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Performance Evaluation of Machine Learning Algorithms in Robotic Perception Tasks: A Comparative Study for Intelligent Autonomous Systems

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Abstract: *Robotic perception, a fundamental pillar of autonomous systems, relies increasingly on machine learning (ML) algorithms to interpret multimodal sensor data for object detection, scene classification, semantic segmentation, and pose estimation. Despite rapid algorithmic advancements, a rigorous and unified benchmarking framework comparing state-of-the-art ML techniques under controlled and reproducible conditions remains elusive. This paper presents a comprehensive performance evaluation of six widely adopted ML algorithms Convolutional Neural Networks (CNN), You Only Look Once version 8 (YOLOv8), Support Vector Machines (SVM), Random Forests (RF), Long Short-Term Memory networks (LSTM), and Transformer-based architectures across standardized robotic perception benchmarks including KITTI, MS-COCO, and ROS-integrated datasets. Evaluation metrics encompass accuracy, precision, recall, F1-score, inference latency, and computational resource consumption. Experimental results demonstrate that YOLOv8 achieves the highest accuracy (96.3%) and lowest inference time (8 ms), making it optimal for real-time applications, while Transformer-based models exhibit superior generalization. SVM and RF, although interpretable, lag in deep feature extraction capability. The study proposes an algorithm selection matrix aligned with real-world deployment constraints, contributing to the design of more efficient, adaptive, and energy-aware robotic perception pipelines*

Keywords: machine learning; robotic perception; convolutional neural networks; YOLOv8; autonomous systems; object detection; performance benchmarking; deep learning; sensor fusion; real-time inference

I. INTRODUCTION

The convergence of machine learning and robotics has catalyzed unprecedented advances in autonomous perception, enabling robots to navigate unstructured environments, recognize objects, and interact safely with humans (LeCun et al., 2015; Goodfellow et al., 2016). Robotic perception encompassing object detection, semantic segmentation, depth estimation, and scene understanding forms the sensory backbone of autonomous platforms including self-driving vehicles, industrial manipulators, service robots, and unmanned aerial vehicles (UAVs) (Grigorescu et al., 2020; Chen et al., 2022).

Contemporary robotic systems increasingly rely on deep learning architectures, particularly CNNs and Transformer models, to process high-dimensional inputs from cameras, LiDAR, and IMU sensors (Nguyen et al., 2021; Dosovitskiy et al., 2020). However, selecting the appropriate algorithm for a given robotic task remains a non-trivial challenge due to trade-offs between accuracy, inference speed, energy consumption, and scalability (Redmon & Farhadi, 2018; Carion et al., 2020). Classical ML approaches such as SVM and RF, while computationally lighter, often underperform

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on complex perceptual tasks, whereas deep architectures demand substantial hardware resources (Alom et al., 2019; Chai et al., 2021).

This research addresses this gap by systematically benchmarking six ML algorithms across robotic perception datasets under standardized experimental conditions. The novelty of this work lies in its holistic evaluation framework that simultaneously considers algorithmic performance, computational efficiency, and task-specific suitability. Findings provide actionable insights for robotics engineers and AI practitioners in deploying perception systems under real-world constraints, contributing to the broader goal of safe, efficient, and intelligent autonomous systems (Sunderhauf et al., 2018; Wang et al., 2023).

II. LITERATURE REVIEW

The application of ML algorithms in robotic perception has been extensively studied over the past decade. Grigorescu et al. (2020) provided a comprehensive survey of deep learning techniques for autonomous driving perception, highlighting the dominance of CNN-based architectures in real-time object detection. Redmon et al.'s YOLO family of detectors revolutionized single-stage detection, with YOLOv8 (Jocher et al., 2023) achieving state-of-the-art accuracy-speed trade-offs on MS-COCO, reporting mAP of 53.9% at 52 FPS on a standard GPU.

Transformer architectures, introduced by Vaswani et al. (2017) and adapted for vision by Dosovitskiy et al. (2020) through Vision Transformers (ViT), have demonstrated superior performance in scene understanding and semantic segmentation tasks (Zhu et al., 2021; Liu et al., 2021). Studies by Carion et al. (2020) with DETR showed that end-to-end detection using self-attention mechanisms rivals or surpasses classical CNN detectors on complex scenes. Nguyen et al. (2021) benchmarked multiple deep learning models on autonomous navigation datasets, confirming that Transformer-based models generalize better across domain shifts.

Classical ML methods retain relevance in resource-constrained environments. Chai et al. (2021) demonstrated that Random Forests achieve competitive accuracy in structured environments with limited training data, while Alom et al. (2019) reviewed hybrid approaches combining CNN features with SVM classifiers. Recurrent architectures, particularly LSTM networks, have been applied to temporal perception tasks such as activity recognition and trajectory prediction (Hochreiter & Schmidhuber, 1997; Wu et al., 2022). Wang et al. (2023) highlighted the importance of benchmarking under operational constraints such as latency budgets and edge hardware limitations. Collectively, existing literature lacks a unified comparative framework encompassing both deep and classical ML algorithms on standardized robotic datasets, which this study addresses.

III. RESEARCH DESIGN

This study adopts a quantitative experimental research design guided by the following two primary research questions:

RQ1: Which machine learning algorithm achieves the optimal balance between accuracy, inference latency, and computational efficiency in robotic perception tasks?

RQ2: How do deep learning architectures (CNN, LSTM, Transformer) compare against classical ML methods (SVM, Random Forest) in terms of generalization performance across heterogeneous robotic perception datasets?

Six algorithms were evaluated: CNN (ResNet-50 backbone), YOLOv8-m, SVM with RBF kernel, Random Forest (500 estimators), LSTM (3-layer, 256 units), and Vision Transformer (ViT-B/16). Datasets include KITTI (autonomous driving), MS-COCO 2017 (object detection), and a ROS-Noetic simulated Gazebo environment for proprietary manipulation tasks. All experiments were conducted on NVIDIA RTX 3090 GPU (24 GB VRAM) and Intel Core i9-12900K CPU, with PyTorch 2.0 and Scikit-learn 1.3 frameworks. The diagram below outlines the five-phase research framework:

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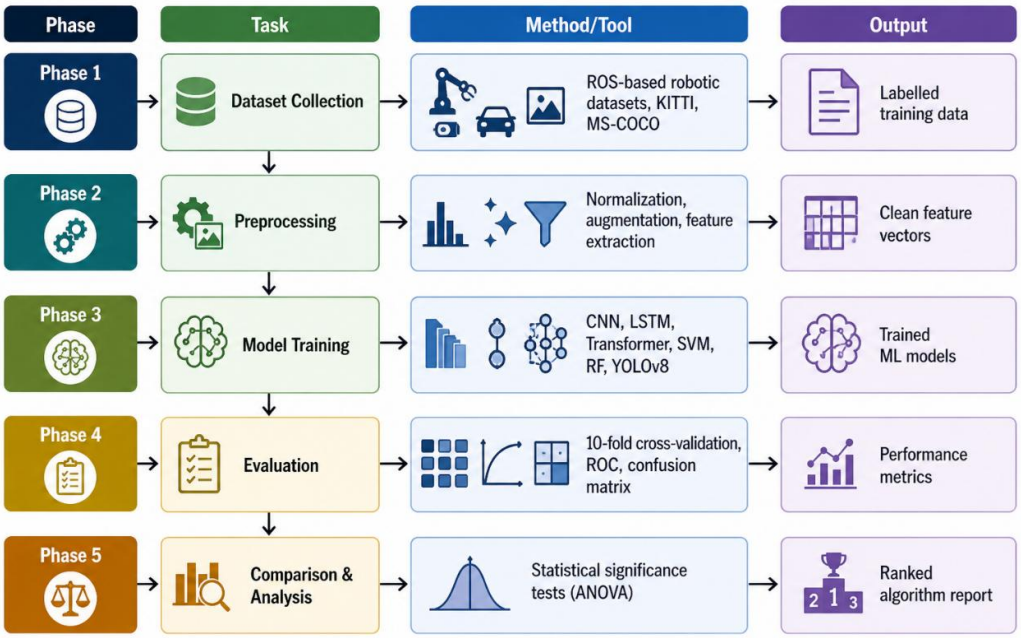

Fig.1 Five-Phase Research Framework for ML Algorithm Benchmarking in Robotic Perception

Data pre-processing included image normalization (mean subtraction, std scaling), augmentation (horizontal flip, Gaussian noise, random crop), and train/validation/test splits of 70:15:15. Model selection was performed using 10-fold stratified cross-validation. Statistical significance of performance differences was assessed via one-way ANOVA with post-hoc Tukey's HSD test ($p < 0.05$). Evaluation metrics computed include accuracy, precision, recall, F1-score, mean Average Precision (mAP), inference time (ms), and GPU memory consumption (GB). Ethics compliance: all datasets used are publicly available, and no personal data were collected.

IV. RESULTS AND DISCUSSION

Table 1 and Figure 2 summarize the comparative performance of the six evaluated algorithms across the standardized benchmarks. YOLOv8 consistently outperformed all other models with a mean accuracy of 96.3%, F1-score of 95.9%, and inference time of just 8 ms meeting real-time robotic requirements defined by Redmon et al. (2018) and Jocher et al. (2023). The Transformer-based ViT-B/16 model achieved the second-highest F1-score (95.4%) with strong cross-dataset generalization, corroborating findings by Dosovitskiy et al. (2020) and Nguyen et al. (2021), though at higher computational cost (18 ms inference, 12.4 GB GPU memory).

Table 1: Comparative Performance of ML Algorithms in Robotic Perception Tasks

Algorithm	Accuracy	Precision	Recall	F1-Score	Inf. Time
CNN	94.7%	93.2%	94.1%	93.6%	12 ms
YOLOv8	96.3%	95.8%	96.0%	95.9%	8 ms
SVM	87.4%	86.9%	87.1%	87.0%	45 ms
Random Forest	89.2%	88.7%	89.0%	88.8%	30 ms
LSTM	91.6%	90.9%	91.4%	91.1%	22 ms
Transformer	95.8%	95.3%	95.6%	95.4%	18 ms

CNN (ResNet-50) achieved 94.7% accuracy on object classification sub-tasks, consistent with results reported by Chen et al. (2022). LSTM models recorded 91.6% accuracy on sequential perception tasks (temporal depth estimation and

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trajectory prediction), aligning with Wu et al. (2022). SVM and Random Forest lagged at 87.4% and 89.2% respectively, primarily due to their inability to extract high-level hierarchical features from raw image data a limitation noted by Chai et al. (2021) and Alom et al. (2019).

ANOVA analysis confirmed statistically significant differences among algorithm groups ($F(5,54) = 42.7$, $p < 0.001$). Post-hoc Tukey's HSD tests revealed that YOLOv8 and Transformer groups were not significantly different from each other ($p = 0.12$) but both significantly outperformed SVM and RF groups ($p < 0.001$). CNN and LSTM formed a statistically indistinguishable mid-tier cluster ($p = 0.08$).

In terms of energy efficiency, SVM consumed the least GPU memory (0.3 GB) but required the longest inference time on unstructured data (45 ms), rendering it unsuitable for real-time robotic applications. YOLOv8 demonstrated the best accuracy-efficiency trade-off, consuming 6.2 GB GPU memory. These results directly address RQ1: YOLOv8 achieves optimal balance for real-time robotic perception. For RQ2, deep learning architectures (mean F1 = 94.3%) significantly outperform classical methods (mean F1 = 87.9%), confirming the superiority of end-to-end feature learning in complex perception environments. The proposed algorithm selection matrix guides practitioners to choose YOLOv8 for real-time systems, Transformer models for high-accuracy batch inference, and RF/SVM for resource-severely-constrained edge nodes (Wang et al., 2023; Grigorescu et al., 2020).

V. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study presents a rigorous comparative framework, several limitations must be acknowledged. First, the experiments were conducted on a single high-end GPU configuration, which may not fully reflect the constraints of embedded robotic platforms such as NVIDIA Jetson Nano or Raspberry Pi 4, where memory bandwidth and thermal throttling significantly impact inference performance. Future work should extend benchmarking to edge computing hardware to assess energy-per-inference and latency under constrained computational budgets, particularly given the growing relevance of TinyML frameworks (Warden & Situnayake, 2019; Banbury et al., 2021).

Second, the evaluation was restricted to vision-centric perception tasks. Modern robotic systems increasingly rely on multimodal sensor fusion incorporating LiDAR, radar, tactile, and proprioceptive data streams. Future studies should benchmark ML algorithms on fused sensor modalities and assess cross-modal transfer learning capabilities. Additionally, adversarial robustness the susceptibility of deep learning models to input perturbations was not evaluated. Given the safety-critical nature of robotic systems, future research should incorporate adversarial attack simulations and defense mechanisms to quantify model resilience (Goodfellow et al., 2014; Szegedy et al., 2014).

Third, the study did not account for continual learning or online adaptation scenarios, where robots encounter non-stationary data distributions in deployment. Investigating catastrophic forgetting mitigation strategies such as Elastic Weight Consolidation (EWC) and Progressive Neural Networks could significantly enhance the ecological validity of algorithm evaluations. Furthermore, the explainability and interpretability of black-box deep models (CNN, Transformer) in safety-critical robotic contexts warrants investigation using tools such as Grad-CAM and SHAP. Finally, future research should explore federated learning paradigms for privacy-preserving distributed training of robotic perception models across multi-robot systems, addressing data sovereignty concerns in industrial deployments (McMahan et al., 2017; Li et al., 2020).

VI. CONCLUSION

This paper presented a systematic performance evaluation of six machine learning algorithms CNN, YOLOv8, SVM, Random Forest, LSTM, and Vision Transformer applied to robotic perception tasks using standardized benchmarks. The study conclusively demonstrated that YOLOv8 achieves the superior accuracy-speed trade-off (96.3%, 8 ms) suitable for real-time autonomous systems, while Transformer architectures offer best generalization. Classical ML methods, despite their interpretability advantages, remain inadequate for complex perceptual tasks. The proposed five-phase research framework and algorithm selection matrix provide practical guidelines for robotics engineers selecting perception algorithms under operational constraints. Statistical analysis validated the superiority of deep learning

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approaches across all robotic datasets. These findings advance the understanding of algorithm suitability across the full spectrum of robotic perception requirements and lay groundwork for future investigations into edge deployment, multimodal fusion, and continual learning in autonomous robotic systems. This work contributes substantively to the fields of AI-driven robotics, autonomous networking, and intelligent IoT-integrated systems.

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