



| RESEARCH ARTICLE

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NEUROMORPHIC COMPUTING FOR NEXT-GENERATION ARTIFICIAL INTELLIGENCE: ARCHITECTURES, APPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

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| ABSTRACT

The growing computational demands of modern Artificial Intelligence (AI) have exposed the limitations of conventional von Neumann computing architectures in terms of energy efficiency, latency, and scalability. Neuromorphic computing has emerged as a revolutionary computing paradigm inspired by the structure and functioning of the human brain. By integrating specialized hardware with brain-inspired neural processing models, neuromorphic systems aim to perform intelligent computation with significantly lower power consumption and faster response times. This paper provides a comprehensive review of neuromorphic computing, including its architecture, fundamental principles, enabling technologies, real-world applications, implementation challenges, and future research opportunities.

| KEYWORDS

Neuromorphic Computing, Spiking Neural Networks, Artificial Intelligence, Brain-Inspired Computing, Edge AI, Intelligent Systems, Low-Power Computing.

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Abstract:-

The growing computational demands of modern Artificial Intelligence (AI) have exposed the limitations of conventional von Neumann computing architectures in terms of energy efficiency, latency, and scalability. Neuromorphic computing has emerged as a revolutionary computing paradigm inspired by the structure and functioning of the human brain. By integrating specialized hardware with brain-inspired neural processing models, neuromorphic systems aim to perform intelligent computation with significantly lower power consumption and faster response times. This paper provides a comprehensive review of neuromorphic computing, including its architecture, fundamental principles, enabling technologies, real-world applications, implementation challenges, and future research opportunities. The study also discusses the integration of neuromorphic processors with edge computing, robotics, the Internet of Things (IoT), and autonomous systems. The findings indicate that neuromorphic computing has the potential to transform intelligent computing by enabling energy-efficient, adaptive, and real-time AI systems.

Introduction:-

Artificial Intelligence has become a driving force behind innovations in healthcare, transportation, cybersecurity, finance, and robotics. However, conventional computing architectures face increasing challenges in supporting complex AI workloads due to high energy consumption, memory bottlenecks, and limited scalability. Neuromorphic computing represents an alternative computational paradigm inspired by the biological structure of the human brain. Instead of separating memory and processing units, neuromorphic systems integrate computation and memory while using spiking neural networks (SNNs) to process information efficiently. This design enables parallel processing, event-driven computation, and low-power operation. This

paper explores the architecture, applications, advantages, challenges, and future directions of neuromorphic computing for next-generation AI systems.

Fundamentals of Neuromorphic Computing:-

Neuromorphic computing seeks to replicate the behavior of biological neural systems through specialized hardware and software.

Core concepts include:-

- Artificial neurons
- Synaptic connections
- Spiking Neural Networks (SNNs)
- Event-driven computation
- Parallel information processing
- Adaptive learning mechanisms

Unlike traditional processors, neuromorphic chips perform computations only when events occur, reducing unnecessary energy consumption.

Neuromorphic System Architecture:-

A typical neuromorphic computing system consists of:-

- Sensory Input Layer
- Spike Encoding Module
- Spiking Neural Network
- Synaptic Learning Engine
- Neuromorphic Processor
- Memory Integration Layer
- Output Decision Module

These components work together to emulate the distributed processing characteristics of biological nervous systems.

Enabling Technologies:-

Neuromorphic computing relies on several supporting technologies.

Spiking Neural Networks (SNNs):-

Process information through discrete electrical spikes rather than continuous numerical values.

Memristor-Based Hardware:-

Provides non-volatile memory and efficient synaptic weight storage.

Event-Based Sensors:-

Capture dynamic visual and sensory information efficiently.

On-Chip Learning:-

Allows continuous adaptation without external training infrastructure.

Low-Power Embedded Hardware:-

Supports deployment in energy-constrained environments.

Applications:-

Robotics:-

- Autonomous navigation
- Object recognition
- Motion planning

Healthcare:-

- Brain-computer interfaces
- Medical signal analysis
- Prosthetic control

Autonomous Vehicles:-

- Real-time perception
- Obstacle detection
- Intelligent driving assistance

Smart Manufacturing:-

- Predictive maintenance
- Industrial automation
- Process optimization

Internet of Things:-

- Intelligent sensors
- Smart homes
- Environmental monitoring

Advantages:-

Neuromorphic computing offers several benefits.

Energy Efficiency:-

Consumes significantly less power than conventional AI hardware.

Real-Time Processing:-

Supports rapid response for time-critical applications.

Parallel Computation:-

Processes multiple information streams simultaneously.

Adaptive Learning:-

Continuously improves performance through experience.

Hardware Scalability:-

Supports distributed intelligent systems.

Comparative Analysis:-

Feature	Conventional AI Hardware	Neuromorphic Computing
Computing Style	Sequential	Parallel
Energy Consumption	High	Very Low
Processing Method	Clock-Driven	Event-Driven
Memory Architecture	Separate	Integrated
Learning Capability	Offline	Online
Biological Inspiration	Limited	High

Challenges:-

Several challenges remain before widespread adoption.

Hardware Availability:-

Commercial neuromorphic processors remain limited.

Software Development:-

Programming frameworks are still evolving.

Algorithm Design:-

Traditional deep learning algorithms require adaptation for spiking neural networks.

Standardization:-

Common development standards are still under development.

Benchmarking:-

Performance evaluation methods vary across research platforms.

Emerging Trends:-**Current research areas include:-**

- Brain-inspired robotics
- Neuromorphic edge computing
- Intelligent autonomous drones
- Hybrid AI architectures
- Explainable spiking neural networks
- Neuromorphic cybersecurity
- Cognitive computing systems

Future Research Directions:-**Future studies should investigate:-**

- Large-scale neuromorphic processors
- Quantum-neuromorphic integration
- Sustainable AI hardware
- Adaptive lifelong learning
- Neuromorphic cloud platforms
- Bio-inspired communication networks
- Autonomous cognitive machines

Conclusion:-

Neuromorphic computing represents one of the most promising directions for the future of artificial intelligence by combining biological inspiration with advanced hardware design. Its event-driven processing model, energy efficiency, and adaptive learning capabilities make it well suited for robotics, autonomous vehicles, healthcare, industrial automation, and IoT applications. Although challenges such as hardware maturity, software ecosystems, and algorithm development remain, continuous advances in neuromorphic engineering are accelerating practical adoption. As demand for efficient and intelligent computing continues to grow, neuromorphic computing is expected to become a key enabling technology for the next generation of AI systems.

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