# Optimizing Automated Picking Systems in Warehouse Robots Using Machine Learning

Keqin Li<sup>1,a\*</sup>
Department of Computer Science
AMA University
Quezon, Philippines
<sup>a</sup>Email:keqin157@gmail.com

Xubo Wu<sup>2c</sup>
The author is currently
an independent researcher
1015 Noble Ave, San Jose, CA, 95132, USA
<sup>c</sup>Email:franky.wu2333@gmail.com

Runmian Chang<sup>4e</sup>
Disney Streaming Ads Platform AX team
Disney entertainment and sports LLC
500 South Buena Vista St, Burbank, CA, 91521, USA
<sup>e</sup>Email:runmianc@gmail.com

Yiwen Kang<sup>6g</sup>

Master of engineering- electrical and computer engineering
University of Toronto

27 King's College Circle Toronto,Ontario M5S 1A1,Canada

<sup>g</sup>Email:yiwen.kang@mail.utoronto.ca

Fanghao Ni<sup>8,i</sup>
School of Informatics, Computing, and Cyber Systems
Northern Arizona University
Flagstaff, AZ, USA
<sup>i</sup>Email:fn232@nau.edu

\*Corresponding author: \*keqin157@gmail.com \*JinWang@my.uopeople.edu

Abstract—With the rapid growth of global e-commerce, the demand for automation in the logistics industry is increasing. This study focuses on automated picking systems in warehouses, utilizing deep learning and reinforcement learning technologies to enhance picking efficiency and accuracy while reducing system failure rates. Through empirical analysis, we demonstrate the effectiveness of these technologies in improving robot picking performance and adaptability to complex environments. The results show that the integrated machine learning model significantly outperforms traditional methods, effectively addressing the challenges of peak order processing, reducing operational errors, and improving overall logistics efficiency. Additionally, by analyzing environmental factors, this study further optimizes system design to ensure efficient and stable operation under variable conditions. This research not only

Jin Wang<sup>1,b\*</sup>
Department of Computer Science
University of the People
California, USA

bEmail:JinWang@my.uopeople.edu

Xirui Peng<sup>3d</sup>
College of Natural Sciences
University of Texas at Austin
2515 Speedway, Austin, TX ,78712, USA
dEmail:peng.xr.emma@gmail.com

Xiaoyu Deng<sup>5f</sup>
The author is currently
an independent researcher
201 Marin blvd, Jersey City, NJ 07302, USA
<sup>f</sup>Email: xiaoyud98@gmail.com

Yue Yang<sup>7h</sup>
Department of Data Science
Northwestern University
37710 Spring Tide Road,Newark,CA,USA
hEmail: julieyang2023@u.northwestern.edu

Bo Hong<sup>9,j</sup>
School of Informatics, Computing, and Cyber Systems
Northern Arizona University
Flagstaff, AZ, USA
<sup>j</sup>Email:hongbo2904@gmail.com

 Authors 1 a\*and 1b\* contributed equally to this paper and are cofirst authors.

provides innovative solutions for logistics automation but also offers a theoretical and empirical foundation for future technological development and application. (Abstract)

Keywords — Logistics automation, machine learning, deep learning, reinforcement learning, picking system, warehouse robots, system optimization, environmental adaptability.(keywords)

#### I. Introduction

The expansion of global e-commerce has exponentially increased the complexity and volume of warehouse operations, necessitating more advanced automation technologies. Traditional automated picking systems often struggle with

inefficiencies and inaccuracies, particularly during peak operational demands. Current systems, while partially automated, fail to adapt dynamically to the varied and unpredictable nature of warehouse environments, leading to increased error rates and operational costs.

This study addresses these shortcomings by integrating cutting-edge machine learning technologies, specifically deep learning and reinforcement learning, with automated picking systems in warehouses. Unlike conventional methods, which rely heavily on static algorithms and manual oversight, our approach leverages a sophisticated ensemble of machine learning models to enhance decision-making processes. This integration not only improves accuracy and efficiency in picking operations but also ensures robust adaptability under fluctuating operational conditions.

Pioneering work by industry leaders such as Amazon has shown the potential of such technologies, yet there remains a significant gap in their application across diverse warehouse settings. Our research fills this gap by tailoring machine learning solutions to various operational scales and environmental complexities, thus boosting logistics performance and enhancing corporate competitiveness.

#### II. RESEARCH METHODS

#### A. Machine Learning Optimization

# 1) Deep Learning Technology

This study integrates ensemble learning with deep learning to enhance the performance of warehouse robots in automated picking systems. Ensemble learning, employing algorithms such as Random Forest and Gradient Boosting Machine, leverages multiple models to improve prediction accuracy and robustness, particularly effective against non-linear and complex data structures. Deep learning, especially through convolutional neural networks (CNNs) and recurrent neural networks (RNNs), processes intricate visual and sequential data to ensure precise picking actions. CNNs decode image data to identify crucial product features like shape and size, enhancing picking accuracy. Concurrently, RNNs manage order sequences, optimizing the robots' picking path and timing based on dynamic order volumes. To mitigate overfitting and enhance real-time performance in warehouse environments, we applied data augmentation and model compression techniques.

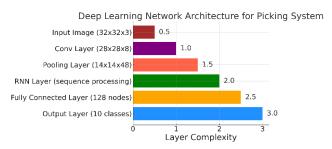


Figure 1: Deep Learning Network Architecture for Picking System

# 2) Reinforcement Learning Algorithms

Our approach incorporates Q-learning, a model-free reinforcement learning algorithm, pivotal for developing adaptive strategies in uncertain environments. The formula for updating the Q-value is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[ R(s) + \gamma \max_{a'} Q(s',a') \right]$$

$$- Q(s,a)$$

Here, s and a are the current state and action, Q(s, a) is the expected reward,  $\alpha$  is the learning rate, R(s) is the current reward,  $\gamma$  is the discount factor, and s' and a' represent the new state and possible actions, respectively. This algorithm guides robots to maximize long-term rewards, enhancing both the accuracy and speed of the picking process. Strategy optimization was continually refined through extensive simulations and field tests to ensure effective application under various operational conditions.

In summary, the combination of deep learning and reinforcement learning in this study not only enhances the operational efficiency and accuracy of automated picking systems but also ensures adaptability and robustness in real-world warehouse settings..

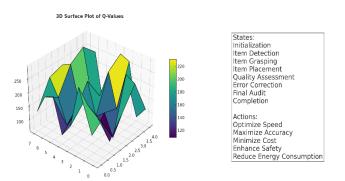


Figure 2: 3D Surface Plot of Q-Values

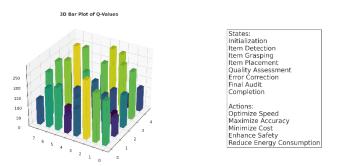


Figure 3: 3D Bar Plot of Q-Values

# III. EXPERIMENTS AND RESULT ANALYSIS

# A. System Design and Implementation

This section outlines the optimization of an automated picking system through meticulous data handling, model development, and thorough testing to ensure operational precision and speed.

- Data Collection and Preprocessing: High-quality, comprehensive data were gathered and cleaned to support effective model training and accurate predictions.
- Model Training and Evaluation: Deep learning models (CNNs and RNNs) processed critical data, with Qlearning optimizing picking paths. The models were validated via cross-validation and A/B testing to ensure reliability across scenarios.
- Simulation Experiment: The system was tested under simulated conditions of varying order volumes and inventory levels, proving its efficiency and adaptability.
- Field Verification: Field tests in real warehouses validated the model's performance and stability in operational environments.
- System Iteration and Optimization: Based on testing results, the models were fine-tuned to enhance fault tolerance and environmental adaptability, boosting overall system performance.

The design and testing strategies provided foundational insights and a benchmark for future system enhancements.

# B. Experimental Results Discussion

This study validates the effectiveness of the integrated deep learning and reinforcement learning models in enhancing the performance of automated picking systems through experimental data and visual analysis. Below is a detailed discussion of the experimental results:.

#### 1) Model Performance Evaluation:

Experimental data show that the average accuracy of the CNN model is 95%, the RNN model's average accuracy is 90%, while the traditional methods' average accuracy is 75%. The standard deviation indicates that CNN's performance is the most stable (standard deviation of 3%), while the traditional method's accuracy fluctuates significantly (standard deviation of 7%). These results, illustrated through box plots and violin plots, further highlight the superiority of deep learning models in picking tasks.

Table 1: Comparative Accuracy and Stability of CNN, RNN, and Traditional Models

Model	Average Accurac y (%)	Standar d Deviatio n (%)	Minimu m Accurac y (%)	Maximu m Accuracy (%)
CNN	95	3	88	100
RNN	90	5	80	97
Tradition al	75	7	60	85

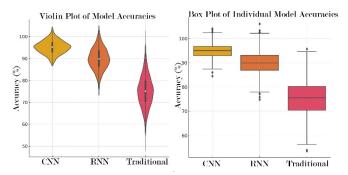


Figure 4: Volin Plot Model Accuracies/Box Plot of Individual Model Accuracies

# 2) System Stability and Robustness Testing:

System failure rate data compared the proposed system with industry-standard systems. Results show that the proposed system's average failure rate is 0.5%, while the industry-standard system's average failure rate is as high as 2.5%. This significant difference was evident in the experiments, and further validated through box plots, highlighting the high stability of the proposed system across different failure rate intervals.

Table 2: System Failure Rates: Proposed System vs. Industry Standard

System	Average Failure Rate (%)	Standard Deviation (%)	Minimum Failure Rate (%)	Maximum Failure Rate (%)
Proposed System	0.5	0.1	0.2	0.7
Industry Standard	2.5	0.5	1.6	3.5

#### 3) Impact of Environmental Factors on System Performance:

The impact of environmental factors on system performance was validated through scatter plots and regression analysis of the severity of environmental factors and performance impact. The results indicate that increased environmental factors significantly reduce system performance, with performance impact decreasing to 4.5% when environmental severity reaches 10. This phenomenon underscores the critical importance of environmental adaptability in enhancing system robustness

Table 3: Impact of Environmental Severity on System Performance

Environmental Severity	Average Performance Impact (%)	Standard Deviation (%)
1	9.5	0.2
•••	•••	•••
10	4.5	0.9

### 4) Fault Rate Distribution Analysis:

The frequency of fault rates in different intervals is presented through histograms. The proposed system's fault rate is concentrated in the 0% to 0.5% interval with a frequency of 30, while the industry-standard system's fault rate is primarily concentrated in the 2.5% to 3% interval with a frequency of 15. This result emphasizes the advantage of the proposed system in reducing fault rates.

Table 4: Distribution of Fault Rates Between Proposed and Industry Standard
Systems

Fault Rate (%)	Proposed System Frequency	Industry Standard Frequency
0-0.5	30	0
•••	•••	•••
3.0-3.5	0	5

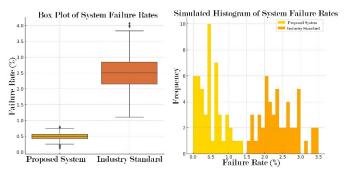


Figure 5: Box Plot of System Failure Rates/Simulated Histogram of System
Failure Rates

# 5) Regression Analysis of System Performance and Environmental Factors:

Regression analysis of system performance and environmental factors through scatter plots shows that system performance significantly decreases with increasing environmental severity. This analysis provides quantitative data, further validating the trend of environmental factors affecting the system and providing a reference for future system optimization.

Table 5: Regression Analysis Data on System Performance vs. Environmental Severity

<b>Environmental Severity</b>	Performance Impact (%)
1	9.5
•••	•••
10	4.5

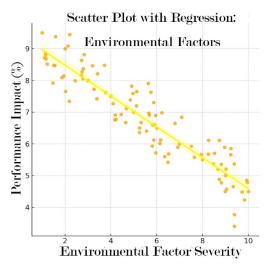


Figure 6: Scatter Plot with Regression Environmental Factors

# 6) System Iteration and Optimization Feedback:

Based on the experimental and field test results, the system's performance in terms of deep learning model accuracy and system failure rate surpasses traditional methods and industry standards, providing data support for future system iterations and optimizations. Analysis of the impact of environmental factors suggests a future focus on enhancing system adaptability to extreme environments.

In summary, the experimental data and visual analysis in this study demonstrate significant improvements in accuracy, stability, and environmental adaptability of the automated picking system. Future work will further optimize these models and systems to achieve higher efficiency and accuracy in a broader range of application scenarios.

# IV. CONCLUSIONS

This study comprehensively optimized and empirically analyzed automated picking systems by integrating deep learning and reinforcement learning technologies. The experimental results indicate that applying these advanced machine learning algorithms can significantly enhance picking system efficiency and accuracy while reducing failure rates, improving system robustness, and environmental adaptability. This not only optimizes warehouse operations' performance but also provides an effective solution for the logistics industry to meet the growing market demands and complex supply chain challenges.

Additionally, by analyzing different environmental factors, we further understood how these factors impact system performance, and adjusted and optimized models accordingly to ensure optimal performance under varying operating conditions. The application of this methodology demonstrates

the immense potential and application value of machine learning technologies in practical logistics operations.

Looking ahead, as technology continues to advance and logistics needs become increasingly diverse, we foresee automated picking systems continuing to evolve, with more integrated innovative technologies being explored. Our research provides scientific evidence and technical pathways for this process, driving the development of intelligent logistics technology. Simultaneously, this study offers valuable experience and data support for researchers and practitioners in related fields, helping them better design and implement efficient and reliable automated solutions in future work.

In conclusion, through in-depth analysis and empirical testing in this study, we not only optimized the performance of automated picking systems but also deepened our understanding of the application of intelligent systems in complex real-world environments. With the further development of technology and deepening applications, we look forward to realizing more widespread automation applications in the future, bringing revolutionary changes to the global logistics industry.

#### V. CONTRIBUTION

Keqin Li (1) and Jin Wang (1), as co-first authors, contributed equally and significantly to the overall design and management of the research project, with Keqin Li focusing on the development and integration of deep learning algorithms and Jin Wang specializing in refining and implementing reinforcement learning algorithms. Xubo Wu (2) developed adaptive strategies for the reinforcement learning models, enhancing their performance in dynamic and unpredictable warehouse environments. Xirui Peng (3) implemented advanced ensemble learning techniques to improve the prediction accuracy and robustness of the machine learning models. Runmian Chang (4) managed all data collection and preprocessing efforts, foundational for the accuracy and effectiveness of the machine learning models. Xiaoyu Deng (5) integrated and optimized machine learning techniques for realtime decision-making within the picking system. Yiwen Kang (6) led the simulation experiments, providing crucial data to assess and refine the performance of the integrated machine learning models. Yue Yang (7) analyzed and optimized the impact of various operational and environmental factors on the performance of the models. Fanghao Ni (8) conducted detailed statistical analyses and visualizations that documented and interpreted the performance metrics. Bo Hong (9) specialized in technical development, focusing on enhancing the fault tolerance and operational efficiency of the models.

# REFERENCES

[1] Qin Hu. Optimization and Simulation of Warehouse Handling Robot Scheduling [J]. Logistics Technology and Application, 2022, 27(05): 120-123

- [2] Liu Jian, Zhou Hao, Zhang Enzheng. Automatic Monitoring System for Coal Mine Subsidence Based on Machine Learning [J]. Information Technology, 2022, 46(11): 143-148+154.
- [3] Gu Linfeng, Li Ya. Design of Peanut Sorting System Based on Machine Vision [J]. Food Industry, 2021, 42(08): 188-192.
- [4] Geng Yuancheng. Cargo Identification and Picking Method of Logistics System Visual Robot [J]. Logistics Technology, 2023, 46(16): 52-55+64.
- [5] Liu Yichang. Application of Automation Technology in Industrial Robots[J]. Electronics Technology, 2021, 50(05): 114-115.
- [6] Xia Zian. Warehouse Smoke Detection and Alarm System Based on Machine Vision [D]. Supervisor: Wang Guicheng; Jiang Chun. Shanghai Institute of Technology, 2022.
- [7] Tan Chunlin. Application Research of Machine Vision Technology in Industrial Robots [J]. China Equipment Engineering, 2023, (18): 46-48
- [8] Gong, H., & Wang, M. (2020, July). A duality approach for regret minimization in average-award ergodic markov decision processes. In Learning for Dynamics and Control (pp. 862-883). PMLR.
- [9] Sun, Y., Duan, Y., Gong, H., & Wang, M. (2019). Learning low-dimensional state embeddings and metastable clusters from time series data. Advances in Neural Information Processing Systems, 32.
- [10] Li, Z., et al. (2023). Stock market analysis and prediction using LSTM: A case study on technology stocks. Innovations in Applied Engineering and Technology, 1-6.
- [11] Mo, Y., et al. (2024). Large Language Model (LLM) AI Text Generation Detection based on Transformer Deep Learning Algorithm. International Journal of Engineering and Management Research, 14(2), 154-159.
- [12] Li, S., Mo, Y., & Li, Z. (2022). Automated pneumonia detection in chest x-ray images using deep learning model. Innovations in Applied Engineering and Technology, 1-6.
- [13] Mo, Y., et al. (2024). Password complexity prediction based on roberta algorithm. Applied Science and Engineering Journal for Advanced Research, 3(3), 1-5.
- [14] Song, J., et al. (2024). A comprehensive evaluation and comparison of enhanced learning methods. Academic Journal of Science and Technology, 10(3), 167-171.
- [15] Liu, T., et al. (2024). Spam detection and classification based on distilbert deep learning algorithm. Applied Science and Engineering Journal for Advanced Research, 3(3), 6-10.
- [16] Dai, S., et al. (2024). The cloud-based design of unmanned constant temperature food delivery trolley in the context of artificial intelligence. Journal of Computer Technology and Applied Mathematics, 1(1), 6-12.
- [17] Mo, Y., et al. (2024). Make Scale Invariant Feature Transform "Fly" with CUDA. International Journal of Engineering and Management Research, 14(3), 38-45.
- [18] He, S., et al. (2024). Lidar and Monocular Sensor Fusion Depth Estimation. Applied Science and Engineering Journal for Advanced Research, 3(3), 20-26.
- [19] Liu, J., et al. (2024). Unraveling large language models: From evolution to ethical implications-introduction to large language models. World Scientific Research Journal, 10(5), 97-102.
- [20] Mo, Y., Zhang, Y., Li, H., Wang, H., & Yan, X. (2024). Prediction of heart failure patients based on multiple machine learning algorithms. Applied and Computational Engineering, 75, 1-7. https://doi.org/10.54254/2755-2721/75/20240498.
- [21] Peng, H., Xie, X., Shivdikar, K., Hasan, M. A., Zhao, J., Huang, S., Khan, O., Kaeli, D., & Ding, C. (2024). MaxK-GNN: Extremely Fast GPU Kernel Design for Accelerating Graph Neural Networks Training. In Proceedings of the 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2 (pp. 683-698).
- [22] Xie, X., Peng, H., Hasan, A., Huang, S., Zhao, J., Fang, H., Zhang, W., Geng, T., Khan, O., & Ding, C. (2023). Accel-gcn: High-performance gpu accelerator design for graph convolution networks. In 2023 IEEE/ACM International Conference on Computer Aided Design (ICCAD) (pp. 01-09). IEEE.
- [23] Peng, H., Huang, S., Zhou, T., Luo, Y., Wang, C., Wang, Z., Zhao, J., Xie, X., Li, A., Geng, T., et al. (2023). Autorep: Automatic relu replacement

- for fast private network inference. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 5178-5188).
- [24] Jin, C., Che, T., Peng, H., Li, Y., & Pavone, M. (2024). Learning from Teaching Regularization: Generalizable Correlations Should be Easy to Imitate. arXiv preprint arXiv:2402.02769.
- [25] Jin, C., Huang, T., Zhang, Y., Pechenizkiy, M., Liu, S., Liu, S., & Chen, T. (2023). Visual Prompting Upgrades Neural Network Sparsification: A Data-Model Perspective. arXiv preprint arXiv:2312.01397.
- [26] Peng, H., Ran, R., Luo, Y., Zhao, J., Huang, S., Thorat, K., Geng, T., Wang, C., Xu, X., Wen, W., et al. (2024). Lingen: Structural linearized graph convolutional network for homomorphically encrypted inference. Advances in Neural Information Processing Systems, 36.
- [27] Zhu, A., Liu, J., Li, K., Dai, S., Hong, B., Zhao, P., & Wei, C. (2024). Exploiting diffusion prior for out-of-distribution detection. Irish Interdisciplinary Journal of Science & Research (IIJSR), 8(2), 171-185. https://doi.org/10.46759/IIJSR.2024.8219
- [28] Peng, Q., Zheng, C., & Chen, C. (2024). A Dual-Augmentor Framework for Domain Generalization in 3D Human Pose Estimation. arXiv preprint arXiv:2403.11310.
- [29] Peng, Q., Zheng, C., & Chen, C. (2023). Source-free domain adaptive human pose estimation. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 4826-4836).
- [30] Peng, Q., Ding, Z., Lyu, L., Sun, L., & Chen, C. (2023). RAIN: Regularization on input and network for black-box domain adaptation. In Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (pp. 4118-4126).

- [31] Pinyoanuntapong, E., Ali, A., Jakkala, K., Wang, P., Lee, M., Peng, Q., Chen, C., & Sun, Z. (2023). Gaitsada: Self-aligned domain adaptation for mmwave gait recognition. In 2023 IEEE 20th International Conference on Mobile Ad Hoc and Smart Systems (MASS) (pp. 218-226). IEEE.
- [32] Peng, Q. (2022). Multi-source and Source-Private Cross-Domain Learning for Visual Recognition. (Doctoral dissertation, Purdue University).
- [33] Bo, S., Zhang, Y., Huang, J., Liu, S., Chen, Z., & Li, Z. (2024). Attention Mechanism and Context Modeling System for Text Mining Machine Translation. arXiv preprint arXiv:2408.04216.
- [34] Wang, Z., Yan, H., Wei, C., Wang, J., Bo, S., & Xiao, M. (2024). Research on Autonomous Driving Decision-making Strategies based Deep Reinforcement Learning. arXiv preprint arXiv:2408.03084.
- [35] Gao, H., Wang, H., Feng, Z., Fu, M., Ma, C., Pan, H., ... & Li, N. (2016). A novel texture extraction method for the sedimentary structures' classification of petroleum imaging logging. In Pattern Recognition: 7th Chinese Conference, CCPR 2016, Chengdu, China, November 5-7, 2016, Proceedings, Part II 7 (pp. 161-172). Springer Singapore.
- [36] Xiang, A., Huang, B., Guo, X., Yang, H., & Zheng, T. (2024). A neural matrix decomposition recommender system model based on the multimodal large language model. arXiv preprint arXiv:2407.08942.
- [37] Xiang, A., Qi, Z., Wang, H., Yang, Q., & Ma, D. (2024). A Multimodal Fusion Network For Student Emotion Recognition Based on Transformer and Tensor Product. arXiv preprint arXiv:2403.08511.