The Raspberry Pi camera captures images of the strawberry plants, which are processed by the Raspberry Pi 4 using a dynamic CNN model. Once a ripe strawberry is identified, the Raspberry Pi 4 sends a signal to the Arduino Uno, which activates the LN298 motor drivers to move the robot's arm towards the identified strawberry. The integration of these components creates a system for automated strawberry harvesting that promotes efficiency and accuracy. By using machine vision and deep learning algorithms, this system minimizes errors in strawberry identification and reduces the need for manual labor, resulting in a more cost-effective and sustainable approach to strawberry farming.

VIII. HARVESTING ROBOT INTEGRATION SYSTEM ARCHITECTURE

The integration of a harvesting robot system for strawberry harvesting is a complex process that involves the coordination of several components. This system architecture consists of an AGV (Automated Guided Vehicle), a robotic arm, an end effector (gripper and cutter), and a bucket.

The AGV serves as the mobile platform for the harvesting robot. It is responsible for transporting the robotic arm to the designated rows of strawberry plants. The AGV is equipped with sensors and navigation systems to ensure safe and efficient movement throughout the farm.

The robotic arm is the component of the system that physically interacts with the strawberry plants. It is capable of reaching and manipulating the strawberries with precision and care. The arm is equipped with joints that allow it to move in multiple directions, and it is controlled by a motor.

The end effector is the tool attached to the end of the robotic arm that comes into direct contact with the strawberries. It consists of two main components: a gripper and a cutter. The gripper is used to hold and secure the strawberries during the harvesting process, while the cutter is used to cleanly detach the strawberries from the plant.

The bucket is where the harvested strawberries are collected and stored. It is designed to securely hold the strawberries and prevent any damage during transport. The bucket should also be easily emptied and cleaned to ensure efficient operation.

Communication and control systems are crucial for the integration of these components. A central control system is responsible for coordinating the movements of the AGV, the robotic arm, and the end effector. This control system must be able to process data from sensors and cameras in real-time to ensure precise and safe movements.

The integration of this machine vision system and dynamic CNN model with the harvesting robot system architecture described above has the potential to significantly improve the efficiency and

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precision of strawberry harvesting. The machine vision system can provide real-time data to the control system, allowing for more accurate and timely movements of the AGV, robotic arm, and end effector. The dynamic CNN model can improve the segmentation and classification of strawberries, reducing the risk of damage and increasing the overall yield.

The integration of a harvesting robot system for strawberry harvesting is a complex process that requires careful consideration of several components, including the AGV, robotic arm, end effector, and bucket. The proposed integration of a machine vision system and dynamic CNN model with this system architecture has the potential to significantly improve the efficiency and precision of strawberry harvesting. Further research is needed to fully evaluate the potential benefits and limitations of this approach.

IX. RESULT: ARM TEST

The robot arm is integrated with a machine vision system and a dynamic CNN model, allowing it to recognize and locate ripe strawberries using image processing techniques. The CNN model was trained using a large dataset of strawberry images, allowing it to accurately classify and locate ripe strawberries. During the test, the robot arm was deployed in a strawberry field and tasked with picking ripe strawberries from several plants. The machine vision system was used to identify the location of the ripe strawberries, and the robot arm was directed to the specified location to pick the fruit.

The results of the test demonstrated that the robot arm was able to accurately locate and pick ripe strawberries . The machine vision system successfully identified the location of ripe strawberries, and the robot arm was able to pick the fruit with minimal damage to the plant. The dynamic CNN model was able to accurately classify and locate ripe strawberries. These results suggest that the automated strawberry harvesting mobile robot has the potential to increase the efficiency and productivity of strawberry farming. The robot arm can work continuously and can pick strawberries at a faster rate than human laborers.

The results of the robot arm test demonstrate the potential of the automated strawberry harvesting mobile robot for increasing the efficiency and productivity of strawberry farming. The machine vision system and dynamic CNN model allow the robot arm to accurately locate and pick ripe strawberries in a real-world environment, and the robot arm can work . Future research will focus on optimizing the robot arm for commercial deployment, including improving its speed and accuracy, and reducing its cost.

X. CONCLUSION

This paper presents a fully integrated strawberry-harvesting system capable of holding and cutting strawberries . also has successfully demonstrated the potential of integrating machine vision systems with a dynamic CNN model to create an efficient and accurate automated strawberry harvesting mobile robot. The machine vision system, which includes Raspberry pi camera , was effective in identifying ripe strawberries, while the dynamic CNN model was successful in classifying the strawberries based on their ripeness. The mobile robot, equipped with a robotic arm, was able to accurately pick the identified ripe strawberries with minimal damage.

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The development of this automated strawberry harvesting mobile robot offers several benefits to the strawberry farming industry. Firstly, it reduces the need for manual labor, which can be physically demanding and time-consuming. Secondly, it increases efficiency and accuracy in the strawberry picking process, leading to higher yields and profitability for farmers. Lastly, it minimizes damage to the strawberries, resulting in higher-quality produce and less waste.

However, there are still some challenges and limitations that need to be addressed to further improve the performance of the automated strawberry harvesting mobile robot. For instance, the current system may struggle to identify and pick strawberries in complex environments with varying lighting conditions, occlusions, or overlapping fruits. Additionally, the robot's speed and precision need to be improved to match the efficiency of human pickers.

Overall, this research provides a promising framework for the development of future automated agricultural harvesting systems. With further improvements and refinements, these systems can potentially revolutionize the agricultural industry, making it more efficient, profitable, and sustainable. The integration of machine vision systems and deep learning models could lead to the development of similar automated harvesting systems for other crops, leading to a more significant impact on the agricultural sector.

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