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Semantic Trajectory Planning for Industrial Robotics

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ABSTRACT

The implementation of industrial robots across various sectors has ushered in unparalleled advancements in efficiency, productivity, and safety. This paper explores the domain of semantic trajectory planning in the area of industrial robotics. By adeptly merging physical constraints and semantic knowledge of environments, the proposed methodology enables robots to navigate complex surroundings with utmost precision and efficiency. In a landscape marked by dynamic challenges, the research positions semantic trajectory planning as a linchpin in fostering adaptability. It ensures robots interact safely with their surroundings, providing vital object detection and recognition capabilities. The proposed ResNet model exhibits remarkable classification performance, bolstering overall productivity. The study underscores the significance of this approach in addressing real-world industrial applications while emphasizing accuracy, precision, and enhanced productivity.

KEYWORDS

Industrial Robotics, Object Detection ResNet Model, Precision and Productivity, Semantic Trajectory Planning

INTRODUCTION

Industrial robotics has a rich background that has evolved over time to meet the needs of various industries. Initially, the focus of industrial robotics was on automating repetitive tasks in manufacturing processes to improve efficiency and productivity. Early industrial robots were primarily used for tasks such as welding, assembly, and material handling (Villani et al., 2018; Saab & Jaafar, 2021). However, with advancements in technology and the emergence of new applications, the role of industrial robots has expanded.

One significant development in industrial robotics is the integration of human-robot collaboration (HRC) in industrial settings. HRC allows humans and robots to work together in a shared workspace, combining the strengths of both to enhance productivity and safety. Authors (Villani et al., 2018; Shen & Saab, 2021; Awad et al., 2022) discuss the importance of safety and

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intuitive interfaces in HRC, highlighting the relevance of collaborative industrial robotics in modern manufacturing environments.

Another area of development in industrial robotics is trajectory planning. Trajectory planning involves generating optimized paths for robots to follow while considering various constraints such as obstacles, kinematic limitations, and task objectives. Authors (Sheng-xi et al. (2018)) focus on trajectory planning for a cutting robot in machining complex surfaces, emphasizing the significance of precise and efficient trajectory planning in achieving accurate tool positioning and smooth motion execution. Optimal trajectory planning is also crucial in industrial robotics to ensure efficient and collision-free robot motion. Authors (Patel et al. (2023)) propose a hybrid S-curve-PSO approach for trajectory planning, aiming to minimize path length and time while avoiding obstacles. This research highlights the importance of semantic trajectory planning in optimizing the performance of industrial robots in the presence of obstacles.

The proliferation of industrial robots across diverse industries has ushered in a transformative era, characterized by notable advancements in productivity, operational efficiency, and labor dynamics. These machines have found applications in sectors spanning manufacturing, healthcare, agriculture, and construction. Their contributions include elevating precision, safety, and productivity within production processes. However, the increased use of industrial robots has also raised concerns about the potential impact on employment (Zhao et al. 2022; Bacchetti et al. 2022). Authors (Zhao et al., 2022) analyze the effect of industrial robots on employment in China, highlighting the need for careful consideration of the labor market implications.

Within the realm of industrial robotics, semantic trajectory planning emerges as a pivotal domain, revolutionizing path planning for robots in complex, dynamic environments. This approach transcends mere trajectory generation, as it meticulously accounts for both the intrinsic physical constraints of the robot and the semantic attributes of the environment. This includes a comprehensive understanding of obstacles, desired task objectives, and paramount safety considerations.

Object detection and recognition have attained paramount significance in the milieu of industrial robots for multifaceted reasons. First and foremost, the capacity for robots to interact seamlessly with their surroundings hinges upon their ability to discern and identify objects with precision. Nowhere is this more salient than in applications like pick-and-place operations, wherein robots are tasked with the precise location and grasp of specific objects. The study by (Ansary et al., 2021) emphasizes the significance of object recognition in empowering autonomous service robots to navigate and interact effectively with real-world environments (Ansary et al., 2021; Ren et al., 2021).

Furthermore, the sphere of object detection and recognition plays a pivotal role in upholding the safety quotient in industrial robot operations. By adeptly detecting and recognizing objects within the robot's working domain, the potential for collisions and accidents is effectively minimized. A notable study delves into the synthesis of vision-based object recognition and human-robot communication, shedding light on the profound importance of this synergy within industrial contexts (Rogowski et al., 2020).

Moreover, object detection and recognition wield transformative potential in enhancing the efficiency and productivity of industrial robots. By accurately identifying objects, robots are primed to execute tasks with optimal efficiency, encompassing activities such as sorting, assembly, and quality control. The deployment of deep learning-based object recognition takes the spotlight, exemplified in its role in fostering equipment intelligence and propelling production automation within the automotive sector (Tan & Xia, 2023).

In addition, the adaptability of robots to dynamic environments relies heavily on their acumen in detecting and distinguishing objects. The industrial robotic landscape frequently presents scenarios involving mobile objects or evolving conditions. Notable discourse has emerged regarding the importance of object detection in multi-robot and swarm robotic applications, underlining its irreplaceable role in these contexts (Yilmaz & Bayindir, 2019).

This research paper presents a significant contribution to the field of industrial robotics through the introduction and validation of an innovative Semantic Trajectory Planning approach. Our study addresses the critical necessity for industrial robots to perform efficient and optimized path planning in complex and dynamic environments. By seamlessly integrating both the robot's physical constraints and semantic data, which encompasses aspects like obstacle awareness and task objectives, our proposed approach elevates not only the overall performance but also the safety and productivity of industrial robots.

Furthermore, our research underscores the pivotal importance of precise object detection and recognition within industrial robot settings. We delve into the application of deep learning-based object recognition, enabling robots to interact seamlessly with their surroundings, ensuring safety through collision avoidance, enhancing task efficiency, and adapting flexibly to changing environmental conditions. These combined contributions form a holistic framework that advances the capabilities of industrial robotics across various industries, promising improved precision and productivity.

RELATED WORK

Recently, the development in the field of artificial intelligence, machine learning, and deep learning, encourages researchers to integrate them in different domains, such as cyber security (Tembhurne et al., 2022; Li et al., 2022; Srivastava et al., 2022; Khoudja et al., 2022; Madan & Bhatia, 2021; Singh & Gupta, 2022; Sahoo & Gupta, 2021; Nguyen et al., 2021), education system (Hu et al., 2022), cloud computing (Anil et al., 2022), big data (Hasib et al., 2021), natural language processing (Yen et al., 2021; Gupta et al., 2023), and healthcare (Shankar et al., 2021; Hammad et al., 2021). In this context, researchers also propose the use of deep learning in the field of robotics. In a study conducted by Sheng-xi et al. (2018), the focus was on the trajectory planning of a 6-degree-of-freedom (6-DOF) cutting robot, specifically designed for machining complex surfaces. The importance of trajectory planning was underscored as a critical element in achieving precise and efficient machining operations. By meticulously accounting for complex surface geometries and the inherent kinematic constraints of the robot, the proposed trajectory planning methodology successfully ensured accurate tool positioning and the seamless execution of motion. This study serves as an example of how semantic trajectory planning can substantially enhance the performance of industrial robots when tailored to specific applications.

Another notable investigation, as presented by recent research Patle et al. (2023), introduces an optimal trajectory planning approach geared towards industrial robots. This approach leverages a hybrid S-curve-PSO (Particle Swarm Optimization) algorithm to optimize robot trajectories effectively. Notably, it underscores the significance of efficient trajectory planning, especially when navigating environments laden with obstacles. The novel approach combines S-curve trajectory profiles with the intelligent PSO algorithm to fine-tune robot trajectories, thereby mitigating the risk of collisions with obstacles. These findings reiterate the vital role of semantic trajectory planning in ensuring both safety and efficiency within industrial settings.

Furthermore, the literature points to a growing demand for enhanced efficiency in the application of industrial robots within production and assembly tasks Wapenhans et al. (1994). Key to addressing this demand is the development of trajectory planning and optimization techniques that take into account the dynamic constraints inherent in robot actuators. These constraints encompass issues such as backlash and various other physical limitations. It becomes evident that by deploying trajectory planning algorithms that tackle these challenges, there is a tangible improvement in the overall performance and productivity of industrial robots. In light of this, semantic trajectory planning assumes particular significance in addressing the practical challenges associated with industrial applications.

In summary, semantic trajectory planning is of exceptional consequence in the realm of industrial robotics. Its role in enabling efficient and optimized path planning for robots in complex and demanding environments is pivotal. By holistically considering the physical constraints of robots, alongside semantic information related to their surroundings, including obstacles and task objectives, semantic trajectory planning algorithms make substantial contributions to bolstering performance, safety, and productivity within industrial robotics.

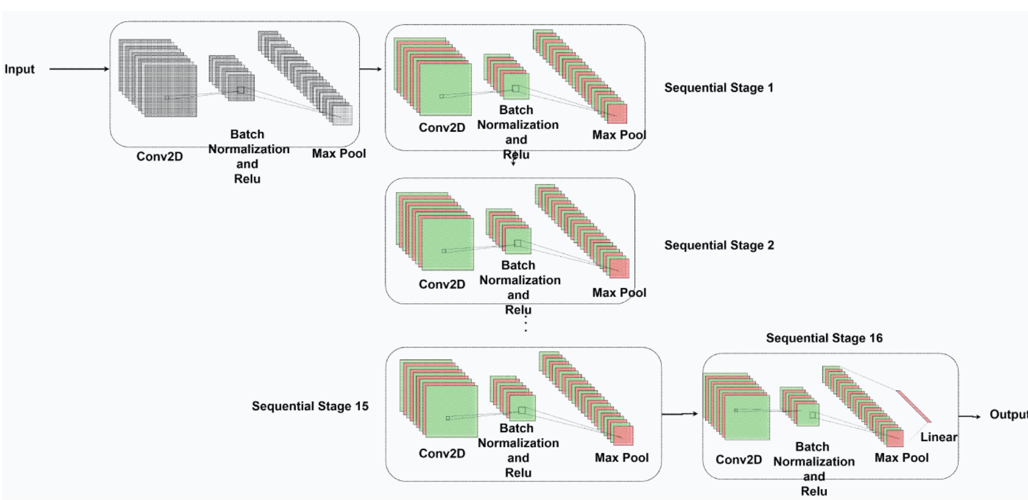
RESEARCH METHODOLOGY

The proposed model architecture leverages the ResNet framework, presented in Figure 1 and the working of the model is explained in Algorithm 1, a deep neural network designed to facilitate the training of exceedingly deep convolutional neural networks. ResNet is known for its successful application in a wide range of computer vision tasks. The architecture comprises a series of convolutional layers and bottleneck blocks. At the core of the architecture, convolutional layers are responsible for extracting high-level features from the input data. Bottleneck blocks, consisting of multiple convolutional layers and batch normalization, play a crucial role in reducing computational complexity and enabling the network to achieve remarkable depth. This depth is essential in capturing intricate features and patterns, particularly in semantic trajectory planning for industrial robotics. The network's structure culminates in an Adaptive Average Pooling layer and a Linear layer, resulting in an output dimension of 1000 for object classification. The model boasts an impressive parameter count of 25,557,032, making it a robust choice for object detection and semantic trajectory planning tasks within the industrial robotics domain. The architecture's overall design permits efficient and accurate object detection while remaining computationally manageable for real-world deployment scenarios.

Algorithm 1. ResNet Model Architecture

```
procedure RESNET
Initialize CNN Layers
Initialize Bottleneck Blocks
        for each CNN Layer do
        Apply Conv2d operation
        Apply Batch Normalization
        Apply ReLU Activation
```

Figure 1. Model architecture



```
        end for
        Apply MaxPooling Operation
         for each Bottleneck Block do
         for each Convolutional Layer in Bottleneck do
         Apply Conv2d operation
         Apply Batch Normalization
         Apply ReLU Activation
         end for
         Apply Conv2d operation for shortcut connection
         Apply Batch Normalization
         Add shortcut to output
         Apply ReLU Activation
         end for
         Apply Adaptive Average Pooling
         Flatten the output
         Initialize Linear Layer for Object Classification
         Apply Linear Transformation
   end procedure
```

RESULT AND DISCUSSION

Training and Testing Accuracy and Loss

In this section, we present the results of training a ResNet model over 50 epochs. We measure the training and testing accuracy as well as the training and testing loss to assess the model's performance. These metrics provide insights into how well the model generalizes to unseen data.

Accuracy

Figure 2 illustrates the changes in training and testing accuracy over the 50 epochs. The blue curve represents the training accuracy, and the orange curve represents the testing accuracy.

As seen in Figure 2, the training accuracy steadily increases as the number of epochs progresses, reaching an impressive level of approximately 98.5% by the 50th epoch. Simultaneously, the testing accuracy follows a similar pattern, demonstrating the model's ability to generalize effectively to unseen data.

Loss

Figure 3 depicts the evolution of training and testing loss throughout all 50 epochs. The blue line shows the loss during training, whereas the orange line shows the loss during testing.

As training progresses, the model becomes better at fitting the training data, as seen by a steady decrease in training loss. Effective convergence is shown by the considerable decrease in training loss by the last epoch. Similarly, there is a consistent drop in the testing loss, indicating that the model is becoming better at generalization.

The ResNet model achieves impressive results in both training and testing, with a loss that effectively converges over both phases. These findings demonstrate that the model performs admirably and may be successfully used to a wide range of picture identification problems.

Classification Report

In order to analyze the performance of our proposed ResNet model, we present the classification report in Figure 3 that includes precision, recall, and the F1-score for each class. Here are some key observations:

Figure 2. Training and testing accuracy

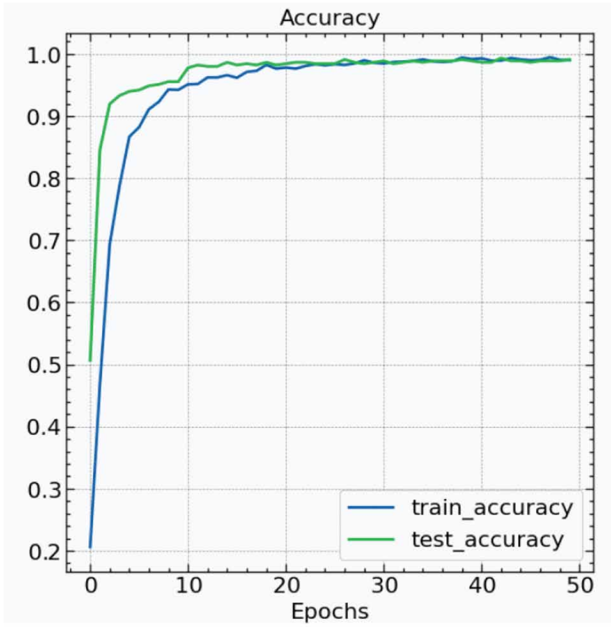
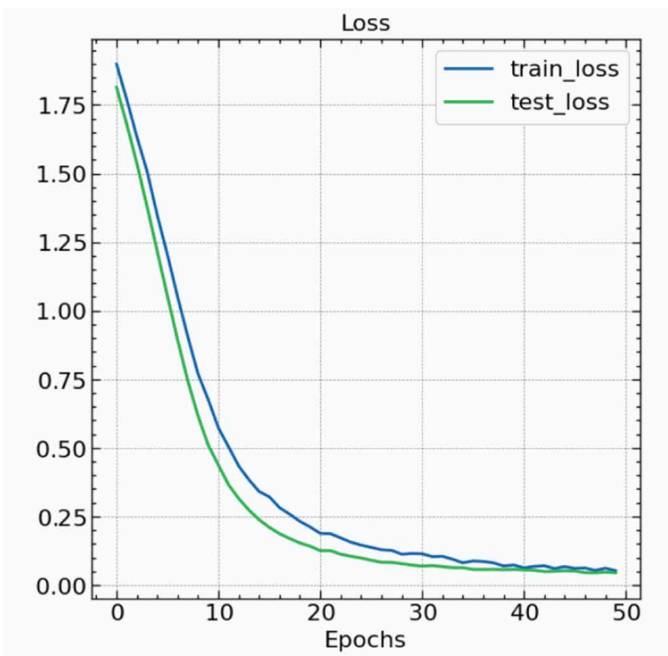


Figure 3. Training and testing loss



- Our proposed model exhibits high precision and recall for most classes, demonstrating its capacity to accurately identify objects across multiple categories.

- The proposed model achieves a 99% accuracy on the dataset, showcasing its ability to generalize effectively to diverse image classes.
- The macro and weighted averages for precision, recall, and F1-score are also high, emphasizing the overall robustness of our ResNet model.

The results in Figure 4 confirm that the proposed model is capable of identifying different objects, and it is suitable for a wide range of image recognition tasks.

Confusion Matrix

Our model's performance evaluation encompasses an array of metrics, as detailed in the previous sections. To provide a comprehensive understanding of our ResNet model's efficacy, we also employ a confusion matrix (Figure 5). This matrix offers valuable insights into our model's classification performance across the seven distinct object categories. It furnishes a detailed summary of the model's predictions, shedding light on both correct and erroneous classifications.

Key observations gleaned from the confusion matrix include:

- The diagonal elements, running from the top-left to the bottom-right, signify true positive (TP) values for each class, representing the count of accurately classified instances.
- Non-diagonal elements draw attention to misclassifications. Notably, our model exhibits an exceptionally low rate of misclassifications.
- The dominant high values along the diagonal underscore the model's remarkable ability to make precise predictions regarding object classes. The primary diagonal indicates that a significant majority of predictions align with the true labels.

In summation, the performance of our ResNet model stands as a testament to its excellence, marked by minimal misclassifications and consistently high accuracy across all object categories. The confusion matrix provides further evidence of the model's prowess in effectively distinguishing between the seven distinct object classes.

Figure 4. Classification report

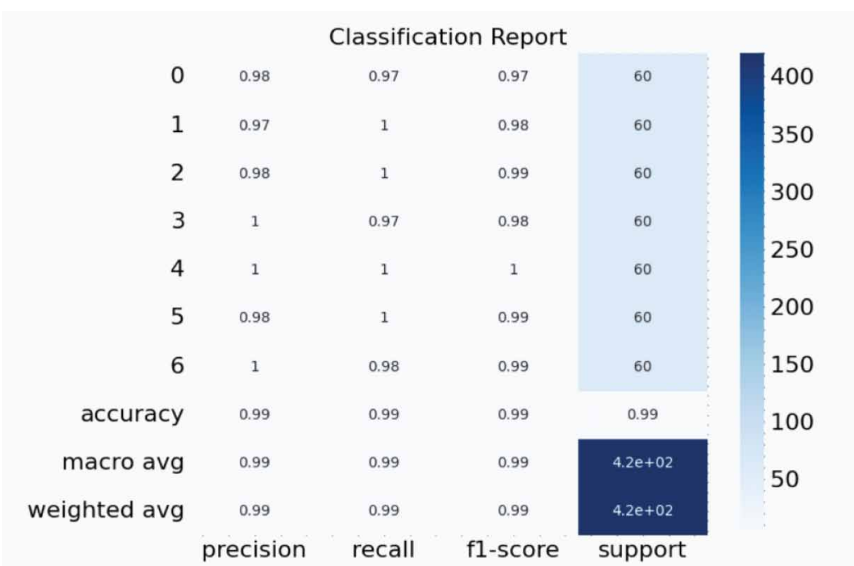
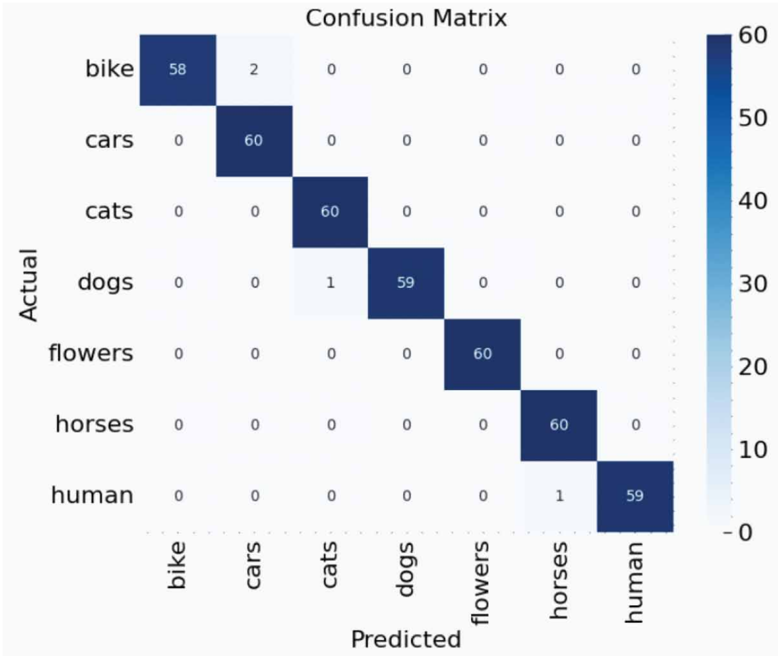


Figure 5. Confusion matrix



CONCLUSION

Our research is focused on improving the efficiency of semantic Trajectory planning for industrial robotics with a particular emphasis on obstacle detection and avoidance. In this context, we used popular ResNet models to identify the obstacles in front of robots The classification report validates the model's precision, recall, and overall accuracy, demonstrating its aptitude for real-world applications. As industrial automation becomes increasingly prevalent, the findings from this research offer a crucial advancement, enhancing the safety and effectiveness of robots deployed in complex, dynamic environments. Our work paves the way for innovative developments in the field of industrial robotics, ensuring a safer and more productive future. In the future, we will focus on testing our model with a bigger dataset and use a more complex deep learning model.

REFERENCES

Anil, B. C., Dayananda, P., Nethravathi, B., & Mahesh, S. (2022). Efficient Local Cloud-Based Solution for Liver Cancer Detection Using Deep Learning. *International Journal of Cloud Applications and Computing*, *12*(1), 1–13. doi:10.4018/IJCAC.2022010109

Ansary, S., Deb, S., & Deb, A. (2021). A Novel Object Slicing-Based Grasp Planner for Unknown 3d Objects. *Intelligent Service Robotics*, *15*(1), 9–26. doi:10.1007/s11370-021-00397-0

Awad, Z., Chibani, C., & Maalouf, N. (2022). Human-Aided Online Terrain Classification for Bipedal Robots Using Augmented Reality. *2022 IEEE International Conference on Robotics and Biomimetics (ROBIO),* 1352–58. doi:10.1109/ROBIO55434.2022.10011705

Bacchetti, A., Lloyd, P., Taccola, S., Fakhoury, E., Cochran, S., & Russell A Harris, P. V. (2022). Optimization and Fabrication of Programmable Domains for Soft Magnetic Robots: A Review. *Frontiers in Robotics and AI*, *9*, 1040984. doi:10.3389/frobt.2022.1040984 PMID:36504496

Gupta, P., Yadav, K., Gupta, B. B., Alazab, M., & Gadekallu, T. R. (2023). A Novel Data Poisoning Attack in Federated Learning Based on Inverted Loss Function. *Computers & Security*, *130*, 103270. doi:10.1016/j.cose.2023.103270

Hammad, , Alkinani, Gupta, & El-Latif. (2021). Myocardial Infarction Detection Based on Deep Neural Network on Imbalanced Data. *Multimedia Systems*, 1–13.

Hasib, K. M., Towhid, N. A., & Islam, M. R. (2021). Hsdlm: A Hybrid Sampling with Deep Learning Method for Imbalanced Data Classification. *International Journal of Cloud Applications and Computing*, *11*(4), 1–13. doi:10.4018/IJCAC.2021100101

Hu, B., Gaurav, A., Choi, C., & Almomani, A. (2022). Evaluation and Comparative Analysis of Semantic Web-Based Strategies for Enhancing Educational System Development. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–14. doi:10.4018/IJSWIS.302895

Khoudja, M. A., Fareh, M., & Bouarfa, H. (2022). Deep Embedding Learning with Auto-Encoder for Large-Scale Ontology Matching. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–18. doi:10.4018/IJSWIS.297042

Li, S., Qin, D., Wu, X., Li, J., Li, B., & Han, W. (2022). False Alert Detection Based on Deep Learning and Machine Learning. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–21. doi:10.4018/IJSWIS.313190

Madan, K., & Bhatia, R. K. (2021). Ranked Deep Web Page Detection Using Reinforcement Learning and Query Optimization. *International Journal on Semantic Web and Information Systems*, *17*(4), 99–121. doi:10.4018/IJSWIS.2021100106

Nguyen, G. N., Le Viet, N. H., & Elhoseny, M. (2021). Secure Blockchain Enabled Cyber–Physical Systems in Healthcare Using Deep Belief Network with ResNet Model. *Journal of Parallel and Distributed Computing*, *153*, 150–160. doi:10.1016/j.jpdc.2021.03.011

Patle, B., Chen, S., Singh, A., & Kashyap, S. (2023). Optimal Trajectory Planning of the Industrial Robot Using Hybrid s-Curve-Pso Approach. *Robotic Intelligence and Automation*, *43*(2), 153–174. doi:10.1108/RIA-07-2022-0187

Ren, P., Xiao, Y., Chang, X., Huang, P.-Y., Li, Z., Gupta, B. B., Chen, X., & Wang, X. (2021). A Survey of Deep Active Learning. *ACM Computing Surveys*, *54*(9), 1–40. doi:10.1145/3472291

Rogowski, A., Bieliszczuk, K., & Rapcewicz, J. (2020). Integration of Industrially-Oriented Human-Robot Speech Communication and Vision-Based Object Recognition. *Sensors (Basel)*, *20*(24), 7287. doi:10.3390/s20247287 PMID:33353038

Saab, S. S., & Jaafar, R. H. (2021). A Proportional-Derivative-Double Derivative Controller for Robot Manipulators. *International Journal of Control*, *94*(5), 1273–1285. doi:10.1080/00207179.2019.1642518

Sahoo, S. R., & Gupta, B. B. (2021). Multiple Features Based Approach for Automatic Fake News Detection on Social Networks Using Deep Learning. *Applied Soft Computing*, *100*, 106983. doi:10.1016/j.asoc.2020.106983

Shankar, K., Perumal, E., Elhoseny, M., Taher, F., Gupta, B. B., & El-Latif, A. A. A. (2021). Synergic Deep Learning for Smart Health Diagnosis of COVID-19 for Connected Living and Smart Cities. *ACM Transactions on Internet Technology*, *22*(3), 1–14. doi:10.1145/3453168

Shen, D., & Saab, S. S. (2021). Noisy-Output-Based Direct Learning Tracking Control with Markov Nonuniform Trial Lengths Using Adaptive Gains. *IEEE Transactions on Automatic Control*, *67*(8), 4123–4130. doi:10.1109/TAC.2021.3106860

Sheng-xi, J., Wang, H., Xia, L., & Zhang, S. (2018). Research on Trajectory Planning of 6-Dof Cutting-Robot in Machining Complex Surface. *Matec Web of Conferences*, *220*, 06003. doi:10.1051/matecconf/201822006003

Singh, A., & Gupta, B. B. (2022). Distributed Denial-of-Service (DDoS) Attacks and Defense Mechanisms in Various Web-Enabled Computing Platforms: Issues, Challenges, and Future Research Directions. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–43. doi:10.4018/IJSWIS.297143

Srivastava, A. M., Rotte, P. A., Jain, A., & Prakash, S. (2022). Handling Data Scarcity Through Data Augmentation in Training of Deep Neural Networks for 3d Data Processing. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–16. doi:10.4018/IJSWIS.297038

Tan, J., & Xia, D. (2023). Automobile Component Recognition Based on Deep Learning Network with Coarse-Fine-Grained Feature Fusion. *International Journal of Intelligent Systems*, *2023*, 1–14. doi:10.1155/2023/1903292

Tembhurne, J. V., Almin, M. M., & Diwan, T. (2022). Mc-DNN: Fake News Detection Using Multi-Channel Deep Neural Networks. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–20. doi:10.4018/IJSWIS.295553

Villani, V., Pini, F., Leali, F., & Secchi, C. (2018). Survey on Human–Robot Collaboration in Industrial Settings: Safety, Intuitive Interfaces and Applications. *Mechatronics*, *55*, 248–266. doi:10.1016/j.mechatronics.2018.02.009

Wapenhans, H., Hölzl, J., Steinle, J., & Pfeiffer, F. (1994). Optimal Trajectory Planning with Application to Industrial Robots. *International Journal of Advanced Manufacturing Technology*, *9*(1), 49–55. doi:10.1007/BF01792867

Yen, S., Moh, M., & Moh, T.-S. (2021). Detecting Compromised Social Network Accounts Using Deep Learning for Behavior and Text Analyses. *International Journal of Cloud Applications and Computing*, *11*(2), 97–109. doi:10.4018/IJCAC.2021040106

Yilmaz & Bayindir. (2019). Simulation of Lidar-Based Robot Detection Task Using Ros and Gazebo. *European Journal of Science and Technology*, 513–29. .10.31590/ejosat.642840

Zhao, Y., Said, R., Ismail, N., & Hamzah, H. (2022). Effect of Industrial Robots on Employment in China: An Industry Level Analysis. *Computational Intelligence and Neuroscience*, *2022*, 1–13. doi:10.1155/2022/9181865 PMID:35898783