



(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 3, March 2025

⊕ www.ijirset.com 🖂 ijirset@gmail.com 🖄 +91-9940572462 🕓 +91 63819 07438





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

Neuromorphic Computing for Big Data Analytics

Jyoti Pal, Anjali Lakhani, Assistant Prof. Arunesh Pratap Singh, Assistant Prof. Bhoomika Patel

U.G. Student, Department of Computer Science and Engineering, Parul University, Vadodara, Gujarat, India

U.G. Student, Department of Computer Science and Engineering, Parul University, Vadodara, Gujarat, India

Assistant Professor, Department of Computer Science and Engineering, Parul University, Vadodara, Gujarat, India

ABSTRACT: Big data's exponential rise has raised the need for smarter and more effective computer architectures. Due to memory constraints and excessive energy consumption, traditional von Neumann-based systems are unable to analyze large volumes of unstructured data. By utilizing spiking neural networks (SNNs) and specialized hardware like memristors and neuromorphic processors, neuromorphic computing which draws inspiration from the composition and operations of the human brain offers a possible substitute.

With an emphasis on real-time processing, pattern identification, and decision-making, this research investigates the use of neuromorphic computing in big data analytics. Neuromorphic systems are perfect for edge computing and Internet of Things (IoT) applications because they provide parallel processing with minimal power consumption, unlike traditional computing. We go over important advancements in neuromorphic hardware, such as TrueNorth from IBM and Loihi from Intel, as well as software frameworks that facilitate extensive data processing.

Experimental investigations show that neuromorphic models outperform classic deep learning algorithms in tasks that require adaptive learning and real-time inference. Furthermore, neuromorphic architectures can improve data security by processing information locally, minimizing the need on cloud-based solutions. But issues like algorithm optimization, hardware scalability, and interaction with current AI frameworks still persist.

In conclusion, by increasing computational efficiency and facilitating intelligent data processing, neuromorphic computing offers a revolutionary approach to big data analytics. Future studies should concentrate on improving hardware dependability, refining neuromorphic algorithms, and creating hybrid AI models that combine deep learning and neuromorphic computing.

KEYWORDS: Neuromorphic computing, big data analytics, spiking neural networks, memristors, edge computing, artificial intelligence.

I. INTRODUCTION

A. Background and Motivation

A vast amount of data is produced in the modern world via a variety of sources, such as social media, healthcare systems, financial transactions, and Internet of Things devices. Traditional computer systems have faced several difficulties as a result of this data explosion, sometimes referred to as "Big Data," especially with regard to scalability, energy efficiency, and processing speed. Traditional von Neumann architectures, which separate memory and processing units, struggle to fulfill the ever-increasing demands of real-time analytics due to the well-known von Neumann bottleneck.

Neuromorphic computing, which takes its cues from the biological structure and processing mechanisms of the human brain, offers a novel solution to these issues. In contrast to conventional designs, neuromorphic systems use specialized hardware such as memristors and neuromorphic processors, together with Spiking Neural Networks (SNNs), to process information effectively. These systems provide real-time adaptive learning, fast calculations, and energy-efficient processing by simulating the communication between neurons and synapses in the brain.

Systems that can handle complex, unstructured, and dynamic data streams are desperately needed as big data analytics increasingly relies on machine learning (ML) and artificial intelligence (AI) models. A major enabler for next-





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

generation AI systems, neuromorphic computing holds promise for advances in autonomous decision-making, pattern recognition, and anomaly detection.

B. The Role of Big Data in Modern Computing

Big data is characterized by the "3Vs":

- Volume: Every second, enormous volumes of both organized and unstructured data are produced
- Velocity: Fast data streams that need to be processed instantly.
- Variety: Data maybe found in a variety of media, such as text, pictures, audio, and video.
- Although they try to solve these problems, traditional computing frameworks like cloud-based AI and high

performance computing clusters frequently have hardware limits, excessive energy consumption, and latency problems. A paradigm change is presented by neuromorphic computing, which provides an effective substitute that fits in nicely with big data analytics requirements.

C. Overview of Neuromorphic Computing

Inspired by biology, neuromorphic computing uses artificial neurons and synapses to mimic how the human brain works. This technique is quite distinct from traditional AI techniques like deep learning, which rely on huge matrix multiplications and backpropagation for training. Neuromorphic systems use event-driven computation, which uses less power since processing occurs only when a signal (spike) is received.

- 1) Spiking Neural Networks (SNNs): Like biological neurons, SNNs communicate by using discrete spikes, as opposed to artificial neural networks (ANNs), which process input continuously.
- 2) **Memristors**: Memristors are non-volatile memory components included in neuromorphic semiconductors that facilitate long-term information storage and synaptic learning.
- 3) **Neuromorphic Hardware**: Neuromorphical algorithms may be efficiently implemented by specialized processors like IBM TrueNorth and Intel Loihi.

Since neuromorphic computing allows for real-time learning, it may be used in edge computing, autonomous systems, and intelligent robots, among other applications.

II. LITERATURE SURVEY

Research on neuromorphic computing, which draws inspiration from the anatomy and physiology of the human brain, has been underway since Carver Mead first proposed silicon-based neuromorphic devices in the 1980s. Neuromorphic systems, as opposed to traditional von Neumann designs, are designed to process information in parallel and event-driven fashion, much like biological neurons. The field has shifted toward real-world AI and big data analytics applications due to advancements in digital neuromorphic circuits, such as IBM's TrueNorth and Intel's Loihi. Earlier research focused on analogue neural network implementations.

A. Traditional Computing Vs Neuromorphic Computing

Processing and memory units are separated in traditional computer designs based on the von Neumann paradigm, which makes handling massive amounts of data inefficient. The von Neumann bottleneck, which limits the speed at which data can flow between memory and processing units, is a significant issue in big data analytics. By combining memory and computation into artificial neurons and synapses, neuromorphic computing overcomes these constraints and enables quicker and more energy-efficient processing, as noted by researchers such as Indiveri et al. (2011).

Furthermore, for matrix-based calculations, deep learning models—which predominate in contemporary AI applications—heavily rely on GPUs and TPUs. However, research by Pehlevan et al. (2018) contends that because of their high power consumption, these designs are not the best for processing data in real time. It has been demonstrated that neuromorphic devices, which make use of Spiking Neural Networks (SNNs), may perform comparably or better on some AI tasks while using a fraction of the energy.

B. Spiking Neural Networks (SNNs) and Their Role in Big Data

Instead of employing continuous activation functions like typical artificial neural networks (ANNs), spiking neural networks (SNNs), which mimic real neurons, use discrete spikes to process information. Because SNNs can efficiently contain temporal information, Maass (1997) showed that they are more computationally powerful than traditional neural networks.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

SNNs may do real-time classification tasks with low energy usage when deployed on neuromorphic hardware, according to recent research by Diehl and Cook (2015). According to experts such as Tavanaei et al. (2019), SNNs can be especially useful in streaming data analytics, where event-driven processing is advantageous, in the context of big data.

C. Advancements in Neuromorphic Hardware

Research on this topic has intensified due to the creation of specialized neuromorphic hardware. Among the most prominent neuromorphic processors are the following:

- 1) **IBM TrueNorth:** Large-scale parallel processing is made possible with the 2014 introduction of TrueNorth, a digital neuromorphic device with one million neurons and 256 million synapses (Merolla et al., 2014). According to studies, TrueNorth uses incredibly little power while achieving state-of-the-art performance in tasks like pattern recognition and picture categorization.
- 2) Intel Loihi: Loihi, which was introduced in 2017, is a major step toward adaptable AI models as it incorporates on-chip learning capabilities. According to Davies et al. (2018), Loihi's asynchronous event-driven design makes it possible for quick learning with low energy consumption, which makes it perfect for edge and Internet of Things applications.
- 3) **SpiNNaker:** SpiNNaker is a real-time simulation tool for large-scale neural networks that was created by the University of Manchester (Furber et al., 2013). Neuromorphic AI applications and neuroscience research have made great use of it.

These advancements in hardware suggest that neuromorphic computing is getting closer to being widely used in big data analytics.

D. Applications of Neuromorphic Computing in Big Data Analytics

Numerous investigations have looked into the combination of big data analytics with neuromorphic computing in various fields:

- 1) Healthcare: Studies using neuromorphic systems for medical image analysis, such as Rajan et al. (2021), have demonstrated that neuromorphic AI models are more effective than conventional deep learning models in processing massive amounts of MRI and CT scan data.
- 2) Cybersecurity: Real-time anomaly detection in network traffic has been investigated using neuromorphic architectures. Event-driven neuromorphic processors may be able to identify cybersecurity threats more quickly and accurately than traditional machine learning models, according to research by Yin et al. (2020).
- 3) Finance: High-frequency analysis is necessary for big data in financial markets. By providing real-time pattern detection with reduced processing overhead, neuromorphic computing can enhance stock market prediction models, as demonstrated by Martinez et al. (2019).
- 4) Autonomous Systems: Massive volumes of sensor data are produced by self-driving automobiles, which require real-time processing. For autonomous cars, neuromorphic computers have shown notable benefits in low-latency decision-making (Schuman et al., 2022).

III. METHODOLOGY

A. Research Approach

An experimental and analytical research methodology is used in this work to assess how well neuromorphic computing performs in big data analytics. The process includes creating a framework for neuromorphic computing, putting Spiking Neural Networks (SNNs) into practice, and comparing the results to those of traditional AI models.

B. Neuromorphic Computing Framework

To improve processing efficiency, the suggested system combines big data analytics with neuromorphic computing. The following are included in the methodology:

- 1) **Data Collection:** Compiling extensive structured and unstructured datasets that are pertinent to big data applications, such as financial transactions, cybersecurity logs, and medical pictures.
- 2) Preprocessing: Preparing data for neuromorphic processing by cleaning, standardizing, and encoding it.
- 3) Model Implementation: Spiking Neural Networks (SNNs) are developed and put into use on neuromorphic hardware, including IBM TrueNorth and Intel Loihi.
- 4) **Training and Inference:** Assessing how well the model performs on different datasets and contrasting the outcomes with those of traditional deep learning techniques.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

C. Data Collection and Preprocessing

Managing enormous volumes of both structured and unstructured data from many areas is necessary for big data analytics. The study's datasets were chosen for their applicability to real-world scenarios where neuromorphic computing can provide notable benefits.

Data Sources and Characteristics:

1) Healthcare

- Dataset: MRI and CT scan images
 - Purpose: The goal is to discover anomalies and perform medical diagnostics.
- Obstacle: Noise reduction, feature extraction, and high-dimensional picture data for illness classification.

2) Finance

- Dataset: High-frequency trading (HFT) data.
- Purpose: Real-time market trend prediction.
- Obstacle: Volatility, extreme data sparsity, and the need for low-latency processing.

3) Internet of Things (IoT)

- Dataset: Sensor data from smart cities and industrial IoT systems.
- Purpose: Predictive maintenance and real-time decision-making.
- Obstacle: Streaming data processing, noise filtering, and limited computing resources at the edge.

4) Cybersecurity

- Dataset: Network traffic logs and security events.
- Purpose: Anomaly detection for intrusion prevention.
- Obstacle: Unbalanced data (few attack events), high dimensionality, and evolving threats.

Preprocessing Steps:

While preserving important information for analysis, efficient preparation guarantees that data is compatible with neuromorphic computer systems. The actions listed below are taken:

- 1) Feature Extraction: To minimize dimensionality, extract important characteristics from raw data.
 - For images: Images are subjected to segmentation and edge detection algorithms.
 - For financial and cybersecurity logs: Logs related to finances and cybersecurity are examined for anomalous markers and time-series patterns.
- 2) Normalization: To increase computing efficiency, numerical values can be rescaled to a predetermined range, such as 0 to 1 guaranteeing consistent input representation to avoid bias in SNN learning.

3) Encoding Techniques:

- Spike Encoding: Spike encoding is the process of transforming category and numerical data into spike patterns that may be processed neuromorphically.
- Rate Encoding: Using a greater spike frequency to represent higher values.
- Latency Encoding: Information that is encoded using the timing of spikes in relation to a reference point is known as latency encoding.
- 4) Data Augmentation: Creating synthetic data for unbalanced datasets (for as increasing the number of assault samples in cybersecurity). Variations in medical pictures (such as rotation and contrast modification) to improve the resilience of the model.
- 5) Streaming Data Handling: Integrating real-time data streams for ongoing learning in financial and Internet of Things applications. Using neuromorphic event-driven techniques to effectively handle streaming data.

Neuromorphic computing models can overcome many of the difficulties experienced by conventional deep learning models by processing large amounts of data effectively by utilizing biologically inspired designs and providing high-quality preprocessing.

D. Model Implementation

The neuromorphic computing idea is implemented using Spiking Neural Networks (SNNs) to efficiently handle massive volumes of data. Model selection, hardware deployment, and neuromorphic architecture-optimized training techniques are all part of the implementation.

IJIRSET©2025





|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

Spiking Neural Networks (SNNs) Implementation

- Framework Used:
 - NEST: An extensive SNN simulation program that is helpful for AI and neuroscience research.
 - o Brian2: An adaptable and effective Python-based SNN simulation framework.
 - SNN Architecture:
 - Preprocessed data (encoded as spike trains) is sent to input neurons.
 - Hidden layers use learning rules inspired by biology to perform spike-based computing.
 - Based on patterns of spike activity, output neurons categorize or forecast results.

• Hardware Deployment:

- o Intel Loihi: A neuromorphic research chip for low-power, event-driven computing is the Intel Loihi.
- IBM TrueNorth: A digital neuromorphic processor designed for parallel, real-time processing is the IBM TrueNorth.
- NVIDIA Jetson: For edge computing applications that call for a hybrid AI strategy, NVIDIA Jetson is utilized.
- Training Strategies:
 - Unsupervised Learning: In order to promote self-learning, Spike-Timing-Dependent Plasticity (STDP) adjusts synaptic weights in response to pre-synaptic and post-synaptic spike timing.
 - o Supervised Learning: Hebbian learning for pattern recognition tasks with error correction.
 - Reinforcement Learning: Neuromorphic rewards-based training for adaptive learning in dynamic settings.

Big data pipelines and neuromorphic models work together to guarantee effective processing while lowering latency and power use.

E. Performance Evaluation Metrics

A number of important performance measures are employed to evaluate the effectiveness of neuromorphic computing in big data analytics:

- 1) Accuracy: Measures the correctness of SNN predictions compared to ground truth.In contrast to conventional deep learning models, such as CNNs and RNNs.
- 2) **Processing Speed:** Analysis of latency in response time, decision-making, and data processing. In realtime applications, neuromorphic models are anticipated to perform better than traditional AI.
- 3) **Energy Consumption:** Compares power efficiency to deep learning models that are accelerated by GPUs. Loihi and other neuromorphic processors use a lot less power.
- 4) **Scalability:** Evaluates the model's ability to adjust to growing data volumes. Assesses the ability of neuromorphic computing to manage massive data processing at the corporate level.

Standardized datasets and real-world case studies are used in experiments to give empirical comparisons.

F. Comparative Analysis

The effectiveness of neuromorphic computing is contrasted with traditional AI models in order to ascertain its benefits in big data analytics:

- 1) Deep Learning Models:
 - Convolution Neural Networks (CNNs): Convolutional neural networks are used for massive data processing based on images, such as in medical imaging.
 - Recurrent Neural Networks (RNNs): When applied to sequential data, such financial market patterns, recurrent neural networks (RNNs) are used.

2) Traditional Machine Learning Models:

- Support Vector Machines (SVMs): For classification tasks, support vector machines, or SVMs, are employed.
- Decision Trees: Decision trees are used in cybersecurity and Internet of Things applications for structured data processing.

Experimental Setup

Both traditional and neuromorphic AI models are used to process benchmark datasets.

Various computing paradigms are contrasted in terms of key criteria, such as accuracy, speed, and energy economy. These studies' findings point to specific domains in which neuromorphic computing offers a clear benefit, especially for low-power, real-time applications.

IJIRSET©2025





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

IV.RESULTS

The purpose of the tests was to assess how well neuromorphic computers handled big data analytics. Accuracy, processing speed, energy usage, and scalability are the criteria used to classify the findings. To assess efficiency and computational efficacy, the neuromorphic models were put to the test against traditional deep learning models.

- Accuracy Comparison: Across a variety of datasets, the neuromorphic models based on Spiking Neural Networks (SNN) showed excellent accuracy. While deep learning models were marginally more accurate, neuromorphic computing produced competitive results while using a lot less power.
- 2) **Processing Speed:** Faster inference times were shown by the neuromorphic models, especially in realtime applications. Because neuromorphic models use event-driven computing, they drastically reduce latency and surpass classic deep learning models in terms of processing speed.
- 3) Energy Consumption Analysis: One of the main benefits of neuromorphic computing was its energy efficiency. When compared to GPUs running deep learning models, measurements revealed that neuromorphic models used a significant amount less power. The findings demonstrate that neuromorphic systems are far more energy-efficient, which makes them perfect for real-time analytics and edge computing.
- 4) Scalability and Real-Time Performance: Neuromorphic models scale effectively, according to experiments conducted on huge datasets. In contrast to batch processing needed for deep learning models, neuromorphic systems handle data in real-time with very little delay. The scalability benefit of neuromorphic systems was demonstrated by their capacity to retain low latency even as dataset sizes grew.
- 5) Observations and Insights: In terms of speed and energy economy, neuromorphic computing performs better than traditional deep learning models in real-time analytics. Even while neuromorphic systems are slightly less precise in some tasks, they make up for it with reduced latency and power efficiency. Rapid on-chip learning is made possible by neuromorphic technology, such Intel Loihi, which eliminates the requirement for cloud computing. Neuromorphic computing's event-driven architecture makes it perfect for streaming data applications like finance and the Internet of Things.

V. DISCUSSION

A. Interpretation of Key Findings

The experimental results show that neuromorphic computing offers significant advantages in terms of processing speed, energy economy, and real-time adaptability, making it a potent alternative to traditional deep learning models in big data analytics. Although the accuracy of deep learning models was marginally higher than that of neuromorphic models, neuromorphic systems' low power consumption and quicker inference periods make them perfect for edge-based, real-time applications.

In anomaly detection and IoT sensor data processing, where event-driven computation enables effective management of continuous data streams, neuromorphic computing showed superior performance. This implies that neuromorphic architectures may be essential for cybersecurity threat detection, autonomous systems, and real-time financial forecasting.

B. Comparison with Existing Studies

The benefits of neuromorphic computing have been examined in a number of earlier studies:

- In line with our findings on energy efficiency, Merolla et al. (2014) demonstrated that IBM's TrueNorth processor could do picture classification with extremely low power usage.
- Davies et al. (2018) provided evidence in support of our findings about real-time inference capabilities by demonstrating the effectiveness of Intel's Loihi processor for adaptive learning.
- Our findings were further supported by Tavanaei et al. (2019), who emphasized the potential of Spiking Neural Networks (SNNs) in large data applications.

Our results are consistent with earlier investigations, demonstrating the suitability of neuromorphic computing for big data processing workloads requiring high speed and low energy consumption.

C. Advantages of Neuromorphic Computing for Big Data Analytics

The integration of neuromorphic computing into big data analytics offers several advantages:

IJIRSET©2025

| An ISO 9001:2008 Certified Journal |





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

- 1) **Energy Efficiency:** When processing big information, conventional GPUs and CPUs use a lot of energy. Because neuromorphic devices use spiking processes and use little power, they are perfect for edge and Internet of Things applications.
- 2) **Parallel Processing:** Neuromorphic systems do calculations in parallel, allowing for quicker data analysis than standard designs that use sequential processing.
- 3) Adaptive Learning: Neuromorphic networks have the ability to learn in real time by modifying their parameters in response to input, unlike deep learning models that need to be pre-trained.
- 4) **Scalability:** Neuromorphic computing makes it possible to handle big datasets well without using a lot of processing power.
- 5) **Lower Latency:** Neuromorphic systems have much lower latency since they analyze data at the edge instead of transmitting it to centralized servers.

Because of these characteristics, neuromorphic computing is especially advantageous for sectors like banking, healthcare, cybersecurity, and smart cities that depend on quick and intelligent data processing.

D. Challenges and Limitations

- Despite these benefits, there are a few drawbacks:
 - 1) Limited Training Efficiency: Traditional backpropagation-based learning in deep learning models is more efficient than the specific training techniques needed for neuromorphic models (e.g., STDP).
 - 2) **Hardware Availability:** The widespread adoption of neuromorphic processors, such IBM TrueNorth and Intel Loihi, is being hindered by their limited availability.
 - 3) **Software Standardization:** The absence of a standardized programming framework in neuromorphic computing, in contrast to TensorFlow and PyTorch for deep learning, complicates development.
 - 4) Algorithm Optimization: Many of the AI models already in use are GPU-optimized; more re-engineering is necessary to adapt them for neuromorphic architectures.

E. Future Implication and Research Directions

In light of the encouraging findings, future studies ought to concentrate on:

- 1) **Hybrid AI Models:** Hybrid artificial intelligence models combine the advantages of deep learning with neuromorphic computing.
- 2) **Neuromorphic Cloud Integration:** Investigating the integration of neuromorphic computing with cloudbased artificial intelligence for extensive analytics.
- 3) **Optimizing Training Methods:** Creating effective learning strategies for Spiking Neural Networks that can compete with conventional deep learning.
- 4) Advancements in Neuromorphic Hardware: Improving the scalability of neuromorphic chips for broad use in artificial intelligence and big data analytics.

VI. CONCLUSION

With notable benefits over conventional computer architectures in terms of energy economy, real-time processing, and flexibility, neuromorphic computing is a revolutionary way to addressing the difficulties of big data analytics. In real-time anomaly detection, financial forecasting, cybersecurity, and Internet of Things applications, neuromorphic systems have proven to perform better thanks to Spiking Neural Networks (SNNs) and specialized hardware like IBM TrueNorth and Intel Loihi.

According to the experimental results, neuromorphic computing outperforms deep learning models in terms of inference times and power consumption, which makes it perfect for edge-based applications where making decisions in real time is crucial. Despite the fact that deep learning models performed marginally better in terms of accuracy than neuromorphic models, neuromorphic architectures are a good substitute for real-time large data processing due to the trade-off between processing speed and energy usage.

Notwithstanding these benefits, neuromorphic computing still has issues with hardware availability, training effectiveness, and scalability. Its broad use is constrained by the absence of standardized frameworks and training methods that are optimized. These constraints should be addressed by continued research into hybrid AI models, enhanced neuromorphic hardware, and cloud-based neuromorphic integration.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 3, March 2025

|DOI: 10.15680/IJIRSET.2025.1403196|

Neuromorphic computing is expected to be a key component of big data analytics and artificial intelligence in the future. As long as advances in neuromorphic chip design, learning algorithms, and AI integration persist, neuromorphic computing is predicted to transform the processing and analysis of massive volumes of data, leading to more intelligent, sustainable, and effective computing solutions.

VII. FUTURE WORK

In order to properly utilize neuromorphic computing in big data analytics, more research and development is needed in a few crucial areas.

- Hybrid AI models that combine the best features of deep learning and neuromorphic architectures may be produced. Pattern recognition is the strength of deep learning, and real-time, energy-efficient processing is made possible by neuromorphic computing. This collaboration can improve AI's capacity for extensive data analysis preferences.
- 2) It's critical to enhance Spiking Neural Network (SNN) training methods. SNNs, in contrast to conventional artificial neural networks, resemble real neurons; yet, training them is still difficult. To improve accuracy and efficiency, research should concentrate on refining learning algorithms like spike-timing-dependent plasticity (STDP).
- 3) Hardware scalability and accessibility must be addressed. While neuromorphic processors such as IBM's TrueNorth and Intel's Loihi show promise, widespread use requires affordable hardware solutions. For commercial and industrial applications, efforts should be focused on creating high-performance, scalable neuromorphic processors.
- 4) For wider deployment, neuromorphic software frameworks must be standardized. Development is currently constrained by the absence of standardized programming environments. Innovation and integration into current big data systems may be accelerated by developing unified software tools and APIs.

Neuromorphic computing has the potential to transform big data analytics by overcoming these obstacles and offering quicker, more effective, and more intelligent computing solutions for the upcoming AI-driven technologies. The combination of cutting-edge machine learning methods with brain-inspired computing holds the key to the future of big data processing, opening the door for game-changing applications in a variety of sectors.

REFERENCES

- [1] Soman, Sumit, and Manan Suri. "Recent trends in neuromorphic engineering." Big Data Analytics 1 (2016): 1-19.
- [2] Satyanarayana, Ashwin, Janusz Kusyk, and Yu-Wen Chen. "Design of Cloud Based Robots Using Big Data Analytics and Neuromorphic Computing." 2018 IEEE Canadian Conference on Electrical \& Computer Engineering (CCECE). IEEE, 2018.
- [3] Huang, Chuanchao. "Special issue on deep learning-based neural information processing for big data analytics." Neural Computing and Applications 32.6 (2020): 1513-1515.
- [4] Basu, Arindam, Chen Yi, and Yao Enyi. "Big data management in neural implants: The neuromorphic approach." Emerging Technology and Architecture for Big-data Analytics (2017): 293-311.
- [5] Yu, Zheqi, et al. "An intelligent implementation of multi-sensing data fusion with neuromorphic computing for human activity recognition." IEEE Internet of Things Journal 10.2 (2022): 1124-1133.
- [6] Chunduri, Raghavendra K., and Darshika G. Perera. "Neuromorphic sentiment analysis using spiking neural networks." Sensors 23.18 (2023): 7701.
- [7] Rathi, Nitin, et al. "Exploring neuromorphic computing based on spiking neural networks: Algorithms to hardware." ACM Computing Surveys 55.12 (2023): 1-49.
- [8] Firoozi, Ali Akbar, and Ali Asghar Firoozi. "Neuromorphic computing in smart infrastructure." Neuromorphic Computing: Transforming Disaster Management and Resilience in Civil Engineering. Cham: Springer Nature Switzerland, 2024. 33-43.
- [9] Gautam, Abhiraj, and Sachin Sharma. "Artificial Narrow Intelligence Inspired Neuromorphic Computing for Logic Operations in Healthcare Appliances." 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT). Vol. 1. IEEE, 2024.
- [10] Roy, Kaushik, Akhilesh Jaiswal, and Priyadarshini Panda. "Towards spike-based machine intelligence with neuromorphic computing." Nature 575.7784 (2019): 607-617. Chen, Shanyu, et al. "How big data and high-performance computing drive brain science." Genomics, proteomics \& bioinformatics 17.4 (2019): 381-392.









INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com