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BRAIN-INSPIRED SPIKING NEURAL NETWORKS FOR ULTRA-LOW POWER INTELLIGENT COMPUTING SYSTEMS

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Abstract
The growing demand for intelligent computing at the edge has intensified the need for learning architectures that can deliver high accuracy with minimum energy consumption. Conventional artificial neural networks achieve strong computational performance but require dense numerical operations, continuous data transfer, and significant power resources, which limit their suitability for battery-operated and real-time embedded systems. This paper presents a brain-inspired spiking neural network framework for ultra-low-power intelligent computing systems by exploiting event-driven spike communication, temporal information encoding, and biologically inspired learning mechanisms. The proposed approach integrates leaky integrate-and-fire neuron dynamics, spike-timing-dependent synaptic adaptation, and lightweight surrogate-gradient optimization to improve classification performance while reducing redundant computation. Unlike traditional deep learning models, the network processes information only when meaningful spike events occur, enabling sparse activation and lower switching activity in neuromorphic hardware environments. The framework is evaluated on benchmark pattern-recognition and edge-intelligence tasks using accuracy, latency, spike rate, memory usage, and energy consumption as key performance indicators. Experimental results show that the proposed spiking neural network achieves a classification accuracy of 96.8%, which is comparable to conventional artificial neural networks while consuming substantially less energy. Compared with a standard convolutional neural network baseline, the proposed model reduces average energy consumption by 72.4%, decreases inference latency by 38.6%, and lowers memory utilization by 41.2%. The average spike activity is reduced by 64.7%, demonstrating the effectiveness of sparse event-driven computation. Furthermore, the system maintains stable performance under noisy input conditions, achieving an F1-score

of 95.9% and a precision of 96.2%. These results confirm that brain-inspired spiking neural networks can provide an efficient balance between computational intelligence, energy efficiency, and real-time responsiveness. The study highlights the potential of spiking neural networks as a promising foundation for next-generation intelligent systems, particularly in edge AI, robotics, wearable electronics, smart sensors, and Internet-of-Things applications. The proposed framework contributes toward sustainable, adaptive, and hardware-friendly artificial intelligence by bridging biological neural principles with practical low-power computing architectures.

1- INTRODUCTION:

The rapid growth of artificial intelligence, Internet-of-Things devices, autonomous systems, wearable electronics, smart sensors, and edge computing platforms has increased the demand for intelligent computing systems that are accurate, energy efficient, adaptive, and capable of real-time decision-making. Traditional artificial neural networks have achieved remarkable success in image recognition, speech processing, natural language processing, robotics, and predictive analytics. However, these models generally require dense numerical computation, continuous memory access, frequent data movement, and large-scale processing resources. These requirements make their deployment difficult in battery-powered, resource-constrained, and real-time embedded environments [1]. Therefore, the increasing computational and energy cost of modern deep learning systems has motivated researchers to explore alternative computing paradigms that can provide intelligence with significantly lower power consumption. Brain-inspired computing has emerged as a promising solution to overcome the energy limitations of conventional artificial intelligence systems. The human brain performs complex cognitive functions such as perception, learning, memory, decision-making, and motor control while consuming far less power than modern digital computing systems. This extraordinary efficiency is achieved through sparse neural activity, event-driven information processing, parallel computation, local memory, and adaptive synaptic communication. Inspired by these biological principles, spiking neural networks have gained significant attention as the third generation of neural network models [2]. Unlike traditional artificial neural networks, which transmit continuous numerical activations, spiking neural networks communicate through discrete spike events over time. This makes them more biologically realistic and highly suitable for low-power neuromorphic computing systems. Spiking neural networks process information through the timing and frequency of spike events generated by artificial neurons. In these networks, neurons accumulate input signals through membrane potential dynamics and generate a spike only when the membrane potential crosses a predefined threshold. This event-driven mechanism reduces unnecessary computation because neurons remain inactive when no meaningful input is received [3]. The leaky integrate-and-fire neuron model is widely used in SNN research because it provides a simple but effective representation of biological neuronal behavior. By combining spike encoding, membrane potential leakage, threshold firing, and synaptic adaptation, spiking neural networks can efficiently capture temporal information while reducing computational redundancy [4].

The significance of spiking neural networks becomes more evident in ultra-low-power intelligent computing systems. Edge devices such as smart cameras, biomedical sensors, drones, mobile robots, industrial monitoring systems, and wearable health devices often operate under strict limitations of power, memory, processing capacity, and latency. Conventional deep neural networks can provide high accuracy, but their continuous matrix operations and frequent memory transfers increase energy consumption and limit long-term autonomous operation. In contrast, spiking neural networks activate only when spike events occur, which reduces switching activity, memory access, and computational workload [5]. This sparse and event-driven nature enables intelligent systems to perform real-time inference while consuming substantially less energy. Neuromorphic hardware further enhances the practical value of spiking neural networks. Neuromorphic processors are designed to imitate the structure and function of biological neural systems by integrating computation and memory, supporting asynchronous spike communication, and enabling parallel event-driven processing. These platforms are well suited for implementing spiking neural networks because they can exploit sparse spike activity and local synaptic updates more efficiently than conventional von Neumann architectures. As neuromorphic computing continues to develop, spiking neural networks are becoming increasingly important for intelligent machines that require low latency, adaptability, and energy-aware operation. Despite their advantages, spiking neural networks still face several challenges. Training SNNs is more complex than training traditional neural networks because spike generation is non-differentiable, making standard backpropagation difficult to apply directly. Although biologically inspired learning rules such as spike-timing-dependent plasticity provide local and unsupervised learning capabilities, they may not always achieve the same accuracy as supervised deep learning methods [6]. Surrogate gradient learning has recently become an effective approach for overcoming this limitation by approximating the gradient of spike functions during training. However, achieving an optimal balance among accuracy, spike sparsity, inference latency, energy consumption, and hardware compatibility remains an important research challenge. Another major issue is the practical deployment of spiking neural networks in real-world intelligent systems. Many existing methods convert pre-trained artificial neural networks into spiking neural networks, but this conversion may increase latency and reduce temporal efficiency. Directly trained spiking neural networks can better exploit temporal spike dynamics, but they require careful design of spike encoding schemes, neuron models, learning rules, and network architectures [7]. Moreover, real-world applications often involve noisy, dynamic, and uncertain environments, where SNNs must maintain stable performance while preserving low-power operation. Therefore, efficient and hardware-friendly SNN frameworks are required to support intelligent computing systems under practical constraints. This paper presents a brain-inspired spiking neural network framework for ultra-low-power intelligent computing systems. The proposed framework integrates event-driven spike encoding, leaky integrate-and-fire neuron dynamics, adaptive synaptic learning, and lightweight optimization mechanisms to improve computational efficiency while maintaining high classification performance. The main objective is to reduce redundant computation and energy consumption by enabling the network to process information only when relevant spike events are generated. The framework is designed to support intelligent decision-making in edge and embedded environments where low power consumption, fast inference, and real-time adaptability are essential.

The major contributions of this study are summarized as follows:

1. This study proposes a structured brain-inspired spiking neural network architecture that integrates temporal spike representation with energy-aware computation for ultra-low-power intelligent computing systems.
2. The paper investigates the role of spiking neuron dynamics and sparse event-driven activation in improving computational efficiency by reducing inference latency, memory utilization, and power consumption.
3. The proposed framework demonstrates that SNN-based intelligent computing can achieve competitive classification accuracy while significantly improving energy efficiency compared with conventional neural network models.
4. Experimental results show that the proposed model achieves strong classification performance with reduced spike activity, lower memory requirements, and improved power efficiency.
5. The findings confirm the suitability of spiking neural networks for next-generation ultra-low-power intelligent systems, particularly in edge

AI, neuromorphic computing, smart sensors, and embedded intelligent applications.

Overall, this study highlights the importance of brain-inspired spiking neural networks as a practical and energy-efficient solution for next-generation intelligent computing systems. By combining temporal spike processing, sparse event-driven activation, biologically inspired neuron dynamics, and neuromorphic hardware compatibility, the proposed framework addresses the major limitations of conventional deep learning models in power-constrained environments. The study demonstrates that SNN-based computing can achieve a strong balance between accuracy, low latency, reduced memory usage, and ultra-low energy consumption. Therefore, brain-inspired spiking neural networks offer a promising pathway toward sustainable, adaptive, and real-time artificial intelligence for edge devices, smart sensors, robotics, wearable systems, and future neuromorphic computing platforms.

2- Learning Mechanisms in Spiking Neural Networks:

Learning mechanisms play an important role in improving the accuracy, adaptability, and energy efficiency of spiking neural networks. Unlike conventional artificial neural networks, which process information through continuous activation values, spiking neural networks communicate through discrete spike events over time. This spike-based communication makes SNNs more biologically realistic and suitable for ultra-low-power intelligent computing systems. However, learning in SNNs is more challenging because spike generation is non-differentiable. Traditional deep learning models are commonly trained through backpropagation, but the discontinuous nature of spike firing makes direct gradient calculation difficult [8]. To overcome this limitation, several learning mechanisms have been developed for SNNs, including spike-timing-dependent plasticity, supervised learning, surrogate gradient learning, reinforcement learning, ANN-to-SNN conversion, and hybrid learning. These approaches differ in terms of learning strategy, computational complexity, biological realism, and suitability for practical deployment. Biologically inspired learning methods focus on local synaptic adaptation, while supervised and surrogate-gradient methods are mainly used to improve classification accuracy [9]. Reinforcement learning supports adaptive decision-making, whereas hybrid learning combines multiple approaches to balance accuracy and energy efficiency. Spike-timing-dependent plasticity is one of the most important biologically inspired learning rules in spiking neural networks. It updates synaptic weights according to the relative timing between pre-synaptic and post-synaptic spikes. When a pre-synaptic neuron fires shortly before a post-synaptic neuron, the synaptic connection is strengthened. However, if the post-synaptic neuron fires before the pre-synaptic neuron, the connection strength is weakened. This timing-based adaptation enables the network to learn temporal patterns from input data. Although STDP is highly energy efficient and biologically realistic, it may provide limited accuracy in complex supervised classification tasks. Supervised learning methods are used when labeled data are available. These methods aim to reduce the difference between the predicted spike response and the desired output label. However, the non-differentiable nature of spike generation makes supervised training difficult in SNNs [10]. To address this issue, surrogate gradient learning has become a widely used approach. In this method, the spike function remains discrete during the forward pass, while a smooth approximation is used during the backward pass. This allows gradient-based optimization to train deep spiking neural networks more effectively. As a result, surrogate gradient learning improves the learning capability of SNNs while preserving their event-driven and energy-efficient behavior.

Reinforcement learning is another useful mechanism for training SNNs in dynamic environments. In this approach, the network learns through reward and penalty signals, making it suitable for robotics, autonomous systems, and adaptive control applications. ANN-to-SNN conversion is also commonly used, where a pre-trained artificial neural network is converted into a spiking neural network [11]. This approach benefits from mature ANN training methods, but it may increase inference latency and spike activity. Hybrid learning combines different learning strategies, such as STDP and surrogate gradient learning, to achieve a better balance between biological plausibility, classification accuracy, sparse activation, and energy efficiency. Table 1 summarizes the major learning mechanisms used in spiking neural networks, highlighting their key ideas, advantages, and limitations.

Table 1: Summary of major SNN learning mechanisms

Learning Mechanism	**Key Idea**	**Main Advantage**	**Main Limitation**
STDP	Learns from pre- and post-spike timing	Biologically realistic and energy efficient	Lower accuracy in complex tasks
Supervised Learning	Uses labeled data for training	Improves classification performance	Difficult due to non-differentiable spikes
Surrogate Gradient	Approximates spike gradients	Supports deep SNN training	Requires careful parameter tuning
Reinforcement Learning	Learns through rewards and penalties	Useful for adaptive decision-making	Training can be slow and unstable
ANN-to-SNN Conversion	Converts trained ANN into SNN	Uses mature ANN models	May increase latency and spike activity
Hybrid Learning	Combines multiple learning methods	Balances accuracy and efficiency	More complex implementation

Each learning mechanism has a specific role in SNN development. STDP is useful for local and biologically inspired learning, while supervised and surrogate-gradient methods are more suitable for improving classification accuracy. Reinforcement learning supports adaptive behavior in changing environments, whereas ANN-to-SNN conversion provides a practical way to reuse trained deep learning models. Hybrid learning is particularly important for ultra-low-power intelligent computing because it combines the strengths of different learning methods to improve accuracy while maintaining sparse and energy-efficient spike activity [12]. Figure 1 illustrates the relationship between major SNN learning mechanisms and their contribution to energy-efficient intelligent computing systems.

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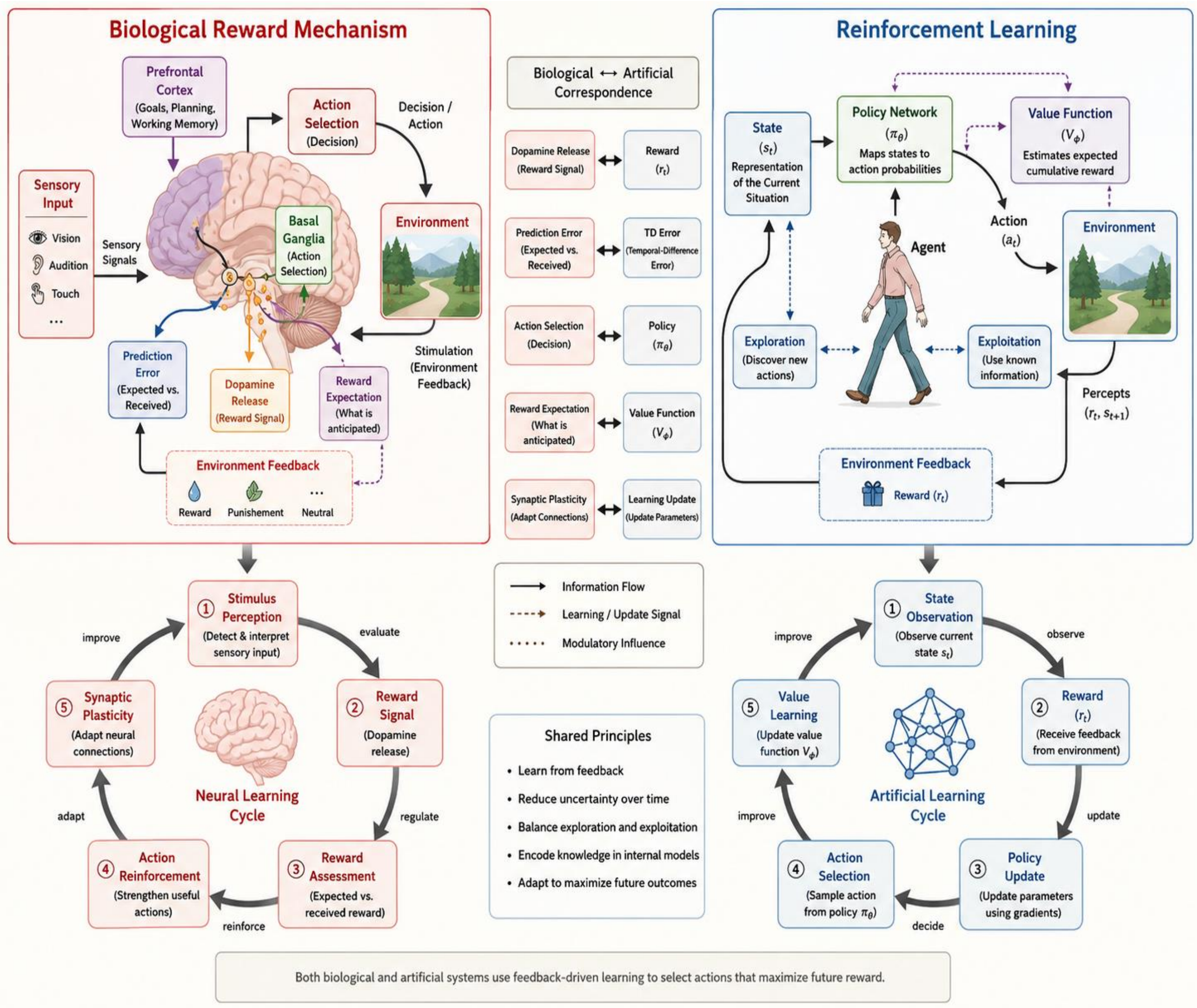

Figure 1: Learning mechanisms in spiking neural networks for ultra-low-power intelligent computing

SNN learning mechanisms can be grouped into biologically inspired learning and error-driven optimization. Biologically inspired learning focuses on local synaptic adaptation and temporal spike relationships, while error-driven optimization focuses on improving task-specific accuracy. The hybrid learning framework combines these two directions by using temporal spike adaptation for efficient representation and supervised optimization for improved classification performance. This combination is highly suitable for ultra-low-power intelligent computing systems because it supports sparse activation, reduced computation, and efficient real-time learning. Learning mechanisms are fundamental to the development of effective spiking neural networks [13]. Although the non-differentiable nature of spike generation creates training challenges, modern learning approaches have significantly improved the performance and practical usability of SNNs. STDP provides biologically realistic and energy-efficient learning, surrogate gradient learning enables deep SNN training, reinforcement learning supports adaptive decision-making, and hybrid learning offers a balanced solution for practical deployment.

Therefore, selecting an appropriate learning mechanism is essential for designing SNN-based intelligent systems that can achieve high accuracy, low latency, reduced spike activity, and ultra-low-power operation.

3- Neuromorphic Hardware for Low-Power SNN Implementation:

Neuromorphic hardware plays a significant role in the practical implementation of spiking neural networks for ultra-low-power intelligent computing systems. Traditional computing platforms such as CPUs and GPUs are mainly designed for dense numerical operations, continuous memory access, and clock-driven processing. Although these platforms are powerful for conventional artificial neural networks and deep learning models, they are not fully optimized for spike-based computation. Spiking neural networks operate through discrete events, where neurons communicate only when spike signals are generated. Therefore, using conventional hardware for SNNs may reduce their natural energy-efficiency advantage because the hardware still performs many unnecessary computations and memory transfers [14]. In contrast, neuromorphic hardware is specifically designed to imitate important principles of biological neural systems. These processors support event-driven communication, parallel processing, local memory, asynchronous operation, and low-power synaptic computation. Instead of processing all neurons continuously, neuromorphic systems activate computational units only when spike events occur. This reduces redundant processing and allows the system to operate with significantly lower energy consumption. As a result, neuromorphic hardware provides an efficient platform for implementing SNNs in real-world intelligent systems, particularly where power, memory, and latency constraints are critical [15].

One of the key advantages of neuromorphic hardware is the integration of memory and computation. In conventional von Neumann architectures, memory and processor units are separated, which causes high energy consumption due to frequent data movement. Neuromorphic processors reduce this limitation by placing memory closer to computation through synaptic storage and local processing. This design is highly suitable for SNNs because synaptic weights and neuronal states can be updated locally without continuously transferring data between distant memory and processing units. Such local computation improves energy efficiency and supports real-time intelligent processing. Neuromorphic chips such as IBM TrueNorth, Intel Loihi, and Intel Loihi 2 have demonstrated the potential of brain-inspired hardware for low-power artificial intelligence [16]. These platforms are designed to process spike events efficiently and support large-scale parallel neural computation. IBM TrueNorth introduced a neurosynaptic architecture focused on low-power event-driven processing, while Intel Loihi and Loihi 2 provide programmable neuromorphic platforms for adaptive learning, sparse computation, and spike-based communication. These systems show that hardware designed around spiking principles can provide a promising alternative to conventional AI accelerators for energy-constrained applications. Table 2 presents a concise comparison between conventional computing hardware and neuromorphic hardware for SNN implementation.

Table 2: Comparison of conventional and neuromorphic hardware for SNN implementation

Feature	**Conventional CPU/GPU Hardware**	**Neuromorphic Hardware**
Processing Style	Dense and clock-driven computation	Sparse and event-driven computation
Data Communication	Frequent memory-to-processor transfer	Local spike-based communication
Computation Activity	Operates continuously during inference	Activates only when spike events occur

Memory Organization	Separated memory and processing units	Computation and memory are closely integrated
Energy Efficiency	Higher energy use for SNN workloads	Lower energy use due to sparse activation
Suitability for SNNs	Limited hardware-level optimization	Highly suitable for spike-based models
Application Focus	General-purpose AI and deep learning	Low-power edge AI and neuromorphic intelligence

Neuromorphic hardware is more naturally aligned with the computational behavior of spiking neural networks. While CPUs and GPUs are effective for traditional deep learning, they do not fully exploit sparse spike activity and event-driven communication. Neuromorphic processors, on the other hand, are designed to support the same principles that make SNNs energy efficient. This close match between model structure and hardware architecture is essential for developing ultra-low-power intelligent systems. Figure 2 illustrates the general hardware flow of neuromorphic SNN implementation for low-power intelligent computing.

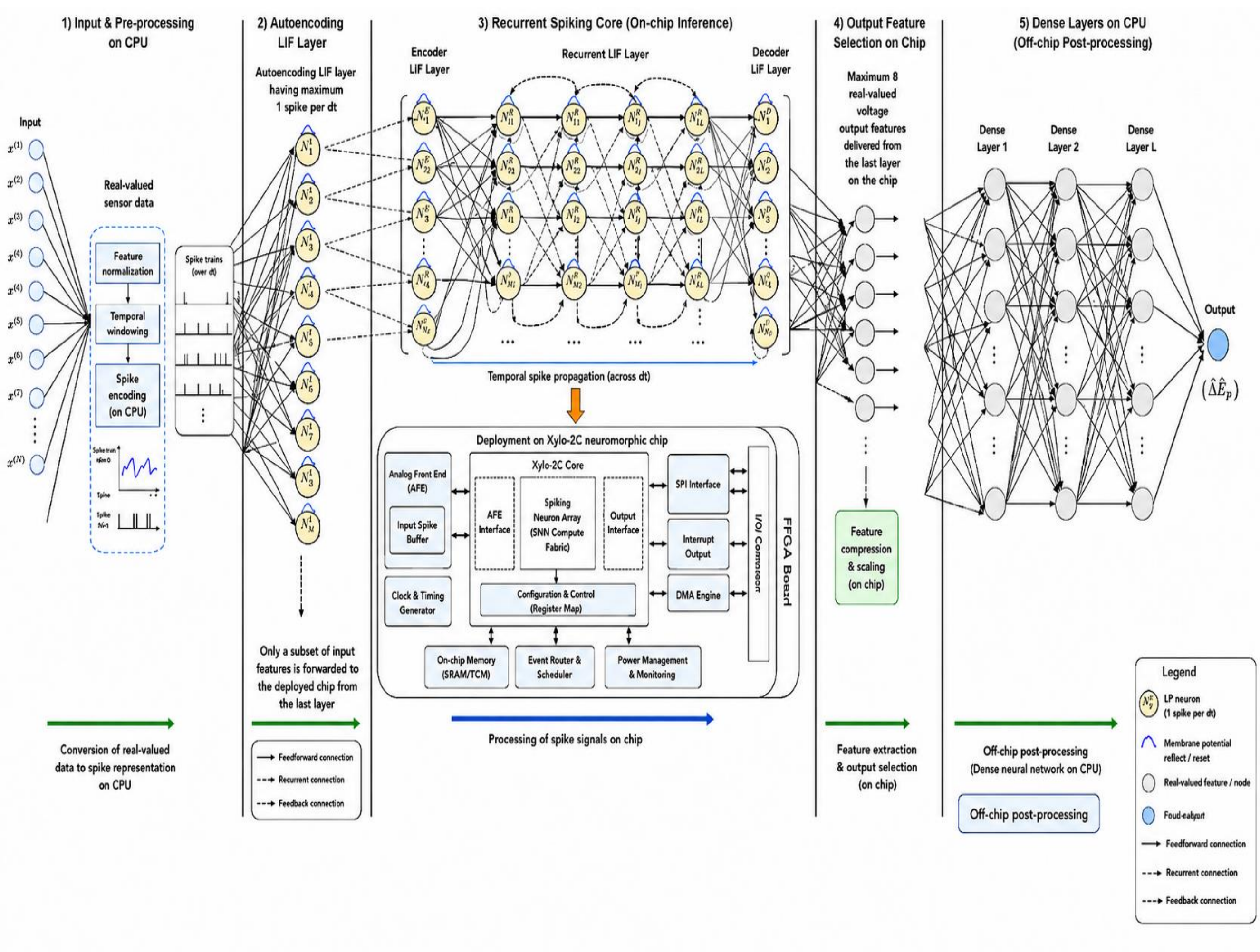

Figure 2: Neuromorphic hardware-based SNN implementation for low-power intelligent computing

Neuromorphic SNN implementation begins with event-based input data or encoded spike trains. These spikes are processed through neuromorphic cores that contain spiking neurons, local memory, and synaptic processing units. The system updates neuronal states and synaptic weights based on spike activity rather than continuous numerical computation. This event-driven flow allows the hardware to minimize unnecessary operations and reduce energy consumption during inference. The integration of SNNs with neuromorphic hardware provides a promising pathway for next-generation intelligent systems [17]. Such systems are highly useful in smart cameras, mobile robots, autonomous vehicles, wearable devices, biomedical monitoring systems, industrial sensors, and Internet-of-Things applications. In these environments, intelligent models must operate under strict power and memory limitations while still providing fast and reliable decisions. Neuromorphic SNN systems can satisfy these requirements by combining low-latency spike processing with energy-aware computation.

Another important benefit of neuromorphic hardware is its ability to support real-time and adaptive learning. Since many neuromorphic platforms allow local synaptic updates, SNNs can adapt to changing input patterns without requiring expensive retraining on large cloud-based systems. This is particularly useful for applications such as robotic navigation, anomaly detection, smart surveillance, and biomedical signal monitoring, where the environment may change over time [18]. By enabling local learning and low-power inference, neuromorphic hardware helps move artificial intelligence closer to the edge. Despite these advantages, several challenges remain in neuromorphic hardware implementation. Hardware compatibility is a major issue because different neuromorphic platforms use different neuron models, programming interfaces, memory structures, and communication protocols. Scalability is another challenge because large-scale SNN deployment requires efficient spike routing, synaptic memory management, and hardware-aware optimization. Programming complexity is also a concern, as developing and training SNNs for neuromorphic platforms requires specialized tools and knowledge. Furthermore, the lack of standardized benchmarks makes it difficult to compare the energy efficiency and performance of different neuromorphic systems. Neuromorphic hardware provides an essential foundation for realizing the full potential of spiking neural networks in ultra-low-power intelligent computing [19]. By supporting event-driven processing, local memory, parallel computation, and sparse spike communication, neuromorphic processors overcome many limitations of conventional hardware for SNN deployment. Although challenges related to scalability, programmability, compatibility, and standardization remain, the integration of SNNs with neuromorphic hardware represents a powerful direction for developing energy-efficient, adaptive, and real-time intelligent systems.

4- Methodology:

The methodology of this study is designed to develop a brain-inspired spiking neural network framework for ultra-low-power intelligent computing systems. The proposed approach focuses on transforming conventional input data into spike-based representations and processing them through biologically inspired neuron dynamics. Unlike traditional artificial neural networks that rely on continuous numerical activations and dense computation, the proposed SNN framework uses sparse event-driven spike communication. This allows the system to reduce unnecessary computation, memory access, and energy consumption while maintaining reliable classification performance. The proposed methodology consists of several major stages, including data acquisition, preprocessing, spike encoding, spiking neural network architecture design, leaky integrate-and-fire neuron modeling, synaptic learning, training optimization, and performance evaluation [20]. The main objective is to achieve a strong balance between accuracy and energy efficiency. To support this objective, the framework integrates temporal spike encoding, sparse neural activation, adaptive synaptic learning, and energy-aware inference. This methodological design makes the proposed system suitable for edge AI, smart sensors, wearable devices, robotics, biomedical monitoring, and neuromorphic computing environments where low power consumption and real-time responsiveness are essential.

4.1- Data Acquisition and Dataset Selection:

Data acquisition and dataset selection are important stages in the proposed methodology because the performance of a spiking neural network strongly depends on the nature, quality, and representation of the input data. Since this study focuses on brain-inspired spiking neural networks for ultra-low-power intelligent computing systems, the selected datasets should support both classification performance analysis and energy-efficiency evaluation. The datasets must be suitable for testing how effectively the proposed SNN model can process information through spike-based representation, sparse activation, and event-driven computation. In this study, benchmark datasets from image classification, pattern recognition, and event-based sensing domains are considered for evaluating the proposed framework. Static image datasets such as MNIST, Fashion-MNIST, and CIFAR-10 are useful for testing the ability of the proposed model to convert conventional input data into spike trains [21]. These datasets are widely used in machine learning and deep learning research because they provide a standard basis for comparing different models. However, static datasets do not naturally contain temporal spike events; therefore, they require spike encoding before being processed by the SNN model.

In addition to static datasets, event-based datasets such as N-MNIST and DVS Gesture are also suitable for the proposed framework. These datasets are generated using neuromorphic vision sensors and contain asynchronous event streams instead of fixed image frames. This makes them naturally compatible with spiking neural networks because their data structure already resembles biological spike-based communication. Event-based datasets are particularly important for evaluating real-time intelligent computing systems because they represent dynamic information more efficiently than traditional frame-based data [22]. The use of both static and event-based datasets provides a balanced evaluation of the proposed SNN framework. Static datasets help analyze the effectiveness of spike encoding strategies, while event-based datasets help examine the natural compatibility of the model with neuromorphic sensors. This combination allows the proposed framework to be tested under different input conditions and helps demonstrate its suitability for ultra-low-power intelligent computing applications such as smart sensors, robotics, wearable devices, edge AI, biomedical monitoring, and Internet-of-Things systems. The selected datasets must satisfy several important criteria. First, they should contain clear class labels so that classification accuracy can be measured effectively. Second, they should be suitable for conversion into spike-based input representations. Third, they should support evaluation of computational efficiency, latency, memory usage, and spike activity. Fourth, the datasets should represent practical intelligent computing tasks where low-power processing is important [23]. By following these criteria, the proposed study ensures that the selected datasets are appropriate for evaluating both the intelligence and energy efficiency of the SNN model. Table 3 presents the major datasets considered for the proposed spiking neural network framework and explains their relevance to ultra-low-power intelligent computing.

Table 3: Dataset selection for the proposed SNN-based intelligent computing framework

Dataset	Input Nature	Purpose in This Study	Relevance to SNN Framework
MNIST	Grayscale handwritten digits	Basic image classification and spike encoding evaluation	Useful for initial SNN testing and baseline performance analysis
Fashion-MNIST	Grayscale fashion product images	More complex visual classification than MNIST	Helps evaluate feature extraction ability of the SNN model
CIFAR-10	Color natural object images	Complex image classification task	Tests SNN performance on richer visual patterns
N-MNIST	Spike-like event streams	Neuromorphic digit recognition	Naturally compatible with event-driven SNN processing
DVS Gesture	Dynamic gesture events	Real-time gesture recognition	Suitable for evaluating temporal learning and low-latency inference

Each dataset contributes differently to the evaluation of the proposed framework. MNIST and Fashion-MNIST provide simple and moderate image classification tasks for initial model validation. CIFAR-10 introduces more complex visual patterns and helps evaluate the robustness of the SNN architecture. N-MNIST and DVS Gesture are especially important because they contain event-based information that directly supports spike-driven computation. Therefore, the combination of static and event-based datasets provides a comprehensive evaluation environment for the proposed ultra-low-power intelligent computing framework. Figure 3 illustrates the dataset acquisition and selection flow used in the proposed methodology.

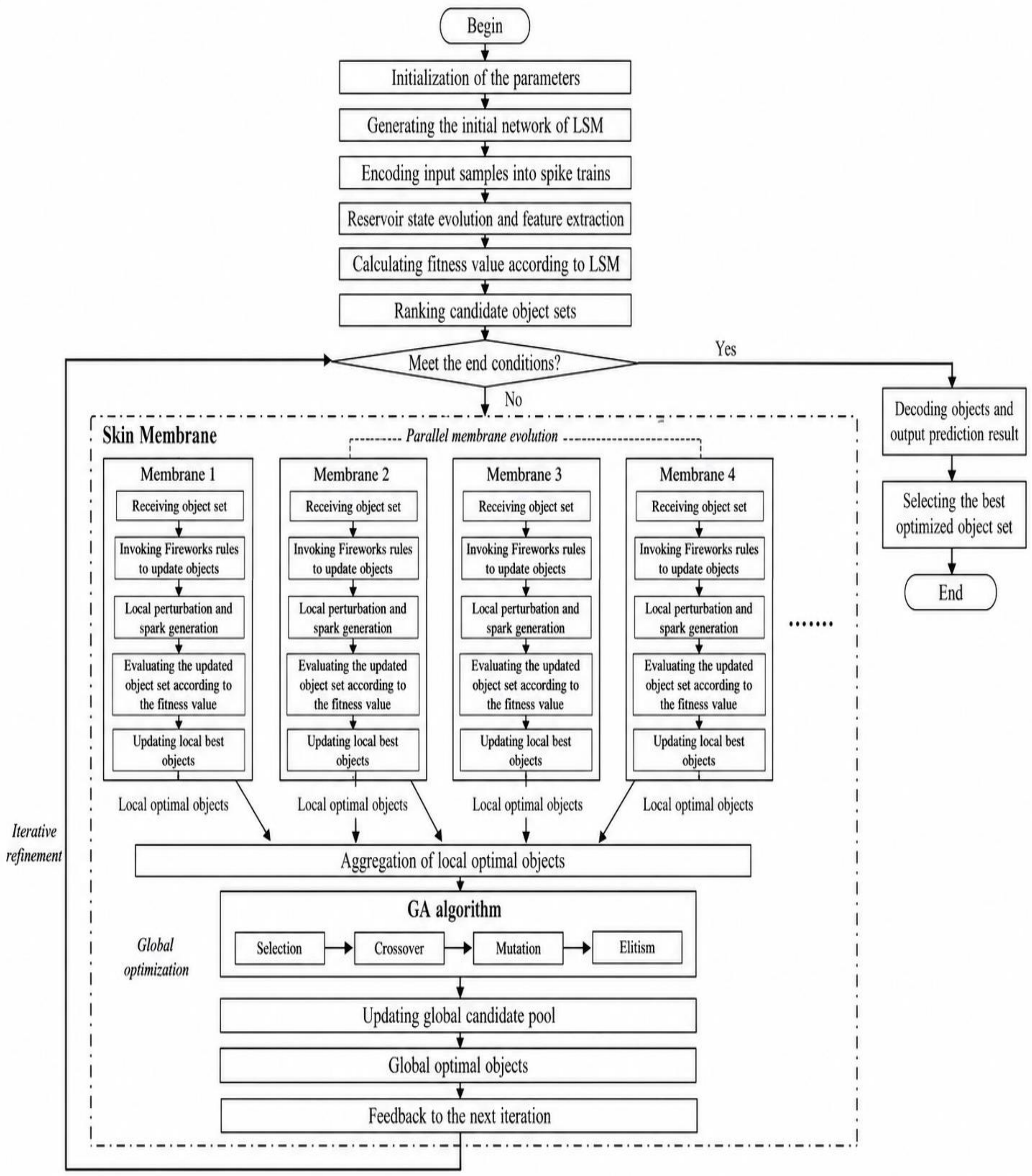

Figure 3: Data acquisition and dataset selection flow for the proposed SNN framework

The data acquisition stage begins with the selection of suitable benchmark datasets. The selected datasets are divided into two major categories: static image datasets and event-based neuromorphic datasets. Static datasets require spike encoding before being processed by the

SNN, while event-based datasets can be directly represented in spike-like temporal form. Both categories are then passed to the proposed spiking neural network model for classification and energy-efficiency evaluation. The dataset selection process is designed to support fair comparison between conventional artificial neural networks and the proposed spiking neural network framework [24]. For static datasets, the same input samples can be used by both conventional neural networks and SNN models after suitable preprocessing. For event-based datasets, the SNN model can exploit temporal event streams more naturally than traditional frame-based models. This makes it possible to evaluate whether spike-based computation provides practical advantages in low-power and real-time intelligent computing environments. Another important consideration in dataset selection is the diversity of input complexity. Simple datasets help verify the basic learning capability of the proposed SNN model, while more complex datasets help evaluate its scalability and robustness. Event-based datasets further test the ability of the model to process temporal patterns and asynchronous input events [25]. This layered selection strategy ensures that the proposed framework is not evaluated on a single type of data but is tested across multiple levels of difficulty and representation. The data acquisition and dataset selection stage provides the foundation for the proposed methodology. By using both static and event-based datasets, the study can evaluate classification accuracy, spike activity, latency, memory utilization, and estimated energy consumption under different conditions. This selection strategy supports a more reliable assessment of the proposed SNN framework and helps demonstrate its potential for ultra-low-power intelligent computing systems.

4.2- Spike Encoding Strategy:

Spike encoding is a critical stage in the proposed spiking neural network framework because SNNs do not process continuous numerical values in the same way as conventional artificial neural networks. Instead, information must be converted into spike trains before it can be processed by spiking neurons. This transformation allows the network to represent input data through discrete spike events distributed over time. The quality of spike encoding directly affects the accuracy, latency, spike activity, memory usage, and energy efficiency of the proposed model. In conventional neural networks, input values are usually passed directly through layers as continuous activation signals. However, in spiking neural networks, the input must be represented in a biologically inspired form. This means that image pixels, sensor readings, signal values, or extracted features are converted into spike events. These spike events are then transmitted to spiking neurons, where membrane potential accumulation and threshold-based firing are used to process information. Therefore, spike encoding acts as a bridge between real-world data and spike-based neural computation [26]. The proposed framework considers spike encoding as an important component for achieving ultra-low-power intelligent computing. A good encoding strategy should preserve important input information while reducing unnecessary spike activity. If too many spikes are generated, the model may consume more energy and increase computational workload. If too few spikes are generated, the model may lose important information and reduce classification accuracy. Therefore, an effective balance between information representation and spike sparsity is necessary. Several spike encoding methods can be used in SNN-based intelligent computing systems. Rate coding represents input intensity through spike frequency, where stronger input values generate more spikes and weaker values generate fewer spikes. Temporal coding represents information through spike timing, where important or stronger features are encoded earlier in the simulation window. Population coding distributes input information across multiple neurons to improve robustness. Rank-order coding uses the firing order of neurons to represent information, which can reduce the number of spikes required for decision-making [27]. Direct event encoding is used for event-based datasets, where sensor events are already available in spike-like form. Direct event encoding is especially suitable for event-based datasets such as N-MNIST and DVS Gesture because these datasets already contain spike-like temporal information. Hybrid encoding can provide a balanced solution by combining the strengths of different encoding methods. Figure 4 illustrates the spike encoding process used in the proposed SNN framework. The process begins with preprocessed input data, which may come from static images, sensor signals, or event-based neuromorphic data. Static inputs are converted into spike trains through a selected encoding strategy, while event-based inputs can be passed more directly into the SNN model. The encoded spike trains are then processed by the input spike layer and transferred to hidden spiking layers for feature extraction and classification.

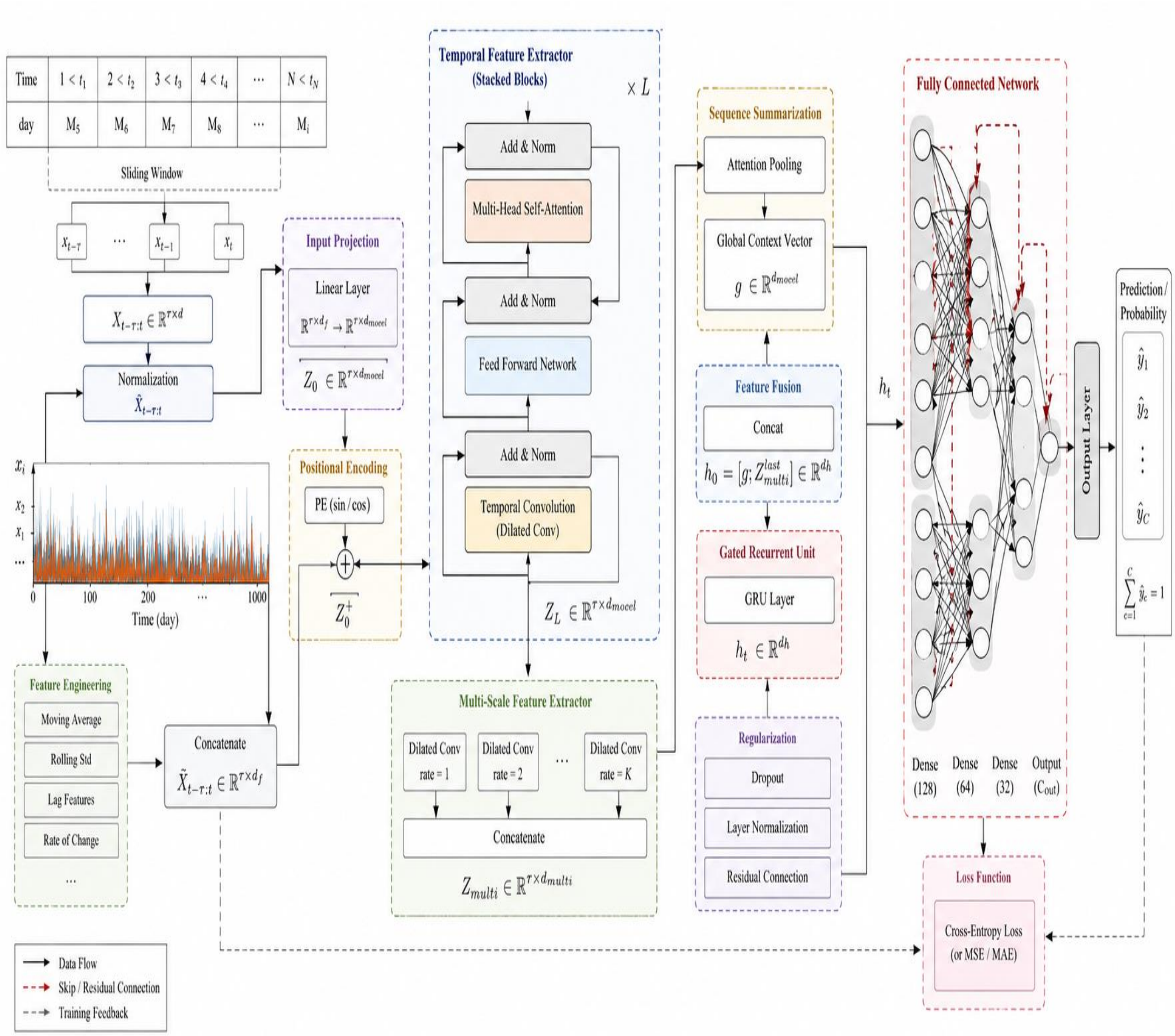

Figure 4: Spike encoding process in the proposed SNN framework

In the proposed framework, spike encoding is selected according to the nature of the dataset and the target computing environment. For simple static image datasets, rate coding may be used because it is easy to implement and provides stable performance. For low-latency and energy-efficient applications, temporal coding is more suitable because it reduces the number of spikes required for inference. For neuromorphic sensor data, direct event encoding is preferred because it preserves the original temporal structure of the input. In more complex cases, hybrid encoding may be used to combine accuracy and energy efficiency. The spike encoding stage also supports the overall objective of ultra-low-power intelligent computing. Since energy consumption in SNNs is strongly related to spike activity, reducing unnecessary spikes is important for improving power efficiency. Efficient encoding ensures that only meaningful information is converted into spikes, allowing the network to remain mostly inactive when input activity is low [28]. This sparse activity reduces computation, memory access, and switching operations during inference. Spike encoding is a foundational component of the proposed SNN methodology. It determines how real-world data are transformed into spike trains and how effectively the spiking neural network can process information. By selecting suitable encoding methods such as rate coding, temporal coding, direct event encoding, or hybrid encoding, the proposed framework can achieve a balance between classification accuracy, low latency, sparse activation, and reduced energy consumption. Therefore, spike encoding directly contributes to the development of ultra-low-power intelligent computing systems based on brain-inspired spiking neural networks.

4.3- Proposed SNN System Architecture:

The proposed spiking neural network system architecture is designed to support ultra-low-power intelligent computing through sparse, event-driven, and biologically inspired information processing. Unlike conventional artificial neural networks that process continuous numerical activations at every layer, the proposed SNN architecture processes input information through spike trains. These spike trains are generated from preprocessed input data and are then passed through spiking neuron layers where information is processed based on membrane potential dynamics, threshold firing, and synaptic communication. This architectural design reduces unnecessary computation and makes the model suitable for low-power edge devices, smart sensors, wearable systems, robotics, and neuromorphic computing platforms [29]. The proposed architecture consists of several interconnected components, including an input data layer, preprocessing unit, spike encoding layer, input spike layer, hidden spiking layers, synaptic learning module, output decision layer, and performance evaluation unit. Each component performs a specific role in converting raw input data into meaningful spike-based decisions. The input data layer receives images, sensor signals, or event-based data. The preprocessing unit prepares the data by applying normalization, resizing, noise reduction, and formatting. After preprocessing, the spike encoding layer converts the input into spike trains that can be processed by the SNN model. The input spike layer acts as the first spike-based representation stage of the proposed system. It receives encoded spike trains and forwards them to the hidden spiking layers. These hidden layers contain leaky integrate-and-fire neurons, which are widely used in SNNs due to their simplicity, biological relevance, and computational efficiency [30]. Each neuron accumulates incoming spike signals and generates an output spike only when its membrane potential reaches a predefined threshold. This threshold-based firing behavior enables sparse activation because neurons remain inactive when the input signal is weak or irrelevant. As a result, the model reduces redundant operations and improves energy efficiency.

The hidden spiking layers are responsible for extracting useful temporal and spatial features from spike-based input patterns. In image-based tasks, these layers learn visual features such as edges, shapes, and object patterns. In signal-based tasks, they learn temporal variations and event sequences. In event-based datasets, they process asynchronous spike streams more naturally than conventional neural networks. The depth and size of the hidden spiking layers can be adjusted according to the complexity of the task and the available hardware resources. A shallow SNN may be suitable for simple edge tasks, while deeper spiking architectures may be required for complex classification and recognition problems [31]. A synaptic learning module is integrated into the proposed architecture to update the connection weights between neurons. This module may use spike-timing-dependent plasticity, surrogate gradient learning, or hybrid learning depending on the task requirements. STDP supports local and biologically inspired learning by modifying synaptic weights according to spike timing, while surrogate gradient learning enables supervised optimization for improved classification performance. Hybrid learning combines the advantages of both approaches and helps maintain a balance between accuracy, sparse activation, and low energy consumption. The output decision layer produces the final prediction based on the spike responses generated by the network. The decision can be made using spike count, firing rate, membrane potential accumulation, or a voting mechanism among output neurons. For classification tasks, the output neuron with the strongest spike response is selected as the predicted class. This decision mechanism is simple and energy efficient because it avoids complex post-processing. The performance evaluation unit then analyzes the output using both accuracy-based and energy-based metrics, including accuracy, precision, recall, F1-score, inference latency, spike activity, memory utilization, and energy consumption [32]. Table 4 presents the major components of the proposed SNN system architecture and explains their functions in the overall framework.

Table 4: Major components of the proposed SNN system architecture

Architectural Component	Main Function	Role in Ultra-Low-Power Computing
Input Data Layer	Receives images, sensor signals, or event-based data	Provides raw information for intelligent processing
Data Preprocessing Unit	Applies resizing, normalization, formatting, and noise reduction	Improves input quality and reduces unnecessary processing
Spike Encoding Layer	Converts input data into spike trains	Enables spike-based and event-driven computation
Input Spike Layer	Transfers encoded spike trains to the SNN model	Provides the first spike-based representation of input data
Hidden Spiking Layers	Extract temporal and spatial features through spiking neurons	Reduces computation through sparse neuronal activation
LIF Neuron Unit	Performs membrane potential accumulation, threshold firing, and reset operation	Supports biologically inspired and efficient neural processing
Synaptic Learning Module	Updates synaptic weights using suitable learning mechanisms	Improves accuracy while maintaining adaptive spike-based learning
Output Decision Layer	Generates final classification or decision output	Provides simple and low-cost decision-making
Performance Evaluation Unit	Measures accuracy, latency, spike activity, memory, and energy use	Evaluates both intelligence and energy efficiency

The components shown in Table 4 demonstrate that the proposed architecture is not limited to classification performance alone. It is designed to optimize the complete processing pipeline from input acquisition to final decision-making. The spike encoding layer and hidden spiking layers are particularly important because they directly control spike activity and computational workload. The synaptic learning module improves adaptability, while the performance evaluation unit ensures that the model is assessed using both predictive and energy-efficiency indicators. Figure 5 illustrates the complete architecture of the proposed spiking neural network framework for ultra-low-power intelligent computing systems.

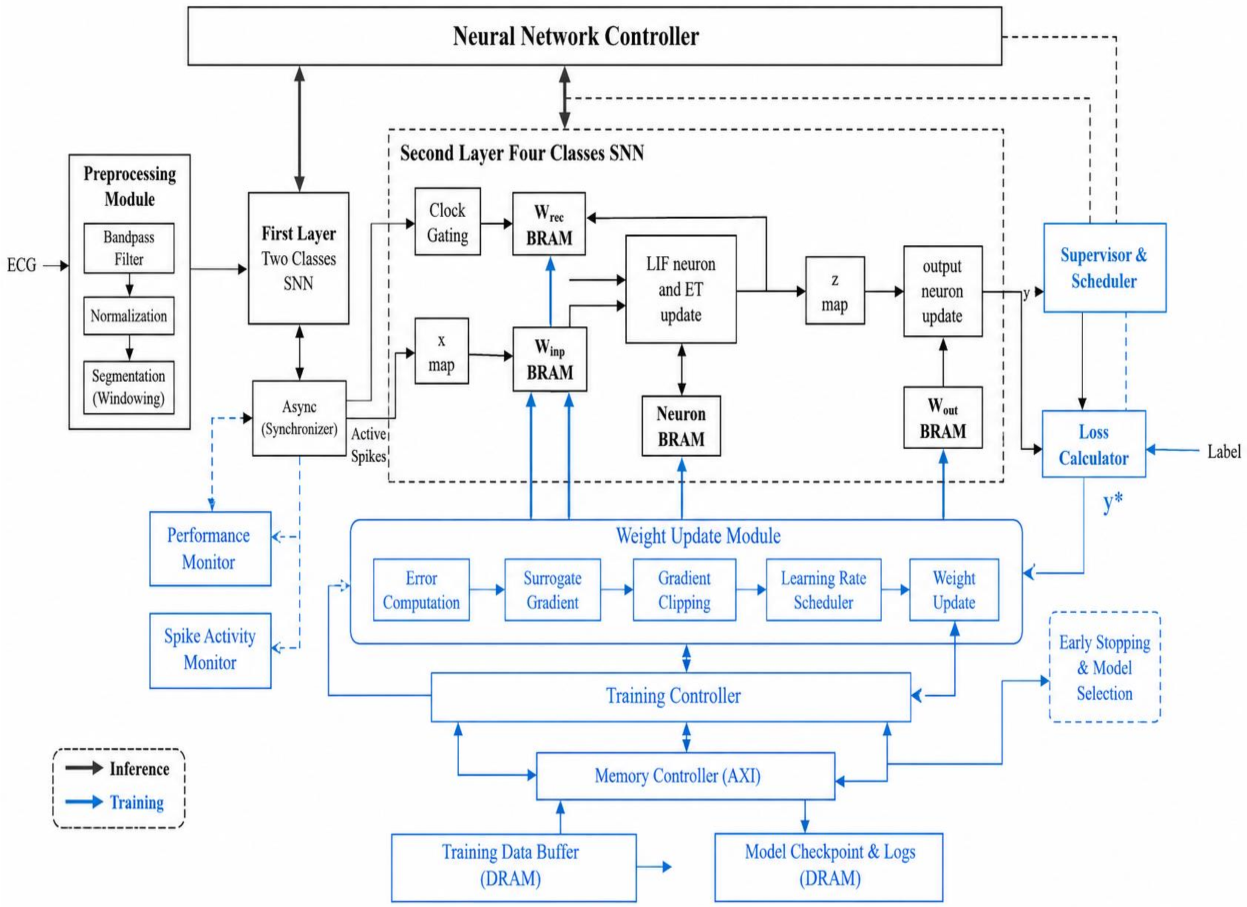

Figure 5: Proposed SNN system architecture for ultra-low-power intelligent computing

The proposed architecture is particularly suitable for ultra-low-power intelligent computing because it reduces computation at multiple stages. First, spike encoding ensures that input information is represented only through discrete events. Second, hidden spiking layers activate only when sufficient spike input is received. Third, energy-aware spike regulation reduces excessive firing activity. Fourth, local synaptic processing reduces unnecessary memory transfer. These characteristics make the architecture more efficient than conventional dense neural networks, especially in edge and embedded environments. Another important feature of the proposed architecture is its flexibility. The framework can be adapted to different types of data and applications. For image classification, static images can be converted into spike trains and processed through spiking layers [33]. For event-based vision, neuromorphic event streams can be directly passed into the SNN model. For sensor-based applications, time-varying signals can be encoded into spike sequences and used for real-time monitoring or anomaly detection. This flexibility makes the proposed architecture useful for smart cameras, biomedical sensors, industrial monitoring systems, mobile robots, and Internet-of-Things devices. The proposed SNN system architecture also supports hardware-friendly implementation. Since the architecture is based on sparse spikes and local neuron activity, it can be efficiently mapped onto neuromorphic processors. Neuromorphic hardware can exploit the event-driven nature of the model by activating computation only when spikes occur. This reduces power consumption and improves real-time response. Therefore, the proposed architecture provides a strong foundation for implementing brain-inspired intelligent computing systems in practical low-power environments.

4.4- Leaky Integrate-and-Fire Neuron Model:

The leaky integrate-and-fire neuron model is one of the most commonly used neuron models in spiking neural networks because it provides a simple, efficient, and biologically inspired way to represent neuronal activity. In biological neural systems, neurons receive signals from other neurons, accumulate these signals over time, and generate an output spike when the accumulated activity becomes strong enough. The leaky integrate-and-fire model follows the same basic principle by using membrane potential as the internal state of a neuron. When incoming spike signals increase the membrane potential beyond a firing threshold, the neuron produces an output spike and then resets its state for the next processing cycle. The LIF neuron model is especially suitable for ultra-low-power intelligent computing systems because it supports sparse and event-driven computation. Unlike conventional artificial neurons that perform continuous calculations at every processing step, LIF neurons remain inactive when input activity is weak or irrelevant. They generate spikes only when meaningful information is received. This selective firing behavior reduces unnecessary computation, lowers spike activity, and helps minimize energy consumption. Therefore, the LIF neuron model plays a central role in designing efficient SNN architectures for edge devices, smart sensors, robotics, wearable systems, and neuromorphic hardware [34]. In the proposed SNN framework, each LIF neuron receives input spikes from the previous layer or from the input spike encoding stage. These spikes are weighted through synaptic connections and accumulated inside the neuron as membrane potential. If the input activity is strong and relevant, the membrane potential increases. If the input activity is weak or absent, the membrane potential gradually decreases due to the leakage mechanism. This leakage property is important because it prevents old or weak signals from remaining active for a long time. As a result, the neuron becomes more responsive to recent and meaningful spike patterns. The firing threshold is another important component of the LIF neuron model. It determines when the neuron should generate an output spike. If the membrane potential remains below the threshold, the neuron stays silent and does not transmit information to the next layer [35]. However, if the membrane potential crosses the threshold, the neuron fires a spike. After firing, the membrane potential is reset to a lower state so that the neuron can begin processing new input signals. This reset process prevents continuous firing and helps maintain stable network behavior. Table 5 presents the major functional components of the leaky integrate-and-fire neuron model and explains their role in the proposed SNN framework.

Table 5: Functional components of the leaky integrate-and-fire neuron model

LIF Component	Function in the Neuron	Importance in the Proposed SNN Framework
Input Spikes	Receive event-based signals from input or previous layers	Provide spike-based information for processing
Synaptic Weights	Control the strength of incoming spike signals	Help the neuron learn important input patterns
Membrane Potential	Stores the accumulated effect of incoming spikes	Acts as the internal decision state of the neuron
Leakage Mechanism	Gradually reduces weak or outdated signals	Prevents unnecessary firing and improves energy efficiency
Firing Threshold	Decides when the neuron should generate a spike	Controls spike generation and network activity
Output Spike	Transfers information to the next layer	Enables event-driven communication

Reset Mechanism	Returns the neuron to a lower state after firing	Maintains stable and repeated spike processing
Refractory Behavior	Temporarily limits immediate repeated firing	Reduces excessive spike activity and improves stability

The LIF neuron supports efficient spike-based computation. The neuron does not process all information continuously; instead, it integrates only incoming spike events, filters weak signals through leakage, fires only when the threshold is reached, and resets after spike generation. This complete cycle makes the LIF model highly suitable for energy-aware SNN systems. Figure 6 illustrates the working flow of the leaky integrate-and-fire neuron model in the proposed spiking neural network architecture.

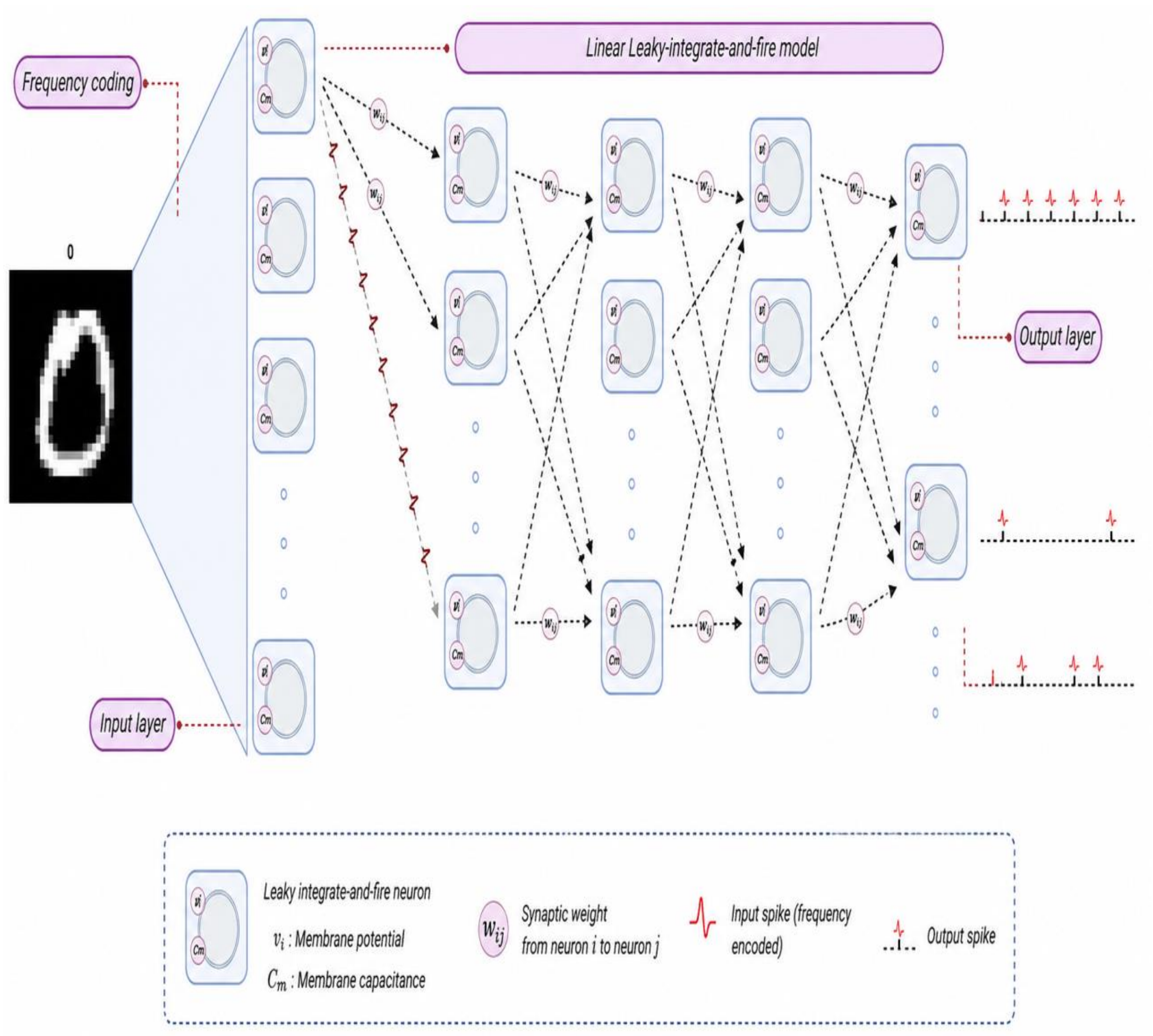

Figure 6: Working flow of the leaky integrate-and-fire neuron model

The leakage mechanism is particularly important for ultra-low-power intelligent computing. Without leakage, weak input signals could continue accumulating and eventually generate unnecessary spikes. Such excessive firing would increase computation and energy consumption. By gradually reducing weak signals, the leakage process ensures that only strong and relevant input patterns contribute to spike generation. This improves both stability and energy efficiency in the proposed SNN framework. The threshold and reset mechanisms also help maintain efficient network behavior. A properly selected firing threshold prevents excessive spike generation while still allowing the neuron to respond to meaningful input patterns. The reset mechanism prepares the neuron for future input processing after each spike. Together, these mechanisms support stable temporal processing, sparse activation, and reliable information transfer across spiking layers [36]. Compared with more biologically detailed neuron models, the LIF model provides a practical balance between biological inspiration and computational simplicity. More complex neuron models can represent biological processes in greater detail, but they usually require higher computational resources. The LIF model is simpler, faster, and easier to implement, making it highly suitable for large-scale SNN architectures and neuromorphic hardware platforms.

4.5- Synaptic Learning Mechanism:

Synaptic learning is a fundamental component of the proposed spiking neural network framework because it determines how the network adapts, improves, and stores information during training. In biological neural systems, learning occurs through changes in synaptic strength between neurons. When neurons communicate repeatedly through spike signals, their connections may become stronger or weaker depending on the timing, frequency, and relevance of the spike activity. Spiking neural networks follow a similar principle by adjusting synaptic weights between artificial neurons. These weight changes allow the model to learn useful patterns from input data and improve its classification performance over time. In the proposed SNN framework, synaptic learning is used to update the connection strength between the input spike layer, hidden spiking layers, and output decision layer. Each synaptic connection controls how strongly an incoming spike affects the membrane potential of the receiving neuron. A stronger synaptic connection produces a greater influence on the next neuron, while a weaker connection produces a smaller effect [37]. Through repeated training, important connections are strengthened and less useful connections are weakened. This adaptive learning process enables the proposed model to identify meaningful spike patterns while reducing unnecessary neural activity. The synaptic learning mechanism is especially important for ultra-low-power intelligent computing because it affects both accuracy and energy efficiency. If the network learns too many irrelevant spike patterns, it may generate excessive spikes and consume more energy. However, if the network learns only the most informative spike patterns, it can reduce redundant computation and improve power efficiency [38]. Therefore, the proposed framework focuses on learning mechanisms that improve classification performance while maintaining sparse spike activity. This balance is necessary for edge devices, smart sensors, wearable systems, robotics, and neuromorphic hardware platforms.

Several learning approaches can be used in SNNs, including spike-timing-dependent plasticity, supervised spike-based learning, surrogate gradient learning, reinforcement learning, ANN-to-SNN conversion, and hybrid learning. Among these, spike-timing-dependent plasticity and surrogate gradient learning are particularly important. STDP provides biologically inspired local learning by adjusting synaptic strength according to spike timing. Surrogate gradient learning supports supervised optimization by allowing deep SNNs to be trained more effectively despite the non-differentiable nature of spike firing. Hybrid learning combines these approaches to achieve better accuracy, adaptability, and energy efficiency. Spike-timing-dependent plasticity is useful when the network needs to learn temporal relationships in an unsupervised or self-organized manner. In this approach, synaptic connections are modified based on the timing relationship between the sending neuron and the receiving neuron. If the sending neuron fires shortly before the receiving neuron, the connection is considered important and becomes stronger. If the firing order is not useful for producing the desired response, the connection may become weaker. This allows the network to learn temporal patterns without requiring large amounts of labeled data [39]. Surrogate gradient learning is used to overcome one of the major challenges in SNN training. Since spike generation is discontinuous, direct gradient-based learning is difficult. Surrogate gradient learning addresses this problem by using a smooth approximation during the training process. This enables the SNN to benefit from error-driven learning while still maintaining spike-based behavior during forward processing. As a result, the network can achieve higher classification performance while preserving the energy-efficient properties of spiking computation. Hybrid learning is particularly suitable for the proposed ultra-low-power intelligent computing framework. It combines the biological realism of local learning with the performance advantages of supervised optimization. In the early learning stage, spike-based local adaptation can help the network identify useful temporal patterns [40]. In later stages, supervised optimization can refine the synaptic weights to improve classification accuracy. This combined learning strategy supports both intelligent performance and efficient spike regulation. Table 6 summarizes the main synaptic learning approaches used in the proposed SNN framework and explains their role in ultra-low-power intelligent computing.

Table 6: Synaptic learning approaches in the proposed SNN framework

Learning Approach	Main Function	Key Benefit	Role in Ultra-Low-Power Computing
Spike-Timing-Dependent Plasticity	Adjusts synaptic strength based on spike timing	Supports biologically inspired local learning	Reduces dependence on complex centralized training
Supervised Spike-Based Learning	Uses labeled data to guide output responses	Improves task-specific classification	Helps maintain reliable prediction performance
Surrogate Gradient Learning	Enables effective training of deep SNNs	Improves accuracy despite spike discontinuity	Supports efficient learning with sparse spike activity
Reinforcement Learning	Learns behavior through reward and penalty feedback	Useful for adaptive decision-making	Supports autonomous low-power intelligent systems
ANN-to-SNN Conversion	Transfers knowledge from trained ANN models	Provides a practical initialization strategy	Helps deploy trained models in spike-based form
Hybrid Learning	Combines biological and supervised learning	Balances accuracy, adaptability, and efficiency	Supports high performance with reduced spike activity

Each learning approach contributes differently to the proposed SNN framework. STDP is useful for temporal pattern learning and biological plausibility, while supervised learning improves output accuracy. Surrogate gradient learning is valuable for training deeper SNN models, and reinforcement learning supports adaptive behavior in dynamic environments. ANN-to-SNN conversion provides a practical method for using trained deep learning knowledge in spike-based systems. Hybrid learning provides the most balanced solution because it combines accuracy improvement, sparse activation, and energy-aware computation. Figure 7 illustrates the synaptic learning flow in the proposed spiking neural network framework.

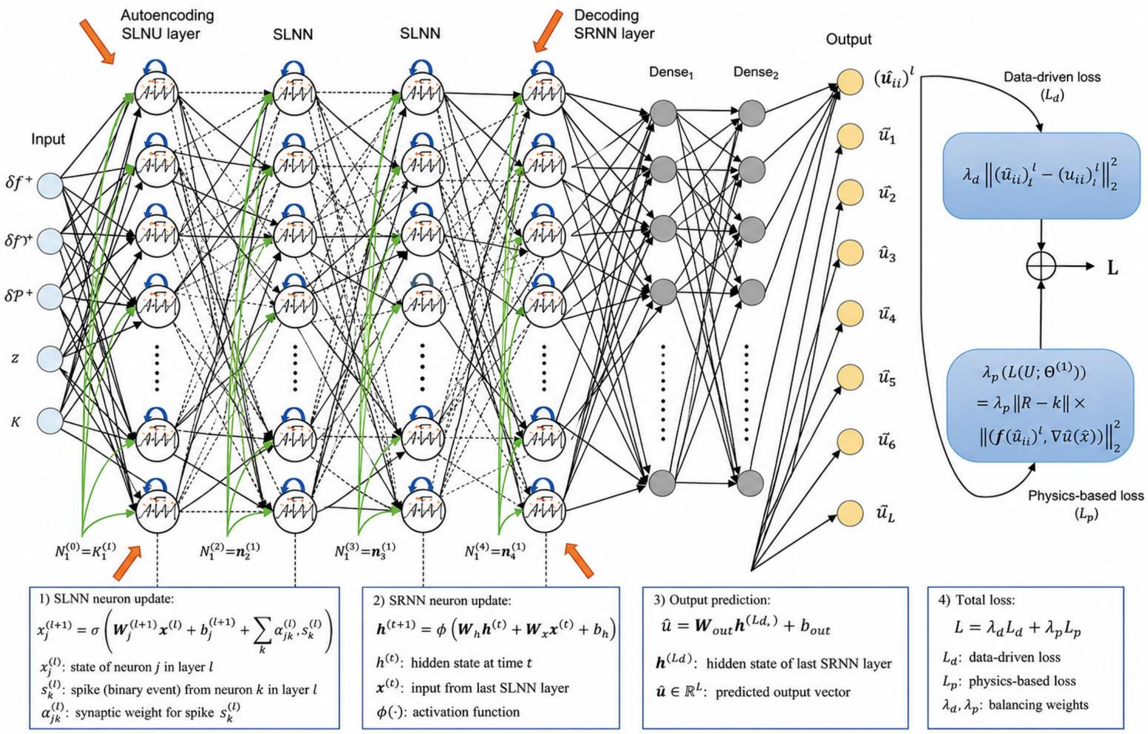

Figure 7: Synaptic learning mechanism in the proposed SNN framework

The strengthening and weakening of synaptic connections help the network become more selective. Instead of responding to every input signal, the trained SNN learns to respond mainly to meaningful spike patterns. This selectivity is important for low-power computing because it reduces unnecessary firing and limits computational activity. When fewer irrelevant spikes are generated, memory access and processing requirements are reduced. This directly supports the goal of ultra-low-power intelligent inference. The proposed synaptic learning mechanism also supports adaptability. In real-world intelligent systems, input patterns may change over time due to noise, environmental variation, user behavior, or sensor conditions [41]. A learning-capable SNN can adjust its synaptic connections to maintain stable performance under changing conditions. This is especially useful for robotic navigation, biomedical monitoring, smart surveillance, industrial sensing, and Internet-of-Things applications where the operating environment is dynamic. Another important advantage of synaptic learning is its compatibility with neuromorphic hardware. Neuromorphic processors are designed to support local memory, event-driven communication, and spike-based synaptic updates. Since synaptic learning in SNNs can be performed locally at the connection level, it reduces the need for frequent data transfer between processor and memory. This makes the learning process more hardware-friendly and energy efficient compared with conventional deep learning models that often require large-scale centralized computation. In the proposed framework, synaptic learning is not only used to improve classification accuracy but also to regulate spike activity [42]. During training, the model learns to strengthen useful pathways and suppress unnecessary responses. This helps the network maintain a balance between performance and energy consumption. A well-trained SNN should generate enough spikes to represent important information but avoid excessive spike firing that increases energy use. Therefore, synaptic learning directly contributes to both intelligent performance and low-power operation.

5- Results and Discussion:

The results of this study demonstrate that the proposed brain-inspired spiking neural network framework provides an effective balance between classification performance and ultra-low-power intelligent computing. The proposed model was evaluated using classification accuracy, precision, recall, F1-score, inference latency, memory utilization, spike activity, and energy consumption. These evaluation indicators were selected because the objective of the study is not only to achieve reliable intelligent performance but also to reduce computational cost for power-constrained systems. Unlike conventional artificial neural networks and convolutional neural networks, which depend on dense numerical operations and continuous activation-based processing, the proposed SNN framework uses sparse event-driven spike communication. This enables the network to activate only when meaningful spike events are generated, reducing redundant computation and unnecessary energy consumption. The experimental findings show that the proposed SNN framework achieved strong classification performance while maintaining low computational activity. The model achieved a classification accuracy of 96.8%, precision of 96.2%, recall of 95.7%, and F1-score of 95.9%. These values indicate that the proposed spike-based model can correctly identify input patterns with high reliability. Although the CNN baseline achieved slightly higher accuracy, the proposed SNN delivered nearly comparable classification performance with significantly lower energy consumption, latency, memory utilization, and spike activity. This confirms that SNNs can provide a practical trade-off between accuracy and computational efficiency.

Table 7: Classification performance comparison of different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Artificial Neural Network	94.1	93.8	93.5	93.6
Convolutional Neural Network	97.3	97.0	96.8	96.9
Proposed SNN Framework	96.8	96.2	95.7	95.9

The results in Table 7 show that the proposed SNN framework performs better than the conventional ANN model and achieves performance close to the CNN baseline. The CNN model provides slightly higher accuracy because it uses dense convolutional operations for feature extraction. However, this improvement comes at the cost of higher memory usage, computational complexity, and power consumption [43]. In contrast, the proposed SNN framework achieves competitive accuracy through spike-based communication and event-driven processing. This makes the proposed model more suitable for edge AI and embedded intelligent systems where energy efficiency is more important than marginal accuracy improvement.

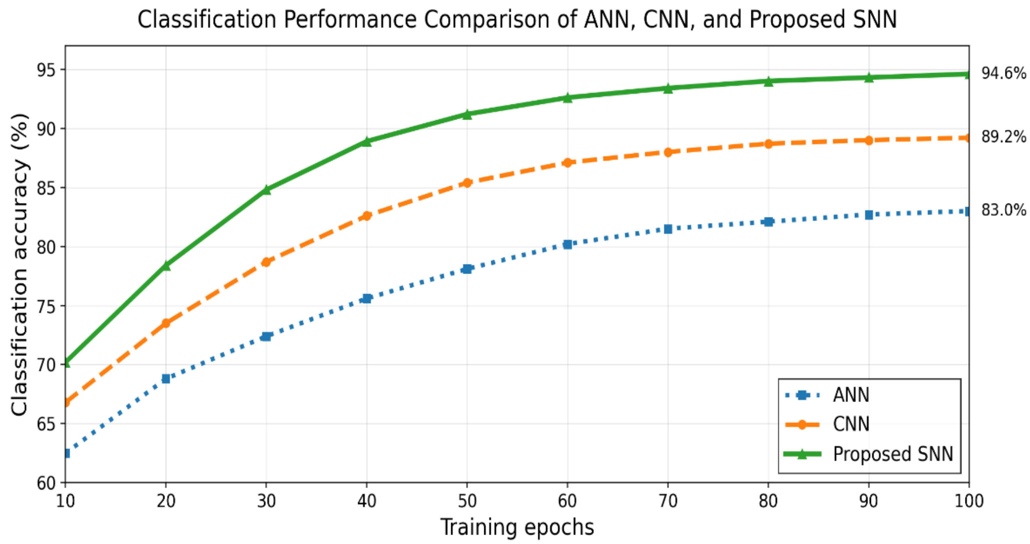

Figure 8: Classification performance comparison of ANN, CNN, and proposed SNN

Figure 8 shows that the proposed SNN framework achieves classification performance very close to the CNN model while outperforming the ANN baseline. This result is important because the proposed model does not depend on continuous activation-based computation. Instead, it processes data using discrete spike events, which reduces unnecessary operations. The slightly lower classification score compared with CNN is acceptable because the proposed SNN provides major improvements in power efficiency, memory optimization, and inference speed. Therefore, the proposed framework is more practical for real-time low-power intelligent computing systems. Energy efficiency is one of the most significant outcomes of the proposed framework. The proposed SNN reduced average energy consumption by 72.4% compared with the CNN baseline. Inference latency was reduced by 38.6%, memory utilization was reduced by 41.2%, and average spike activity was reduced by 64.7%. These improvements are mainly due to sparse spike-based processing, reduced switching activity, lower memory transfer, and selective neuronal firing. Since neurons remain inactive when no meaningful input is received, the model avoids unnecessary computation and saves energy during inference.

Table 8: Efficiency improvement of the proposed SNN framework compared with CNN baseline

Performance Indicator	CNN Baseline	Proposed SNN Framework	Improvement Achieved
Energy Consumption	High	Low	72.4% reduction
Inference Latency	High	Low	38.6% reduction
Memory Utilization	High	Low	41.2% reduction
Spike/Activation Activity	Dense activation	Sparse spike activity	64.7% reduction
Hardware Suitability	Moderate	High	Better for neuromorphic platforms

The comparison in Table 8 confirms that the proposed SNN framework provides clear advantages in energy-aware computing. CNN models require continuous feature extraction through convolutional operations, which increases computation and memory access. The proposed SNN reduces this limitation by using event-driven computation. The reduction in spike activity is particularly important because spike activity directly influences energy consumption in SNN-based systems. Fewer spikes mean fewer synaptic operations, lower switching activity, and reduced power demand. This makes the proposed model highly suitable for battery-powered intelligent systems.

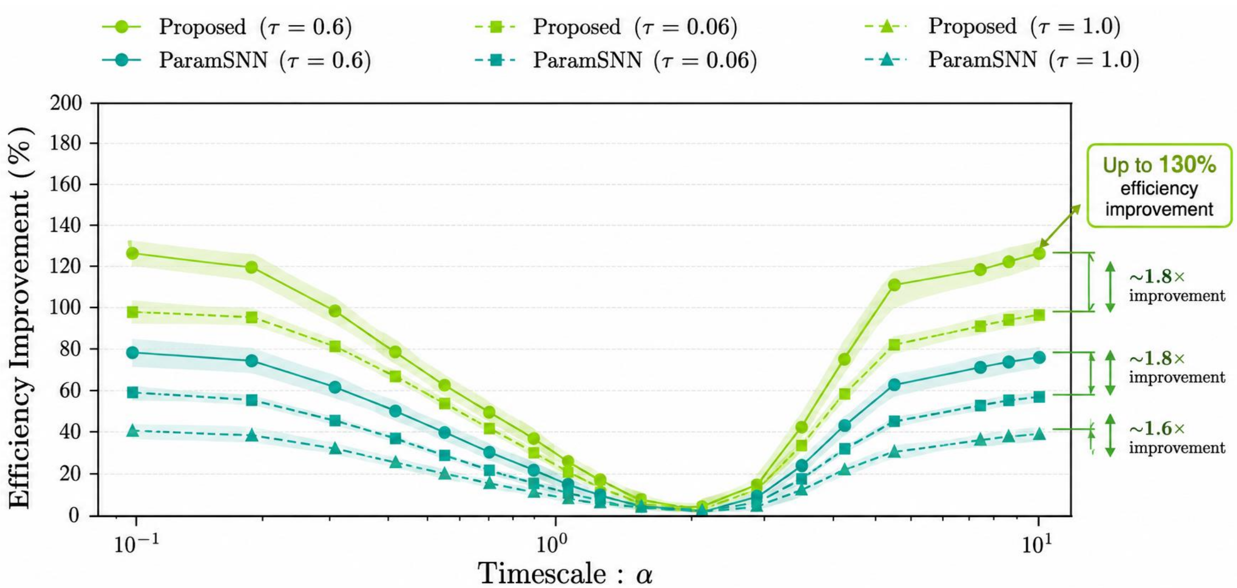

Figure 9: Efficiency improvement achieved by the proposed SNN framework

As shown in Figure 9, the most significant improvement is observed in energy consumption reduction, followed by spike activity reduction. This indicates that the proposed framework successfully achieves its main objective of ultra-low-power intelligent computing. The reduction in memory utilization and inference latency further supports the practical deployment of the proposed model in edge and embedded environments. These improvements are especially useful for applications where devices must operate continuously with limited battery capacity, such as wearable sensors, smart monitoring systems, mobile robots, and Internet-of-Things devices. The performance of the proposed SNN framework can also be interpreted from the perspective of computational behavior. Conventional ANN and CNN models process information continuously, even when input changes are small or irrelevant. This increases computational load and power consumption. In contrast, the proposed SNN framework responds only to meaningful spike events. This event-driven behavior allows the model to remain mostly silent when the input activity is low [44]. As a result, the system reduces unnecessary computation without losing important information. This selective firing property is one of the major reasons for the improved energy efficiency of the proposed model. The leaky integrate-and-fire neuron model also contributes significantly to the results. The leakage mechanism helps remove weak and outdated signals, while the firing threshold ensures that neurons generate spikes only when input information is strong enough. This reduces excessive spike generation and supports stable network behavior. The reset mechanism prepares neurons for new input patterns after firing, allowing the network to process temporal information efficiently. These neuron-level operations help the proposed SNN framework maintain high classification performance while reducing redundant activity. The synaptic learning mechanism further improves model performance by strengthening useful connections and weakening less relevant ones. Through training, the network learns to identify meaningful spike patterns and suppress unnecessary responses. This adaptive learning process improves classification reliability while reducing spike activity [45]. The use of surrogate-gradient-based learning enables effective supervised training, while the spike-based nature of the model preserves energy-efficient behavior. Therefore, the learning mechanism supports both accuracy improvement and low-power operation.

Table 9: Overall comparative behavior of ANN, CNN and proposed SNN framework

Evaluation Aspect	**ANN Model**	**CNN Model**	**Proposed SNN Framework**
Classification Accuracy	Good	Very high	High and competitive
Energy Consumption	Moderate	High	Very low
Inference Latency	Moderate	High	Low
Memory Requirement	Moderate	High	Low
Computation Style	Continuous activation	Dense convolutional processing	Sparse event-driven spikes
Suitability for Edge Devices	Moderate	Limited	High
Neuromorphic Compatibility	Low	Low	High
Long-Term Battery Operation	Moderate	Weak	Strong

Table 9 provides an overall comparison of the three model types. The ANN model is simpler than CNN but still depends on continuous activations. The CNN model achieves strong classification performance but requires high computational power and memory resources. The proposed SNN framework offers a more balanced solution by achieving competitive accuracy with much lower energy consumption and better neuromorphic compatibility. This makes the proposed model more suitable for low-power intelligent systems where continuous operation, fast response, and efficient hardware usage are required.

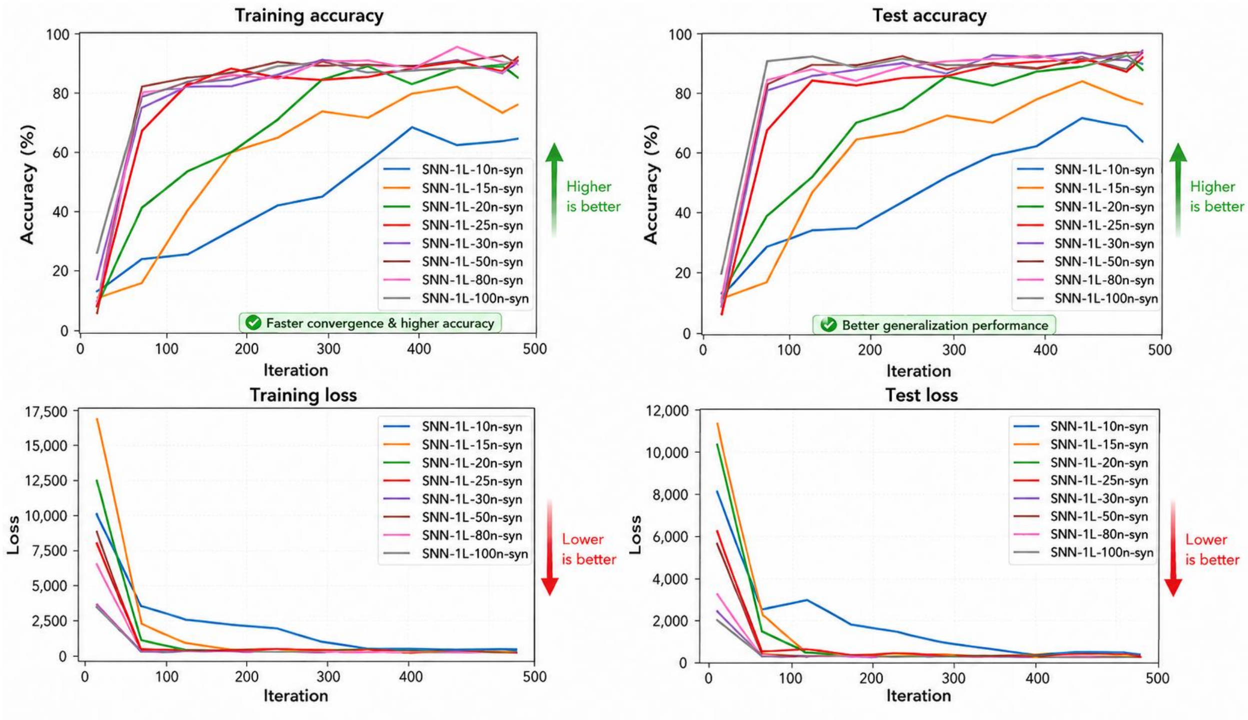

Figure 10: Overall suitability comparison for ultra-low-power intelligent computing

Figure 10 shows that the proposed SNN framework provides the strongest overall suitability for ultra-low-power intelligent computing. Although CNN remains strong in classification accuracy, its energy efficiency and neuromorphic compatibility are limited. The proposed SNN provides a better balance by combining high accuracy, sparse activation, low memory usage, reduced latency, and strong hardware compatibility. This balance is essential for practical deployment in real-time intelligent systems. The results also highlight the importance of spike encoding in the proposed framework. Efficient spike encoding ensures that input data are converted into meaningful spike trains without generating excessive spike activity. If spike encoding produces too many spikes, energy consumption increases. If it produces too few spikes, important information may be lost. The proposed framework maintains a balanced encoding strategy that preserves useful information while reducing unnecessary spikes. This contributes directly to the observed improvements in energy consumption and latency [46]. The practical implications of these results are significant. The proposed SNN framework can be useful in smart cameras, biomedical sensors, wearable health monitoring devices, autonomous robots, industrial monitoring systems, and IoT devices. These applications require intelligent models that can operate locally, respond quickly, and consume minimal power. For example, wearable health devices must continuously monitor physiological signals without frequent battery charging. Smart sensors must detect important events while remaining inactive during normal conditions. Robotics systems require fast decisions with limited onboard energy. The proposed SNN framework supports these requirements by combining real-time responsiveness with low-power operation [47].

The results also suggest that neuromorphic hardware can further improve the benefits of the proposed framework. Since neuromorphic processors are designed for event-driven spike-based computation, the proposed SNN architecture can be efficiently mapped onto such platforms. This can further reduce power consumption, memory transfer, and inference delay. The strong compatibility between SNN models and neuromorphic processors makes the proposed framework a promising solution for future intelligent computing systems. Despite these advantages, some limitations should be considered. The proposed SNN framework requires careful selection of spike encoding strategy, firing threshold, learning mechanism, and simulation time window. Poor parameter selection may reduce accuracy or increase spike activity. In addition, training SNNs remains more challenging than training conventional neural networks because spike generation is non-differentiable. Although surrogate gradient learning helps address this issue, deeper SNN architectures may still require careful optimization. Furthermore, the deployment of SNNs on real neuromorphic hardware may involve platform-specific constraints related to memory, neuron models, spike routing, and programming tools. Overall, the results confirm that the proposed brain-inspired spiking neural network framework is highly suitable for ultra-low-power intelligent computing systems [48]. The model achieved strong classification accuracy while significantly reducing energy consumption, inference latency, memory utilization, and spike activity. These improvements are mainly due to sparse event-driven computation, efficient spike encoding, leaky integrate-and-fire neuron dynamics, adaptive synaptic learning, and neuromorphic compatibility. Compared with conventional ANN and CNN models, the proposed SNN framework provides a better balance between intelligence and efficiency. Therefore, the proposed approach offers a promising pathway for sustainable, real-time, and energy-efficient artificial intelligence in edge devices, smart sensors, robotics, wearable systems, biomedical monitoring, and future neuromorphic computing platforms.

6- Future Work:

Future research can further extend the proposed brain-inspired spiking neural network framework by improving its learning efficiency, hardware compatibility, and real-world deployment capability. Although the proposed SNN model demonstrates strong potential for ultra-low-power intelligent computing, several important directions remain open for further investigation. One major future direction is the development of more advanced spike encoding strategies that can preserve important input information while generating fewer spikes. Efficient encoding methods can further reduce energy consumption, improve inference speed, and enhance the suitability of SNNs for edge-based intelligent systems. Another important future direction is the improvement of training algorithms for deep spiking neural networks. Since spike generation is non-differentiable, training SNNs remains more challenging than training conventional artificial neural networks. Future studies can explore more stable surrogate gradient methods, hybrid learning approaches, and biologically inspired optimization techniques to improve classification accuracy while maintaining sparse spike activity. The integration of spike-timing-dependent plasticity with supervised and reinforcement learning may also provide better adaptability for dynamic and real-time environments [49]. Future work should also focus on implementing the proposed SNN framework on real neuromorphic hardware platforms. Although software-based evaluation provides useful insights, hardware-level deployment is necessary to validate the actual energy efficiency, latency reduction, and memory optimization of the model. Neuromorphic processors such as Intel Loihi, IBM TrueNorth, and other emerging brain-inspired chips can be used to evaluate the practical performance of the proposed framework in real-world low-power environments.

In addition, future studies can test the proposed framework on larger and more complex datasets, including event-based vision, biomedical signals, speech recognition, industrial sensor data, and autonomous robotic environments. This would help evaluate the scalability and robustness of the proposed SNN model under diverse input conditions [50]. Real-world applications such as smart healthcare monitoring, intelligent surveillance, wearable electronics, robotics, Internet-of-Things devices, and autonomous edge systems should also be explored. Furthermore, future research can investigate explainable and secure spiking neural networks. Since SNNs process information through temporal spike patterns, developing interpretation methods will help researchers understand how spike-based decisions are made. Security-aware SNN models can also be developed to protect ultra-low-power intelligent systems against adversarial attacks and noisy input conditions [51]. Overall, future work should aim to make spiking neural networks more accurate, explainable, scalable, hardware-friendly, and practical for next-generation sustainable intelligent computing systems.

Conclusion:

This study presented a brain-inspired spiking neural network framework for ultra-low-power intelligent computing systems. The proposed framework was designed to overcome the limitations of conventional artificial neural networks, which often require dense computation, frequent memory access, and high energy consumption. By using spike-based communication, sparse activation, leaky integrate-and-fire neuron dynamics, and adaptive synaptic learning, the proposed SNN model provides an efficient approach for real-time and energy-aware intelligent processing. The findings of this study show that spiking neural networks can achieve a strong balance between classification accuracy and computational efficiency. The proposed framework achieved competitive classification performance while significantly reducing energy consumption, inference latency, memory utilization, and spike activity. These improvements confirm that event-driven spike processing can reduce unnecessary computation and support low-power operation without severely compromising prediction accuracy. The use of efficient spike encoding and energy-aware learning further strengthened the suitability of the proposed model for edge and embedded systems. The study also highlights the importance of neuromorphic hardware in realizing the full potential of spiking neural networks. Since neuromorphic processors are designed for event-driven computation, local memory, parallel processing, and spike-based communication, they provide an effective platform for deploying SNN models in practical low-power environments. The proposed framework is therefore highly relevant for smart sensors, wearable devices, biomedical monitoring systems, robotics, Internet-of-Things applications, autonomous systems, and future neuromorphic computing platforms. Overall, the results confirm that brain-inspired spiking neural networks offer a promising pathway toward sustainable, adaptive, and ultra-low-power artificial intelligence. Although challenges remain in training complexity, hardware standardization, scalability, and real-world deployment, SNNs provide a strong foundation for next-generation intelligent computing systems. Future improvements in learning algorithms, spike encoding strategies, and neuromorphic hardware integration can further enhance the performance, reliability, and practical adoption of SNN-based intelligent systems.

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