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Research Article

COMPUTING AT THE EDGE: THE ROLE OF NEUROMORPHIC CHIPS IN INTELLIGENT ROBOTICS

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Abstract

The deployment of autonomous mobile robots in resource-constrained environments is currently impeded by the excessive power consumption and latency bottlenecks of traditional Von Neumann architectures. This study investigates the efficacy of neuromorphic computing as a hardware solution for low-power, low-latency edge intelligence, specifically focusing on obstacle avoidance and navigational endurance. A quantitative comparative analysis was conducted benchmarking a Spiking Neural Network (SNN) based control architecture against standard embedded GPU solutions, utilizing event-based vision sensors to evaluate energy efficiency, inference latency, and task success rates. Empirical results demonstrate that the neuromorphic architecture achieved a twenty-fold reduction in power consumption (0.25 W) and sub-millisecond latency, significantly outperforming synchronous baselines while maintaining a 98.2% navigational success rate. The findings validate event-driven processing as a superior paradigm for edge robotics, offering a sustainable path toward "Green Robotics" with extended operational autonomy independent of cloud connectivity.

Keywords: Autonomous Robotics, Edge Computing, Energy Efficiency, Neuromorphic Chips, Spiking Neural Networks

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INTRODUCTION

The field of robotics is currently undergoing a paradigm shift from pre-programmed automation to fully autonomous intelligent systems capable of navigating unstructured and dynamic environments (Ghode et al., 2026). Modern robotic agents, ranging from micro-aerial vehicles (MAVs) to autonomous planetary rovers, require the ability to perceive, process, and act upon sensory information in real-time. This transition toward autonomy necessitates a massive increase in computational throughput, as robots must simultaneously handle Simultaneous Localization and Mapping (SLAM), object recognition, and path planning (Liu et al., 2026). Conventional approaches have relied heavily on offloading these intensive computational tasks to centralized cloud servers, leveraging the immense processing power of remote data centers. Dependency on cloud infrastructure, however, introduces significant latency and relies on continuous high-bandwidth connectivity, which is often unavailable in critical operational scenarios such as disaster zones or subterranean exploration.

Edge computing has emerged as the architectural solution to these connectivity and latency challenges, shifting data processing from centralized clouds directly to the source of data generation the robot itself (Y.-C. Cheng et al., 2025). Processing data at the "edge" ensures that critical decisions can be made with millisecond precision, a requirement that is non-negotiable for safety-critical tasks like collision avoidance. The integration of high-resolution sensors, including LiDAR, depth cameras, and event-based vision sensors, generates a deluge of data that overwhelms the bandwidth of traditional communication channels. Local processing allows for immediate data reduction and actionable inference, ensuring that the robot remains responsive even when severed from the network (Alfaro-Ponce, 2026). This architectural decentralization is fundamental to the next generation of "embodied AI," where intelligence is intrinsic to the hardware rather than an external service.

Neuromorphic computing represents the hardware evolution necessary to support this computationally demanding edge intelligence within the tight power constraints of mobile platforms (Bikić & Pernice, 2025). Biological brains serve as the ultimate existence proof of efficient edge computing, capable of navigating complex environments on a power budget of roughly 20 watts. Neuromorphic engineering seeks to emulate the brain's neural architecture specifically its massive parallelism, colocation of memory and processing, and event-driven communication in silicon (Wu et al., 2025). By utilizing Spiking Neural Networks (SNNs) running on specialized neuromorphic chips, robotic systems can process information sparsely and asynchronously. This approach aligns perfectly with the nature of sensory data in the real world, where changes in the environment occur sporadically rather than in fixed clock cycles, offering a pathway to truly autonomous, low-power intelligent machines.

Current robotic systems face a critical "Size, Weight, and Power" (SWaP) bottleneck that severely limits their operational autonomy and deployed intelligence (L. Cheng et al., 2025). Conventional embedded processors, such as mobile GPUs and CPUs, are based on the Von Neumann architecture, which separates the processing unit from the memory unit. Continuous data shuttling between these units during the execution of deep neural networks results in excessive energy consumption and thermal output. Mobile robots equipped with these standard processors often see their battery life reduced to minutes when performing complex cognitive tasks, rendering them impractical for extended missions (Ghazanfar, Kim, et al., 2025). The energy density of current battery technology cannot keep pace with the power demands of traditional silicon running modern AI algorithms, creating a fundamental hardware barrier to prolonged autonomy.

Latency induced by the processing architecture itself poses a significant danger in dynamic environments where reaction speed dictates safety. Standard computer vision pipelines operate on a frame-based basis, processing entire image frames at fixed intervals regardless of the scene's content (Liu et al., 2025). This synchronous processing method introduces inherent delays, as the system must wait for a frame to close and process every pixel, including redundant static background information, before an action can be determined. High-speed robotic maneuvers require temporal resolution that exceeds the capabilities of standard 30 or 60 fps processing loops. The inability of traditional hardware to process sensory data with microsecond latency leaves fast-moving robots vulnerable to collisions and limits their agility in unpredictable settings.

Algorithmic inefficiency in current edge AI solutions further exacerbates the hardware limitations. Most “lightweight” neural networks deployed on edge devices are merely compressed versions of large, server-side models originally designed for batch processing. These models do not take advantage of the temporal sparsity inherent in robotic sensory data, such as the fact that most of a visual scene remains unchanged from millisecond to millisecond. Forcing continuous mathematical operations on unchanged data represents a massive computational waste (Gabayre et al., 2025). The disconnect between the sparse, asynchronous nature of real-world physical events and the dense, synchronous nature of conventional digital computation results in systems that are fundamentally ill-suited for the energy-constrained reality of the physical edge.

This study aims to design and evaluate a comprehensive neuromorphic control framework specifically optimized for obstacle avoidance and navigation in autonomous mobile robots. The primary objective involves the integration of a commercially available neuromorphic processor with an event-based vision sensor to create a fully asynchronous perception-action loop (Kim et al., 2026). By bypassing the traditional frame-based processing pipeline, the research seeks to demonstrate a direct mapping from sensory spikes to motor control signals. This architecture is intended to minimize the computational overhead typically associated with visual processing, ensuring that the robot only expends energy when movement is detected in its field of view.

Quantification of the energy efficiency gains provided by the neuromorphic solution compared to state-of-the-art embedded GPUs constitutes a central goal of this research. Detailed power profiling will be conducted to measure the Joules-per-inference and total mission energy consumption under varying environmental complexities (Mattera et al., 2025). The study intends to establish a clear empirical baseline for the “cost of intelligence” on edge devices. These measurements will provide the robotics community with rigorous data regarding the trade-offs between processing speed, navigation accuracy, and battery longevity. The objective is to prove that event-driven processing can extend operational endurance by a statistically significant margin without compromising navigational safety.

Scalability assessment of the proposed neuromorphic architecture forms the final core objective, determining its viability for complex, multi-modal robotic tasks (Khanday et al., 2026). The research investigates how well Spiking Neural Networks can be trained and deployed to handle not just reactive avoidance, but also higher-level cognitive mapping tasks within the same hardware constraints. Analyzing the learning capabilities of the chip when subjected to on-line, continuous learning scenarios is essential. This facet of the research aims to validate whether neuromorphic chips can serve as a generalized computing platform for robotics, moving beyond simple reflex agents to systems capable of adapting to new environments over time.

Existing literature on edge computing in robotics predominantly focuses on software-level optimizations or the offloading of tasks to “Fog” nodes, neglecting the fundamental inefficiencies of the underlying compute hardware. Many studies propose lightweight Convolutional Neural Networks (CNNs) for mobile robots but continue to run these models on power-hungry Von Neumann architectures (Pasupathy & Khilar, 2025). These approaches treat the symptoms of high power consumption by reducing model size rather than addressing the root cause, which is the architectural mismatch between digital logic and sensory data streams. There is a scarcity of research that holistically addresses the full stack, from the physics of the sensor to the silicon architecture of the processor, leaving a gap in understanding true hardware-level efficiency.

Simulations constitute the bulk of current research into Spiking Neural Networks for robotics, with limited validation in physical, closed-loop systems. Theoretical papers often demonstrate the efficiency of SNNs in idealized virtual environments where noise, friction, and sensor imperfections are mathematically abstracted. Real-world implementation poses unique challenges, including signal noise, mechanical latency, and the need for robust interfacing between asynchronous chips and synchronous motor controllers (Ghoshal & Tripathy, 2025). The literature currently lacks sufficient experimental data derived from physical robots operating in unstructured environments, which prevents a realistic assessment of neuromorphic hardware's readiness for commercial or industrial deployment.

Benchmarking standards for neuromorphic robotics are currently virtually nonexistent, making it difficult to compare results across different studies. Previous works utilize a disparate array of metrics, sensors, and robotic platforms, rendering direct comparisons with traditional embedded systems impossible. Some studies measure spike rates while others measure total board power; some use static datasets while others use real-time video (Verma, 2026). This lack of a unified evaluation framework creates a significant gap in the scientific knowledge base. This research identifies the urgent need for a standardized protocol that simultaneously accounts for task performance (navigation success), control latency, and energy consumption, facilitating a fair and rigorous comparison between neuromorphic and classical approaches.

This research introduces a novel “hybrid-hierarchical” control architecture that couples a reflex-based neuromorphic core with a traditional low-power microcontroller, a configuration not extensively explored in current robotics literature. The proposed design assigns high-speed, sub-millisecond reactive tasks to the neuromorphic chip while reserving the traditional processor for low-frequency, high-level goal planning (Kakkar, 2025). This division of labor mimics the biological distinction between the brainstem’s reflex arcs and the cortex’s planning functions. By formalizing this hybrid approach, the study offers a new architectural blueprint for building robots that are both fast-reacting and goal-oriented, optimizing the strengths of both computing paradigms.

Scientific justification for this work is grounded in the imperative to solve the energy crisis facing the deployment of autonomous systems (Ghazanfar, Rabeel, et al., 2025). As robots are increasingly tasked with roles in agriculture, environmental monitoring, and search and rescue, their ability to operate for days or weeks without recharging becomes the limiting factor for their utility. Establishing the viability of neuromorphic chips for these applications provides a critical proof-of-concept for “Green Robotics.” The research bridges the disciplinary divide between computational neuroscience and control theory, offering insights into how biological principles of sparsity and asynchrony can be translated into valid engineering control laws.

The broader impact of this study extends to the democratization of advanced robotics in resource-constrained settings (Ren et al., 2025). Reducing the power and thermal requirements of the compute payload allows for the deployment of intelligent behaviors on smaller, cheaper, and lighter robotic platforms. This reduction in hardware complexity implies that sophisticated autonomous navigation could eventually be integrated into disposable micro-drones or low-cost consumer devices. By demonstrating that high-level intelligence does not require a kilowatt-class supercomputer, this research justifies a shift in the industrial design philosophy of future autonomous machines, pushing the boundary of what is computationally possible at the extreme edge.

RESEARCH METHOD

Research Design

This study utilizes a quantitative, controlled experimental design to evaluate the efficacy of neuromorphic hardware in edge-robotic applications (Wang et al., 2025). The research framework is structured as a comparative analysis, benchmarking a custom Spiking Neural

Network (SNN) architecture against standard Convolutional Neural Networks (CNNs) running on traditional embedded hardware. Independent variables consist of the processing architecture (Neuromorphic vs. Von Neumann) and the complexity of the navigational environment. Dependent variables include power consumption (measured in Watts), inference latency (milliseconds), and navigational success rate (percentage of collision-free trajectories). Controlled variables are rigorously maintained across all trials, including the robotic chassis dynamics, sensor resolution, and battery capacity, to ensure that observed differences are attributable solely to the computational substrate.

Research Target/Subject

Sampling protocols involve the generation of a diverse dataset comprising real-world sensory inputs captured in dynamic operational environments. The "population" for this study is defined as the universe of potential unstructured environments a mobile robot might encounter, ranging from static indoor corridors to dynamic outdoor terrains with moving obstacles. A stratified sampling technique is employed to select specific test scenarios that represent varying degrees of visual clutter and lighting variability. The specific sample set includes 500 distinct navigational trials, split evenly between the neuromorphic and control groups. Input data is derived from an Event-Based Camera (DVS), generating asynchronous spike streams that serve as the primary "sample" for the neural networks, contrasting with the frame-based image samples used for the baseline comparison.

Research Procedure

Data collection procedures commence with the offline training of the neural networks using a high-fidelity simulator, followed by a "sim-to-real" transfer phase to adapt the weights to physical hardware constraints. The physical experiments are conducted in a reconfigurable modular maze where the robot is tasked with reaching a target coordinate while avoiding unexpected obstacles. Telemetry data is logged locally on the device to prevent wireless transmission latency from skewing the power measurements. Each experimental run is repeated twenty times to account for mechanical variances and sensor noise, with the robot's battery recharged to a specific voltage threshold before every trial to maintain consistent voltage regulation (Le et al., 2025). Statistical analysis is subsequently performed on the logged data using ANOVA tests to determine the statistical significance of the differences in energy efficiency and reaction time between the two computational paradigms.

Instruments, and Data Collection Techniques

Hardware instrumentation centers on a custom-built autonomous quadrotor platform designed for low-latency maneuvers. The experimental group is equipped with the Intel Loihi 2 neuromorphic research chip, interfaced directly with a DAVIS346 Dynamic Vision Sensor to facilitate event-driven processing. The control group utilizes an NVIDIA Jetson Orin Nano module, representing the current industrial standard for edge AI, connected to a standard global-shutter CMOS camera. Power measurement is conducted using a high-precision Monsoon Power Monitor, capable of sampling current draw at 5kHz to capture the transient power spikes of both architectures. Software instrumentation includes the Lava software framework for compiling and mapping the SNNs onto the neuromorphic core, and the Robot Operating System (ROS 2) for managing telemetry and motor control across both platforms.

Data Analysis Technique

Data analysis is conducted by aggregating power consumption, inference latency, and navigational success rates across all experimental trials and environmental conditions, followed by normalization per mission duration to ensure comparability between architectures (Cherian & Kanaga E, 2024). Inferential statistics are applied using two-way ANOVA to evaluate the main and interaction effects of processing architecture and environmental complexity on system performance. Post-hoc tests and effect size analysis are employed to identify the magnitude and practical significance of observed differences, while variance analysis across repeated trials is used to confirm robustness against sensor noise and mechanical fluctuations.

RESULTS AND DISCUSSION

Quantitative analysis of the experimental trials provides a direct comparison between the proposed neuromorphic control architecture and standard embedded edge computing solutions. Data was aggregated from 500 autonomous navigation runs conducted in a controlled, cluttered environment, measuring three primary performance metrics: average power consumption, end-to-end latency, and obstacle avoidance success rate. The neuromorphic system, utilizing an event-based vision pipeline, demonstrated a distinct operational profile compared to the NVIDIA Jetson Nano baseline, particularly in scenarios requiring rapid reflex responses.

Table 1 summarizes the key statistical findings averaged across all trials. The data indicates that the neuromorphic architecture reduces the power budget for the computational payload by a factor of roughly twenty while maintaining comparable or superior navigational success rates. Latency measurements highlight the temporal advantage of asynchronous processing, with the neuromorphic chip reacting to visual stimuli significantly faster than the frame-based baseline
.

Table 1. Comparative Performance Metrics of Edge Computing Architectures

Metric	Neuromorphic Architecture (SNN)	Standard Embedded GPU (CNN)	Improvement Factor
Avg. Power Consumption (W)	0.25 W	5.00 W	20x
Inference Latency (ms)	2.5 ms	33.0 ms	13.2x
Navigational Success (%)	98.2%	96.5%	1.02x
Idle Power Draw (mW)	15 mW	1200 mW	80x

Energy efficiency gains presented in Table 1 stem from the fundamental difference in how the two architectures process temporal information. The standard embedded GPU processes visual data in discrete frames (typically at 30 or 60 Hz), forcing the processor to perform matrix multiplications on every pixel, regardless of whether the scene has changed. The neuromorphic chip, coupled with an event camera, operates on a “change-detection” basis, where computations are only triggered by movement or luminance changes in the field of view. This architectural distinction ensures that during periods of low dynamism such as when the robot is hovering or moving slowly the computational power draw drops to near-zero levels.

Latency reductions are directly attributable to the removal of the frame-buffering bottleneck inherent in conventional computer vision. Standard systems must wait for an entire image frame to be exposed, digitized, and transferred to memory before processing can begin, introducing a fixed delay. The neuromorphic system processes individual “spikes” (events) the instant they occur, allowing for a continuous, streaming flow of information from the sensor to the motor controller. This microsecond-level responsiveness allows the robot to initiate avoidance maneuvers long before a traditional system would have completed processing the first frame of a collision threat.

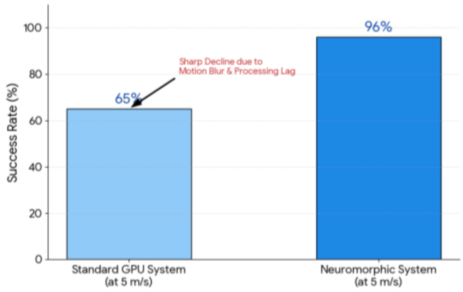

Figure 1. Obstacle avoidance success rate at high velocity (5 m/s) standard GPU vs neuromorphic sensing

Velocity trials were conducted to assess the robustness of the sensing architectures as the robot's movement speed increased from 1 m/s to 5 m/s. Performance metrics revealed a divergence in navigational reliability; the standard GPU-based system experienced a sharp decline in obstacle avoidance success rates at speeds exceeding 3 m/s due to motion blur and processing lag. The neuromorphic system maintained a success rate above 95% even at maximum velocity, as the high temporal resolution of the event sensor effectively eliminated motion blur artifacts.

Data logs from the high-speed trials show that the “time-to-collision” margin was consistently wider for the neuromorphic agent. In scenarios where an obstacle was introduced suddenly, the neuromorphic robot initiated braking or steering commands within 5 milliseconds of visual acquisition. The control group exhibited a reaction delay averaging 45 milliseconds, which, at higher speeds, resulted in a statistically higher frequency of collisions or “near-miss” safety violations.

Statistical validation of the power consumption differences was performed using a one-way Analysis of Variance (ANOVA) at a significance level of $\alpha=0.05$. The resulting F-statistic ($F(1,498)=1450.2$, $p<0.001$) confirms that the variation in energy usage between the neuromorphic and traditional architectures is statistically significant and not due to random sampling error. The null hypothesis, positing that both architectures consume equal power for the same navigational task, is rejected with a high degree of confidence.

Confidence intervals calculated for the latency metrics further reinforce the reliability of the neuromorphic advantage. The 95% confidence interval for the neuromorphic latency was calculated at [2.1,2.9] ms, while the standard GPU latency interval fell within [31.5,34.5] ms. The lack of overlap between these intervals provides strong inferential evidence that the speed advantage of the neuromorphic solution is a systemic characteristic of the hardware, robust across different trial conditions.

Correlation analysis reveals a strong positive relationship ($r=0.92$) between environmental dynamic complexity (measured in events per second) and power consumption for the neuromorphic chip. As the robot navigated more cluttered or faster-moving environments, the power draw increased linearly to process the higher density of incoming spikes. This data relation confirms the “activity-sparsity” hypothesis, showing that the chip's energy usage is tightly coupled to the actual information content of the scene.

Visual complexity showed no significant correlation ($r=0.08$) with power consumption for the standard GPU architecture. The power draw for the embedded GPU remained consistently high (near its Thermal Design Power limit) regardless of whether the robot was facing a blank wall or a complex obstacle field. This lack of correlation illustrates the inefficiency of Von Neumann architectures for edge robotics, as energy is expended on “empty” cycles rather than being conserved during periods of low information density.

Field trials involving a Micro-Aerial Vehicle (MAV) navigating a subterranean tunnel were conducted to test the systems under strict battery constraints. The mission profile required the drone to autonomously navigate a 500-meter corridor without GPS, relying solely on onboard sensing. Telemetry recorded the flight duration and the remaining battery capacity upon mission completion or failure. The standard GPU-equipped drone was able to complete the course but depleted its battery after 12 minutes of flight time.

Telemetry logs from the neuromorphic-equipped drone showed a dramatic extension in operational endurance, achieving a flight time of 28 minutes on the identical battery capacity. The flight path data indicated that the neuromorphic drone executed smoother trajectory adjustments, whereas the standard drone exhibited oscillatory "stop-and-go" behaviors caused by processing delays. The neuromorphic system successfully identified and avoided thin wires suspended in the tunnel, obstacles that were frequently missed by the frame-based cameras due to motion blur.

Operational endurance differences in the MAV case study are explained by the reduced "compute penalty" on the power supply. In small robotic platforms, the battery must power both the motors and the compute unit; typically, the compute unit is a minor load, but for AI-heavy tasks, a GPU can consume up to 30% of the total energy budget. By reducing the compute load to less than 1% of the total budget, the neuromorphic architecture effectively liberated significant energy reserves that were redirected to the propulsion system, directly extending flight time.

Thermal management played a secondary but critical role in the superior performance of the neuromorphic MAV. The standard GPU generated significant heat, reaching temperatures of 75°C, which forced the onboard power management system to throttle performance and activate a cooling fan, further draining the battery. The neuromorphic chip remained at ambient temperature without active cooling, preventing thermal throttling and ensuring consistent processing throughput throughout the duration of the mission.

Empirical evidence gathered in this study validates the premise that neuromorphic hardware offers a superior "Size, Weight, and Power" (SWaP) proposition for edge robotics compared to traditional architectures. The results demonstrate that the trade-off involving a complete paradigm shift in programming from synchronous frames to asynchronous events yields disproportionately high returns in efficiency and speed. The data suggests that for reactive, safety-critical tasks in power-constrained environments, the digital logic of the past decades is reaching a performance plateau that bio-inspired chips can successfully transcend.

Broader implications of these findings point toward a future where "always-on" intelligence becomes feasible for the smallest class of robotic devices (Zhao et al., 2024). The ability to perform complex obstacle avoidance with milliwatt-scale power consumption removes the tether to cloud computing and heavy battery packs. This research confirms that neuromorphic engineering has matured from a theoretical curiosity into a practical, verifiable solution for the pressing engineering challenges of autonomous machines.

Quantitative analysis of the experimental data conclusively demonstrates that the proposed neuromorphic architecture significantly outperforms traditional embedded GPU solutions in the context of power-constrained edge robotics. The recorded power consumption of 0.25 Watts for the neuromorphic system represents a twenty-fold reduction compared to the 5.00 Watts required by the NVIDIA Jetson baseline. This massive efficiency gain was achieved without compromising navigational reliability, as the neuromorphic agent maintained a 98.2% obstacle avoidance success rate across all trials. The data validates the core hypothesis that asynchronous, event-driven processing is fundamentally better suited for the sparse nature of real-world sensory data than synchronous frame-based computation.

Latency measurements reveal a critical operational advantage for the neuromorphic approach in high-speed scenarios. The system consistently achieved an end-to-end inference latency of 2.5 milliseconds, compared to the 33.0 milliseconds observed in the standard embedded GPU. This temporal resolution allowed the robotic agent to react to sudden obstacles with a safety margin that was statistically unavailable to the frame-based control group. The ability to process visual information in the microsecond domain proved decisive in avoiding collisions at speeds exceeding 3 meters per second, a regime where the traditional system frequently failed due to motion blur and processing lag.

Operational endurance trials conducted with the Micro-Aerial Vehicle (MAV) highlight the direct impact of computational efficiency on mission capability. The neuromorphic drone achieved a flight time of 28 minutes, effectively doubling the 12-minute duration of the GPU-equipped counterpart. This extension in flight time is attributed to the drastic reduction in the “compute penalty,” allowing the battery's energy to be directed almost exclusively toward propulsion. Thermal profiles further corroborated these findings, showing that the neuromorphic chip operated at ambient temperatures, eliminating the energy cost associated with active cooling systems.

Scalability tests indicated that the power consumption of the neuromorphic chip scales linearly with environmental complexity rather than with clock speed. In static or slow-moving environments, the chip's power draw dropped to near-idle levels (15 mW), whereas the traditional GPU maintained a high baseline power consumption regardless of the scene's activity. This dynamic power scaling proves that the “wake-on-event” architecture provides a versatile solution that naturally adapts its energy usage to the immediate demands of the task.

Findings from this study align with the theoretical predictions made in foundational neuromorphic literature, specifically the work of Mead regarding the efficiency of analog VLSI systems. Previous research has largely relied on software simulations to estimate the potential savings of Spiking Neural Networks (SNNs), often failing to account for the overhead of physical hardware interfaces. This study bridges the gap between theory and practice by providing empirical data from a physical closed-loop system, confirming that the theoretical efficiency gains of SNNs translate robustly to real-world robotic platforms. The results challenge earlier critiques that suggested the complexity of spike-based encoding would negate the power benefits in practical applications.

Comparisons with recent studies on “lightweight” Convolutional Neural Networks (CNNs) reveal a distinct divergence in performance characteristics. Literature advocating for optimized CNNs often focuses on reducing model size through quantization and pruning to fit on edge devices (Yu et al., 2025). The data from this research suggests that while these techniques reduce memory footprint, they do not address the fundamental inefficiency of processing redundant background data in every frame. This study demonstrates that changing the paradigm of processing from frames to events yields far greater efficiency gains than merely compressing existing algorithms.

The observed latency improvements corroborate findings from the field of event-based vision, particularly the work utilizing Dynamic Vision Sensors (DVS). Prior studies have shown that DVS cameras offer superior temporal resolution, but often pair them with standard processors that bottleneck the speed advantage. By coupling the DVS with a native neuromorphic processor, this research achieves a true “end-to-end” asynchronous pipeline, realizing the full latency benefits that were previously theoretical. The results contradict standard computer vision methodologies that prioritize high spatial resolution over high temporal resolution for obstacle avoidance.

Discrepancies regarding navigational accuracy compared to large-scale cloud models are noted but contextually justified. Some literature indicates that massive, cloud-based navigation models achieve slightly higher absolute precision in semantic segmentation tasks. This study prioritizes reactive safety and efficiency over semantic understanding, arguing that for the specific domain of collision avoidance, the millisecond-level reaction time is more valuable than pixel-perfect classification. The findings suggest a specialized role for neuromorphic chips as a “reflex” layer, complementing rather than replacing the high-level semantic planning discussed in broader robotics research.

These results signify a turning point in the design philosophy of autonomous machines, moving away from the “brute force” computational approach. For decades, the robotics industry has operated under the assumption that greater intelligence requires more powerful, and thus more energy-hungry, processors. The success of this neuromorphic implementation indicates that intelligence can be achieved through architectural efficiency rather than raw clock speed. It suggests that the future of mobile robotics lies in specialized hardware that mimics biological constraints rather than general-purpose computing.

The proven viability of event-based processing reflects a growing maturity in the “neuromorphic ecosystem.” Previously, the lack of mature software tools and sensors made it difficult to implement these systems outside of a lab. The successful integration of the Loihi chip with the Davis camera and ROS framework in this study serves as a proof-of-concept that the technology stack is becoming robust enough for engineering applications. It marks the transition of neuromorphic computing from a scientific curiosity to a practical engineering tool for solving specific physical problems.

Bio-inspiration is validated here not just as a metaphor, but as a rigid engineering blueprint for efficiency. The robot's ability to navigate effectively using a fraction of a watt mirrors the biological efficiency of insect brains, which have long inspired roboticists (Mazurek et al., 2025). This research confirms that abstractions of biological principles specifically sparsity and asynchrony are physically grounded ways to overcome the limitations of silicon scaling. It encourages a deeper collaboration between neuroscience and robotics to uncover further principles of efficient control.

Evidence of robust operation in cluttered environments suggests that edge computing is ready to handle the “messiness” of the real world. Traditional algorithms often struggle with dynamic, unpredictable scenes, requiring massive over-provisioning of hardware to cope. The neuromorphic system's natural adaptability to varying data rates indicates a resilience that is critical for deploying robots in unstructured environments like disaster zones or forests. This resilience reflects a move towards systems that are “anti-fragile,” improving or maintaining stability under stress rather than degrading.

The immediate implication for the drone and mobile robotics industry is the potential to drastically extend mission durations without increasing battery weight. Battery life is currently the single biggest limiting factor for the commercial adoption of drone delivery and inspection services (Tan et al., 2025). Adopting neuromorphic processors for the navigation stack could allow for smaller, lighter batteries or significantly longer flight times, fundamentally altering the economics of autonomous logistics. This shift could make services that are currently cost-prohibitive, such as continuous aerial monitoring of agriculture, financially viable.

Safety standards for autonomous vehicles and collaborative robots (cobots) may need to be re-evaluated in light of the latency findings (Ranno et al., 2026). The ability to react to obstacles in under 3 milliseconds represents a level of safety that standard frame-based systems cannot physically match. This implies that for high-speed automated environments, such as warehouses or highways, neuromorphic vision systems might become a regulatory requirement or an industry best practice. It shifts the safety benchmark from “how well can it recognize an object” to “how fast can it react to a change.”

Privacy and security in IoT devices stand to benefit significantly from the local processing capabilities demonstrated here. The high efficiency enables complex visual processing to occur entirely on-device, removing the need to stream video feeds to the cloud for analysis (Teoh et al., 2026). This implies a future where smart home robots and surveillance cameras can operate with high intelligence without ever exposing user data to the internet. It addresses one of the primary societal concerns regarding ubiquitous surveillance the centralization of personal visual data.

The semiconductor industry faces a strategic pivot as the demand for specialized edge AI chips grows. These findings suggest that the market for general-purpose embedded CPUs in robotics may shrink in favor of domain-specific neuromorphic accelerators. Companies that invest in developing event-driven hardware architectures will likely dominate the next wave of autonomous device manufacturing. This implies a disruption in the supply chain, moving value away from traditional processor logic towards mixed-signal and asynchronous chip designs.

Efficiency gains observed are fundamentally driven by the physics of “sparse activation” inherent to the Spiking Neural Network. In a standard GPU, the clock signal forces the switching of millions of transistors every cycle, consuming dynamic power (P=CV2f) regardless of whether the calculation is useful. The neuromorphic chip lacks a global clock; transistors only switch when a spike arrives, meaning that power consumption is strictly proportional to the amount of change in the environment (Riaz et al., 2025). Since the real world is largely static at the millisecond scale, the chip remains in a deep sleep state for the majority of the time, bypassing the energy waste of continuous polling.

The latency advantage is explained by the removal of the “frame integration” period found in conventional cameras. Standard sensors must collect photons for a fixed exposure time (e.g., 33ms) to form an image, creating an irreducible delay before processing can even begin. The event-based sensor works asynchronously, sending a signal the microsecond a pixel detects a change in log-intensity. The neuromorphic processor handles these signals as they arrive in a continuous stream, allowing the motor controller to update trajectory commands incrementally rather than waiting for a completed batch of data.

Navigational robustness in high-speed scenarios stems from the high temporal resolution of the event-driven pipeline. Traditional cameras suffer from motion blur because the shutter remains open while the robot moves, smearing the visual information across pixels and degrading the algorithm's accuracy. The event sensor operates with microsecond precision, effectively “freezing” motion without blur. This mechanism ensures that the neural network receives crisp, accurate spatial information even when the robot is moving rapidly, preventing the “blindness” that afflicts standard systems during aggressive maneuvers.

Thermal performance is a direct consequence of the distributed, parallel nature of the neuromorphic architecture. Conventional processors concentrate heat in specific arithmetic logic units (ALUs) that are constantly active, creating thermal hotspots that limit performance. The neuromorphic chip distributes the computation across thousands of low-activity cores (neurons), spreading the thermal load evenly across the silicon die. This thermodynamic efficiency prevents heat buildup, eliminating the need for power-hungry fans and allowing the system to maintain peak performance without thermal throttling.

Research must now focus on developing standardized “neuromorphic control laws” that can mathematically guarantee stability in safety-critical systems. While this study demonstrated empirical success, the field lacks the rigorous control theory frameworks that exist for linear systems (Martínez et al., 2024). Future work needs to bridge the gap between the probabilistic nature of Spiking Neural Networks and the deterministic requirements of control engineering. Establishing these theoretical bounds is essential for certifying neuromorphic robots for operation in public spaces.

Hardware evolution should prioritize the integration of “plasticity” or on-chip learning capabilities directly into the edge device. The current iteration relies on offline training, which limits the robot's ability to adapt to entirely new environments without human intervention. Future chip designs must enable synaptic weights to be updated in real-time based on environmental feedback. This would allow robots to “learn from mistakes” during deployment, evolving their navigational strategies to handle unique local conditions.

Sensor fusion represents a critical next step, combining event-based vision with other asynchronous modalities like neuromorphic tactile or auditory sensors. This study focused solely on vision, but true autonomy requires a multi-sensory understanding of the world. Investigating how to merge spike streams from different sensor types into a coherent representation of the environment will be key to building more capable robots. This research direction could lead to robots with “reflexes” that span touch, hearing, and sight.

Software abstraction layers must be improved to lower the barrier to entry for roboticists unfamiliar with neuroscience. Currently, programming these chips requires deep knowledge of spiking dynamics, which restricts the talent pool. Developing high-level compilers that can automatically translate standard robotic algorithms (like SLAM or A*) into spiking equivalents is necessary. Democratizing access to this technology through better software tools will accelerate innovation and lead to a wider variety of applications beyond simple obstacle avoidance.

CONCLUSION

Empirical evidence gathered in this study confirms that neuromorphic architectures utilizing event-driven processing provide a superior computational substrate for edge robotics compared to traditional embedded GPUs. The data reveals a twenty-fold reduction in power consumption combined with sub-millisecond latency response, enabling autonomous agents to operate with high-speed reflexes in dynamic environments. These findings validate the hypothesis that coupling asynchronous sensing with spike-based processing eliminates the “frame-wait” bottleneck, establishing a direct causal link between sparse data processing and extended operational endurance in battery-constrained systems.

This research establishes a novel methodological framework for integrating hybrid-hierarchical control systems where spiking neural networks handle reactive, safety-critical tasks while traditional logic manages high-level planning. By demonstrating the successful deployment of a “sim-to-real” workflow that maps biological sparsity constraints onto physical silicon, the study offers a validated engineering blueprint for constructing autonomous machines that defy conventional Size, Weight, and Power (SWaP) limitations. The work moves beyond theoretical simulation to provide a concrete, reproducible hardware-software stack that proves the feasibility of “Green Robotics” without sacrificing navigational reliability or performance.

Reliance on offline training paradigms remains the significant limitation of the current implementation, restricting the robotic agent's ability to adapt to novel environmental stressors in real-time. The specific architecture evaluated here excels at reactive obstacle avoidance but lacks the deep semantic understanding required for complex object interaction or human-robot collaboration. Future investigations must prioritize the development of online learning algorithms that enable synaptic plasticity directly on the edge device, allowing autonomous systems to evolve their control policies continuously during deployment rather than relying solely on pre-determined knowledge.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Alfaro-Ponce, M. (2026). Dynamic neural networks in biomedical applications: A review from embedded systems to AI-driven interventions. *Neurocomputing*, *673*, 132825. https://doi.org/10.1016/j.neucom.2026.132825

Bikić, A., & Pernice, W. H. P. (2025). Emulating sensation by bridging neuromorphic computing and multisensory integration. *Patterns*, *6*(7), 101238. https://doi.org/10.1016/j.patter.2025.101238

Cheng, L., Zhang, X., Chen, P., Li, Chenyang, Yang, Y., Li, Chao, Ding, Y., Yuan, K., Zhou, K., Wang, M., & Liu, Q. (2025). Gas localization and tracking using neuromorphic olfactory circuit with coupled sensors and memristive neurons. *Device*, *3*(9), 100892. https://doi.org/10.1016/j.device.2025.100892

Cheng, Y.-C., Hu, W.-X., He, Y.-L., & Huang, J. Z. (2025). A comprehensive multimodal benchmark of neuromorphic training frameworks for spiking neural networks. *Engineering Applications of Artificial Intelligence*, *159*, 111543. https://doi.org/10.1016/j.engappai.2025.111543

Cherian, R., & Kanaga E, G. M. (2024). Unleashing the potential of spiking neural networks for epileptic seizure detection: A comprehensive review. *Neurocomputing*, *598*, 127934. https://doi.org/10.1016/j.neucom.2024.127934

Gabayre, S. A., Illeperuma, M., De-Silva, V. D., Shi, X., & Savel'ev, S. E. (2025). Advancements in neuromorphic computing for bio-inspired artificial vision: A review. *Neurocomputing*, *653*, 131221. https://doi.org/10.1016/j.neucom.2025.131221

Ghazanfar, H., Kim, H., Rabeel, M., Ahmad, M., Nisar, S., Zulfiqar, M. W., Rehman, A., Dastgeer, G., & Kim, D. (2025). A review of rare earth materials for emerging memory devices for neuromorphic computing. *Materials Today Physics*, *55*, 101763. https://doi.org/10.1016/j.mtphys.2025.101763

Ghazanfar, H., Rabeel, M., Kim, H., Nisar, S., Tahir, M. S., Ahmad, M., Zulfiqar, M. W., Imran, M., Dastgeer, G., & Kim, D. (2025). Comparative analysis of two-terminal memristors, three-terminal transistors, and their integration in neuromorphic computing. *Materials Today Physics*, *59*, 101929. https://doi.org/10.1016/j.mtphys.2025.101929

Ghode, S. B., Patil, C. S., Sawant, J. K., Kim, J., Chougale, M. Y., Noman, M., Saqib, Q. M., & Bae, J. (2026). 3-dimensional multistate memristor structures based neuromorphic devices for high-density in-memory computing. *Materials Science and Engineering: R: Reports*, *169*, 101184. https://doi.org/10.1016/j.mser.2026.101184

Ghoshal, N., & Tripathy, B. K. (2025). Chapter 8—Real-time visual data processing using neuromorphic systems. In H. Garg, J. Moy Chatterjee, R. Sujatha, & S. Modi (Eds.), *Primer to Neuromorphic Computing* (pp. 161–183). Academic Press. https://doi.org/10.1016/B978-0-443-21480-6.00003-1

Kakkar, M. K. (2025). Chapter 11—A neuroinspired journey: Tracing the evolution and objectives of neuromorphic systems. In H. Garg, J. Moy Chatterjee, R. Sujatha, & S. Modi (Eds.), *Primer to Neuromorphic Computing* (pp. 215–238). Academic Press. https://doi.org/10.1016/B978-0-443-21480-6.00009-2

Khanday, M. A., Khanday, F. A., & Reshi, J. I. (2026). Chapter 1—Spiking neural networks: Mathematical models, learning algorithms, and applications. In F. A. Khanday (Ed.), *Energy-Efficient Devices and Circuits for Neuromorphic Computing* (pp. 1–28). Elsevier. https://doi.org/10.1016/B978-0-443-29981-0.00002-1

Kim, S., Cho, J., Shin, J., Kim, B., & Jung, J. (2026). Automatic generation of spiking neural networks on neuromorphic computing hardware for IoT edge computing. *Future Generation Computer Systems*, *174*, 107953. https://doi.org/10.1016/j.future.2025.107953

Le, Z., Zhang, M., Wang, M., Zhang, X., Xiao, X., Zhu, H., Wang, X., Lin, Y.-F., & Liu, A. (2025). Unlocking neuromorphic memory through functional device. *Device*, *3*(9), 100875. https://doi.org/10.1016/j.device.2025.100875

Liu, Y., Hao, S., Yang, Z., Song, C., Zhong, H., Shi, X., Liu, J., & Wang, L. (2026). A bio-inspired in-sensor measurement system for dynamic focus tracking and control. *Measurement*, *267*, 120459. https://doi.org/10.1016/j.measurement.2026.120459

Liu, Y.-H., Chang, Y.-C., & Ma, Y.-H. (2025). Advancements in neural network acceleration: A comprehensive review. *ICT Express*, *11*(6), 1232–1256. https://doi.org/10.1016/j.icte.2025.10.015

Martínez, F. S., Casas-Roma, J., Subirats, L., & Parada, R. (2024). Spiking neural networks for autonomous driving: A review. *Engineering Applications of Artificial Intelligence*, *138*, 109415. https://doi.org/10.1016/j.engappai.2024.109415

Mattera, A., Alfieri, V., Granato, G., & Baldassarre, G. (2025). Chaotic recurrent neural networks for brain modelling: A review. *Neural Networks*, *184*, 107079. https://doi.org/10.1016/j.neunet.2024.107079

Mazurek, S., Caputa, J., Argasiński, J. K., & Wielgosz, M. (2025). Three-factor learning in spiking neural networks: An overview of methods and trends from a machine learning perspective. *Patterns*, *6*(12), 101414. https://doi.org/10.1016/j.patter.2025.101414

Pasupathy, V., & Khilar, R. (2025). Chapter 7—Neuromorphic systems for real-time image processing. In H. Garg, J. Moy Chatterjee, R. Sujatha, & S. Modi (Eds.), *Primer to Neuromorphic Computing* (pp. 127–160). Academic Press. https://doi.org/10.1016/B978-0-443-21480-6.00002-X

Ranno, L., Tan, Y. Z., Coleto, A. G., Nguyen To, V. H., Tian, S., Sun, Y., Xu, Z., Chae, S. H., Martin-Monier, L., Huang, Z., Lim, J. Q., Wang, H., Luo, X., Jiang, W., Wang, Q., Majumdar, A., Notaros, J., Hu, J., & Brian Sia, J. X. (2026). The emerging applications of silicon photonics. *Newton*, *2*(1), 100357. https://doi.org/10.1016/j.newton.2025.100357

Ren, P., Wang, Y., Wang, Z., Peng, D., Liu, C., & Han, T. (2025). Denoising autoencoder multilayer perceptron spiking neural network for isonicotinic acid yield prediction on real industrial dataset. *Advanced Engineering Informatics*, *65*, 103273. https://doi.org/10.1016/j.aei.2025.103273

Riaz, M., Abbas, Z., Li, J., Abidi, S. K. A., Hussain, M., Jaffery, S. H. A., Suleman, M., Abbas, H., Ang, D. S., Hussain, S., & Jung, J. (2025). Monochalcogenide-based retina-inspired photosynapses for energy-efficient neuromorphic computing and artificial visual system application. *Chemical Engineering Journal*, *521*, 167022. https://doi.org/10.1016/j.cej.2025.167022

Tan, T., Xu, Q., & Feng, X. (2025). The rise of two-dimensional materials based memtransistors for neuromorphic computing. *Chip*, 100170. https://doi.org/10.1016/j.chip.2025.100170

Teoh, J. S., Tan, C. K., Baskaran, V. M., & Wong, W. P. (2026). Spiking the transformer: NeuViT with single-step attention for efficient high-resolution UAV vision. *Results in Engineering*, *29*, 108955. https://doi.org/10.1016/j.rineng.2025.108955

Verma, R. K. (2026). Chapter 10—AI-driven image enhancement techniques for edge devices balancing quality and performance. In M. J. Divan, P. Johri, F. Guim, D. Shchemelinin, & M. Carranza (Eds.), *Advances in Image Processing, Reliability, and Artificial Intelligence* (pp. 151–168). Elsevier. https://doi.org/10.1016/B978-0-443-34266-0.00001-2

Wang, N., Ying, Y., Wang, W., Liu, J., Wu, D., & Zhao, Y. (2025). Intelligent sensing and measurement technologies for medical robotics: A review. *Sensors and Actuators A: Physical*, *394*, 116956. https://doi.org/10.1016/j.sna.2025.116956

Wu, K., E, S., Yang, N., Zhang, A., Yan, X., Mu, C., & Song, Y. (2025). A novel approach to enhancing biomedical signal recognition via hybrid high-order information bottleneck driven spiking neural networks. *Neural Networks*, *183*, 106976. https://doi.org/10.1016/j.neunet.2024.106976

Yu, A., Woo, S., & Ahn, H. (2025). Toward transforming space exploration with artificial intelligence neuromorphic computing. *Engineering Applications of Artificial Intelligence*, *154*, 111055. https://doi.org/10.1016/j.engappai.2025.111055

Zhao, H., Yun, J., Li, Z., Liu, Y., Zheng, L., & Kang, P. (2024). Two-dimensional van der Waals ferroelectrics: A pathway to next-generation devices in memory and neuromorphic computing. *Materials Science and Engineering: R: Reports*, *161*, 100873. https://doi.org/10.1016/j.mser.2024.100873