Identification of Smart Object Using IoT based Technique

Zahoor Hussain[1], Fida Hussain Khoso[2,*], Shunaila Jabeen[3], Dhani Bux Talpur[4], Muhammad Ahsan Riaz[5], Azhar Iqbal[6]

[1]Department of Computer Science, HITMS, Hyderabad, Pakistan
[2]Department of Computer Science, DUET, Karachi, Pakistan
[3]Karakoram International University, Diamer Campus, Chilas, Pakistan
[4]Department of Information and Computing, University of Sufism and Modern Sciences, Bhitshah, Pakistan
[5]Department of Electronic Engineering, DUET, Karachi, Pakistan
[6]Department of Mathematics, DUET, Karachi, Pakistan
[*]Corresponding author: fidahussain.khoso@duet.edu.pk

Abstract

The Internet of Things (IoT) is the composition of smart devices, which perform intelligent interaction with other smart machines around the environment. As a result, smart devices established an inclusive communication mechanism and disseminated the most relevant information to targeted objects. Nowadays, the manufacturing industries, departmental stores, and super-market have variety of products for their customers and have the traditional arrangements of products based on colors, weight and category which is tiresome and time consuming process while this manuscript presents the design and implementation of smart object identification prototype model consist of sensors where the system identifies the objects based on colors and weight using sensor technology along with IoT devices. The proposed system automates the issues of manual arrangements while inserting the object into the relevant container according to its specifications. Initially, the smart system identifies the color of the object, calculates the number of objects along with their respective weight, and then in the next step pushes the object to the relevant containers.

Keywords—Microcontroller, photo-electric sensor, weight sensor, servo motor

1 Introduction

In the recent era, modern technologies control the infrastructure, monitor the production, calculate the items, and manage the products accordingly. The usage of smart systems is the most effective mechanism to enhance working efficiency in an industrial environment, such as the usage of automated machines, robots, and smart grids. In the 4.0 industrial revolution, industry depends upon the efficient utilization of smart systems to increase production in an efficient manner and cut down labor costs. The 4.0 industrial revolution utilized the cyber physical system, which is the combination of embedded software, sensors, and IoT-based devices to control the machines. Since the industry relies heavily on IOT based devices, sensor technologies, and smart systems, it has become automated, and machines work more efficiently than humans do. To modernize the market requirements, the industries prefer to develop the autonomous smart system embedded with IOT devices and sensor technologies, which shifts the traditional systems towards the modern system, such as the traditional power system shifted into a smart grid system. The proposed system is a step forward solution to overcome the human efforts during the arrangement of industrial items based on color, weight, and quantity. Section one comprises the background; section two depicts the relevant literature, while section three presents comparative analysis, and sections four and five comprise the logical architecture of the proposed system. Sections six and seven represent the prototype model of the proposed system, along with scenario-based results, while section eight discusses the Tabular Result Discussions.

ISSN: 2523-0379 (Online), ISSN: 1605-8607 (Print)
DOI: https://doi.org/10.52584/QRJ.2302.06

1.1 Literature review

Pakistan's industrial sector is a growing area based on the traditional production system, which causes more recurring costs that influence the buying power of consumers. Meanwhile, it also affects the quality and quantity of production. In the current era, the emergence of the 4.0 industrial revolution, the industrial sector in Pakistan has replaced the traditional system with smart IOT and sensor-based technologies. To cope with these issues gradually, electric power distribution companies replaced traditional electricity meters with smart meters. Moreover, departmental stores also deployed an advanced technological system to guide consumers in the right direction, while some shopping centers have introduced smart parking systems to increase customer comfort. Industrial sectors have also emphasized the use of smart technologies to replace traditional mechanisms. Although the automated machines and AI based Robots working as alternate of labor in some areas, a huge number of industries still rely on traditional mechanisms to sort consumer goods based on their color and weight.

The manual sorting system is a tiresome mechanism to complete the task, and manual sorting leads to inconsistencies and requires more human resources for the completion of the whole process. In contrast, developed countries use intelligent machines to complete tasks more efficiently and on time, minimizing labor costs and increasing production in sophisticated ways. The related work depicts the most relevant smart system that reflects modern technologies to execute tasks automatically, in contrast to manual scheduling. In literature, a few researchers proposed different smart systems based on IOT, sensor technologies, and computer vision technology to replace the conventional mechanism. One of the researchers exposes the neural networks to perform small-target ship detection via a remote sensing image, and the innovative CSDP module is developed, which in turn utilizes deep large kernel convolution to foster the sensory field of shallow features and combines the channel positions by utilizing point convolution to have a better performance of feature extraction. Lastly, the MPDIoU loss function can resolve the problem of class-imbalance amid remote sensing small target ships and Moreover, it is notable that numerous advanced countries like South Korea, Canada, United States and alongside China as well as some different countries where 4.0 industrial modern technology is used to replace the conventional system [1] such as Welding robots are essentially built on standard industrial robot platforms, enhanced with module of welding function.

The initial generation of robots utilized a "teach-and-repeat" operating mode, which could replace human hands in carrying out a significant share of repetitive welding operations. While these robots can be operated with relative simplicity, they demand specialized individuals for schematic programming before the welding process. Moreover, they can exhibit a degree of flexibility through the utilization of a sensing system [2]. Furthermore, they can be integrated with additional tools to meet the needs for flexible invention. Robots of the particular class have gained growing attention from researchers in concerned domains, as it represents the final objective for welding manufacturing automatically [3]. Currently, this is confined to the phase of tentative investigation. Like soldering technology with robotics shifts tasks from a repetitive mode of repeatedly applying a self-governing method, obtaining outward evidence becomes crucial, thus increasing the significance of sensors [4]. Humans could observe the external world through different human senses such as smell, touch, sight, and hearing, among others. However, more than 80% of the data is acquired through visual sensing during automated welding. There are numerous sensors that may be used in welding applications, including current sensors [5, 6], acoustic sensors [7, 8], visual sensors, photoelectric sensors, and voltage sensors, etc. However, just as the eye serves as a view to the human spirit, when combined with other sensory modalities [9-15], the data acquired through visual perception is more precise, more insightful, and exhibits more resistance to obstruction [16, 17]. It is important to highlight that in many situations where human eyesight may be insufficient, machine vision technology can perform exceptionally well. The main factor behind the widespread use of vision systems is the sensing technology developed for welding robots. Numerous vision systems and techniques have been developed for these critical areas and have greatly advanced welding automation. Systems employing visual sensing technology generally involve robust vision frameworks and inactive vision systems [18]. The primary distinction is that passive vision offers illumination using a welding arc or a standard light source, and the object under inspection itself is visible in the image [19]. In comparison, active vision usually employs a laser generator as the light source, creating images that reveal the object's characteristics via laser points or structured light projected onto its surface. Vision technology possesses many pros, but again, this may or may not be correctly applied to the whole process of welding. The existing vision mechanisms aimed at various welding phases vary meaningfully in their vision methods and in the image processing region, efficiency, and final precision, application range, and various other components. There are a handful of detailed articles abstracting vision technology in welding from the aforesaid context, stopping fast comprehension of the present developmental program of the field [20-22].

One of the types of research that is very close to the proposed work is SEMAR, a platform that leverages IoT technologies to enable smart, real-time environmental monitoring and analysis. It is able to perform as a cloud server for mixing different IoT application systems. It provides different integration proficiencies for the collection, analysis of sensor data and subsequent display on a just one and a single platform [23] by offering built-in functions for data communications, classifications, synchronizations, and aggregations by adapting machine learning algorithms in Big Data environments. Furthermore, it facilitates the use of plug-ins by enabling external mechanisms to retrieve data via the Representational State Transfer (REST) API. Though SEMAR has been efficiently utilized in multiple IoT applications, enhancements to the platform would be anticipated to fulfill the demands of IoT applications that may require greatly advanced data processing algorithms [24]. More recently, Artificial Intelligence (AI) has turned out to be a very widespread data processing algorithm. AI has been moved by thoughts flowing in the human brain [25]. It can produce intelligent systems that may operate, learn, and provide feedback intelligently as human beings do [26, 27]. Actually, AI is a field of intelligent systems that not only provides a widespread range of tools and techniques, but also offers algorithms for data processing that can help computers do specific tasks in a better way. Natural Language Processing (NLP), machine learning, optimization, deep learning, robotics, pattern recognition, and computer vision could be comprised as subfields of AI. Owing to its ability to resolve multiple complex issues, AI is now widely adopted in different applications entailing IoT [28]. As technology moves to a more advanced level and advanced user scenarios arise, perfect and speedy on-spot detection sensors are necessary for caring and controlling the quality and the safety of food. The outstanding photography and image processing proficiencies of smartphones have greatly supported the integration, miniaturization, and visual care of sensors, enabling them to be essential tools for portable real-time determination. The "on–off–on" fluorescence sensor has gained considerable interest because of its outstanding qualities, such as exceptional selectivity, high sensitivity, strong resistance to interference, and the ability to tailor the probe's structure. However, portable sensors, in this perspective, with intelligent analysis and sensing systems have been greatly stated as per the "on–off-on" fluorescent signals and indicate their huge potential and importance in different fields [29]. The industry, considering the growing need for variety and customization, has seen large-scale personalized production emerge as a key trend in today's manufacturing industry. Although modern automation systems built around industrial robots offer high operating quality, speed, and precision, they show limited adaptability when faced with complex, unexpected, or changing environmental conditions. These mechanisms cannot fulfill the growing requirements of comprehensive, custom-designed systems in an intelligent manufacturing setting. As per the statistics, around 40% of the cost and 70% of the production time until now need manual operations done by personnel, because of their cognitive flexibility and ability. Henceforth, it is utmost important to control and examine operators' functionalities in production by applying cutting-edge technology, like sensor technology and deep learning. Apart from the great success in health care and human–machine collaboration, action appreciation is progressively being utilized in manufacturing for evaluating and quantifying the performance being displayed by the specialized personnel, enabling them to provide continuous support and adapt to personnel in assembly lines, conducting maintenance work, and demystifying the intentions of operators [30].

2 Comparative Analysis

Table 1 shows the existing system where the objects have been identified based on their weight and properties to automate the manual process to save time and financial implications.

2.1 Logical Architecture of Identification of Smart Object using IoT based Technique

Figure 1 depicts the logical architecture of the proposed system, IOSM, where colorful objects first go through an IR sensor, which senses the existence of an object, its weight, color, and counts objects. The next step is to identify the colors of objects, which is performed by a color identification sensor. Once the object color and weight have been intensified, the next step is to move the object on the relevant containers, which is done by a servomotor.

2.2 Working Environment of Sensors

Figure 2 shows the working mechanism of the sensor when any sort of object has been passed through the

TABLE 1: Comparison table between ISOIT and existing system

Developed System	**Year**	**Color Based Identification**	**Weight Based Identification**	**Unidentified Sorting**	**Information Storage**	**Object Counting**
Identification of Smart Object using IoT based technique	**2024**	✓	✓	✓	✓	✓
IoT Based Smart Palm Oil Seed Segregator using RGB Color [29]	**2023**	✓	✗	✗	✗	✗
Color-Based Agro Product Sorting and Disease Detection [30]	**2024**	✓	✗	✗	✗	✗
Tomato Sorting System Based on Machine Vision [31]	**2023**	✓	✗	✗	✗	✓
A Survey of Sensor-Based Sorting Technology [32]	**2024**	✓	✗	✗	✗	✗
Reference Image Aided Color Matching Design [33]	**2024**	✓	✗	✗	✓	✗

Fig. 1: Logical Architecture of ISOIT

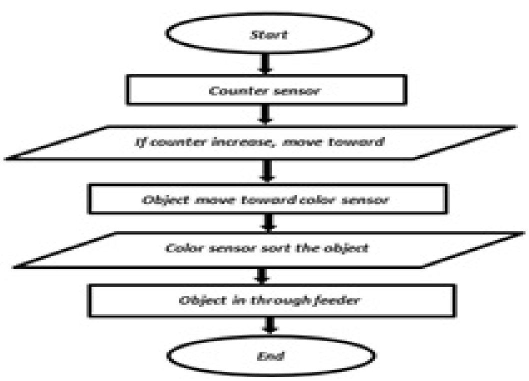

Fig. 2: Color Indentation Mechanism

feeder. The task of the sensor is to identify the color, weight, and relevant containers and move the object based on their identification to the containers. The results are also shown on the LED.

2.3 Prototype System Development of ISOIT

The design and development of the proposed ISOIT have been shown in Figure 3. The proposed system is used to sort the various kinds of objects based on their colors and weight. It helps to regulate manual color-based sorting and automate the whole process to save time and human resource efforts. The prototype model in Figure 3 comprised different kinds of components such as color sensors, weight sensors, and infrared sensors. The color sensor is a type of photoelectric sensor, which is used to detect the color of a particular object. A weight sensor is an alternative type of sensor for a load cell or force sensor[31]. They transform applied weight into an electrical signal, which can then be processed and utilized in a wide range of applications. Moreover, an Arduino microcontroller is used for centralized control of devices for the whole SBSOIM model, which acts as the brain of the system. Another component, the servo motor, is a compact device with an output shaft that can be set to precise angular positions by providing it with an encoded control signal. As long as the coded signal exists on the input line, the servo maintains the angular position of the shaft.

3 Results and Discussion

In the result section, the different scenarios have been extracted from the ISOIT system to validate the system accuracy and precision of results. The figures below depict relevant results on LED as well as the result tables.

3.1 Analysis of Scenario-1

Scenario-1

In Figures 4 and 5, the prototype model starts with a

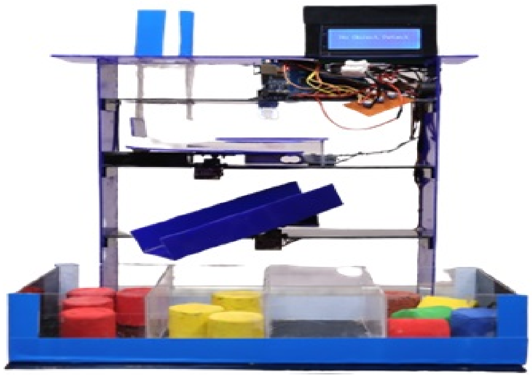

Fig. 3: Prototype model of ISOIT

Fig. 6: inserting object

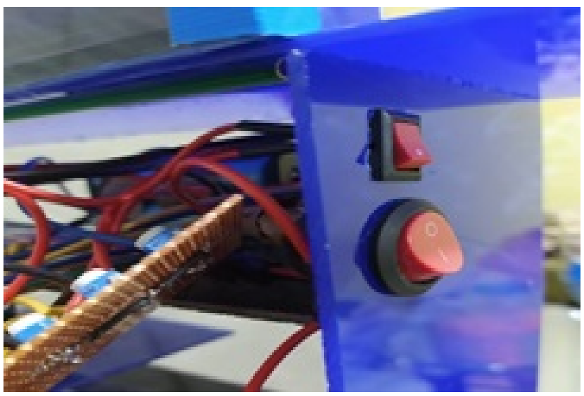

Fig. 4: power button

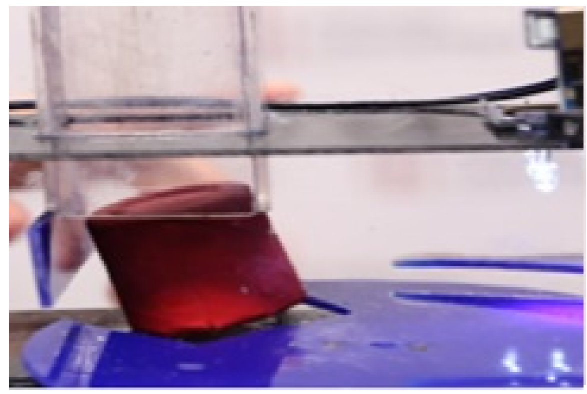

Fig. 7: IR sensor detects object

start button and an LED connected to a battery, which will start with all the components, such as Arduino, servomotor, LED, sensors, etc., and Figure 5 shows the LED that is used to display the results.

Scenario-2

The validation scenario has been shown in Figure 6, a heavy red object is inserted from the tube as an input to the sorting machine. In Figure 7, the object enters and is detected by the IR sensor by emitting a light. Once the light strikes an object, the object is detected

Fig. 5: led display system

and transferred to the next level.

Scenario-3

The figure 8 shows the object reachability to the place where the color sensor detects the color of an object and disseminates to the cell where an object weight measurement has been calculated. The input is transferred to Arduino, which starts processing and emits the output to the first servo motor, which rotates the disc and transfers the object towards the bridge, as shown in Figure 9.

Scenario-4

The figure 10 shows the placement of the object in the relevant container, rotates the bridge according to the given degree, and inserts the object into the desired container. Figure 11 depicts the object's readability of color and weight as shown by the LED display.

3.2 Analysis of Scenario-2

Scenario-1

As shown in Figure 12, a yellow object is inserted into the machine from the tube as an input to the sorting machine. While Figure 13 depicts the object entering and being detected by the IR sensor by emitting a

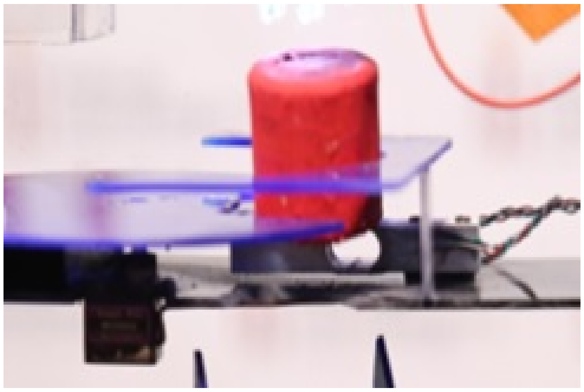

Fig. 8: Color and weight detection

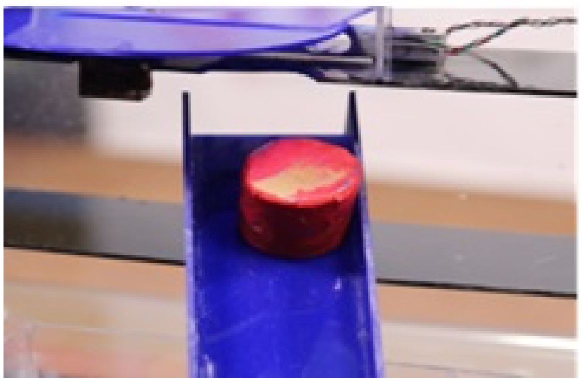

Fig. 9: bridge an object to a container

light, when light strikes an object, the object is detected and transferred to the next level.

Scenario-2

The figures 12 and 13 validated the results, to identify the color and weight of the object, and placed the second object having the same color and weight into the relevant container.

Scenario-3

As shown in Figures 14 and 15, the number of objects of the same color is identified. Figure 16 shows a single

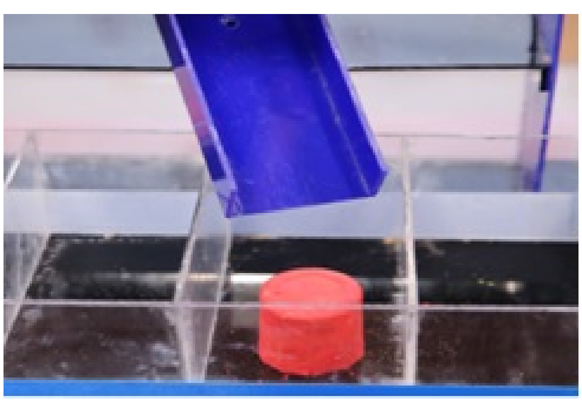

Fig. 10: object inserted in container

Fig. 11: Led current result

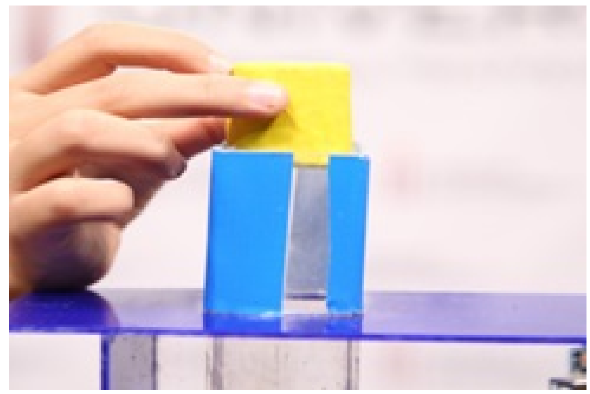

Fig. 12: inserting object

object, and Figure 17 shows two.

3.3 Analysis of Scenario-3

Scenario-1

The figure 18 and Figure 19 show the various objects with different color has been inserted into the SOSM machine, and the machine identifies the color along with their respective weight and put into the relevant containers.

Scenario-2

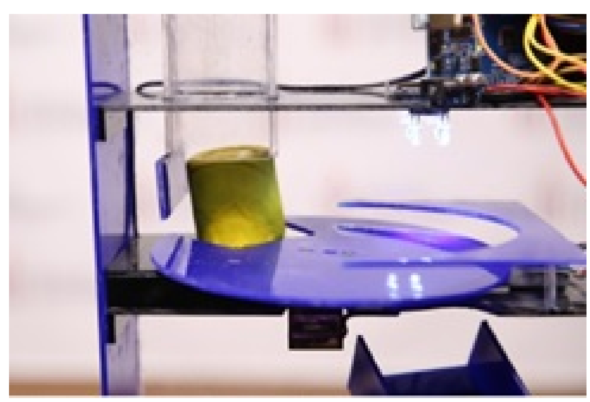

Fig. 13: IR sensor detects object

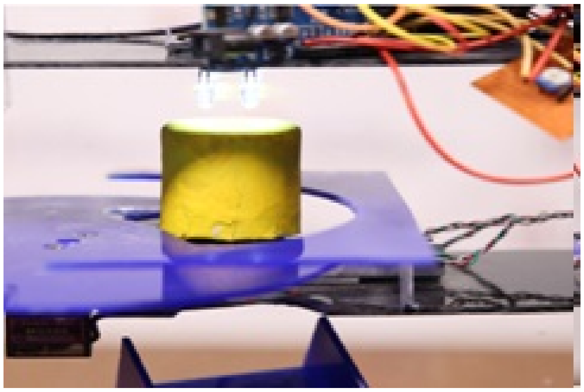

Fig. 14: Color and weight sensor detection

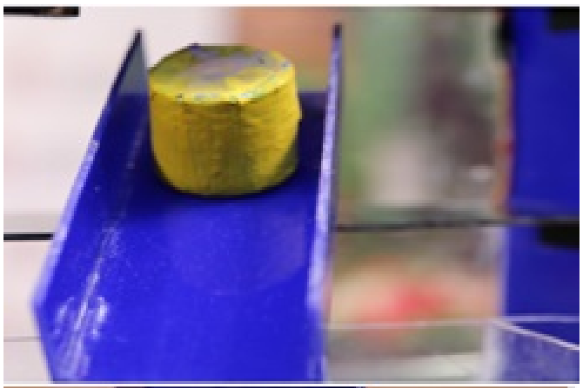

Fig. 15: bridge an object to a container

Fig. 17: Led current result

Fig. 18: bridge directs an object to a container

In scenario two, Figures 20 and 21 depict the detection results of the SOSM system. Where the LED shows the number of different objects with their color and weight.

3.4 Tabular Result Discussion

In this section, the extract result has been analyzed and discussed. The designed scheme is capable of identifying the color sorting, distance measurements, and object identification. The SBSOIM is a smart system that is able to automate the object identification, color sorting, and distance measurement. The tabular result below shows the accuracy of system performance in different scenarios.

3.5 Distance Measurement

Table 2 presents the accuracy rate of the device in measuring distance after selecting and placing an object. The color-classification items have been given their particular place right after the robotic arm chooses

Fig. 16: object inserted in container

Fig. 19: object inserted in container

Fig. 20: Led displays the current result

Fig. 21: Led displays the total result

an object. We employ the rules of 2D distance measurement and make an effort to test over 30 times in a manual manner. The table indicates that the device achieves an 86% accuracy rate in object arrangement, meaning that when the robotic arm fails to detect an object's color, it stays in its current position. Subsequently, that is considered to be a failure turn, and it occurs at least six times across a total of 45 detections.

TABLE 2: Distance Measurement

Task	Attempt	Success	Failure	Success %
Red	15	13	2	86%
Green	15	13	2	86%
Yellow	15	13	2	86%
Overall	45	39	6	86%

3.6 Color Matching and Sorting Accuracy

We repeatedly tested the color-sorting component of the developed system to evaluate the accuracy of color detection by the PixyCMU camera sensor. As can be seen in Table 3, it can be noticed that the PixyCMU cam has effectively detected the colored items (green, yellow, and red) with 86% accuracy, as it is light-sensitive. This procedure is frequent for at least ten times against every colored object [32]. The device's color detection accuracy varies depending on the distance of the objects from the Pixy sensor as well as the surrounding lighting conditions. However, it demonstrated optimal performance under normal lighting conditions. Once the item's color was accurately detected, the robotic arm successfully picked up the object and placed it in the appropriate location for color sorting. At last, the robotic arm effectively embraces the items, and it can choose and put an object with 86% accuracy.

3.7 Object Size Detection Rate

The table 4 shows the object size detection rate by the machine.12 different sizes of objects have been assigned to the machine to detect the size of the object. The results depict 100% accuracy detection rate as shown in Table 4.

TABLE 3: Color Matching and Sorting Accuracy

Task	Red	Yellow	Green
Task 1	✓	✓	•
Task 2	✓	✓	✓
Task 3	✓	✓	✓
Task 4	•	✓	✓
Task 5	✓	✓	✓
Task 6	✓	✓	✓
Task 7	✓	•	✓
Task 8	✓	✓	✓
Task 9	✓	✓	✓
Task 10	✓	✓	✓
Task 11	✓	•	✓
Task 12	✓	✓	✓
Task 13	✓	✓	✓
Task 14	✓	✓	✓
Task 15	✓	✓	✓
Success	14	13	14
Failure	1	2	1
Success (%)	93%	86%	93%

4 Conclusion

The ISOIT system has been developed and designed to regulate manual work, which is performed by human resources at multiple fields. The proposed system automates the task and efficiently handles the required

TABLE 4: Object Size Detection Rate

Object Size	Attempt	Success	Failure	Success %
Large	12	12	0	100%
Medium	12	11	1	92%
Small	12	10	2	83%
Overall	36	33	3	92%

work. It can identify the specific color and quality of the object and place it in the desired location and successfully measure the distance. The system will be efficient enough to capabilities to identify the objects and monitoring items at industrial levels.

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