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CNN-Based dual arm robot for automated electronic component packing

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Abstract—Convolutional Neural Network Twin Arm Robot for Automated Packing of Electronic Components is an intellectual robotic system that is developed as a COCA (Collaborative Operation Control Agent) operational handler of the identification and packaging process of miniature size electronic components like resistors, LEDs, and capacitors. To achieve the correct and lightweight object recognition, the system has been constructed using the MobileNetV2 CNN model with the help of the Raspberry Pi microcontroller and a USB web camera. Upon object detection, two 4-DOF robotic arms are operated by Arduino Mega 2560 and servo motors as well as another one is operated by the servo motors to carry out the packaging. Twin-arm System: It is implemented to enhance the speed and accuracy of the assembly of the minute electronic components. The system uses two 5V SMPS units for power supply, and L-clamps provide mechanical stability. Overall, the integration of computer vision, deep learning and robotics in this project makes the system scalable and efficient and suitable for industrial applications.

1 Introduction

The electronics manufacturing sector requires automation of small and delicate parts such as resistors, LEDs, capacitors and microchips. Manual processes are very expensive, ineffective, and subject to mistakes, which has led to the need to automate them to enhance efficiency, speed, and accuracy. Arranging and wrapping of parts should be carried out with accuracy to eliminate flaws and wastage. Such activities, which are usually carried out by human workers or low-level robots, are the cause of fatigue, errors, and low productivity. Automation, in particular, AI, and robotics can help improve efficiency, accuracy, and minimize human error. Object recognition, which is one of the uses of CNNs, has been demonstrated to be a potentially viable solution to automating these processes. This project implements the robotic system based on CNNs and robotics to sort and package electronic parts automatically. It has a MobileNetV2 object recognition model and a Raspberry Pi to process and two 4-DOF robotic arms to be operated using an Arduino Mega 2560. The system separates the tasks among the robots to enhance speed and accuracy. This system focuses on achieving higher accuracy compared to systems that prioritize speed and multi-object detection, and thus it is applicable to structured environments [4] [11].

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The system is scalable, adaptable and flexible to various industrial settings. In this project, Convolutional Neural Network (CNN) is only used as the system prioritizes precise image classification rather than high speed multi object detection which is identified by yoloV8. For our project the CNN model is enough to get better experimental results. [10] the proposed system focuses on accuracy more than real time detection. This experimental setup focuses on classification accuracy under structured conditions, where a CNN model effectively satisfies the system requirements. It is affordable for small, and medium-sized businesses because it uses inexpensive hardware. The aim of this is to minimize the use of human labour, increase sorting and packaging preciseness, and efficiency. Finally, this system combines AI and robotics to work out component sorting and packaging. It enhances the productivity of manufacturing, precision and scalability and provides an affordable and smart solution to the electronic industry.

1.1 Why CNN?

We chose CNN (Convolutional Neural Networks) since they perform very well with image data, particularly in objects detection and classification. We have a camera that is used to identify various electronics parts prior to sorting and packing and therefore we require something that can actually distinguish an object in a photograph. This is the type of job CNN is set to do. They infer important information on edges, shapes, textures, patterns on their own. You don't have to spend hours to hand-engineer features, as we do with older machine learning algorithms, which frankly do not stand a chance when the components are complex. Electronic parts may resemble each other almost perfectly. Yet a good CNN studies out those little variations that there are between a resistor, a capacitor, or a connector and fixes the taxonomic position. It has the effect of fewer errors and easier classifying. Speed is also important. By setting CNNs to run at a speed compatible with real time work, this is just what we have in automation. As our dual arm robot operates in both directions simultaneously, the vision system must move with them where it identifies and categorizes the parts in a blink of an eye to ensure all is in motion.

1.2 Distinction from Existing CNN-based Sorting Systems

Most current sorting systems employing CNNs currently remain single arm. They are good at identifying and labelling objects, but slow in dealing with a single object. That is an issue with large factories that are concerned about speed. These robots are sure to know where to locate objects, and they lack good planning of their motions. They find it hard when we attempt to get them to use more than one arm, and almost never find them running in real time upon a real production line. The older systems do not even bother to use their CNN models in factories. They lose the fundamentals, such as arranging various objects, ensuring that moving components do not contact each other, or crating items in the most effective way. Due to all this, individuals tend to merely utilize these systems to conduct laboratory research. This new system reverses the fact that it relies on two robot arms and a more intelligent CNN model to categorize and sort objects [6]. Working on two hands simultaneously makes work much faster. The entire system is a combination of real time vision, coordinated arm movements and automated packing in one system that is intended to be used in factory floors. This is not a new method that is only faster. It is more organized, willing to scale up to large industrial requirements. The difference is that it uses parallel synchronized arms, which are in turn combined with "state of art" CNN-based sorting. Now it is not only about the ability to recognize object one can do but about the clever collaboration of the arms, all adjusted to the full automation of industry.[5] That's the real upgrade here.

2 Literature Survey

Robotic automation has now grown to a great extent particularly in assistive technology and industry. It is emphasized in many studies that robotics, machine learning (ML), and convolutional neural networks (CNNs) can enhance people’s lives, especially in medicine and industry. Efficient control mechanisms are one of the problems in robotics. Cook & Polgal (2014) [1] explain the overlap of assistive technology and robotics and refer to such devices as robotic arms, helping individuals with disabilities enhance motor functions. On the same note, Brose et al. (2010) [2] reiterate that robotics can enhance mobility and dexterity to the person with a disability, but that the design of the interfaces must be easy to use. Myoelectric control systems which were studied by Oskoei and Hu (2007) [9] transformed rehab robotics by applying muscle signals in controlling the prosthetics. These systems have spread to industrial automation making robots more precise. Another area of interest has been real-time control particularly with industrial automation. In factories, real-time detection and tracking of objects like the RGB-D camera-based systems discussed by Liu et al. (2015) [7] are important in the effective automation of dynamic workplaces. One way to apply electronic components sorting and packaging to the concept of Zhao et al. (2022) [3] is to enhance the YOLO-V3 model to enhance the real-time identification of objects in the automation of industries, which will be directly applicable in this process. Hu et al. (2017) consider these features to be autonomous navigation and obstacle avoidance, which require the use of cameras such as the RealSense, and it is important to note that these robots have to operate in a cluttered environment and work with delicate parts. The next step, which is the application of MasR-CNN to detect and segment objects in cluttered scenes (Lin et al., 2020) [8] makes sorting and packing operations more accurate. The model has been effectively implemented in the industrial setting in order to enhance accuracy in robotics. Mahler et al. (2017) indicated that CNNs may be applied to real-time grasp planning, which is essential in delicate handling operations such as packaging electronic component. This method, along with deep learning, will guarantee an efficient robotic handling, which reduces damages. In a nutshell, accuracy, precision, and efficiency in the applications of deep learning, CNNs, and robotics have significantly enhanced the manufacturing of electronics, including object identification, selection, and packaging. Smarter and more efficient automation systems are on the way thanks to these developments.

3 Proposed Methodology

3.1 Existing System

The existing sort and pack systems of electronic components are largely manual or semi-automation with a few sensing capabilities. They are commonly based on conveyor belts in which manual workers pick and pack parts or simple robotic arms without intelligent object localization. Human error, fatigue and failure to operate these systems with different components fast and at the right time hinder their efficiency. Moreover, robotic arms currently in operation are not flexible and thus, they have to be reconfigured manually when dealing with other parts or packaging. These systems struggle to handle high production volumes and are often slower and less accurate, and consequent increase in labour costs and decrease in production.

3.2 Proposed System

The proposed system is an advance system compared to the existing automated systems as it combines Convolutional Neural Networks (CNNs) and robotic arms to sort and pack the components. With a CNN model, MobileNetV2, and a Raspberry Pi along with a USB Webcam, the system can recognize objects, such as resistors, capacitors and LEDs, in real time without any manual programming. The Arduino Mega 2560 will be used to control two 4-DOF robot arms with servo motors to pick and package packages, thereby being faster and more precise. The dual-arm operation improves the throughput. Two 5V SMPS units supply power to the system with the help of L clamps to keep the system steady. Also the system can be scaled and is not limited to new components or packaging processes without major reprogramming. It seeks to decrease the human labour power, decrease errors, and provide a cost-effective solution to industrial automation in the electronics production.

3.3 Software Used

The simulation of the CNN-based component classification and robotic arm control was developed in Python using Python IDLE. The CNN model, image processing algorithms, and the control logic were coded, debugged and tested in a simple and efficient programming environment. To perform image preprocessing, model training, prediction and calculating coordinates to move robotic arm, IDE was utilized with Python libraries such as NumPy, OpenCV, and TensorFlow/Keras.

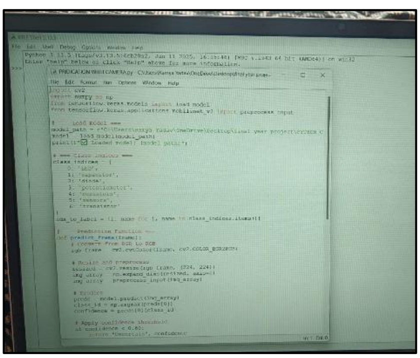
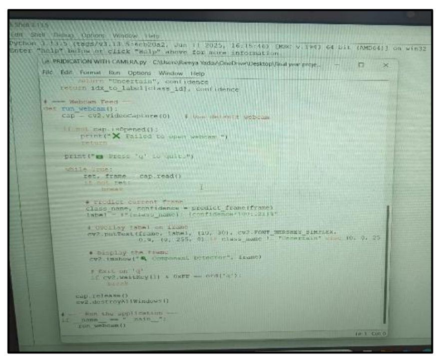

Fig. 1. Python IDLE Software.

3.4 System Architecture

The suggested system is divided into three parts namely, object recognition module, robotic arm control module and power and support system.

3.4.1 Object Recognition Module

Object recognition module will be comprised of a Raspberry Pi board, which will be connected to a USB web-camera. CNN model MobileNetV2 is implemented in the Raspberry Pi in such a way that it would handle the images of electronic parts which are placed in the assembly line and the images of which are captured by the webcam. The parts of the prototype are separated into resistors, capacitors and LEDs and based on them, a prototype which would enable identification of objects accurately and lightweight was developed. The Raspberry Pi will transmit the identification data to the robotic arm control module and the information will be processed by the control module.

3.4.2 Robotic Arm Control Module

The system consists of two robotic arms, each with 4 degrees of freedom which were operated using Arduino Mega 2560. The arms have servo motors to control each arm so that the servo moves in the correct position. One of the arms is applied in picking the found part and the other in the packaging process. The arms operate in parallel, allowing multiple operations to be performed simultaneously at once to guarantee this effective operation of the system.

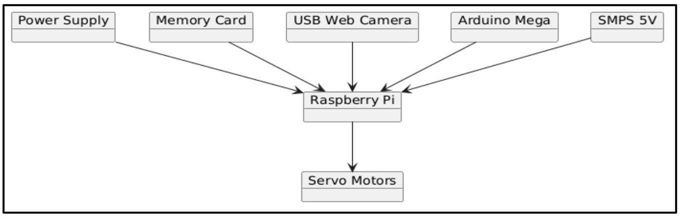

Fig. 2. System Architecture.

3.4.3 Power and Support System

The power and support system includes two 5V SMPS units to power Raspberry Pi, Arduino and servo motors. L clamping is to mechanically hold the robotic arms, L clamp offers stability and that may also enhance the precision in the course of the operation. The system is designed for continuous operation in industrial environment to assure performances and sound utilization of the system at the production sites.

3.5 Expected Outcomes

The outcomes of the proposed system are as below:
• Greater Efficiency: With the sorting and packaging process automated, it will take a lot of time in contrast to a manual one and in terms of sort and packaging process. The single robotic arm with a parallel dual arm will be more effective in throughput/speed.
• Precision And Accuracy: The object recognition system that is proposed is founded on deep learning and, thus, the proposed system can identify the components with high accuracy and precision, and minimize the errors due to human fatigue and manual misidentification.
• Scalability and Flexibility: The system will be modular and low-cost hardware (Raspberry Pi, Arduino) and it can be re-configured easy and system can be easily expanded. It can be adjusted to fit in new parts or changes happening to the packaging process without the process forcing to change substantially in the workflow.
• Reduced Labour Cost: With the automation of the process of sorting and packaging, fewer workers will be necessary during the process and the result will be lower labour costs and there will be no chances of human error during the repetitive duties.
• Cost-Effectiveness: The application of low-priced parts, such as Raspberry Pi, USB webcams, servo motors, and so on, will make sure that the system is not too costly, but at the same time, offers high-performing and reliable outcomes.
• Increased Flexibility: The system is very flexible because of the capacity to alter it to suit other types of electronic components to suit the various industries and packaging needs with ease. This is the flexibility that will be a desirable quality that will further their application.

4 Results and Discussion

This part of the paper is an evaluation of the performance of the proposed Convolution Neural Network Twinned Arm Robot in Automated Sorting and Packing Electronic Components. The outcomes are correctness of components identified, the rate of functioning of the system and its overall effectiveness. The system functionality is also analysed and is compared to the manual and automatic systems available. The results are then discussed with reference to the strengths, limitations and improvements that can be made on the system. The proposed system that combines a convolutional neural network and a twin arm robotic system is suggested to carry out the automated sorting of electronic components. It is meant to minimize the use of man power, enhance accuracy, and productivity within electronic manufacturing. The system is an amalgamation of computer vision and deep learning with robotic automation to classify and sort the components in real time accurately. sorting of electronic components. It is meant to minimize the use of man power, enhance accuracy, and productivity within electronic manufacturing. The system is an amalgamation of computer vision and deep learning with robotic automation to classify and sort the components in real time accurately.

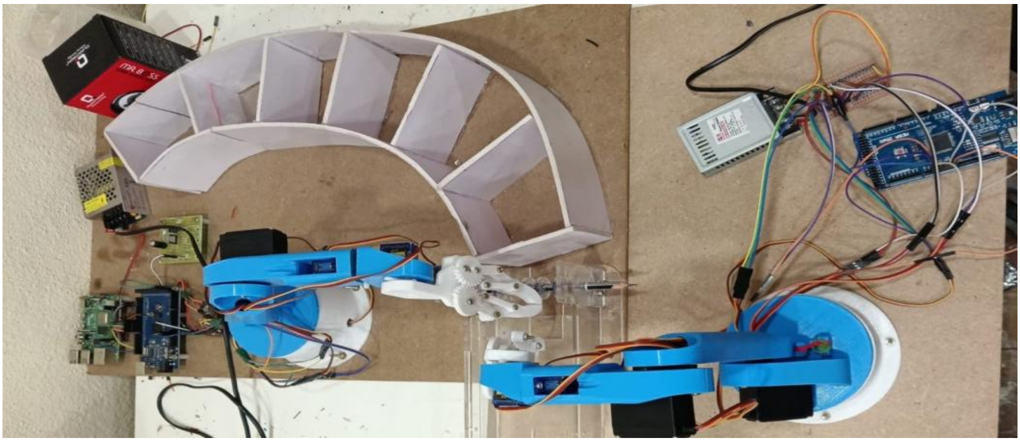

Fig. 3. Hardware Structure

4.1 Accuracy of the Component Identification

This is due to the fact that the components identified in the study accurately reflect the materials that comprised the final product.4.1 Accuracy of the Component Identification This is because the components as identified during the study are reflective of the materials that were used to make up the final product. The accuracy rate of MobileNetV2 CNN model of identifying the various kinds of electronic components is the first part of the system performance. The system was tested on a data set of image data of resistors, capacitors, LEDs and other small parts which are common in electronics manufacturing. The model had the ability to identify the components with reasonable amount of accuracy as observed in table 1.
A total of 2000 electronic component images were used for training, in that each group (500 Resistors, Capacitors, LEDs, Transistors) of parts is trained. Each category used 80% of the

data for training and 20% for testing. The model was also trained in different lighting conditions such as shadow and industrial LED lighting.

Table 1. Accuracy of Component Identification Using MobileNetV2 CNN Model

Component Type	Number of Samples	Correctly Identifie	Accuracy (%)
Resistors	500	490	98.0
Capacitors	500	485	97.0
LEDs	500	475	95.0
Transistors	500	470	94.0
Overall	2000	1920	96.0

The total Accuracy of the system was found to be 96.0% that is very much better compared to the traditional manual pattern recognition methods in which a human error leads to an identification error. It was the most effective in recognition of the resistors and capacitor with a 98 and 97 percent accuracy respectively. The identification of the LEDs and the transistors however was slightly lower than the rest and can be attributed to the fact that these components were in different shape and size.

4.2 Speed and Throughput

The other factor that is of great significance in the operation of the entire system is the duration of time within which the robotic arms can handle the sorting and packaging task. The system throughput was tested which is determined as the quantity of components in a single unit time. The various parts provide the throughput of the system as indicated in the table 2. Each component is processed, and results are obtained within a short time. The processing time varies between 3.2 and 4 seconds depending on the component. Overall, there are 4000 components that are processed every hour.

Table 2. Throughput for Sorting and Packaging of Electronic Components

Component Type	Processing Time per Component (seconds)	Components Processed per Hour
Resistors	3.2	1125
Capacitors	3.5	1028
LEDs	3.8	947
Transistors	4.0	900
Overall	3.6	4000

On all types, the system was capable of attaining throughputs of 4000 parts per hour as shown in Table 2. The robotic arms perform picking and packaging operations in approximately 3.6 seconds per component. This rate is quite high compared to the manual systems whereby the labour would take a relatively extended duration to pick and pack every unite of the product.

4.3 Simulation

The picture shows the real-time output of the CNN-based component detection system when it is running in Python IDLE. The model has successfully identified the LED component with 93.6 percent confidence level which is displayed at the top of the detection window. The background shows the training and prediction logs showing the execution progress and processing time (ms/step) of the model on a step-by-step basis. This is a demonstration of the CNN model in which the trained dataset is utilized to actively classify images and provide predictions.

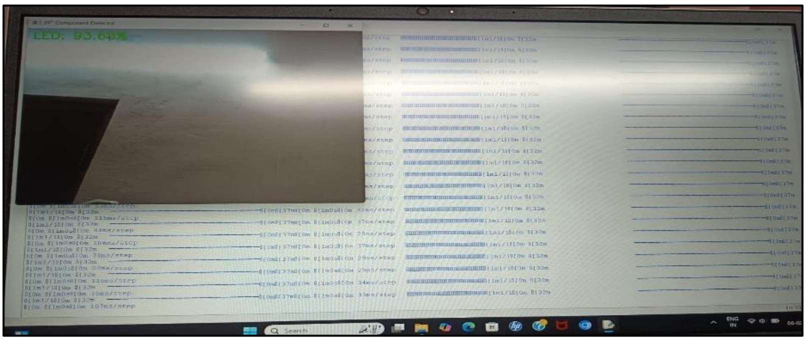

Fig. 4. Software Simulation

4.4 System Efficiency

The suitability of the system in general was assessed by the amount of time it requires to complete one full sorting and packaging cycle since component recognition until packaging. The complete process of identification, picking, and packaging takes approximately 10 seconds per component. This is very minimal as compared to the inefficiencies in the past manual systems which may consume a lot of time to carry out such activities due to human errors and fatigue.

4.5 Graphical Assessment of Performance

Two graphs are introduced below in order to contribute another insight to the performance of the system. The figure represents the precision of a model of mobile net (MobileNetV2) to identify electronic components of various kinds. The model is plotted with different types of components, to display the effectiveness of the entire system in the recognition of the resistors, capacitors, LED and transistors.

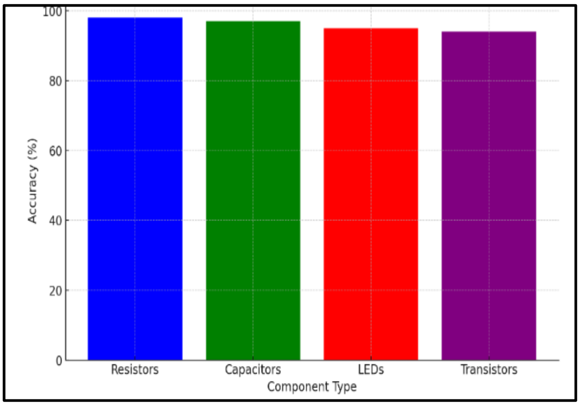

Fig. 5. Accuracy factor of Component Identification

The graph indicates the throughput of the system i.e. the quantity of components of each type that are processed in an hour. The findings demonstrate that the system is capable of handling quite a number of components Resistors and capacitors were processed faster compared to other components.

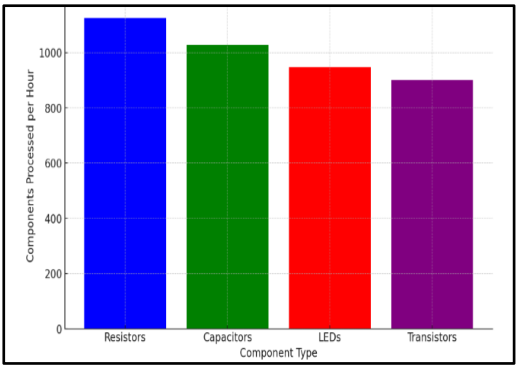

Fig. 6. Sorting and Packaging S throughput.

The suggested Convolutional Neural Network Twin Arm Robot is an efficient method to automate the process of sorting and wrapping electronic parts with the highest identification rate of 96.0% and speed of sorting 4000 pieces per hour, which is much better than manual methods. It can accommodate different components, as its scalability and adaptability enable it to be used in industrial use. Nevertheless, the results can be enhanced, especially with respect to identifying LEDs and transistors by training the CNN model on a more varied dataset, in particular, under varying lighting conditions. Moreover, more sophisticated robotic arms with higher degrees of freedom would be of use in the context of precision and system flexibility. Generally, the system provides a cost-effective, high speed and high throughput, component handling system and would be suitable in industries that need automation.

5 Conclusion

To summarize the discussion, Convolutional Neural Network Twin Arm Robot to Automated Electronic Component Sorting and Packaging has a major boost in automation. The solution will have 96 percent accuracy and faster processing speed by integrating the MobileNetV2 CNN algorithm of real-time object recognition with a dual-arm robotic system. It is independent in detecting and processing small components, minimizing the human error, fatigue and labour expenses. Its scalability and flexibility make the system flexible to different applications in the electronic manufacturing industry offering an efficient and cost-effective alternative to the current semi-automated and manual systems.

Table 3. Comparison Between Three Methods

Method	Accuracy	Packing Time (Sec)	Cost
Manual	85%	10	Low
Semi-Auto	90%	6	Medium
Proposed System	96%	3	Moderate

The proposed system is highly accurate and fast to use as opposed to the traditional manual and semi-automated systems. Manual systems have high levels of fatigue and errors, have low accuracy of less than 90 percent and low processing speed of two to three hundred components per hour. The semi-automated systems are quicker but need human control and are not flexible. Conversely, the proposed system has complete freedom, less human involvement and is a more efficient and strong system to use in mass production.

5.1 Future Work

Although the proposed system has good results, there are some areas that need enhancement. The precision of the component identification in different lighting conditions and backgrounds should be improved. The next step in the work would be the training of the CNN model using a larger and more varied source, the parts of variable shapes, sizes, and textures. Also, it may be necessary to improve the flexibility and accuracy of robotic arms by increasing their number of degrees of freedom and working with complex parts. The system would also be able to be expanded to include more complex packaging processes, e.g. multi-part assembly or fragile components. The AI-controlled predictive maintenance of the robotic arms and vision systems, the cloud data storage, and live monitoring could be added in the future as the upgrades to provide more flexibility and performance. Lastly, the potential of the system to be applied in other industries such as food and pharmaceuticals may present new avenues of automation other than electronic products.

5.2 Limitations

5.2.1 Component Overlapping

As the electronic components are glued to one another the CNN finds it difficult to see their edges. It causes things to be incorrectly classified, and the robot arm will not be able to pick them in the right manner.

5.2.2 Sensitivity to Lighting

When the lighting is changed or the shadows turn, elements begin to appear dissimilar. The CNN relies on everything to appear the same each time, and thus such changes disorient it and cause errors.

5.2.3 Camera Calibration Needed

To identify positions, it is necessary to position and adjust the camera in the right way. When it is not on, the coordinates will be disoriented and the robotic arm will be sent to the incorrect location.

5.2.4 Synchronization Complexity

It becomes tricky when two robotic arms are being operated simultaneously. You must have spot on timing and a good flow of communication among them. When a slipping object occurs, the arms may collide with one another, or put the bits out of order.

5.2.5 Cost of Dual-Arm System

Stereo operation requires an additional pair of motors, controllers and sensors that increase hardware expenses. Worse still, it is more expensive, in terms of maintenance and system integration, than a one arm system.

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