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4-DoF Robotic Arm for Picking and Moving RGB Colour-Based Objects Using the Support Vector Machine Method

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Abstract – *This study discusses the design and implementation of an RGB colour pattern recognition system using the Support Vector Machine (SVM) method on a 4-DoF robotic arm to perform autonomous object transfer tasks. This system integrates computer vision, artificial intelligence, and trajectory planning technologies to improve the adaptability and precision of the robot manipulator's movements. The pattern recognition process is performed by acquiring images with a camera mounted on a support pole, then extracting and normalizing colour values in the R, G, and B channels. These RGB values are input features for colour pattern classification using an SVM with a Radial Basis Function (RBF) kernel, with regularization parameter $C = 100$ and kernel $\gamma = 100$. The training results show that the SVM model can classify three colour classes (red, yellow, and blue) with an accuracy rate of 96.67%. The classification data is then used to control the movements of three robots with red, orange, and blue arms, each tasked with picking up and moving objects of the corresponding colour. The robot trajectory was planned using the Cubic Trajectory method, resulting in smooth, coordinated joint movements with an average task completion time of approximately 10 seconds. Based on 60 trials, the system achieved a success rate of 98.33%, with only one failure due to gripper-position inaccuracy. The results of this study indicate that combining the SVM and Cubic Trajectory methods can improve the efficiency and accuracy of robotic arm systems for colour-based object recognition and manipulation, with potential applications in artificial intelligence-based industrial automation systems.*

Keywords – *Cubic Trajectory; Multi-Class Classification; Pattern Recognition; Robotic Arm; Support Vector Machine.*

I. Introduction

THE development of industrial robotics technology has contributed significantly to improving efficiency, accuracy, and productivity in various modern manufacturing sectors. Industrial robots now serve not only as mechanical tools, but have evolved into intelligent systems capable of performing complex tasks automatically and repeatedly with a high degree of accuracy [1–3]. This development is supported by advances in sensor technology, actuators, microprocessor-based control systems, and artificial intelligence, which enable robots to adapt to changes in working conditions. Thus, robotics has become an essential pillar in the implementation of innovative manufacturing-based industrial automation systems [1, 2] and Industry 4.0 [4].

One of the most widely used types of industrial robots is the arm robot, or manipulator. Arm robots have a kinematic structure resembling the human hand, with several degrees of freedom (DoF) that produce translational and rotational movements to perform various tasks [5, 6], such as picking up and placing objects [7]. The 4-DoF manipulator robot is one of the most efficient configurations for research because it balances movement complexity and ease of control [8]. Manipulator robots are widely used in assembly, packaging, and goods transfer processes that require high precision and consistency over long periods [9, 10].

Artificial intelligence has become an essential component in robot control systems, improving the adaptability of manipulator robots to dynamic environments. Applying machine learning algorithms in robotic arms enables robots to recognize patterns, make autonomous decisions, and adjust their actions based on the sensor data received [11, 12]. The integration of artificial intelligence enables robots to execute commands statically and to interpret visual information, such as the shape, colour, and position of objects, to perform appropriate actions.

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A critical approach in artificial intelligence is pattern recognition, which plays a role in identifying specific objects or characteristics from input data obtained by sensors. Pattern recognition techniques are widely used in robotics for tasks such as object detection [13], motion tracking [14], and colour and shape classification [15, 16]. In the context of robotic arm systems, pattern recognition provides relevant information for decision-making, enabling robots to determine the appropriate course of action based on the actual conditions of the working environment.

RGB colour pattern recognition is one concrete implementation of classification systems in robotics. The Support Vector Machine (SVM) method is one effective technique for classifying colour patterns due to its ability to distinguish data from various classes with optimal decision boundaries [17]. By applying SVM to the vision system of a manipulator robot, the robot can recognize the colours of objects such as red, yellow, and blue, then decide on the action to move the object to the appropriate location. This study can be helpful in industrial applications that require automatic sorting or classification based on product colour.

This research aims to design and implement an RGB colour pattern recognition system using the Support Vector Machine method on a 4-DoF robotic arm to improve the robot's ability to perform autonomous object transfer tasks. The benefits of this research are expected to contribute to the development of intelligent robotics systems in industrial automation, particularly in creating robots that can adapt to variations in object colours without human intervention. In addition, this research can also serve as an academic reference for the development of SVM-based classification methods in the field of visual pattern recognition in robotic systems.

II. Research Methods

i. 4-DoF Robotic Arm

The 4-DoF robotic arm used in this study is a laboratory-scale prototype designed to demonstrate the basic working principles of industrial manipulator robots. This robotic arm system consists of three robot units with different colour identifications, red, orange, and blue, as shown in Figure 1. Each robot unit has a mechanical structure with dimensions of $d_1 = 10\,\text{cm}$, $a_2 = 20\,\text{cm}$, $a_3 = 20\,\text{cm}$, and $a_4 = 10\,\text{cm}$. Link a_4 functions as a gripper or object clamp.

As the primary actuator at each robot joint, a servo motor with a rotation range of 0° to 180° is used, enabling precise movement at each arm segment. The movement of the four servo motors is controlled by a driver that stabilizes and regulates the control signals from the system centre. The main component of the robot controller is an Arduino microcontroller, which serves as a processor for data processing and the generation of control signals for the actuators. In addition, this system is designed to communicate serially with software on a computer, resulting in integration between computer-based data processing and direct control of the robot's hardware. This integration makes the 4-DoF robotic arm function as both a mechanical device and an intelligent system, enabling it to be optimized for a range in robotics and artificial intelligence experiments.

Figure 1: 4-DoF Robotic Arm.

This robotic arm uses forward kinematics to describe the direction and relationships among joint motions [5, 18]. The forward kinematics model is used to determine the end-effector's final position from the joint rotation angles [19]. In this system, *joint_1* regulates movement in the horizontal direction, representing rotation around the x and y axes. Furthermore, *joint_2* and *joint_3* contribute to vertical movements that affect position changes along the y-axis and the height of the robot arm. Meanwhile, *joint_4* serves as a gripper control mechanism for grasping and releasing objects.

$$\begin{aligned} x &= (a_2 \cos\theta_2 + a_3 \cos(\theta_2+\theta_3)) \cos\theta_1, \\ y &= (a_2 \cos\theta_2 + a_3 \cos(\theta_2+\theta_3)) \sin\theta_1, \\ z &= d_1 + a_2 \sin\theta_2 + a_3 \sin(\theta_2+\theta_3). \end{aligned} \tag{1}$$

The forward kinematics formulation, as shown in Equation (1), is used to calculate the Cartesian position of the end-effector from the joint angles. Thus, this system enables transformation from joint space to workspace, allowing the robot's movement direction and position to be mathematically predicted. This approach is an essential basis in planning trajectories and controlling the position of the robotic arm with precision according to the desired task requirements.

ii. Pattern Recognition with SVM

This robotic arm system is also equipped with a camera mounted on a support pole as the primary device for image acquisition. The camera is directly connected to an image-processing program running on a computer. Through this system, the camera captures objects in the work area and crops the image to include only the detected objects. Next, the image processing program extracts the colour intensity value of each pixel and calculates the red (R), green (G), and blue (B) colour components in the form of normalized values [20], as shown in Equation (2). The normalized RGB component values serve as input features that capture the colour patterns of objects. This data is then processed using the Support Vector Machine (SVM) method to accurately classify colour patterns, which serves as the basis for the robot's decision-making in object-transfer tasks.

$$R_n = \frac{R}{R+G+B}, \quad G_n = \frac{G}{R+G+B}, \quad B_n = \frac{B}{R+G+B} \tag{2}$$

Support Vector Machine (SVM) is one of the machine learning algorithms used to solve classification and regression problems, especially in pattern recognition and high-dimensional data processing [17, 21]. The central concept of SVM is to find the best separating hyperplane that maximizes the separation distance (margin) between data from two or more classes. In other words, SVM attempts to find a decision boundary that maximizes the distance between data points from different classes, resulting in an accurate classification model with good generalization capabilities for new data.

Mathematically, SVM works by finding *support vectors*, which are data points closest to the separating boundary, and determining the position of the hyperplane [22, 23]. In cases where data cannot be separated linearly, SVM uses a kernel function to map the data to a higher-dimensional space so that it can be separated linearly in that space. Some commonly used kernel types include linear kernel, polynomial kernel, and radial basis function (RBF) kernel. This study uses the RBF kernel.

To handle multi-class cases, SVM is extended using strategies such as One-vs-All [21, 24]. In RGB colour pattern recognition research, the One-vs-All approach is used because the number of classes is limited to three (red, yellow, and blue). Figure 2 shows the One-vs-All SVM architecture for RGB colour pattern recognition. To improve the ability to separate non-linear data, an RBF kernel is used to map the data to a higher-dimensional space [25]. The RBF kernel is the similarity function between two data vectors, x_i and x_j, as in Equation (3).

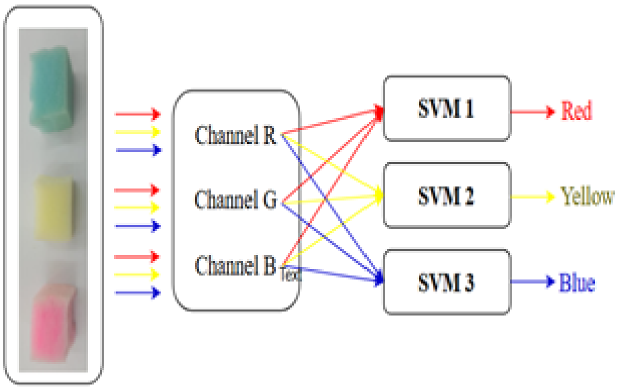


Figure 2: One-vs-All SVM architecture for RGB colour pattern recognition.

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \tag{3}$$

With $K(x_i, x_j)$: the kernel value between two data points, $\|x_i - x_j\|^2$: Euclidean squared distance, and γ: kernel parameter that regulates the influence range of a data point.

The main optimization problem in SVM is to find a hyperplane that optimally separates the classes [26, 27]. For non-linear data, the calculation is performed using Equation (4).

$$\max_{\alpha} \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{4}$$

with constraints:

$$0 \leq \alpha_i \leq C, \quad \text{and} \quad \sum_{i=1}^{N} \alpha_i y_i = 0$$

Where α_i is the Lagrange multiplier, C is the regularization parameter, y_i is the class label, and $K(x_i, x_j)$ is the RBF kernel as in Equation (3).

After the α_i parameters are obtained, the decision function is written in Equation (5).

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \tag{5}$$

Algorithmic steps:

Stage 1: Data Preparation Collect normalized RGB data (R, G, B) as input. Assign class labels (Red = 1, Yellow = 2, Blue = 3).

Stage 2: Multi-Class Model Formation Train k SVM models with One-vs-All strategy.

Stage 3: RBF Kernel Application Compute kernel values using Equation (3). Select C and γ through trial or validation.

Stage 4: Training Process Solve optimization to obtain α_i and b. Identify support vectors.

Stage 5: Testing Process For test input x, compute decision function in Equation (5) and select class with highest output.

iii. Trajectory Planning

Trajectory planning in robotic arms determines the motion path for each joint so the end-effector moves from initial to target position precisely and within defined time. Each servo motor is controlled to produce coordinated movements, enabling the robot to reach the object, grasp it, and move it to a target location.

This study used the Cubic Trajectory method to command joint motion. The method uses a third-order polynomial to generate smooth position, velocity, and acceleration profiles [19, 28]. Equation (6) represents the Cubic Trajectory model:

$$q(t) = q_s + 3\left(\frac{q_f - q_s}{t_f^2}\right)t^2 - 2\left(\frac{q_f - q_s}{t_f^3}\right)t^3 \quad (6)$$

Where q_s is the initial joint position, q_f is the final joint position, and t_f defines movement duration. This guarantees zero initial and final velocity and acceleration, providing continuous and stable motion.

III. Results and Discussion

The object detection system in this study is equipped with a camera mounted on a 35 cm high support pole. The camera acquires images in a prepared work area with a white background, thereby increasing contrast and accuracy in object detection. The objects used in the experiment are box-shaped and sized to fit the capacity of the robot gripper, so that the process of picking up and moving objects is carried out efficiently. This experimental instrument consists of three robotic arm units, each tasked with picking up and moving objects based on the identified colour, as shown in Figure 3. The design of this system aims to test the coordination between visual recognition and robotic motion control in a colour-based object-picking and moving task.

The experiments in this study were conducted on a prototype-scale robotic system located in a laboratory. Data sampling was conducted indoors under stable, consistent lighting conditions. A white background was chosen for the experiments to facilitate the detection of objects with uniform shapes using image processing techniques. In this experiment, variations in lighting conditions and different backgrounds, such as those that might occur outside a controlled laboratory environment, were not tested. The camera used in this experiment was mounted statically on a pole, with a fixed position and viewing angle, so that the distance between the camera and the object remained approximately 30 cm.

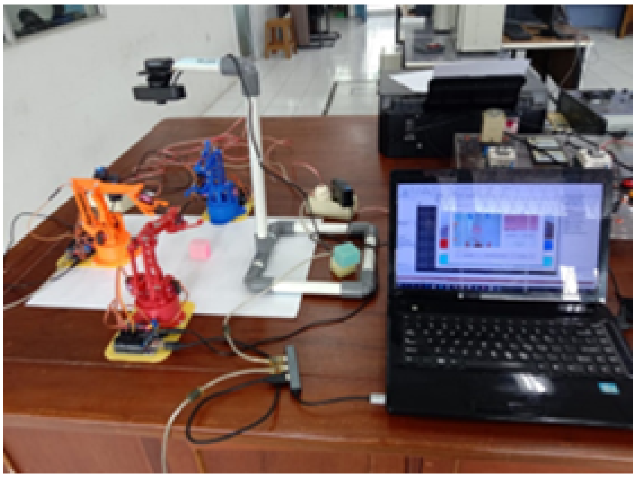


Figure 3: Experimental instruments of three robotic arms in picking up and moving objects.

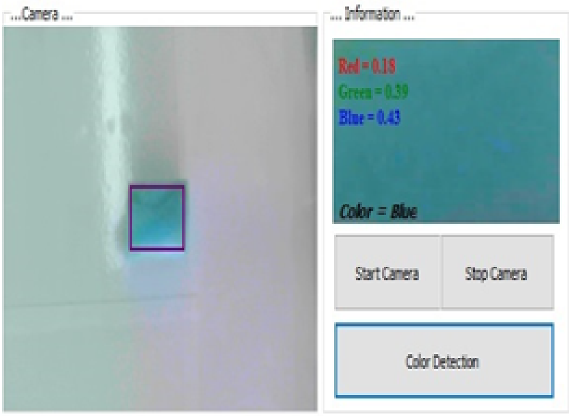
The first experiment tested the colour detection system by alternating red, yellow, and blue objects on a white board prepared as a test background. A camera was then used to capture images of each object on the board. The captured images are shown in Figure 4, where cropping was performed to isolate the main object from the background. Next, the image processing system calculated the colour intensity values in each of the red (R), green (G), and blue (B) channels of the object. The RGB values obtained were used as a numerical representation of the object's colour characteristics, which were then fed into the SVM algorithm for classification.

Training data were obtained by measuring colour intensity values in the red (R), green (G), and blue (B) channels for each red, yellow, and blue object. Ten data samples were collected for each colour to ensure sufficient representation of colour intensity, which may vary due to lighting or object position. The RGB values obtained are presented in Table 1 as the primary dataset in the classification system training process. To simplify the identification process, each object colour category is assigned a numerical label: red is labelled as 1, yellow as 2, and blue as 3. This labelling aims to make it easier for the SVM-based classification system to recognise and distinguish each colour.

This study has limitations in its testing, which covers only three basic colours (red, yellow, and blue) as a first step to evaluate the effectiveness of the proposed

(a)

(b)



(c)

Figure 4: Object colour detection: (a) Red, (b) Yellow, and (c) Blue.

method. This testing aims to gain a basic understanding of the model's performance under controlled conditions. However, to improve the model's generalisation and expand its application in real-world contexts, further testing will be conducted with a more diverse range of colours. Thus, additional studies will include trials under various colour conditions to ensure the model's robustness in handling more complex environmental diversity and scenarios.

The dataset presented in Table 1 is then represented in a three-dimensional (3D) graph to visualize

Table 1: Object colour dataset.

No	R	G	B	Label	Description
1	0.46	0.27	0.27	1	Red Object
2	0.40	0.30	0.31		
3	0.43	0.32	0.30		
4	0.42	0.34	0.28		
5	0.40	0.31	0.29		
6	0.38	0.30	0.32		
7	0.40	0.29	0.31		
8	0.41	0.30	0.28		
9	0.39	0.31	0.30		
10	0.39	0.30	0.31		
11	0.41	0.37	0.22	2	Yellow Object
12	0.43	0.36	0.23		
13	0.38	0.37	0.21		
14	0.39	0.38	0.23		
15	0.42	0.38	0.20		
16	0.41	0.38	0.21		
17	0.40	0.37	0.24		
18	0.42	0.36	0.22		
19	0.40	0.39	0.22		
20	0.44	0.40	0.16		
21	0.19	0.39	0.43	3	Blue Object
22	0.18	0.40	0.43		
23	0.21	0.36	0.41		
24	0.16	0.41	0.45		
25	0.20	0.39	0.41		
26	0.19	0.37	0.44		
27	0.16	0.40	0.44		
28	0.18	0.39	0.42		
29	0.17	0.40	0.43		
30	0.18	0.38	0.42		

the distribution of data in a space with three colour components: R (Red), G (Green), and B (Blue). This representation aims to provide a clearer picture of the distribution of colour intensity values for each tested object and to show the separation between colour classes in feature space. Figure 5 shows the results of the 3D graph visualization, where each data point is labelled by its category: red, yellow, or blue.

The collected dataset was then trained using an SVM with an RBF kernel. The selection of the C and kernel γ parameters in the Support Vector Machine (SVM) model was based on the test results shown in Table 2. Each object was tested 20 times, resulting in a total of 60 experiments. From the test results, it can be concluded that variations in the C parameter, ranging from 1 to 10,000, did not affect the stability of the learning process, as evidenced by relatively consistent accuracy across objects. The parameter γ was deter-

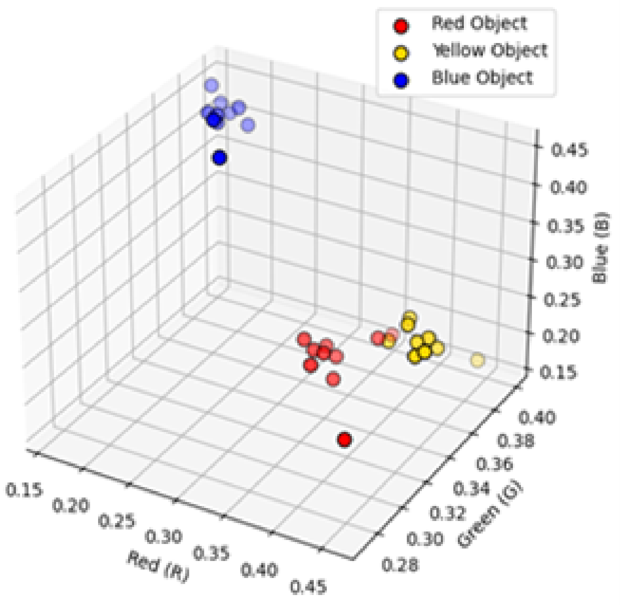


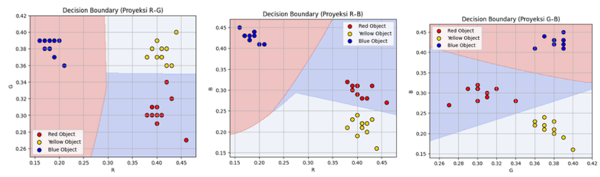
Figure 5: Representation of colour patterns from the 3D display.

Table 2: SVM testing for various C parameters and γ kernels.

C	Kernel (γ)	Data sample	Accuracy (%)		
			Red	Yellow	Blue
1	1	20	70	50	85
	10	20	90	85	85
	100	20	90	100	100
	1000	20	90	100	100
	10000	20	90	100	100
10	1	20	85	75	85
	10	20	95	100	90
	100	20	90	100	100
	1000	20	90	100	100
	10000	20	90	100	100
100	1	20	90	90	85
	10	20	95	100	95
	100	20	90	100	100
	1000	20	90	100	100
	10000	20	90	100	100
1000	1	20	95	100	90
	10	20	95	100	95
	100	20	90	100	100
	1000	20	90	100	100
	10000	20	90	100	100
10000	1	20	95	100	90
	10	20	95	100	95
	100	20	90	100	100
	1000	20	90	100	100
	10000	20	90	100	100

mined from a range of values between 100 and 10,000, where each experiment produced an average accuracy of 96.67%. Therefore, the selected parameter C value is 100, and γ is also set to 100, as these values provide an optimal balance in computation, avoiding numbers that are either too large or too small.

This training aimed to develop a classification model capable of optimally distinguishing object colour patterns based on RGB features. The training results were then visualized in two dimensions by projecting onto the R–G, R–B, and G–B planes, as shown in Figure 6. This visualization shows a clear separation between colour classes, indicating that the SVM model successfully found an effective decision boundary for each colour category. Based on the evaluation results, the model achieved excellent performance with a classification accuracy of 96.67%, indicating that the SVM method with an RBF kernel could accurately classify red, yellow, and blue objects.



(a) (b) (c)

Figure 6: Decision boundary as a representation of the separator in SVM-based colour pattern recognition (a) R-G projection (b) R-B (c) B-G projection

Table 3 presents the results of model evaluation using precision, recall, and F1-score metrics for parameter selection $C = 100$ and kernel $\gamma = 100$, which provide a more complete picture of model performance. The results show that SVM performs well in terms of F1-Score.

Table 3: Model evaluation using precision, recall, and F1-Score metrics.

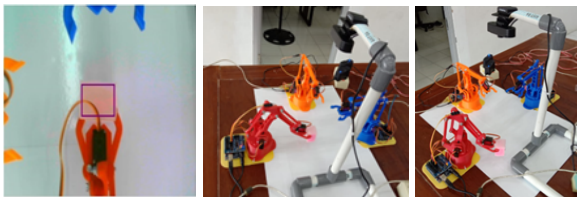
Object	Precision (%)	Recall (%)	F1-Score (%)
Red	100	90	94
Yellow	95	100	98
Blue	95	100	98

In the following experimental stage, three robotic arms were used, each distinguished by colour: red, orange, and blue. Each robotic arm was given a predesigned trajectory to move to the object's position, grasp it, and move it to the destination. The trajectory design for each robotic arm is detailed in Table 4. The red robot handles red objects in this system when the SVM algorithm classifies them as red. The same principle applies to the orange robot for yellow objects and the blue robot for blue objects.

In the experiment conducted on red objects, the objects were placed in the prepared detection area. The system camera detected the objects and forwarded the

Table 4: Trajectory for the robotic arm.

No	Joint Angle (Degree)				Description
	θ_1	θ_2	θ_3	θ_4	
1	90	90	90	90	The robot approaches the object, and the gripper picks it up.
2	90	142	7	76	
3	90	160	45	76	
4	90	160	45	102	The robot moves the object.
5	80	100	44	102	
6	80	140	10	102	The gripper releases the object, and the robot returns.
7	80	140	10	76	
8	90	90	90	90	



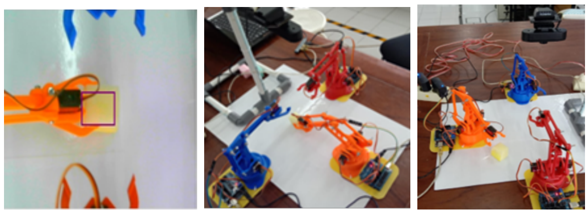
(a) **(b)** **(c)**

Figure 7: Red robot picking up and moving red objects (a) Object detection (b) Approaching and picking up objects (c) Placing objects

captured images to the SVM-based processing module, which successfully identified them as red. Based on the classification results, the red arm robot received commands to move to the object's position, pick up the object, and move it along the trajectory designed and stored in the computer program, as listed in Table 4. The test results showed that the red robot could perform all stages of the task well and with precision, from identification to object transfer. Figure 7 shows the red robot's implementation process for picking up and moving red objects effectively in accordance with the system's colour pattern recognition results.

Similar experiments were also conducted on yellow and blue objects to test the system's consistency in recognizing colour patterns and coordinating robotic movement. In tests with yellow objects, the SVM algorithm accurately classified colours, so the system automatically assigned the orange robotic arm to pick up and move the yellow objects. The orange robot could perform its task well according to the predetermined trajectory. Figure 8 shows documentation of the orange robot's process.

Furthermore, the SVM system also successfully recognized colour patterns when testing blue objects.



(a) **(b)** **(c)**

Figure 8: Orange robot picking up and moving yellow objects (a) Object detection (b) Approaching and picking up objects (c) Placing objects

Based on the classification results, the blue arm robot received commands to pick up and move blue objects to a predetermined location. The experiment's results showed that the blue robot could perform all stages of the task well. Figure 9 shows a visualization of the blue robot's process.

Table 5: Success rate of three robotic arms in picking up and moving objects.

Robot	Experiments	Success	Accuracy (%)
Red	20	20	100
Orange	20	20	100
Blue	20	19	95
Average			98.33

(a) Object detection. **(b)** **(c)**

Figure 9: Blue robot picking up and moving blue objects (a) Object detection (b) Approaching and picking up objects (c) Placing objects.

Although the integration of SVM with 4-DoF robotic arms has been extensively explored in previous literature, this study makes a significant contribution by integrating SVM with trajectory planning for multi-robot coordination. The main contribution of this research lies in the application of SVM not only as a tool for classification or object recognition, but also in designing and coordinating the movements of these robots together. Thus, this system focuses not only on controlling a single robot but also on efficient synchronization and trajectory planning for multiple robots simultaneously, which distinguishes it from previous studies that focused more on individual control. This contribution opens up opportunities for the development of more adaptive and efficient multi-robot systems, with the potential for application in various industrial and research applications, such as factory automation or environmental exploration.

The tests were conducted 20 times for each arm robot, namely the red, orange, and blue robots, bringing the total number of experiments to 60. Table 5 shows the accuracy of each robot's experiment in performing the action of picking up coloured objects. Based on the observations, all robots could perform their tasks well according to the commands given through the pattern recognition and trajectory planning systems. Of the total experiments, only one failure occurred in the blue robot when picking up objects, which was likely caused by the inaccuracy of the gripper's position relative to the object. Thus, the overall success rate of the system reached 98.33%, indicating good performance. The average time required for each robot to complete one work cycle—starting from the initial position, performing the object picking and moving process, and returning to its original position—was approximately ±10 seconds, indicating the system's efficiency in performing tasks with a stable response time.

IV. Conclusion

The RGB colour pattern recognition system using the SVM method with RBF kernel on a 4-DoF robotic arm has been proven capable of classifying red, yellow, and blue object colours with an accuracy rate of 96.67%. Integrating a camera-based vision system, SVM algorithm, and path planning using the Cubic Trajectory method results in effective coordination between colour detection and robot movement in object picking and moving tasks. Test results show that three robotic arm units with different colour identifications can perform their tasks well, with an overall success rate of 98.33% and an average completion time of approximately ±10 seconds. This experiment proves that the combination of machine learning-based pattern recognition and motion control systems can improve the performance and efficiency of manipulator robots in industrial automation applications.

However, there are limitations in this study, including object detection that does not yet use different lighting variations, a whiteboard background, camera distance from the object, and viewing angle that are also not yet varied, as well as objects that are still uniform. These aspects need to be considered in further research to improve the reliability and generalization of the results. For future studies, the system can be developed by adding a more diverse number of colour classes and integrating deep learning methods to enhance generalization capabilities under varying lighting and background conditions.

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