Designing an Intelligent Self-LearningRobot for Adaptive Object Sorting

Abstract


(.ieee.org.2019)

The challenge faced by many self-learning robots in primary and secondary education is that they are often programmed for specific tasks. As a result, these robots frequently struggle to adapt to diverse environmental scenarios.

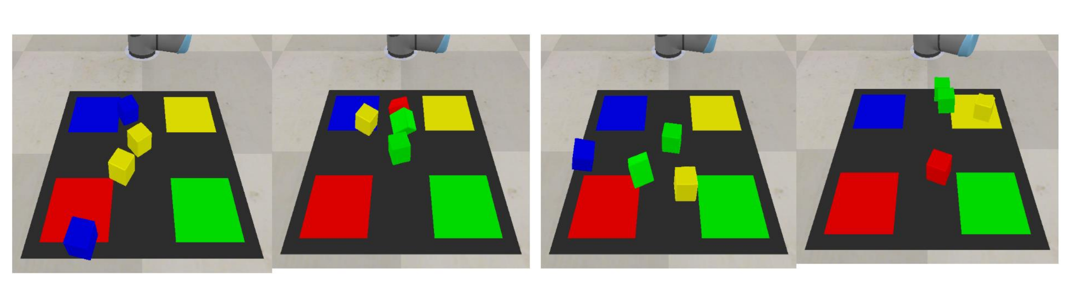
To enhance the integration of AI-driven self-learning robots in educational settings across the Kingdom of Saudi Arabia and globally, and to prepare students for the 4th and 5th industrial revolutions, this project proposes a multi-step deep reinforcement learning paradigm. This approach enables an adaptive robot to learn to sort cubic and irregular solid blocks, represented in four colors, to designated locations. The project modifies an existing pixel-wise critic Q-valued network by incorporating a lighter deep learning vision model alongside a compact fully convolutional neural network.

This combination aims to estimate the optimal decision-making policy and predict the action-value function for three primary actions: pushing, grasping, and placing. The research seeks to compare the generalization capabilities of the two trained models—one for irregular blocks and one for cubic blocks—by evaluating their performance on a fixed test set featuring cluttered blocks and variations in color representation

Introduction

The fifth industrial revolution emphasizes human-robot collaboration, highlighting the need for adaptive robotic systems in education and industrial application domains , but Training a system to work together and learn how to sort objects in a messy or cluttered area is very challenging.

How can a customized Pixel-wise Q-valued critic network (system that helps make smart decisions in changing environments) agent enable sorting of cubic and mixed objects in dynamic environments?


A. Sample of cubic solid blocks

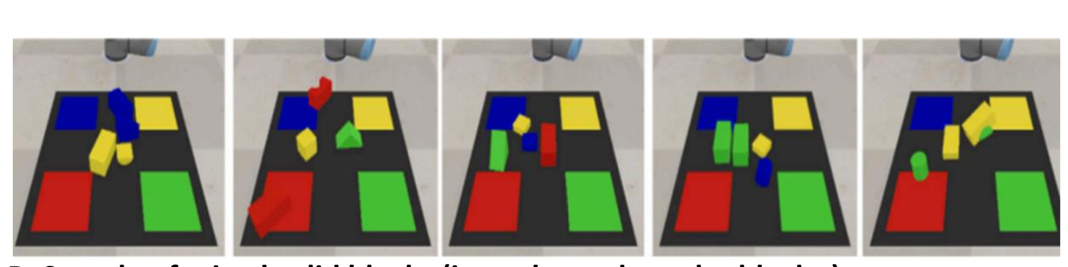
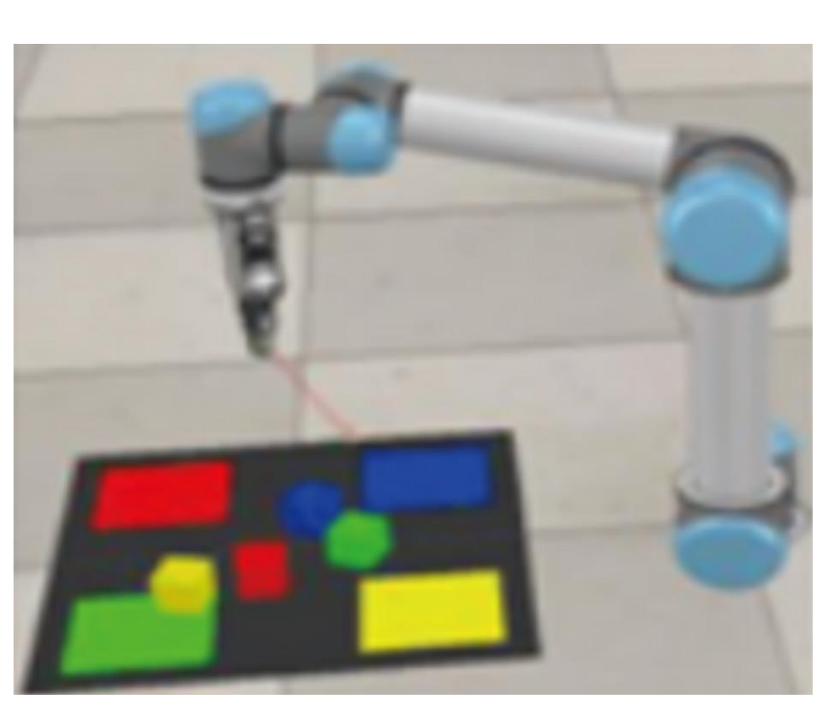

B. Sample of mixed solid blocks (irregular and regular blocks)

Figure 1: Examples of observation scene containing either cubic or irregular solid objects

Motivation

More than 60% of self-learning robots in educational settings struggle to generalize beyond specific tasks or adapt to varied environments despite advances in AI and robotics . Often used in primary and secondary education, these robots are typically designed for specialized functions. As a result, they rely on predetermined reactions, limiting their ability to engage emotionally or reason analytically. This rigidity prevents them from adapting to changing classroom conditions, diverse student interactions, or unexpected obstacles, compromising their effectiveness in educational settings.



Methodology

System Pipeline

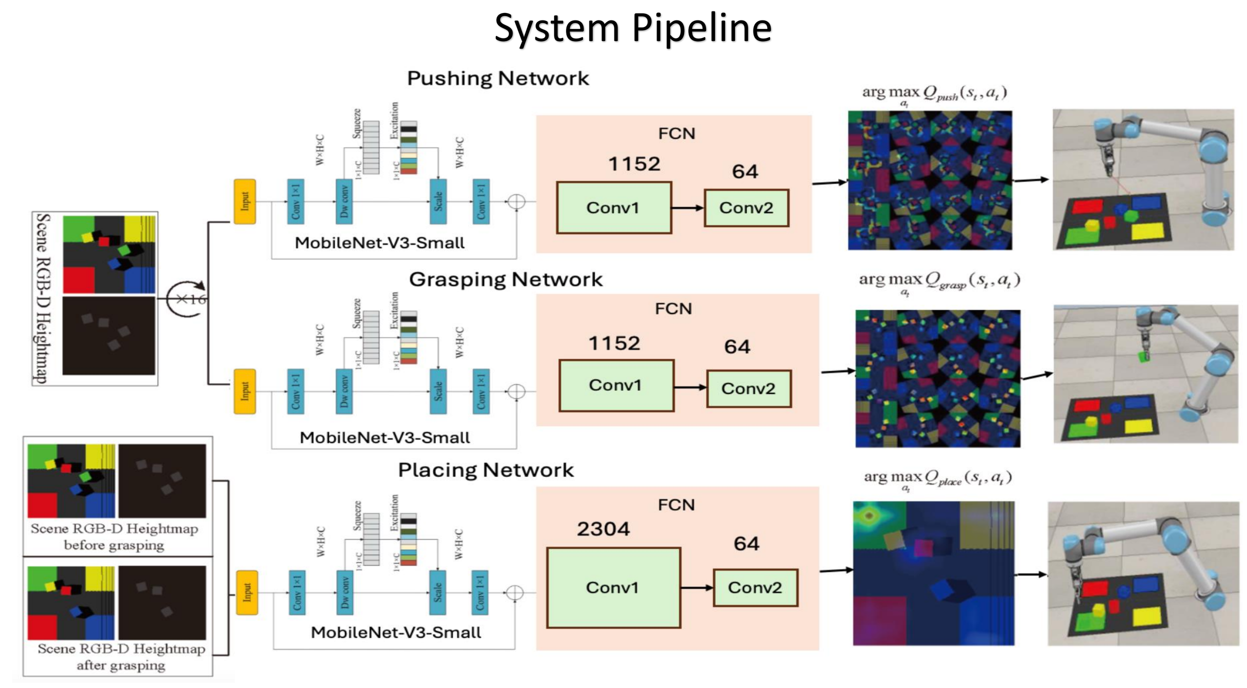


Figure 3: The proposed deep reinforcement learning system for performing object sorting while executing three main tasks: pushing, grasping, and placing

Design: A lightweight Pixel-wise Q-valued critic network with MobileNetV3-Small and a condensed Fully convolutional network (FCN) , trained using stochastic gradient descent optimization scheme

Training: The agent was trained for 25,000 time step on dynamic environments with irregular and cubic blocks for object sorting

Testing: Models were tested on cubic blocks with different colors, using metrics: AE, GSR, PSR, and SSR

Comparison: The models were compared for generalization based on standard performance metrics

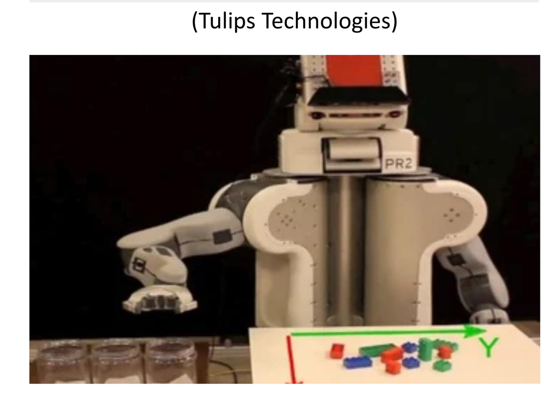
Applications


(istockphoto.2017)


(depositphotos.com 2020)


(Tulips Technologies)


(neom .com)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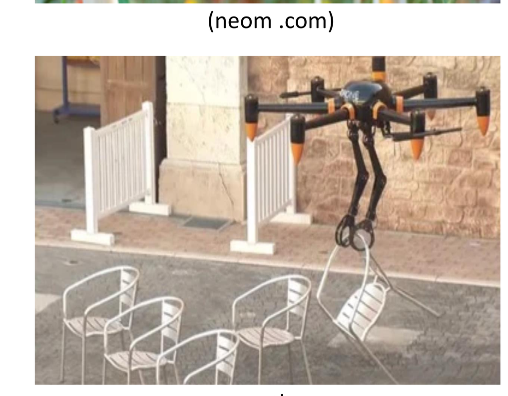
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Figure 5: AI-powered industrial robots performing quality assurance, packaging, and shipping to enhance efficiency and reduce waste (products from Tulips Technologies).

Contact

Figure 4 :Training phase performance index measured from PQCN-Mobilenet-V3-Small-FCN-1152optimized with stochastic gradient descent with momentum after training for 25,000 action steps.

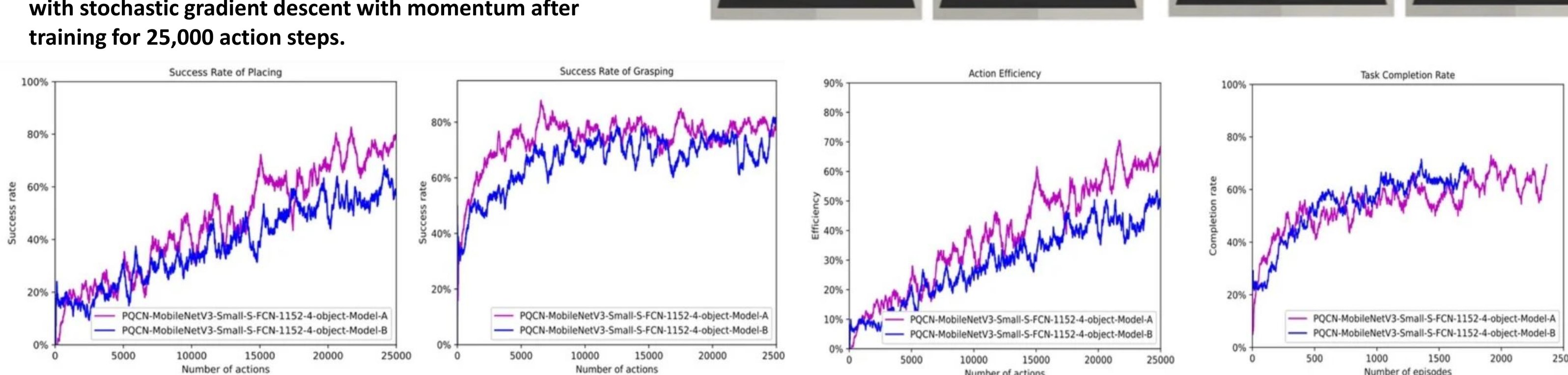

Figure 5: Testing environment: generated from fixed observation scenes that shows 4 object blocks have unique sets of challenges: sparse, clutter, occluded, and variation of object colors

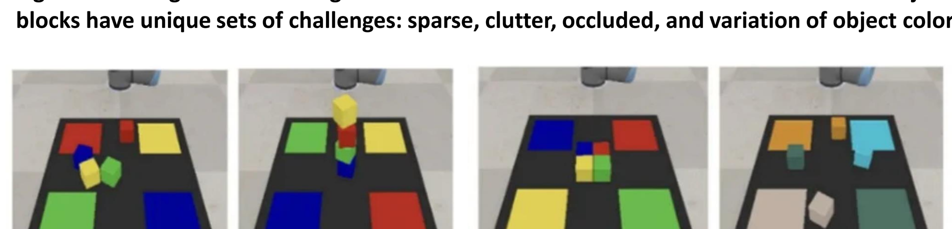

Table 1: PQCN-MobileNetV3-Small-FCN-1152-Model-A evaluated on fixed testing environments

Performance Metrics	Test 1	Test 2	Test 3	Test 4	Mean
Action Efficiency	79.25	38.11	35.44	27.53	45.08 ± 20.11
Grasp Success Rate	78.66	64.21	39.84	73.67	63.35 ± 14.94
Place Success Rate	95.64	56.57	69.14	32.51	63.46 ± 22.77
Sort Success Rate	91.12	45.16	75.00	65.00	69.07 ± 16.66

Table 2: PQCN-MobileNetV3-Small-FCN-1152-Model-B evaluated on fixed testing environments

Performance Metrics	Test 1	Test 2	Test 3	Test 4	Mean
Action Efficiency	70.73	63.18	44.23	35.46	53.40 ± 14.16
Grasp Success Rate	76.19	60.61	46.49	60.81	61.03 ± 10.51
Place Success Rate	83.14	85.27	72.52	51.80	73.18 ± 13.26
Sort Success Rate	95.00	80.83	80.00	65.83	80.41 ± 10.32