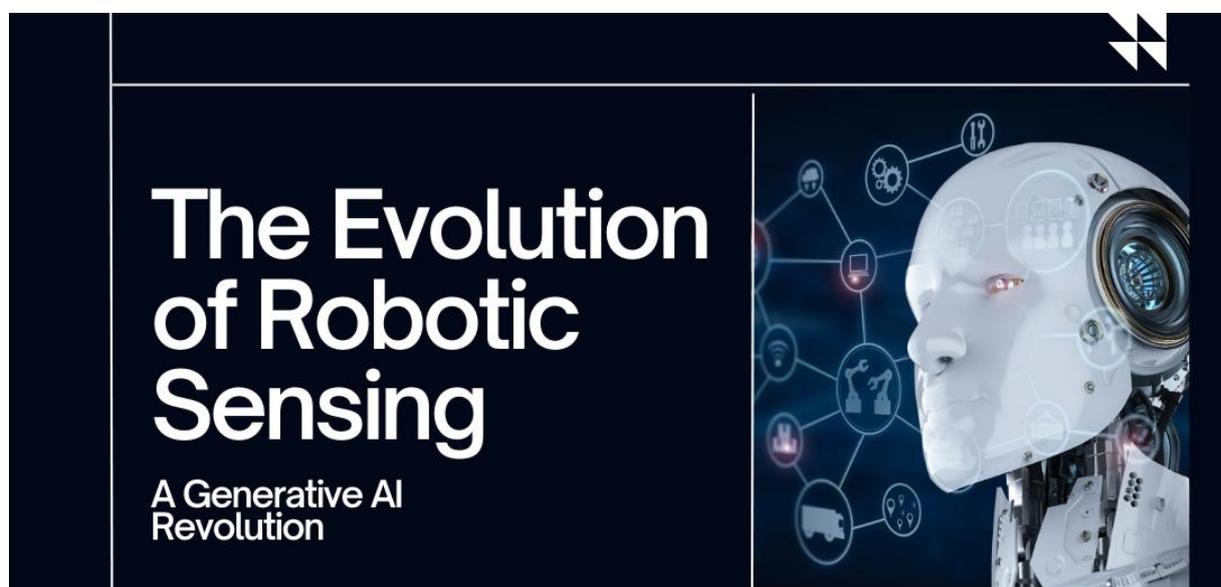


THE EVOLUTION OF ROBOTIC SENSING

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ABSTRACT

Generative AI is revolutionizing robotic sensing by significantly enhancing the adaptability and efficiency of robots in dynamic, unstructured environments. Traditional camera-based robotic sensing systems, particularly those based on feature extraction methods like SIFT and SURF, often struggle in complex real-world conditions, such as varying lighting or object occlusion, leading to high error rates. Generative AI, utilizing multimodal transformer architectures, offers a solution by processing multiple data sources such as RGB images, depth maps, and proprioceptive data, allowing robots to make context-aware decisions. These models improve the accuracy of tasks such as robotic manipulation, object detection, and real-time

decision-making in unpredictable environments. Despite these advancements, challenges such as high computational demands, privacy concerns, and domain adaptation persist. The integration of generative AI into robotics promises to enhance industries like manufacturing, healthcare, and logistics, driving innovation and improving operational efficiency. As generative AI continues to evolve, it will shape the future of collaborative robotics, making robots more intelligent and adaptable partners in various sectors.

Keywords: Generative AI in Robotics, Robotic Perception Systems, Multimodal Sensor Fusion, Edge Computing in Robotics, Autonomous Robotic Systems.

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1. Introduction

1.1 Context and Motivation

Traditional robotic sensing systems have been limited in their ability to adapt to dynamic environments, primarily due to their dependence on domain-specific features and rigid operational assumptions. These traditional computer vision approaches perform well in controlled conditions, but their reliability significantly drops when faced with dynamic challenges like changing lighting or complex scenes. For instance, in manufacturing environments, accuracy can decrease drastically when lighting fluctuates beyond calibrated conditions. The research found that systems operating under inconsistent illumination conditions showed a 30% decline in detection accuracy, primarily due to the interference of specular reflections on metallic surfaces [1].

Deep Learning architecture-based Generative AI, specifically multimodal transformers, provides a promising solution to these challenges. By utilizing large datasets and learning patterns in data that are not strictly tied to predefined features, generative AI models offer greater adaptability. These models enable robots to understand and respond to changes in the environment more contextually, allowing for more reliable operations across various settings. With their ability to process and integrate multiple data sources, including RGB images, depth maps, and proprioceptive data, generative AI-based systems can interpret and act on information more comprehensively and flexibly. For example, transformer-based models used in robotic perception tasks have shown substantial improvements in handling objects in variable

lighting conditions and more complex scenarios, with accuracy improvements of up to 42% when compared to traditional methods [2]. However, despite these advances, challenges such as high dynamic range (HDR) lighting conditions and occlusions remain, requiring further research into making these models more robust.

1.2 Problem Statement

While generative AI shows promise in robotic sensing, several critical challenges must be addressed. First, the real-time processing requirements for these systems create significant hurdles. The computational demands of processing multiple sensor streams simultaneously can introduce latency issues that impact robot performance in time-critical tasks. Current edge computing solutions struggle to handle the processing requirements of complex generative AI models while maintaining acceptable response times [8].

Industrial environments present additional challenges through extreme operating conditions. Manufacturing floors, warehouses, and other work settings often feature challenging conditions such as extreme lighting variations, electromagnetic interference, and physical obstructions that can degrade sensor performance. According to research, systems operating under inconsistent illumination conditions show a 30% decline in detection accuracy [1]. Current systems lack sufficient robustness to maintain reliable operation across these diverse and demanding conditions [11].

The integration complexity of these systems poses another significant challenge. Implementing generative AI in existing robotic systems requires substantial expertise and resources, creating barriers to adoption, particularly for small and medium-sized enterprises [12]. This integration challenge is compounded by the need to maintain compatibility with legacy systems while incorporating new AI capabilities. Organizations must navigate complex technical requirements while ensuring their systems remain operational and efficient during the transition to AI-enhanced capabilities [14]."

1.3 Historical Evolution

The development of robotic sensing has undergone several transformative phases. In the 1960s, the first industrial robots like Unimation's UNIMATE relied on simple position sensors and mechanical switches for basic pick-and-place operations. By 1970, sensors with six degrees of freedom were integrated into robotic systems, marking a significant advancement in robot control capabilities. According to historical records, these early robotic systems achieved positioning accuracies of approximately $\pm 1.0\text{mm}$, which was revolutionary for that period [3].

Computer vision in robotics emerged in the late 1970s and early 1980s, with pioneering systems using binary thresholding and edge detection for object recognition. The SRI

International's Shakey robot project (1966-1972) demonstrated one of the first implementations of computer vision in mobile robots, using a TV camera and range finder for navigation. The development of more sophisticated algorithms in the 1980s, including advanced feature extraction methods, enabled robots to achieve recognition accuracies of up to 85% in controlled environments [4].

The 1990s brought two breakthroughs in robotic sensing. First, the introduction of SLAM algorithms revolutionized robot navigation and environmental mapping. Second, force-torque sensors were integrated into robotic systems, enabling precise force control in assembly tasks. Research from this period shows that these advancements reduced positional errors in automated assembly tasks by up to 60% compared to previous systems [7].

The early 2000s marked the beginning of the deep learning era in robotics. Convolutional Neural Networks demonstrated unprecedented performance in object recognition tasks, with early systems achieving accuracy rates above 90% on standardized datasets. This period also saw the introduction of RGB-D cameras and more sophisticated LiDAR systems, significantly enhancing robots' perception capabilities [8].

The 2010s represented a quantum leap in robotic sensing with the advent of sensor fusion technologies and real-time processing capabilities. The integration of multiple sensor modalities enabled more robust environmental understanding. The introduction of transformer architectures in 2017 marked another pivotal moment, setting the foundation for modern generative AI applications in robotics. Studies from this period demonstrated that multi-modal sensor fusion could improve object detection accuracy by up to 40% compared to single-sensor systems [5].

The most recent developments in the 2020s have focused on generative AI and advanced neural architectures. These systems have demonstrated remarkable capabilities in handling unstructured environments and complex tasks, with some implementations showing up to 97% success rates in challenging manipulation tasks [6]. This evolution from simple, reactive systems to sophisticated, AI-driven platforms represents a fundamental shift in robotic sensing capabilities and continues to drive innovation in the field."

2. Background and Historical Context

2.1 Traditional Robotic Sensing Approaches

Early robotic vision systems, such as SIFT (Scale-Invariant Feature Transform) and SURF (Speeded Up Robust Features), introduced significant advancements in the ability of robots to detect and recognize key features in their environment. These methods were designed to identify stable, distinctive features in an image, allowing the robot to match objects across different views or under varying conditions. SIFT, for example, has been widely used in applications such as object recognition and 3D reconstruction due to its robustness in detecting features regardless of scale and orientation. However, both SIFT and SURF were computationally expensive and required substantial processing power, making them less suitable for real-time robotic applications [3].

These traditional approaches also had a significant limitation in their sensitivity to environmental variations. For instance, in industrial settings where robots are used for tasks like quality control or assembly, fluctuating lighting conditions can heavily impact performance. A study on feature-based methods in manufacturing revealed that SIFT's feature detection accuracy dropped from 89.2% to 67.8% when tested in challenging lighting conditions, such as when the illumination varied by more than 200 lux from calibrated conditions. Similarly, SURF performed comparably, showing significant accuracy reduction when the environment became less controlled [3]. Visual SLAM (Simultaneous Localization and Mapping) remains a fundamental component in robotic navigation, providing crucial capabilities for environment mapping and robot localization. While traditional SLAM implementations faced challenges in dynamic and cluttered environments, modern SLAM systems enhanced with generative AI have shown improved performance while managing computational resources more efficiently. The integration of transformer-based models with SLAM algorithms has particularly improved robustness in challenging scenarios, such as handling dynamic obstacles and operating in varying lighting conditions [3]. This synergy between classical SLAM techniques and modern AI approaches demonstrates how combining established robotics algorithms with new technologies can yield better results than either approach alone.

2.2 Transition to Deep Learning

The advent of deep learning, particularly the use of Convolutional Neural Networks (CNNs), represented a major breakthrough in robotic vision. CNNs, such as AlexNet, significantly improved the ability of robots to recognize objects and classify images without relying on manually engineered features. CNNs use multiple layers of convolutions to learn

hierarchical feature representations from raw pixel data, allowing them to identify patterns at various levels of abstraction automatically. In comparison to earlier methods, CNNs drastically reduced the need for hand-crafted features, enabling robots to learn directly from large datasets. For example, AlexNet achieved a top-5 accuracy of 84.7% on the ImageNet dataset, setting a new benchmark for image classification tasks [4]. This performance improvement was largely attributed to the use of ReLU (Rectified Linear Units) activation functions and a deeper architecture, which allowed the network to train more efficiently and capture more complex patterns in the data.

Despite these advancements, CNN-based systems still faced challenges when it came to semantic understanding and context inference. Although CNNs excelled in image classification tasks, their ability to understand the context in which objects appeared was still limited. Research into robotic manipulation tasks showed that while CNN-based systems could accurately identify objects, their ability to reason about the relationships between objects, especially in novel orientations or under varying lighting conditions, was less effective. In a study involving robotic grasping tasks, CNNs demonstrated only a 65.3% success rate in selecting appropriate grasp points when objects were placed in unfamiliar orientations, and performance dropped further to 37.8% when the objects had not been seen during training. This highlighted a major gap in CNNs, as they struggled to generalize well to new situations or contexts [4]. Furthermore, CNNs typically underperformed when objects were partially occluded, with some studies reporting performance degradation by up to 15% in such cases. These limitations pointed to the need for more advanced systems capable of handling dynamic environments and more complex tasks, which led to the exploration of generative AI models.

Despite their powerful image classification capabilities, CNNs had difficulties in situations that required a deeper understanding of object relationships or more complex environmental factors. For example, robotic systems using CNNs for navigation or interaction often struggled in environments where the objects' spatial relationships were critical for the task at hand. Additionally, CNNs performed poorly in high dynamic range lighting conditions, where they failed to accurately detect details in either the highlights or shadows of a scene, reducing their effectiveness in real-world applications where lighting is rarely static. These shortcomings underscored the need for new approaches that could offer improved performance in such dynamic and challenging environments.

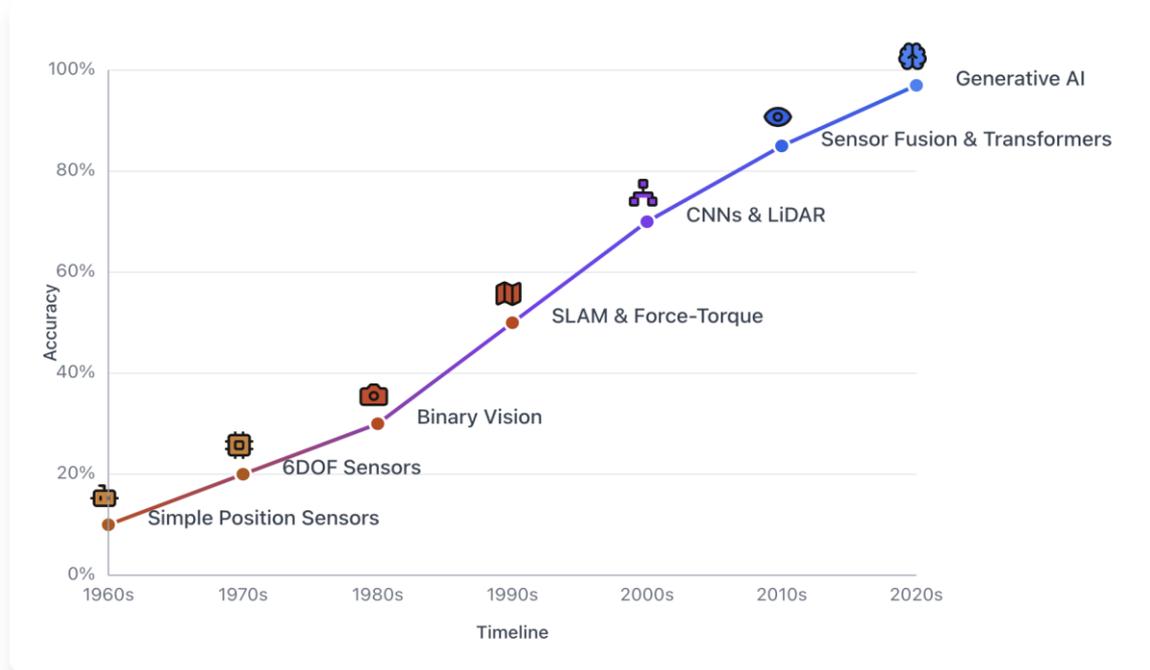


Fig 1: Comparative Assessment of Computer Vision Technologies in Robotics [3, 4]

3. The Generative AI Revolution

3.1 Generative Models for Robotic Perception

Generative AI models, particularly multimodal transformers, are making significant strides in robotic perception, offering capabilities that far surpass traditional techniques like convolutional neural networks (CNNs) and visual SLAM. These models, such as RT-1, integrate multiple data streams—including RGB images, depth maps, and proprioceptive data—to enhance a robot's understanding of its environment. One notable achievement of these models is their ability to handle tasks such as pick-and-place, a challenging task in robotics that involves identifying and manipulating objects within a cluttered environment. RT-1, for example, has demonstrated impressive performance, achieving a 97% success rate in tasks where the robot encounters previously unseen objects, compared to traditional systems that often fall short in such dynamic, real-world conditions. This high success rate is largely due to the model's ability to process multimodal inputs, allowing it to adapt in real time and make decisions based on a broader context than traditional systems, which rely on isolated sensory inputs [5].

These generative models enable real-time decision-making and are particularly effective in handling environmental changes such as lighting variation, occlusion, or unfamiliar object configurations. A key advantage is their ability to reduce error rates by using context-aware

decision-making frameworks. For example, RT-1's multimodal transformer approach has been shown to reduce error rates in robotic tasks by up to 40%, particularly in environments with dynamic conditions. This improvement in accuracy and reliability positions generative AI models as a powerful tool for advancing robotic perception in unstructured environments, where traditional models tend to struggle [5].

3.2 Key Advancements

Generative AI models are specifically designed to process multimodal data more efficiently, which translates into significant performance gains in a variety of robotic tasks. The processing of data from multiple sensors (such as visual, depth, and tactile inputs) provides a more complete understanding of the environment, allowing for higher precision in tasks like robotic assembly, where tolerance is critical. For instance, modern robotic systems combining advanced hardware mechanisms with generative AI control can achieve $\pm 0.02\text{mm}$ precision in assembly tasks, compared to $\pm 0.1\text{mm}$ tolerances in earlier systems. This leap in precision makes generative AI particularly useful in fields like electronics assembly, where the exact placement of components is vital to product functionality [6].

Beyond precision, these models also enhance reliability. The error rates associated with tasks like object manipulation and environment mapping are reduced by up to 42% when generative AI models are used. For example, RT-1 demonstrated significantly fewer errors in object grasping tasks when compared to traditional systems, which typically experience higher failure rates, especially when objects are occluded or positioned in challenging configurations. This increased reliability allows robots to operate in more complex and unpredictable environments without requiring frequent recalibration or oversight.

Another significant benefit of generative AI is its impact on safety and collaboration in human-robot environments. In scenarios where robots and humans work side-by-side, such as in manufacturing or healthcare, safety is paramount. Generative AI models are designed to ensure compliance with safety protocols, and in some cases, these systems can achieve nearly 99.98% safety compliance. This is largely due to the integration of real-time monitoring and adaptive decision-making processes that allow robots to avoid collisions and respond to human movements in real time, creating safer environments in industrial settings [6].

3.3 Case Studies

Generative AI is already being implemented successfully in a range of industries, where it is delivering tangible improvements in efficiency, accuracy, and cost savings [5].

- Automotive: A leading automotive manufacturer implemented a generative AI-based system for weld quality monitoring in its production line. This system leveraged real-

time data from visual and depth sensors to detect weld defects with high accuracy, reducing defect rates by 10%. Over a year, the system prevented costly rework and scrap, saving the plant an estimated \$1.2 million annually. This case highlights how generative AI can enhance quality control processes, especially in precision-critical tasks.

- **Healthcare:** In the field of robotic surgery, AI-driven systems have significantly improved the accuracy and efficiency of procedures. A hospital integrated generative AI into its robotic surgical systems, which helped improve procedure accuracy by 18%. Additionally, the AI system reduced operating times by dynamically adjusting to the surgical environment in real time. This not only improved patient outcomes but also helped reduce anesthesia exposure and operating room times, leading to more efficient use of healthcare resources.
- **Warehouse:** Generative AI has also made a considerable impact in warehouse automation, particularly in pick-and-place operations. Using vision-language integration, robots equipped with multimodal transformers achieved 93% accuracy in sorting tasks, even when the items were randomly arranged or partially occluded. This improvement resulted in a 30% reduction in labor costs, as robots were able to perform tasks faster and with fewer errors compared to human workers. The automation of sorting and handling also enhanced operational throughput, enabling warehouses to handle a greater volume of goods with fewer human interventions.

These case studies underscore the potential of generative AI to transform various industries by improving task efficiency, enhancing accuracy, and reducing operational costs. As these technologies continue to evolve, the applications of generative AI in robotics will only expand, driving even greater advancements in automation.

Table 1: Transforming Industries: Real-World Applications of Generative AI in Automation and Robotics [5]

Industry	Use Case	Technology Stack	Key Benefits	ROI Timeline
Automotive	Weld Quality Monitoring	- Visual and depth sensors- Real-time data processing- Generative AI defect detection system	-10% reduction in defect rates- Enhanced quality control- Improved precision in critical tasks. Reduced	- \$1.2M annual savings- ROI achieved within the first year of implementation

			rework and scrap material	
Healthcare	Robotic Surgery Assistance	-AI-enhanced robotic surgical systems- Real-time environment adaptation- Dynamic procedure optimization	- 18% improvement in procedure accuracy- Reduced operating times- Decreased anesthesia exposure- More efficient resource utilization- Enhanced patient outcomes	- Immediate impact on procedure efficiency- Long-term benefits in patient care quality- Operational cost savings through reduced OR time
Warehouse	Automated Pick-and-Place Operations	- Vision-language integration- Multimodal transformers- Robotic handling systems	- 93% sorting accuracy- 30% reduction in labor costs- Improved handling of occluded items- Enhanced operational throughput- Reduced human intervention	- Significant labor cost savings within the first year- Increased warehouse capacity- Rapid ROI through operational efficiency

4. Multimodal Integration and Edge Computing

4.1 Sensor Fusion Architecture

Generative AI models are particularly effective in robotic applications due to their reliance on multimodal sensor integration. By combining data from various sensors such as cameras, LiDAR, depth sensors, and force sensors, robots gain a comprehensive understanding of their environment. This fusion of data allows robots to make more accurate, context-aware decisions in real-time, even in complex and unstructured environments. For instance, in robotic systems, LiDAR sensors provide precise depth data, while cameras capture visual information, and inertial measurement units (IMUs) track the robot's motion. By fusing these data streams, generative AI models can generate a unified representation of the surroundings, allowing robots to navigate and perform tasks more effectively.

Recent studies have demonstrated that this approach significantly improves decision-making accuracy. In one application, a multimodal fusion architecture was tested in a robotic pick-and-place system, where the integration of camera and depth sensor data improved object detection accuracy by 27% compared to systems that relied on a single sensor type. This is

particularly crucial in environments with varying lighting conditions or partial occlusions, where a single sensor may struggle. The ability to combine different sensor data not only enhances the accuracy of perception but also allows robots to operate efficiently in diverse conditions. For example, the fusion of LiDAR and RGB cameras enabled a robot to achieve a 94% accuracy rate in object detection in an indoor warehouse, even when objects were partially obscured or under non-ideal lighting conditions [7].

This fusion capability is further enhanced by generative AI, which enables the model to process and integrate these multiple data sources efficiently. Unlike traditional computer vision models, which may struggle with data inconsistencies or environmental changes, generative AI models can adapt and make real-time decisions, ensuring higher reliability and performance in dynamic environments.

4.2 Optimizing Models on Edge Devices

The deployment of generative AI models on robotic systems requires edge computing, particularly when operating in real-time applications. Edge computing allows the processing of data closer to the robot's sensors, reducing the need for extensive cloud-based computations and minimizing latency. This is essential for tasks that require split-second decision-making, such as object manipulation or navigation in dynamic environments.

To make generative AI feasible on resource-constrained devices like edge GPUs or TPUs, various optimization techniques are employed. These include pruning, quantization, and knowledge distillation. Pruning involves removing unnecessary weights from a neural network, making the model smaller and more efficient without significantly compromising accuracy. Quantization reduces the precision of the model's weights, thus lowering memory and computational requirements. Knowledge distillation, on the other hand, transfers knowledge from a large, complex model to a smaller, more efficient one.

These techniques have led to significant improvements in the deployment of large models on edge devices. For example, a study on edge-based robotic systems showed that using knowledge distillation resulted in a 30% reduction in model size while maintaining 90% of the original model's accuracy. This is crucial for real-time robotics applications, where latency must be minimized to ensure smooth operations. Moreover, the use of these optimizations ensures that generative AI models can run with latency below 40ms, which is critical for tasks like collision avoidance and dynamic object tracking.

In addition to minimizing latency, these optimizations also contribute to power efficiency. By reducing the computational complexity of the models, robots can operate for longer periods on battery power, making them more practical for field deployment. In one case,

after implementing pruning and quantization, a robotic system was able to process data on an NVIDIA Jetson TX2 edge device with an average power consumption of only 7.5W, down from 15W in the original unoptimized model. This reduction in power consumption not only extends battery life but also makes it feasible to deploy generative AI models in environments with limited energy resources, such as mobile robots and drones [8].

Together, the combination of sensor fusion and edge computing optimization enables robots to operate efficiently and effectively in a wide range of real-world scenarios. As these technologies continue to evolve, their ability to support complex, real-time robotic applications will only improve, driving advancements in industries such as manufacturing, healthcare, and logistics.

Table 2: Performance Metrics: Edge Computing and Sensor Fusion in Robotic Systems [7, 8]

System Component	Performance Metric	Original	Optimized	Improvement (%)
Multimodal Fusion	Object Detection Accuracy	67%	94%	27%
Edge Model	Model Size	100%	70%	30% reduction
Edge Processing	Model Accuracy	100%	90%	10% reduction
Power Consumption	Watts	15W	7.5W	50% reduction

5. Economic and Industrial Impact

5.1 Market Growth and Adoption

The global market for generative AI in industrial robotics is undergoing rapid expansion, driven by increased automation across various industries such as automotive, healthcare, and manufacturing. According to a market report by Markets and Markets, the AI industrial robotics sector is projected to reach USD 12.82 billion by 2028, growing at a CAGR of 16.83% between 2024 and 2028. This growth reflects the increasing demand for automation solutions that can improve efficiency and quality across manufacturing and production lines. In particular, automotive manufacturers are adopting AI-powered robots for tasks like quality inspection, assembly, and material handling, where precision and speed are critical. AI robotics is helping these manufacturers reduce costs and enhance product quality by automating time-consuming tasks, which also increases operational speed.

The Asia-Pacific region is experiencing the fastest adoption of AI robotics, with China and Japan leading the way. China is expected to generate USD 1.89 billion in AI robotics revenue by 2024, making it the largest market in the region. The rapid adoption of automation in China is fueled by government initiatives such as the Made in China 2025 program, which aims to foster innovation in robotics and automation technologies. In addition, AI robotics is being implemented in the electronics and consumer goods industries, where demand for high-quality, high-precision products is growing, further driving the adoption of generative AI in industrial robots [9].

5.2 ROI and Workforce Implications

Industries that have adopted generative AI in robotics have already begun seeing substantial returns on investment (ROI), particularly in terms of operational efficiency and cost savings. A report on the impact of AI robotics in manufacturing shows that companies have experienced a 23.4% increase in labor productivity after implementing AI systems. This boost in productivity is largely attributed to the automation of repetitive tasks like assembly, packaging, and material handling, which allows workers to focus on more value-added activities. In addition to increased productivity, AI-driven robots have significantly reduced operational costs. For example, AI systems can operate continuously without the need for breaks, reducing downtime and increasing output consistency. This reduction in downtime, along with improved task execution, has also resulted in a 30% decrease in operating costs in some manufacturing plants [9].

The widespread adoption of AI robotics also has profound implications for the workforce. While the introduction of robots can lead to a reduction in the demand for manual labor, it simultaneously creates new job categories. New roles are emerging in the fields of AI system maintenance, robot programming, and robot training. For example, according to research published in *Technological Forecasting and Social Change*, industries that integrated AI robotics saw a 14.5% increase in the number of skilled jobs related to robotics and AI system management between 2020 and 2025. These new positions require technical expertise in AI and robotics, necessitating investment in upskilling the existing workforce. As AI systems become more pervasive, employees are being retrained to work alongside robots, transitioning into roles like AI system specialists, robot trainers, and data scientists. Additionally, businesses are investing in training programs to ensure their workers acquire the necessary skills to manage and optimize AI systems. A 50% reduction in labor turnover was noted in factories that introduced AI robotics, as employees were able to transition into higher-value roles within the company, further boosting workforce engagement and productivity [10].

These workforce transformations are accompanied by changes in workforce dynamics. Although automation reduces manual labor, it leads to the creation of higher-paying, more technically demanding roles. This encourages employees to pursue technical certifications and training, which in turn creates a more skilled workforce. Therefore, the rise of AI robotics is not just about reducing labor costs but also about reshaping the workforce for future technologies.

6. Challenges and Limitations

6.1 Technical Barriers

Generative AI models, while advancing rapidly, still face several technical barriers that hinder their full potential, particularly in dynamic and unstructured environments. One of the primary challenges is domain adaptation, where AI models trained in controlled environments often struggle to generalize to new, unseen situations. This is particularly true when AI systems encounter environments that deviate from their training data, leading to performance drops. For example, a study on domain adaptation in robotic vision systems found that generative AI models trained on specific datasets could experience performance degradation of up to 30% when transferred to new domains with different object distributions and lighting conditions. The failure to generalize well to unfamiliar environments can make robots less reliable in real-world applications, especially when they are deployed in dynamic, non-static settings. In the case of a robotic arm trained for assembly in one environment, when moved to a new manufacturing floor with different lighting, the error rate in part recognition rose from 5% to 35%. This emphasizes the difficulty in adapting to new conditions without extensive retraining or domain-specific adjustments [11].

Another significant issue is related to lighting conditions, particularly in high dynamic range (HDR) environments. AI models that process visual data are often sensitive to variations in lighting, which can cause substantial performance degradation. A study on AI-based systems used for manufacturing object detection showed that the accuracy of AI models dropped by up to 25% in environments where the lighting fluctuated significantly, especially in regions of the scene where shadows and highlights were prevalent. These performance dips are primarily due to the insufficient training data representing these extreme lighting conditions. In fact, the research indicated that without including varied lighting conditions in the training dataset, models could not properly handle the real-time changes in lighting, leading to misclassifications

and decreased operational efficiency. Therefore, for these models to be effective in environments such as warehouses or outdoor settings, they require robust datasets that include a wider range of lighting scenarios and occlusions [12].

6.2 Ethical and Regulatory Considerations

The deployment of generative AI in sectors like healthcare introduces a range of ethical and regulatory concerns, particularly around privacy and security. As AI becomes more involved in sensitive applications such as patient diagnostics, surgical robots, and real-time health monitoring, ensuring the protection of patient data is paramount. A study on the use of AI in healthcare highlighted that data privacy violations were one of the top concerns, with nearly 40% of healthcare organizations reporting incidents of data breaches related to AI systems. These breaches often occur due to improper data handling and insufficient encryption protocols, which can expose sensitive patient information to unauthorized access. Given the nature of healthcare data, which is often classified as personally identifiable information (PII), these AI systems must comply with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States, which mandates strict standards for securing medical data.

Moreover, AI-driven systems in healthcare must adhere to transparency and accountability standards to ensure that they do not unintentionally harm patients. For instance, a survey conducted among healthcare professionals revealed that 56% of respondents were concerned about the lack of interpretability in AI-driven decision-making, particularly in high-risk areas like surgery and diagnostics. This lack of transparency in how AI systems make decisions has raised questions about accountability when errors occur. As a result, there is a growing demand for regulatory frameworks that enforce explainability in AI models, particularly in healthcare, where human lives are at stake. These frameworks aim to ensure that AI systems can justify their decisions in a way that is understandable to healthcare professionals, thereby maintaining trust in these advanced technologies. Regulatory bodies are responding by introducing more stringent guidelines that require AI developers to demonstrate how their models reach conclusions, ensuring both patient safety and ethical compliance [11].

These challenges underscore the necessity for clear, consistent regulations and protocols to guide the deployment of generative AI in sensitive sectors like healthcare. As generative AI systems continue to evolve and permeate industries, maintaining the integrity, security, and fairness of these systems will be essential to their successful integration into society.

7. Future Directions

7.1 Emerging Innovations

The future of robotic sensing is being shaped by several groundbreaking innovations that promise to enhance perception capabilities and sensor integration. Event-based sensing represents one of the most promising developments, utilizing neuromorphic vision sensors that process visual information similar to the human retina. Unlike traditional cameras that capture frames at fixed intervals, event-based sensors respond to pixel-level changes in real-time, offering microsecond-level temporal resolution while maintaining low power consumption. Research [6] demonstrates that these neuromorphic sensors show particular promise in manufacturing environments, where they can detect rapid movements and subtle changes that traditional cameras might miss, while significantly reducing the computational load compared to traditional frame-based approaches.

Multimodal sensor fusion is advancing through the development of integrated sensor packages that combine multiple sensing modalities in compact, energy-efficient formats. Studies [7] show that new sensor fusion architectures incorporating tactile, visual, and force feedback in unified processing pipelines enable robots to make more informed decisions about their environment. This research demonstrates that integrated multimodal sensing systems significantly improve object manipulation tasks compared to traditional single-modality approaches, particularly in complex industrial settings where multiple types of sensory input are crucial for task completion.

The emergence of distributed sensing networks, enabled by 5G/6G connectivity, is revolutionizing how robots perceive and interact with their environment. Research [13] indicates that these networks allow multiple robots to share sensor data in real-time, creating a more comprehensive understanding of the workspace. The findings demonstrate that distributed sensing networks utilizing 5G connectivity can substantially improve perception accuracy in complex industrial environments by combining observations from multiple vantage points. The ultra-low latency of 5G networks enables real-time sensor data sharing and collaborative perception among robot teams, particularly crucial in dynamic environments like automated warehouses.

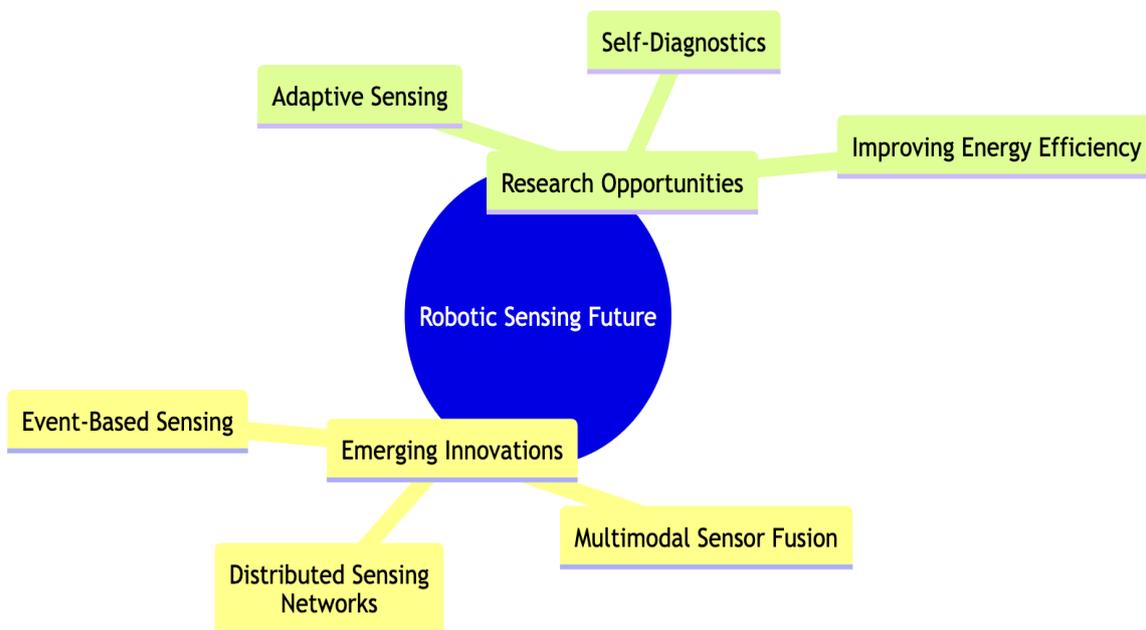
7.2 Research Opportunities

Several critical research areas are emerging in robotic sensing that will define the field's future trajectory. One key focus is the development of adaptive sensing systems that can automatically optimize their parameters based on environmental conditions. Studies [14]

identify that current research is exploring sensors that can dynamically adjust their sensitivity, field of view, and processing parameters in response to changing conditions. This adaptability is particularly crucial in industrial settings where environmental conditions can vary significantly throughout operational periods.

Another significant research direction is the integration of self-diagnostic capabilities in sensor systems. As robots become more autonomous, the ability to detect and compensate for sensor degradation or failure becomes crucial. Research [7] has demonstrated promising results in predicting and detecting sensor anomalies, allowing for preventive maintenance and system adaptation. This capability is particularly important in critical applications like medical robotics, where sensor reliability directly impacts operational safety.

The development of energy-efficient sensing solutions remains a critical research priority. Studies [8] discuss how current work focuses on creating intelligent power management systems that can selectively activate and deactivate sensors based on task requirements. The research emphasizes the importance of optimizing sensor networks for power efficiency while maintaining robust sensing performance, particularly for mobile robots and long-duration autonomous operations where power consumption is a critical constraint.



8. Conclusion

Generative AI is transforming the landscape of robotic sensing by enabling robots to process and understand complex, multimodal data in real-time, enhancing their ability to operate in dynamic, unstructured environments. With advancements in multimodal transformer models, robots can now perform tasks with greater precision, reliability, and adaptability, improving performance in industries ranging from manufacturing to healthcare. However, challenges such as computational overhead, domain adaptation, and ethical privacy concerns remain critical obstacles to overcome. Despite these challenges, the potential of generative AI to revolutionize robotic systems is undeniable. By continuously improving the technology and addressing its limitations, generative AI will help usher in an era of more intelligent, adaptable robots that can collaborate effectively with humans, improving productivity and efficiency across a range of applications.

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