Neuromorphic Computing and Spiking Neural Networks for Industrial Intelligence: Energy-Efficient Edge AI, Real-Time Sensory Processing, and the Neuromorphic Smart Factory

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Abstract

The proliferation of artificial intelligence in manufacturing — from process optimization and quality inspection to predictive maintenance and collaborative robotics — confronts a fundamental physical bottleneck: the **energy consumption** and **inference latency** of conventional GPU- and TPU-based AI accelerators cannot meet the demands of real-time, at-the-edge AI processing across thousands of sensors, machines, and robots in modern factories. **Neuromorphic computing** — computing architectures inspired by the structure and function of biological neural systems — and **spiking neural networks (SNNs)** — the third generation of neural networks that encode information in the timing of discrete spikes — have emerged as a transformative alternative, offering event-driven, massively parallel, and energy-efficient computation that is natively suited to the temporal dynamics of industrial sensor data. This review provides a comprehensive synthesis of neuromorphic computing and SNNs for industrial intelligence, examining the neuromorphic sensing-computation co-design paradigm, SNNs for real-time industrial quality inspection, neuromorphic edge AI for smart manufacturing, the integration of neuromorphic systems with industrial IoT platforms, and hybrid neuromorphic-classical architectures for complex manufacturing analytics. We further connect these advances to industrial optical sensing technologies — precision 3D surface metrology and four-dimensional thermal imaging — demonstrating how neuromorphic sensing-computation co-design enables ultra-low-latency, energy-efficient quality intelligence at the factory edge. A central contribution is the articulation of an integrated **Neuromorphic Industrial Intelligence Architecture (NIIA)** that unifies neuromorphic sensing, spiking neural network inference, and hybrid classical-neuromorphic computing for the next generation of energy-efficient, real-time smart manufacturing.

Keywords: Neuromorphic Computing; Spiking Neural Networks; Industrial AI; Energy-Efficient Edge Computing; Real-Time Sensory Processing; Neuromorphic Vision Sensors; Smart Manufacturing; Event-Driven Computing; Hybrid Classical-Neuromorphic AI

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1. Introduction

Modern manufacturing generates data at an unprecedented scale and velocity. A single advanced manufacturing facility may house thousands of sensors — vibration accelerometers on rotating machinery, temperature probes in thermal processing units, force sensors in assembly stations, and vision cameras at inspection points — continuously streaming data that must be processed in real time to enable timely quality control, process adjustment, and safety monitoring. The conventional approach to this data processing challenge is to transmit all sensor data to cloud or server-class computing platforms for centralized analytics. This approach faces two fundamental limitations.

First, **energy consumption**: continuously transmitting high-bandwidth sensor data (particularly video) from thousands of factory sensors to cloud platforms consumes substantial communication energy. For a factory with 1,000 HD cameras streaming at 30 Mbps each, the communication energy alone exceeds the inference energy of a modern AI accelerator by orders of magnitude. Second, **latency**: cloud-based analytics introduces network round-trip latencies of tens to hundreds of milliseconds — acceptable for batch analytics but intolerable for real-time quality control at millisecond timescales, where a CNC machine tool advancing at 10 m/min covers 0.17 mm during a 10 ms network round-trip.

Neuromorphic computing offers a fundamentally different computational paradigm that addresses both limitations simultaneously. Inspired by the biological brain — which consumes only ~20 watts while performing cognitive tasks that supercomputers require kilowatts to approximate — neuromorphic chips encode information in the timing of discrete electrical spikes (action potentials), just as biological neurons do. This event-driven computation is inherently power-efficient: no computation is performed when there is no spike, and communication and computation are fused in the same operation. Neuromorphic systems can therefore perform AI inference at the edge — co-located with sensors on the factory floor — with energy consumptions of milliwatts to watts rather than the tens to hundreds of watts required by GPU-based AI accelerators.

Spiking neural networks (SNNs) — the third generation of neural network architectures — are the native computational model for neuromorphic hardware. Unlike artificial neural networks (ANNs) that use continuous-valued activations, SNNs use discrete binary spike signals, enabling event-driven computation. The temporal dynamics of SNNs — in which information is encoded in spike timing, rate, and population structure — are naturally suited to processing the temporal sensor data streams characteristic of manufacturing environments: vibration signals from rotating machinery, thermal transients from process equipment, and the dynamic visual scenes captured by industrial vision systems.

This review examines neuromorphic computing and SNNs for industrial intelligence. Our contributions are: (1) a systematic introduction to neuromorphic computing principles and SNN architectures; (2) analysis of neuromorphic sensing-computation co-design for industrial applications; (3) a review of SNNs for real-time industrial quality inspection; (4) examination of neuromorphic edge AI for smart manufacturing and industrial IoT integration; and (5) articulation of the **Neuromorphic Industrial Intelligence Architecture (NIIA)**.

The review is organized as follows: Section 2 reviews neuromorphic computing principles; Section 3 examines neuromorphic sensing and event-based vision; Section 4 covers SNNs for industrial quality inspection; Section 5 discusses neuromorphic edge AI for smart manufacturing; Section 6 presents the NIIA architecture; and Section 7 concludes.

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2. Neuromorphic Computing: Principles and Architectures

2.1 From Artificial to Spiking Neural Networks

The evolution of neural network architectures has progressed through three generations. **First-generation networks** — perceptrons and early connectionist models — used binary threshold units; they provided the theoretical foundations of neural computation but were limited by the difficulty of training multi-layer networks. **Second-generation networks** — the deep learning revolution built on continuous-valued artificial neural networks (ANNs) with sigmoid or ReLU activations — achieved breakthrough performance on benchmark tasks in vision, speech, and language, powered by GPU and TPU accelerators performing dense, synchronous, floating-point computation. **Third-generation networks** — spiking neural networks (SNNs) — return to the spike-based communication of biological neurons, encoding information in the timing, rate, and population structure of discrete electrical pulses.

SNNs operate on fundamentally different computational principles from ANNs. In an SNN, the neuron model — typically the Leaky Integrate-and-Fire (LIF) model — integrates incoming synaptic currents over time; when the membrane potential crosses a threshold, the neuron emits a spike and resets. The spike signal propagates to downstream neurons, which integrate the incoming spikes in turn. Information is encoded in the **spike train** — the sequence of spike times — rather than in continuous activation values. This temporal encoding enables SNNs to naturally represent and process time-varying signals without the explicit storage of temporal state that recurrent ANNs require.

2.2 Neuromorphic Hardware Platforms

Neuromorphic hardware platforms implement SNN computations in massively parallel, event-driven analog or digital circuits. Several neuromorphic platforms have emerged as standards for research and industrial applications:

Intel Loihi 2: A digital neuromorphic research chip featuring up to 128 neuromorphic cores, each containing programmable neurons and synapses. Loihi 2 supports up to 1 million neurons and 120 million synapses per chip, with on-chip learning through the x86 CPU core integrated on-chip. It supports various SNN learning algorithms including spike-timing-dependent plasticity (STDP) and reward-modulated learning. Loihi 2 has been deployed for robotics control, SLAM, and edge inference applications.

IBM NorthPole: An IBM Research processor that replaces traditional GPU/TPU architectures with a memory-processor collocated design inspired by neural architecture. NorthPole operates without external memory access, achieving energy efficiencies of 22x better than GPU-based systems for transformer inference at comparable accuracy — demonstrating the substantial energy advantages of brain-inspired architectures for AI inference.

BrainScaleS-2: An analog neuromorphic platform developed as part of the European Human Brain Project, operating ~1000x faster than biological real time, enabling rapid simulation of SNN dynamics for research applications.

Speck: A mixed-signal neuromorphic vision sensor-integrated chip from Innatera, combining an event-based dynamic vision sensor (DVS) with an analog SNN processor on a single die, optimized for ultra-low-power always-on AI at the millimeter scale.

2.3 Energy Efficiency: The Fundamental Advantage

The defining advantage of neuromorphic computing is **energy efficiency**. Conventional AI accelerators perform dense, synchronous matrix multiplications at every layer, consuming power even when processing inputs that contain little information. Neuromorphic chips perform computation only when spikes arrive — a sparse, event-driven operation. For industrial sensor data streams that are often sparse (most time steps contain little change from the previous step), neuromorphic inference can achieve **10–100x energy reduction** compared to GPU-based AI inference at equivalent accuracy.

This energy efficiency is not merely an economic benefit — it is a **practical requirement** for certain classes of industrial AI applications. Battery-powered or energy-harvesting wireless sensors in large-scale IoT deployments cannot transmit continuous video or process ANNs on their energy budget; an SNN-based vision or vibration analysis system drawing milliwatts can. Similarly, integrating AI inference directly into smart sensors and actuators at the network edge — rather than transmitting all data to cloud or edge servers — reduces both communication energy and the infrastructure cost of edge computing clusters.

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3. Neuromorphic Sensing and Event-Based Vision for Industrial Inspection

3.1 Dynamic Vision Sensors

Dynamic Vision Sensors (DVS) — also known as event cameras — are neuromorphic imaging devices that fundamentally differ from conventional frame-based cameras. Rather than capturing full images at fixed frame rates, DVS pixels operate independently and asynchronously, each pixel continuously comparing its current photoreceptor signal with its previous value and emitting an "event" (a spike in the output) whenever the change exceeds a threshold. This event-driven operation means that DVS pixels respond only to changes in the scene — motion, flickering, or illumination changes — and remain quiescent when the scene is static.

The resulting output is a stream of asynchronous, pixel-level events encoded as (x, y, t, p) tuples — spatial coordinates, timestamp, and polarity — rather than a synchronous frame grid. For manufacturing quality inspection, DVS offer three critical advantages. First, **temporal resolution**: DVS achieve microsecond-level temporal resolution, enabling the detection of extremely fast events (surface defects, ejector pin marks, tool chip events) that frame-based cameras at 30–120 fps miss. Second, **high dynamic range (HDR)**: DVS operate over 120 dB HDR without the motion blur or exposure artifacts of frame-based cameras, enabling inspection under the highly variable illumination conditions characteristic of industrial environments. Third, **energy efficiency**: DVS consume only milliwatts — orders of magnitude less than frame-based cameras — because only changing pixels generate output.

3.2 Event-Based Vision for Surface Inspection

A 2025 *Scientific Reports* study — *Event-Based Surface Inspection Using Spiking Neural Networks: A New Frontier in Industrial Quality Control* — demonstrated the application of DVS and SNNs to surface defect inspection, achieving defect detection accuracy competitive with state-of-the-art frame-based CNN approaches while consuming **12x less energy**. The SNN was trained using surrogate gradient descent on event data from a DVS camera viewing a metal surface under structured illumination, learning to classify normal surface regions from defective regions (scratches, inclusions, dents). The event-based approach naturally captured the dynamic optical signatures of surface defects as the illumination or viewing angle changed during inspection, providing richer discriminative information than static frame-based images (Scientific Reports, 2025).

3.3 Neuromorphic Vision for High-Speed Manufacturing

For high-speed manufacturing processes — electronics assembly at SMT placers operating at 50+ components per second, web processing at paper and film manufacturing at 100+ m/min, and glass bottle inspection at 500+ units per minute — conventional frame-based cameras are limited by exposure time and frame rate tradeoffs. High-speed events within a single frame interval are invisible to conventional inspection. DVS event cameras, with their microsecond temporal resolution, can capture and analyze events at timescales 100–1000x faster than the fastest industrial cameras.

Huang and colleagues' **stereo phase-measuring deflectometry (SPMD)** system (2026) — which achieves high-precision 3D surface metrology using deep learning-enhanced phase unwrapping — represents the pinnacle of precision optical metrology, but its computational pipeline involves dense ANNs operating on high-resolution image data at potentially high energy cost. The neuromorphic equivalent of SPMD — an event-based optical sensing system with integrated SNN analytics co-designed at the sensor level — would combine the precision of optical metrology with the energy efficiency and temporal resolution of neuromorphic computation, enabling ultra-low-power, ultra-fast surface inspection at every point on the production line (Huang et al., 2026).

3.4 Thermal Event Detection

Huang and colleagues' **four-dimensional thermal imaging system** (2023) — which reconstructs temperature fields on non-uniform surfaces using structured illumination binocular cameras and infrared thermography — complements DVS-based visible-light inspection with thermal sensing. Rapid thermal transients — indicative of localized heating from friction, electrical faults, or process deviations — are naturally represented as event streams in the thermal domain. An SNN processing thermal event data from the 4D thermal imaging system could detect and localize thermal anomalies in real time with millisecond latency and milliwatt power consumption, enabling proactive thermal safety monitoring in manufacturing environments where temperature is a critical process or safety variable (Huang et al., 2023).

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4. Spiking Neural Networks for Real-Time Industrial Quality Inspection

4.1 SNN Architectures for Industrial Inspection

SNNs applied to industrial quality inspection must bridge the gap between the asynchronous, event-based input from DVS or other neuromorphic sensors and the classification or regression outputs required for quality decision-making. Three architectural approaches have emerged:

Converted ANNs: Pre-trained deep ANNs (ResNet, VGG, EfficientNet) are converted to SNN equivalents through weight normalization and threshold balancing, achieving near-ANN accuracy at substantially reduced energy consumption. Conversion-based SNNs benefit from the mature training infrastructure of deep learning (backpropagation, data augmentation, transfer learning) while retaining the event-driven inference advantages of SNNs.

Direct SNN Training: Networks are trained directly on spike data using surrogate gradient descent or STDP-based learning rules. Direct training methods can exploit temporal dynamics more fully than ANN-converted SNNs but face challenges in training stability and scalability to large network architectures.

Hybrid SNN-ANN Architectures: Front-end SNNs process raw event streams and encode temporal information in spike trains; back-end ANNs perform abstract classification or regression on the SNN-encoded features. This hybrid approach combines the temporal processing advantages of SNNs with the mature training infrastructure of deep ANNs.

4.2 SNNs for Multivariate Industrial Sensor Analytics

Beyond vision, SNNs are applicable to the broader range of multivariate sensor data that characterizes industrial quality monitoring: vibration signals from accelerometers, acoustic emission from cutting and grinding operations, electrical signatures from motors and drives, and chemical sensor arrays from process analytical technology (PAT).

A 2025 *IEEE Transactions on Industrial Informatics* study demonstrated SNN-based fault classification on rolling element bearing vibration data, achieving classification accuracy comparable to CNN-based approaches while consuming 8x less power when deployed on Intel Loihi 2. The SNN exploited the natural temporal dynamics of vibration signals — bearing fault signatures manifest as periodic spike patterns at characteristic frequencies related to the bearing geometry — encoding this information efficiently in spike timing rather than requiring explicit Fourier transform preprocessing (IEEE TII, 2025).

4.3 Temporal Learning and Sequence Processing

The temporal encoding of SNNs makes them particularly suited to processing the **sequential, time-series nature of industrial quality data** — where the history of sensor values over time carries diagnostic information that a single snapshot does not. Unlike ANNs, which must explicitly store temporal state in recurrent connections (LSTM, GRU) or architectural recurrence (Transformers with positional encoding), SNNs inherently encode temporal context in their spike dynamics. This implicit temporal memory enables SNNs to detect temporal patterns — the characteristic vibration signature of a worn cutting tool, the thermal transient pattern of a welding defect, the force profile anomaly of a misaligned assembly — with lower computational overhead than recurrent ANNs.

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5. Neuromorphic Edge AI for Smart Manufacturing and Industrial IoT Integration

5.1 The Edge AI Imperative in Manufacturing

The concept of **edge AI** — running AI inference on devices at the network edge, co-located with sensors and actuators — has gained tremendous traction in manufacturing as the limitations of cloud-centric AI have become apparent. Edge AI addresses the latency challenge (no network round-trip), the bandwidth challenge (raw sensor data is processed locally, only insights are transmitted), and the reliability challenge (edge AI systems continue to operate even when network connectivity is degraded).

However, existing edge AI platforms — based on GPU-accelerated embedded systems (NVIDIA Jetson, Google Edge TPU) — consume 5–30 watts even at modest performance levels, requiring active cooling, substantial power supplies, and installation environments that are impractical for many factory floor locations. Neuromorphic edge AI platforms — using SNN inference chips operating at milliwatts — remove these deployment constraints entirely, enabling AI inference on small, passive, battery-powered or energy-harvesting edge devices distributed throughout the factory.

5.2 Neuromorphic AI Accelerators for Industrial Edge Deployment

The deployment of neuromorphic computing for industrial edge AI is accelerating as hardware platforms mature and ecosystem support expands. Intel Loihi 2 has been deployed in research and industrial pilot studies for robotics, autonomous vehicles, and industrial monitoring. The **Intel Neuromorphic Research Community** (INRC) has grown to include over 200 member institutions working on industrial applications including predictive maintenance, process control, and quality inspection.

Speck — the mixed-signal neuromorphic chip from Innatera — represents a paradigm shift in always-on industrial sensing: integrating a DVS pixel array, analog SNN processor, and power management unit on a single millimeter-scale chip that draws less than 1 mW in always-on operation. Such chips can be embedded directly in industrial sensors — vibration sensors on rotating machinery, proximity sensors at assembly stations, temperature sensors in thermal processing — adding local AI inference capability without altering the sensor form factor or power budget.

5.3 Neuromorphic Computing for Industry 4.0 and Industry 5.0

A 2024 *Frontiers in Manufacturing Technology* analysis — *Neuromorphic Computing for Industry 4.0 and Industry 5.0: Review and Future Directions* — comprehensively reviewed the application of neuromorphic computing to smart manufacturing, identifying real-time quality monitoring, predictive maintenance, and process control as the primary application domains where neuromorphic advantages are most decisive. The analysis projected that neuromorphic edge AI would become a **standard component of the Industry 5.0 smart factory architecture** — alongside digital twins, collaborative robots, and human-machine interfaces — as the technology matures and industrial ecosystem support expands (Frontiers in Manufacturing Technology, 2024).

5.4 Energy-AI Tradeoffs in Industrial Deployment

A critical practical consideration in neuromorphic industrial AI deployment is the **energy-accuracy tradeoff**: SNNs trained with surrogate gradient descent or STDP can occasionally achieve lower accuracy than optimally tuned ANNs on benchmark tasks, particularly for complex, high-dimensional quality inspection tasks. The relevant comparison, however, is not neuromorphic vs. cloud ANN accuracy but **system-level energy at comparable accuracy**: when the energy cost of transmitting raw sensor data to the cloud (communication energy) is included in the comparison, neuromorphic edge inference typically outperforms cloud ANN at every accuracy level.

For manufacturing quality applications where the acceptable accuracy threshold is defined by the quality specification — not by the maximum achievable accuracy — neuromorphic systems operating at 95% accuracy and 10 mW are superior to cloud ANNs operating at 97% accuracy and 50 W, because the quality-relevant decision (accept/reject) can be made at the edge with millisecond latency and negligible energy, without the latency and energy cost of cloud round-trip.

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6. Synthesis: The Neuromorphic Industrial Intelligence Architecture

6.1 Architecture Overview

The synthesis of findings across the reviewed literature points toward a coherent integrated architecture — the **Neuromorphic Industrial Intelligence Architecture (NIIA)** — that organizes neuromorphic computing components into a layered framework for energy-efficient, real-time smart manufacturing.

Neuromorphic Sensing Layer: Event-based dynamic vision sensors (DVS) and neuromorphic acoustic/vibration/thermal sensors provide event-driven sensor outputs that encode information in spike timing. These sensors operate at milliwatt power levels with microsecond temporal resolution, capturing high-fidelity temporal and spatial information about manufacturing processes and products. Huang et al.'s SPMD (2026) and 4D thermal imaging (2023) systems represent precision optical sensing technologies that, when combined with neuromorphic sensor Readout electronics, would yield ultra-low-power, high-precision neuromorphic metrology stations for surface quality monitoring.

Spiking Neural Network Inference Layer: SNNs — implemented on Intel Loihi 2, Innatera Speck, or next-generation neuromorphic chips — perform real-time AI inference on the event streams from neuromorphic sensors. SNNs process temporal sensor dynamics natively, detecting defect signatures, classifying quality states, and generating alerts with millisecond latency and milliwatt power consumption.

Hybrid Classical-Neuromorphic Integration Layer: For manufacturing analytics tasks that exceed the current capabilities of SNN architectures — such as cross-factory quality benchmarking, supply chain optimization, or large-scale process modeling — the NIIA integrates classical cloud/edge computing platforms that receive condensed event summaries (rather than raw data) from the neuromorphic layer. This hybrid architecture achieves system-level energy efficiency: low-level perception runs on neuromorphic edge chips, while high-level analytics run on classical cloud infrastructure.

Edge-Cloud Orchestration Layer: An orchestration layer manages the division of labor between neuromorphic edge inference and classical cloud analytics — routing event summaries to the cloud when high-level analytics are needed, and maintaining full autonomy at the edge when real-time local decisions are sufficient.

This four-layer architecture draws on contributions across the reviewed literature: neuromorphic computing principles and platforms, DVS and event-based vision for surface inspection, SNN architectures for industrial quality inspection, neuromorphic edge AI for smart manufacturing (Frontiers in Manufacturing Technology, 2024; IEEE TII, 2025), and industrial sensing (Huang et al., 2026; Huang et al., 2023).

6.2 Neuromorphic-Optical Sensor Co-Design

The most advanced neuromorphic industrial intelligence systems will emerge from **co-design** — joint optimization of the sensor hardware and the SNN algorithm as an integrated system, rather than retrofitting SNN processing to conventional sensor outputs. In co-designed systems, the sensor and the neural network are optimized together: the sensor's event generation parameters are tuned to maximize the discriminative information in the event stream for the target quality task, and the SNN architecture is optimized for the specific statistical structure of the event data.

This co-design principle is exemplified by the integration of precision optical metrology with neuromorphic sensing. Huang et al.'s SPMD system (2026) generates high-precision surface form data at each measurement point; if paired with a neuromorphic SNN co-processor that processes the phase and slope data in event-driven fashion, the result would be a **neuromorphic optical coordinate measuring system** — combining the precision of SPMD with the energy efficiency and speed of neuromorphic computation — capable of performing dense surface quality inspection at every point on the production line without the power and bandwidth overhead of conventional frame-based machine vision.

6.3 Open Challenges

1. **SNN training algorithms**: Despite significant progress, SNN training algorithms — particularly for large-scale, deep architectures — remain less mature than ANN training. Surrogate gradient descent enables training on benchmark tasks but can struggle with complex industrial inspection tasks requiring fine-grained discrimination. Developing more powerful SNN training methods is a critical research frontier.
2. **Benchmark datasets and standardization**: The lack of standardized industrial event-based datasets — equivalent to ImageNet for computer vision or MVTec AD for industrial anomaly detection — slows the development and comparison of SNN approaches for manufacturing. Building large-scale, annotated event-based industrial inspection datasets is a priority.
3. **Hardware ecosystem maturity**: While neuromorphic chips have advanced rapidly, the software ecosystem — compilers, debuggers, profilers, and deployment tools — lags behind the mature CUDA/TensorFlow/PyTorch ecosystem for GPU-based AI. Developing industrial-grade neuromorphic software tools is essential for manufacturing deployment.
4. **Integration with existing industrial infrastructure**: Neuromorphic sensors and chips must interface with existing industrial communication protocols (OPC UA, MQTT, Profinet), data formats, and control systems. Industrial-grade integration standards and reference architectures are needed.
5. **Determinism and real-time guarantees**: Industrial control systems require deterministic timing guarantees. Neuromorphic systems, with their asynchronous, event-driven operation, must provide formal real-time timing guarantees to satisfy industrial safety and certification requirements.

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7. Conclusion

This review has examined neuromorphic computing and spiking neural networks for industrial intelligence, covering neuromorphic computing principles and architectures, event-based vision and DVS for surface inspection, SNNs for real-time quality monitoring, neuromorphic edge AI for smart manufacturing, and the integrated Neuromorphic Industrial Intelligence Architecture.

Three key findings emerge. First, **neuromorphic computing addresses the fundamental energy-latency bottleneck** of conventional AI accelerators in manufacturing: event-driven, spiking neural network computation on neuromorphic chips achieves 10–100x energy reduction compared to GPU-based inference at equivalent accuracy, enabling AI at the edge with milliwatt power budgets and millisecond latencies.

Second, **event-based vision sensors and SNN processing pipelines** are uniquely suited to the temporal dynamics of industrial quality data: DVS cameras capture microsecond-resolution optical events that reveal surface defect signatures invisible to frame-based cameras, while SNNs naturally encode temporal patterns in spike timing without the overhead of explicit temporal modeling.

Third, **neuromorphic-optical sensor co-design** — combining precision optical metrology (SPMD, 4D thermal imaging) with neuromorphic SNN analytics — represents the frontier of ultra-low-power, high-precision industrial quality intelligence, promising a new generation of smart sensors that embed AI inference at the sensing site.

The proposed **Neuromorphic Industrial Intelligence Architecture (NIIA)** — unifying neuromorphic sensing, SNN inference, hybrid classical-neuromorphic computing, and edge-cloud orchestration — charts a course toward manufacturing systems in which AI intelligence is distributed, energy-efficient, and always-on: embedded in every sensor, every actuator, and every machine on the factory floor, enabling real-time quality intelligence at every point in the production process.

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