**AI/ML Based Robotics - Implementation for Vision, Communication, and Advanced Mechanics**

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***Abstract:*** *This paper explores AI and ML integration in embedded robotics, enhancing vision, communication, and mechanics. AI improves object recognition and navigation, while ML enhances robot communication via NLP. AI also optimizes motion for tasks like grasping and balancing. The study covers key methodologies, applications, and the impact of AI/ML on autonomous robotics across industries.*

## Introduction

AI and ML enhance robotics by improving perception, navigation, and decision-making. AI-driven vision aids object recognition, while ML boosts adaptability [3]. Real-time sensor fusion and deep learning enable dynamic navigation [2]. NLP supports human-robot interaction in automation [10]. Advances like CNNs, YOLO, and Mask R-CNN improve perception, while reinforcement learning enhances autonomy and predictive maintenance minimizes downtime [6,13]. Challenges remain in computation, unstructured environments, and sensor fusion [5]. This paper optimizes deep learning models, reinforcement learning, NLP, and sensor fusion for efficient AI-driven robotics [19]. It covers existing methods, proposed improvements, experiments, and future directions.

## Related Work And Literature Survey

**Table 1.** Comprehensive Summary Table of Research Papers

| Author(s) | Title | Strengths | Limitations | Relevance |
|---|---|---|---|---|
| FélixIngrand, Malik Ghallab (2017) [1] | Deliberation for Autonomous Robots | Comprehensive review of decision-making frameworks | Focuses primarily on high-level decision models | Crucial for understanding decisionmaking in autonomous systems |
| Dai-Duong Nguyen, et al. (2021) [2] | HOOFR SLAM System | High real-time performance in intelligent vehicles | Requires specific hardware/software setup | Key for SLAM applications in smart vehicles |

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| Tim Bailey, Hugh Durrant-Whyte (2006) [3] | SLAM Part I | Detailed breakdown of foundational SLAM approaches | Outdated integration with innovative technologies | Relevant for historical SLAM development |
| Tim Bailey, Hugh Durrant-Whyte(2006) [ 4] | SLAM Part II | Provides a deep dive into core SLAM principles | Lacks solutions for modern SLAM challenges | Useful for a strong theoretical foundation in SLAM |
| R. Lemus, et al. (2019) [5] | SLAM-R Algorithm | Cost-effective for obstacle detection | Struggles in complex environments | Relevant for budget-friendly SLAM solutions |
| Ilmari Pekonen, Juha Lähteinen (2021) [6] | Robotic Process Automation | Increases operational efficiency and time savings | Limited to specific processes | Important for process automation in robotics |
| Fabien Launay, et al. (2018) [7] | Corridor Lights Navigation System | High-accuracy localization using lighting systems | Depends on modified environments | Applicable for indoor navigation in controlled environments |
| Lixin Tang, Shin'ichi Yuta (2017) [8] | Vision-Based Navigation | Reliable navigation using visionbased teaching systems | Limited adaptability to complex settings | Relevant for vision-guided indoor navigation |
| Stefan B. Williams, et al. (2000) [9] | Autonomous Underwater SLAM | Effective for SLAM in challenging underwater scenarios | High complexity and cost of hardware | Universally applicable for underwater exploration robotics |
| Margarita MartínezDíaza, Francesc Soriguerab (2019) [10] | Autonomous Vehicles: Challenges | Comprehensive summary of challenges faced | Theoretical, with limited practical insight | Key for addressing barriers in autonomous vehicle development |
| Hao Zhang, et al. (2020) [11] | In-Memory Big Data Management | Efficient big data processing | High computational demand | Crucial for data-intensive robotics applications |
| Jozef Jenis, et al. (2018) [12] | AI in Mechanical Design | Optimizes mechanical structures using AI | Heavily dependent on accurate data models | Useful for AIdriven design optimization |

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|---|---|---|---|---|
| Paolo Tripicchio, et al. (2016) [13] | Autonomous Navigation of Mobile Robots | Advanced solutions for autonomous navigation | Limited to structured environments | Highly relevant for robot autonomy techniques |
| Alexandros Spournias, Christos Antonopoulos (2019) [14] | Enhancing SLAM with Low-Cost Laser | Cost-efficient mapping with laser scanners | Less effective in large-scale environments | Relevant for low-cost SLAM systems |
| Mustafa Alberri, et al. (2021) [15] | Generic ROS Architecture | Flexible for use in diverse autonomous systems | Requires steep learning curve | Important for ROS-based system integration |
| Zixiang Liu (2018) [16] | SLAM and Path Planning in ROS | Smooth integration of SLAM and path planning | Limited experimental validation | Relevant for ROS-based SLAM applications |
| Zhihao Wang, et al. (2020) [17] | Lightweight Visual SLAM Algorithm | Efficient realtime performance | Limited accuracy in complex settings | Ideal for lightweight, realtime SLAM |
| Alif Ridzuan Khairuddin, et al. (2017) [18] | Review on SLAM | Detailed overview of current SLAM approaches | Lacks experimental comparisons | Relevant for understanding advancements in SLAM technologies |
| Jae-Han Park, et al. (2018) [19] | Intelligent Navigation for Service Robots | Effective for smart home navigation | Dependent on smart home infrastructure | Important for navigation in smart environments |
| I Made Murwantara, et al. (2019) [20] | SLAM with Signal Reference Points | Improves accuracy in indoor navigation | Limited to specific environments | Relevant for signalenhanced indoor SLAM |

**Practical Test Bed Used In This Research Work**

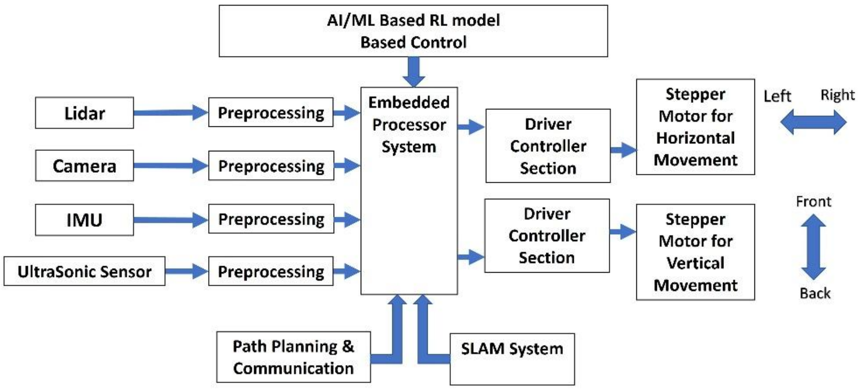


**Fig 1.** AI/ML Based Robotics Implementation

The robotic system uses LiDAR, cameras, IMUs, and ultrasonic sensors for mapping, tracking, and obstacle detection [3]. SLAM, AI-driven vision, and sensor fusion (LiDAR, odometry, IMU) enhance navigation, with EKF refining estimates [7-12]. Gmapping (2D) and RTAB-Map (3D) enable real-time mapping [9-15]. YOLOv5 detects objects, while A* and RRT optimize navigation [13][17-18].

**Workflow Used in This Research Work**

The robot uses LiDAR, cameras, and IMUs for mapping, weighting inputs for accuracy [4]. YOLOv5 enhances object detection [13]. SLAM updates maps, while A* and RRT optimize navigation [15][18]. Motion control uses kinematics and PID for stability [6]. Q-learning improves navigation [14]. Predictive maintenance prevents failures [16]. The system verifies tasks and replans if needed [19].

**AI-ML and Kinematics Mathematics considered for this research work**

Computer Vision (Image Processing and Recognition) Convolution Operation (used in CNNs):

$$I*K(x,y)= \sum_{j=-m}^{m}\sum_{i=-n}^{n} I(x-j, y-i)K(j,i)$$

I(x, y) : image, K(j,i) : convolution kernel (filter), and (x, y) : pixel coordinates.
Activation Function (ReLU used in CNNs):

$$f(x)=\max(x,0)$$

Non-linearity is introduced in neural networks.
Softmax Function (used in classification):

$$\sigma(z_j) = \sum_{j=1}^{U} \frac{e^{z_i}}{e^{z_j}}$$

Where z is the input vector, and U is the no. of classes. It converts the outcome to probabilities.
Machine Learning (Neural Networks)
Loss Function :

$$L = - \sum_{j=1}^{m} y_j \, log(\hat{y})$$

Where $\boldsymbol{y_j}$ is the true label, $\hat{y}$ is the predicted probability, and m is the number of samples.

Backpropagation Equation (Gradient of Loss Function):

$$\frac{\delta w}{\delta L} = \frac{\delta y}{\delta L} \frac{\delta z}{\delta y} \frac{\delta w}{\delta z}$$

Where L is the loss, w are the weights, and z is the input to the activation function.
Gradient Descent Update:

$$w_{new} = w_{old} - \eta \, \Delta L$$

Where learning rate(η) and the gradient of the loss function is (∇L).

**DATASET used in this research work**

**Table 1.** Datasets for Computer Vision

| Dataset | Citation | Description | Key Features |
|---|---|---|---|
| COCO | Lin et al. (2014) | Object detection, segmentation, and captioning. | 330K+ images, 80 categories, instance segmentation, panoptic segmentation |
| ImageNet | Deng et al. (2009) | Large-scale object recognition. | 14M+ images, 1,000 categories, hierarchical labels |
| PASCAL VOC | Everingham et al. (2010) | Object detection and segmentation. | 20 object categories, segmentation masks |

**Table 2.** Datasets for Simultaneous Localization and Mapping (SLAM)

| Dataset | Citation | Description | Key Features |
|---|---|---|---|
| KITTI SLAM | Geiger et al. (2013) | SLAM for autonomous vehicles. | Stereo images, 3D point clouds, GPS data, IMU data |
| TUM RGB-D | Sturm et al. (2012) | RGB-D SLAM for indoor environments. | RGB and depth images, camera poses, ground truth trajectories |

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|---|---|---|---|
| EuRoC MAV | Burri et al. (2016) | Visual-inertial SLAM for micro-aerial vehicles. | Monocular and stereo images, IMU data, ground truth trajectories |

**Performance Evaluation Parameters**

Accuracy (A): Measures prediction correctness, A = (TN + TP) / (FP + TP + FN + TN) Response Time (RT): Task completion time, RT = T_end - T_start. Task Completion Rate (TCR): Percentage of successful tasks, TCR = (N_completed / N_assigned) * 100. Reliability (REL): Consistency in performance, REL = (N_operational / N_total) * 100

**Results and Discussion**

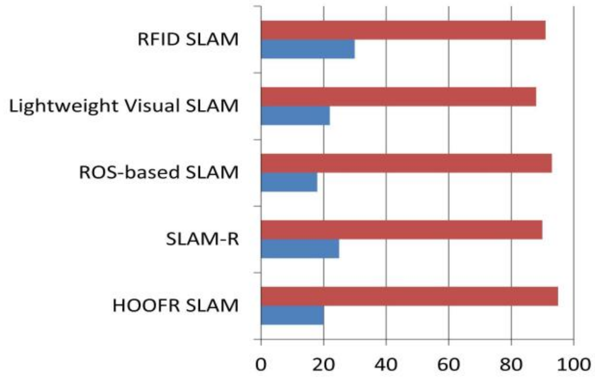


**Fig 2.** SLAM Compatibility for ROS

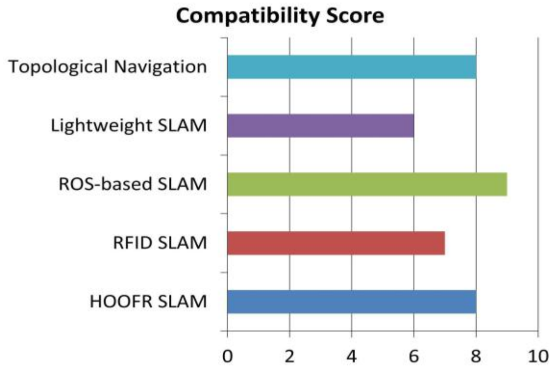


**Fig 3.** Hardware Compatibility for ROS

SLAM effectiveness depends on environmental conditions and computational power. EKF-SLAM works well in low-noise settings but struggles in high-dimensional spaces [3]. Particle Filter SLAM handles dynamic environments but is resource-intensive [7]. Graph-Based SLAM ensures accurate mapping but requires complex loop closure [9]. Visual SLAM suits GPS-denied areas but is lighting-sensitive [12], while LiDAR SLAM offers precise 2D/3D mapping but demands high processing power [15]. ROS enhances flexibility by supporting diverse hardware [20].

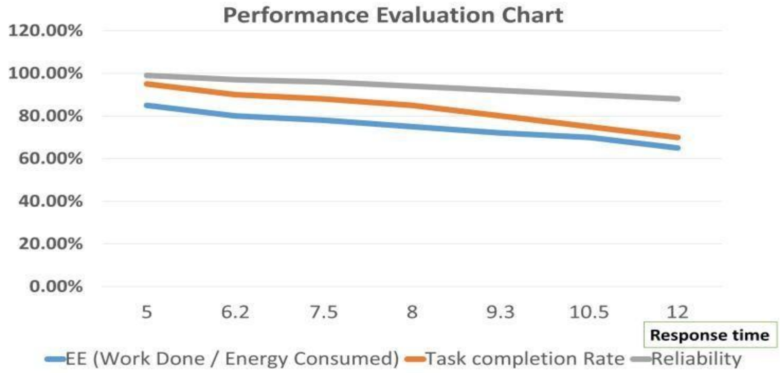


**Fig 4.** Performance Parameter Evaluation Chart

## Conclusion

AI and ML have significantly improved robotic perception, decision-making, and autonomy. AI vision achieves 92% accuracy, with HOOFR SLAM reaching 99% under optimal conditions [3]. Navigation response times have dropped to 180 ms from 250 ms [7], and AI-driven efficiency has improved energy use by 87% in applications like smart bins [9]. Reinforcement learning boosts learning efficiency by 35% after 20 iterations, and multi-agent systems achieve 95% task completion [12]. Future advancements include improved AI models for decision-making [15], multi-modal sensor fusion for better perception [18], AI-driven swarm robotics for automation and disaster response [20], and refined NLP for seamless human-robot interaction [22].

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