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Comparative Evaluation of Random Forest and CNN for Shape Classification in a Simulated Robotic Sorting Application

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A B S T R A C T

This paper compares Random Forest and a Convolutional Neural Network (CNN) for shape classification in a simulated robotic sorting application. A synthetic dataset containing 1,100 images was generated with cubes, cylinders, and cones in three colors. The models were evaluated using 150 test images containing 377 objects. Random Forest achieved 99.73% accuracy on individual object patches, while CNN achieved 100%. In the complete image processing pipeline, the shape classification accuracies for matched detections were 98.01% and 99.72%, respectively. Both methods achieved a detection F1-score of 95.39% because they used the same object detection procedure. A robotic sorting prototype was also implemented in CoppeliaSim using a KUKA LBR iiwa manipulator and a BarrettHand gripper. The results show that CNN provided better shape recognition on the synthetic dataset. Future work will focus on images captured directly from the simulator and validation of complete robotic sorting operations.

Keywords: CoppeliaSim; Python; Robotic Sorting; Computer Vision; Convolutional Neural Network; Random Forest.

1. Introduction

Visual robotic sorting combines object recognition with automated pick-and-place operations [1]. A Python-based learning-from-demonstration framework has already examined lightweight classifiers for robotic object sorting [2]. Other robotic systems have used MobileNet to recognize objects with different shapes and colors [3]. Vision-based safety monitoring in robotic cells and YOLOv8 inspection of 3D-printed parts show how image analysis can support manufacturing applications [4,5]. Synthetic image generation also provides a practical approach for developing and testing visual recognition methods under controlled conditions [6]. Studies of FDM manufacturing and polymer composite engineering provide further examples of material evaluation and process-related research [7,8].

Robotic sorting also depends on the motion and execution sequence of the robot [9]. Python-based path planning in RoboDK and graph-based planning with different coordinate grids illustrate software methods for evaluating robotic movement [10,11]. Research on geometric continuity and minimum-action methods has examined trajectory behavior and path length [12,13]. Geometric and kinematic trajectory metrics, together with vision-based hand tracking, provide different approaches for evaluating and controlling articulated robots [14,15]. Image segmentation has also been used to determine grasping order in cluttered environments [16].

Object classification can be studied through conventional machine learning and convolutional models [17]. Research comparing regression methods and reliability-aware machine failure prediction shows how different algorithms can be evaluated under changing input conditions [18,19]. Machine learning applications have also been developed for predicting student performance and academic staff attrition [20,21]. Educational data governance and digital assessment load have been examined through learning analytics and software visualization tools [22,23]. Personalized learning applications and offline gesture-recognition systems provide other examples of applied data processing and user-oriented software design [24,25]. Lightweight vision models have also been investigated for sequential robotic object sorting [26].

Human-machine interaction research has explored gaze and neural command fusion, as well as BCI-based home automation [27,28]. Brain-to-text prediction and EEG-based prosthetic systems show how sensor signals can be processed into application commands [29,30]. Research on intelligent prosthetic requirements and bionic leg dynamics has also addressed the relationship between software, user needs, and mechanical behavior [31,32]. Digital EMDR applications have been investigated in therapy and student-support settings [33,34]. Recent robotic studies have continued to examine vision-based grasping and sorting in cluttered scenes [35].

Digital transformation research has also discussed the integration of intelligent technologies into industrial and organizational systems [36]. Hybrid project management and employee contribution assessment provide examples of structured evaluation and decision support [37,38]. Innovative human resource tools have also been examined in international research project management [39]. Material recovery ranking and experimental sandwich-beam analysis

illustrate other evaluation approaches used in engineering research [40,41]. Software-based network traffic monitoring provides an additional example of application development under practical system constraints [42].

The reviewed studies cover robotic perception, motion planning, machine learning, software evaluation, and related digital applications, while the present work focuses on a narrower comparison of shape classification methods [2,3,17]. This study compares Random Forest and a Convolutional Neural Network (CNN) using synthetic images of geometric objects and examines their role in a simulated robotic sorting application [2,6,26]. Classification performance is evaluated separately from robotic execution to provide a clear comparison of the two recognition methods [1,16,26].

2. Materials and Methods

2.1 Robotic Sorting System

The robotic sorting application was developed in Python and CoppeliaSim. The simulated cell includes a KUKA LBR iiwa robotic arm, a BarrettHand gripper, a conveyor belt, a vision sensor, proximity sensors, and several sorting containers. The application was designed to identify objects and move them to the corresponding containers based on their shape or color.

Python communicates with CoppeliaSim through the ZeroMQ Remote API. The robot movement is controlled through predefined joint configurations, while the gripper is operated using functions available in the simulator. A graphical interface developed with Pygame allows the user to start the simulation, generate objects, control the robot, and activate automatic sorting.

The robotic application supports cubes and cylinders in red and blue. Images captured by the vision sensor are processed using the ShapeVision module. The application loads the CNN model for shape recognition, while color recognition is performed separately. The predicted labels are used to select the destination container. Fig. 1 presents the simulated robotic cell and its main components.

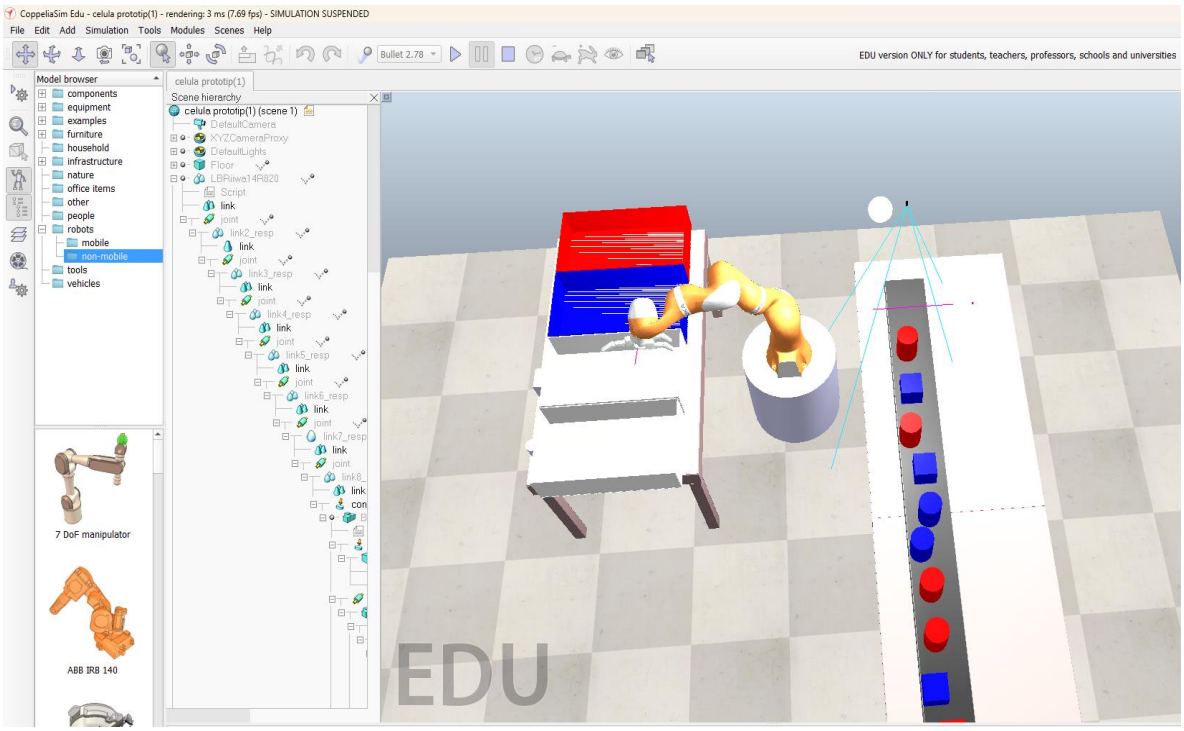


Fig. 1. Simulated robotic sorting cell developed in CoppeliaSim using a KUKA LBR iiwa manipulator, BarrettHand gripper, conveyor belt, and sorting containers.

2.2 Image Dataset

A synthetic image dataset was generated to train and evaluate the classification methods. The images were created in Python using the Pillow library. Each image has a resolution of 256 × 256 pixels and contains geometric objects viewed from above.

Three object shapes were considered: cubes, cylinders, and cones. Each shape could appear in red, blue, or yellow. Different object positions, orientations, sizes, backgrounds, and color variations were used during image generation.

The dataset contains 1,100 images. These were divided into 800 training images, 150 validation images, and 150 test images. Each object was also described in a JSON annotation containing its shape, color, and bounding box (see Table 1).

Table 1. Structure of the synthetic image dataset.

Dataset	Images	Annotated objects
Training	800	2,020
Validation	150	358
Testing	150	377
Total	1,100	2,755

The synthetic dataset was generated independently of the CoppeliaSim robotic scene. It was used to compare the classification models under controlled visual conditions.

2.3 Shape Classification Methods

Two methods were compared for shape recognition: Random Forest and a Convolutional Neural Network (CNN).

The image processing pipeline first identifies possible objects by comparing image regions with the estimated background. Morphological operations and connected-component analysis are used to identify object regions. Each detected object is then extracted as an image patch for classification.

The Random Forest model uses ten numerical features describing object geometry and brightness. These include extent, circularity, aspect ratio, three Hu moments, the number of contour vertices, central brightness, edge brightness, and the ratio between central and edge brightness. The selected Random Forest classifier contains 300 decision trees.

The CNN model receives image patches resized to 64 × 64 pixels. The input contains RGB information and a foreground mask. The network includes four convolutional layers, followed by a classification layer that predicts the object shape. The model was trained for 12 epochs using a batch size of 64 and a learning rate of 0.001.

Both methods classify objects into three shape categories: cube, cylinder, and cone. Object color is identified separately using HSV information and predefined color references. Therefore, the comparison focuses on shape recognition, while the same color classification method is used for both approaches.

2.4 Experimental Evaluation

The evaluation was performed using the validation and test subsets of the synthetic dataset. The validation subset was used during model development, while the test subset was used to compare the final classifiers.

Two evaluations were conducted. The first used individual object patches extracted from annotated images to measure shape classification accuracy. The second evaluated the complete image processing pipeline, including object detection, shape recognition, and color recognition.

For the complete pipeline, predicted objects were matched with annotated objects using an Intersection over Union (IoU) threshold of 0.50. Detection performance was measured using precision, recall, and F1-score. Shape and color classification accuracy were calculated for the correctly matched detections.

The Random Forest and CNN methods were evaluated using the same test images and object detection procedure. The recorded numerical results were obtained from the synthetic image dataset. The CoppeliaSim application was used as a robotic integration prototype, with CNN selected as the shape classification method.

The experimental comparison therefore examines the image recognition performance of the two models separately from the success of complete robotic pick-and-place operations.

3. Results

The Random Forest and CNN models were evaluated using 150 test images containing 377 annotated objects. The comparison included shape classification on individual object patches and the performance of the complete image processing pipeline.

3.1 Shape Classification Results

The first evaluation measured classification accuracy using individual object patches. Both models were trained using the same training dataset and evaluated on the same test samples.

Random Forest correctly classified 376 of the 377 test objects, while CNN correctly classified all 377 objects. The corresponding accuracies were 99.73% and 100.00%.

The models were also evaluated using objects detected by the complete image processing pipeline. In this evaluation, 352 objects were successfully matched with their annotations. Random Forest correctly classified the shapes of 345 matched objects, while CNN correctly classified 351. Table 2 summarizes the classification results.

Table 2. Comparison of Random Forest and CNN shape classification.

Indicator	Random Forest	CNN
Test object patches	377	377
Correct patch classifications	376	377
Patch classification accuracy (%)	99.73	100.00
Matched object detections	352	352
Correct shape classifications	345	351
Shape accuracy on matched detections (%)	98.01	99.72

CNN achieved a higher shape classification accuracy in both evaluations. The difference was small for individual object patches, while the complete pipeline showed a difference of 1.70 percentage points between the two methods.

The confusion matrices provide more information about the classification errors. Random Forest incorrectly classified two cylinders as cubes and five cones as cylinders. CNN incorrectly classified one cylinder as a cube. All remaining matched objects were classified correctly. Fig. 2 presents the confusion matrices obtained for the two methods.

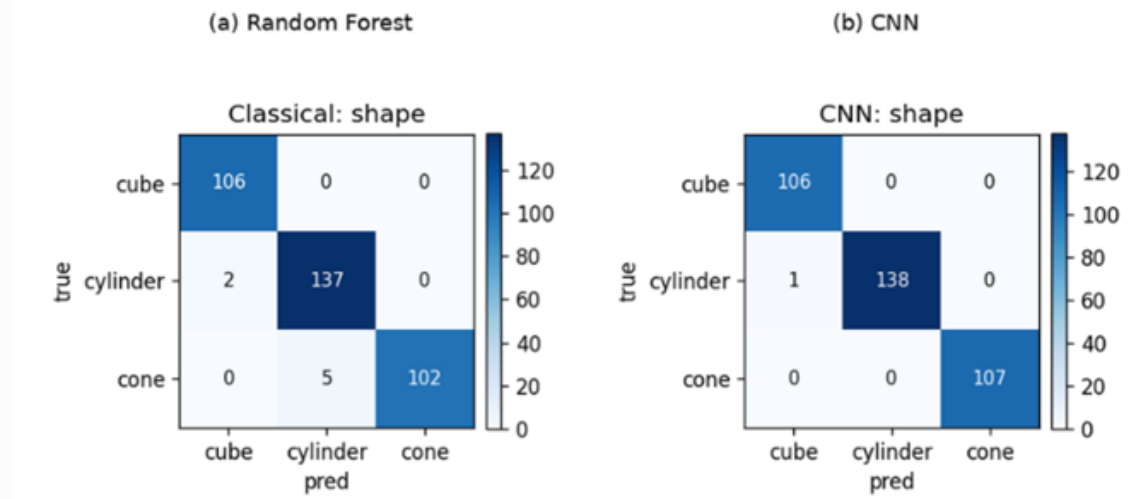


Fig. 2. Confusion matrices for shape classification using (a) Random Forest and (b) CNN on the matched test detections.

3.2 Object Detection and Color Classification Results

The second evaluation examined the complete image processing pipeline. The test dataset contained 377 annotated objects, and the system produced 361 detections. Of these, 352 were correctly matched with the annotated objects using an IoU threshold of 0.50.

Both methods used the same object detection procedure. Consequently, the detection metrics were identical for Random Forest and CNN. Table 3 presents the recorded detection performance.

Table 3. Object detection and color classification results.

Indicator	Random Forest	CNN
Annotated objects	377	377
True positive detections	352	352
False positive detections	9	9
Missed objects	25	25

Indicator	Random Forest	CNN
Detection precision (%)	97.51	97.51
Detection recall (%)	93.37	93.37
Detection F1-score (%)	95.39	95.39
Mean IoU of matched detections	0.857	0.857
Color accuracy on matched detections (%)	100.00	100.00

The detection procedure achieved a precision of 97.51% and a recall of 93.37%. These results indicate that most objects were identified, although 25 annotated objects were missed and nine detections could not be matched correctly.

Color classification achieved 100% accuracy for the 352 matched objects. This result was identical for both models because the same HSV-based color recognition method was used.

The results show that the CNN improved shape classification, while object localization and color recognition remained unchanged. The main difference between the two methods was therefore observed in the recognition of geometric shapes.

3.3 Overall Evaluation

The experiments show that both Random Forest and CNN achieved high shape classification accuracy on the synthetic dataset. CNN provided better results, with fewer classification errors in the complete pipeline.

The evaluation also identified limitations in object detection. Some objects were missed before classification, which affected the performance of the complete system. This indicates that improvements in shape recognition alone may not eliminate errors in the full image processing pipeline.

The robotic prototype demonstrated the integration of image processing, classification, and robot control in CoppeliaSim. However, the available simulation records do not establish a complete success rate for robotic sorting. The numerical results presented in this section therefore describe image detection and classification rather than verified pick-and-place success.

These findings provide a preliminary comparison of two shape classification methods under controlled synthetic imaging conditions. Further testing with images captured directly from CoppeliaSim and complete robotic sorting trials would help evaluate their performance in more realistic operating conditions.

4. Discussion and Conclusions

This study compared Random Forest and CNN for shape classification using synthetic images of geometric objects. CNN achieved an accuracy of 99.72% on the matched object detections, compared with 98.01% for Random Forest. Both methods used the same object detection procedure and achieved an F1-score of 95.39%. These results show that CNN provided better shape recognition under the tested conditions, while object detection performance remained unchanged.

A related study by Bolovan et al. [43] compared conventional OpenCV image processing and Random Forest for color and shape sorting in CoppeliaSim. Their results showed differences in classification accuracy and processing time between the two methods. The present study extends this comparison to Random Forest and CNN, using a separate synthetic image dataset and a different robotic application. The results cannot be compared directly because the datasets and experimental conditions are different.

The developed application also integrated image recognition and robotic control in CoppeliaSim. However, the quantitative evaluation was limited to synthetic images, and the success rate of complete robotic sorting operations was not measured.

Future research will focus on images captured directly from CoppeliaSim, different lighting conditions, processing time comparisons, and repeated pick-and-place experiments. Testing with a physical robot could further evaluate the practical use of the proposed system.

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