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EVOLUTION BASED SUSTAINABILITY OF SPIKING NEURAL NETWORK: A DEEP REVIEW OF SNN ARCHITECTURE AND COMPARISON OF ITS APPLICATIONS

[1]Ms. Minal Atul Sarode and [2]Ms. Arti Bansode

[1, 2]Department of Information Technology, S.I.E.S (Nerul) College of Arts, Science & Commerce,Maharashtra

[1]minals@sies.edu.in / [2]artib@sies.edu.in

ABSTRACT

Artificial Intelligence is the concept where the ability of a machine to carry out cognitive tasks for problem-solving is tested.Multiple subfields of AI have emerged in the last few decades including machine learning, deep learning, natural language processing, fuzzy logic and so on. Deep neural networks have achieved considerable success over the past ten years in a variety of fields. However, deep neural networks have significant computing expenses, huge data requirements, and high energy usage. Exploiting deep neural networks in those applications has been extensively researched due to the recent increase in demand for the autonomy of machines in the real world, Since real-time responses are required in these applications, energy and computing efficiency are crucial due to the limited energy source. Spiking neural networks that are physiologically plausible have lately provided a promising solution to these previously unachievable applications.This paper discusses one such subfield of AI, Spiking Neural Network.The paper presents architectural enhancements in SNN to make it more and more sustainable and robust thereby ensuring provision for maximum accuracy in solving variety of problems across the globe. The paper further discusses the various applications of SNN specific to pattern recognition, logic gates implementation and image and sound processing with the reference from numerous review articles.

Keyword: *Artificial Neural Network, Spike Neural Network(SNN), Deep Learning, spike-timing-dependent plasticity(STDP), Logic Gates,Pattern recognition*

1. INTRODUCTION

The ability of a machine to carry out cognitive tasks including perceiving, learning, thinking, and problem-solving is known as artificial intelligence, or AI. The standard for AI is set at the level of human reasoning, speech, and vision teams.Modern AI technology handles complex data that perhaps an individual cannot handle. AI automates repetitive processes so a workforce can concentrate on high-level, value-added tasks.AI has various sub-fields :Machine Learning, Deep Learning, Natural Language processing, Expert Systems and Fuzzy Logic.

Deep learning as a subset of Machine Learning which in turn is a subset of AI is continually changing, suggesting new neural network topologies, deep learning challenges, and even entirely new ideas for the future generation of Neural Networks, like the Spiking Neural Network (SNN), despite the fact that Deep Learning is extremely effective in a range of tasks across industries.One such evolution is researchers have developed SNN as a quick and energy-efficient method of computation using spiking neuromorphic substrates.

Spiking neural networks are artificial neural networks that closely resemble real neural networks. In addition to synaptic and neuronal state, time is a main factor in the working model of SNNs. According to the theory, neurons in the SNN only transmit data when a membrane potential, a property of neurons related to their electrical charge on their membrane, reaches a predetermined level, or the threshold, as opposed to at the end of each propagation cycle as they do in conventional multi-layer perceptron networks.

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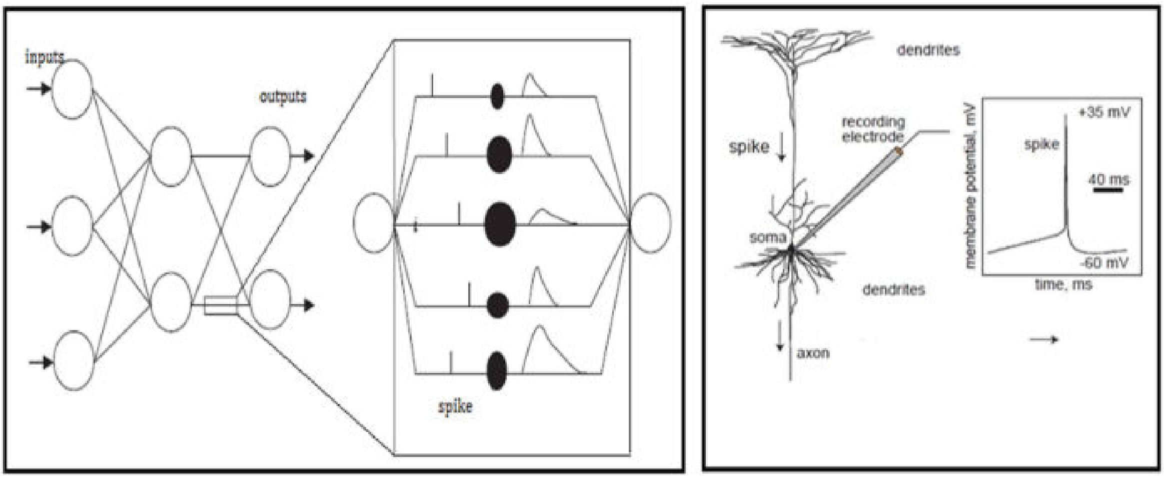
When a neuron's membrane potential reaches a certain level, it fires, sending a signal to other neurons that cause those neurons to change their membrane potentials in response to the signal. When a threshold is crossed, a neuron model known as a spiking neuron fires.



Despite their striking similarity to biological neurons, artificial neurons function differently. The structure, computations, and learning principles of biological and artificial neural networks are fundamentally different.

SNN aims to resemble biological neural networks. SNN operates with discrete events that occur at predetermined times rather than continuously changing time values as ANN does. A set of spikes is entered into SNN, and a set of spikes is produced as the output.The general idea of SNN is, the value of each neuron to be kept equivalent to the current electrical potential of biological neurons.Using a mathematical model and depending upon a spike received from an upstream neuron, a neuron's value might fluctuate thereby increasing or decreasing its value. As the neuron crosses a certain threshold, the neuron in consideration drops its value below its average as soon as it passes, at which point it will transmit a single impulse to every downstream neuron connected to the original one.The neuron will thus have a refractory phase that is comparable to a biological neuron. Spiking neural networks (SNNs) have been shown to be capable of more sophisticated calculations than earlier generations thanks to the use of a neuron that is more biologically inspired,utilising the polychronous characteristics of highly-recurrent networks with synaptic delays of various durations to produce a huge variety of potential patterns with a small number of neurons and synapses.

1.1Spike Based Neural Codes

Spiking neural networks created artificially are intended to do neural computation. The variables crucial to the calculation must be specified in terms of the spikes with which spiking neurons communicate. A variety of neuronal information encodings have been proposed based on biological knowledge:

Based on biological knowledge,the neuron encoding can be specified to be of type:

A. Binary Coding:

in which a neuron is either active or inactive within a specific time interval, firing one or more spikes throughout that time frame.

B. Rate Coding*:*

Information communication is based on the rate of spikes in an interval. Rate encoding is driven by the fact that physiological neurons fire more often in response to greater inputs.

It can be applied to the interpretation of spike trains or to single neurons. In the first scenario, neurons are simply referred to as rate neurons, which at each time step change the "rates" of real-valued input values into "rates" of output. And in the second scenario, it is directly applied to the neuron.

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C. Fully Temporal Codes

Encoding a temporal code relates to specifying the exact time of each spike which is connected to a specific internal or external event and needs to be fully reliable and accurate.

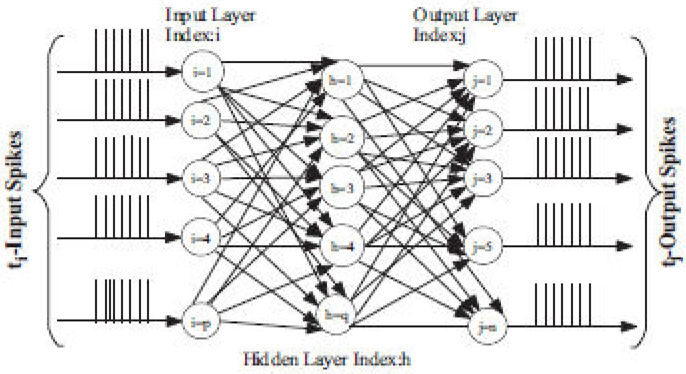
D. Latency Coding

Latency coding uses the timing of spikes, information encoding is based on the time interval between a certain internal or external event and the first spike.

SpikeProp and the Chronotron are the examples of supervised and unsupervised learning methods who implemented this encoding. In a process roughly related to rank-order coding, information about a stimulus is encoded in the order in which neurons within a group fire their initial spikes.

1.2. SNN Architecture

Configurable scalar weights describe spiking neurons and linking synapses in the SNN architecture. As the first step in creating an SNN, the analogue input data is encoded into the spike trains using either a rate-based method, a type of temporal coding, or population coding.



Architecture of a multilayer spiking neural network.

Source

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In SNN, two neurons connected by one synapse are referred to as presynaptic neuron and postsynaptic neuron. Conductance of the synapse determines how strongly two neurons are connected and learning can be achieved through modulating the conductance following an algorithm named spike-timing-dependent-plasticity (STDP)

1.3. Learning Rules in SNN's

Alteration of scalar-valued synaptic weights achieves learning in almost all ANN architectures. Further, Spiking allows for the replication of a form of bio-plausible learning rule. The term spike-timing-dependent plasticity (STDP) provides multiple variations of this learning rule that have been uncovered by neuroscientists .

The weight (synaptic efficacy) connecting a pre- and postsynaptic neuron is changed depending on their respective spike times within tens of millisecond time intervals. This is the main characteristic of this system. Based on data that is both temporally and locally local to the synapse, the weight modification is made. Unsupervised and supervised learning techniques in SNNs are described below:

A. Unsupervised Learning

Data is transmitted unlabeled, and the network is not informed of its performance.SNN finds statistical correlations in data and responds to them. An excellent illustration of this is Hebbian learning and its spiking generalisations, like STDP.Thus,finding correlations and later use to group or organise data afterwards.

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According to its definition, STDP is a process that either enhances or decreases a synaptic weight depending on when the postsynaptic neuron fires after the presynaptic neuron.

B. Supervised Learning

The goal of supervised learning is to correlate (classes of) inputs with desired outputs by pairing data (the input) with labels (the targets) (a mapping or regression between inputs and outputs). The network's weights are updated using an error signal that is computed between the target and the actual output.

While reinforcement learning only gives us a general error signal ("reward") that indicates how well the system is working, supervised learning enables us to use the targets to directly update parameters.

2. Traditional Neural Network Vs SNN

Spiking neural networks are heterogeneous two-layered feed-forward networks with lateral connections in the second hidden layer. Biological neurons use quick, abrupt voltage increases to transmit information. These signals are referred to as action potentials, spikes, and pulses. Because they can encode temporal information in their signals, spiking neuron networks are more effective than their non-spiking counterparts, but they also need different and biologically more accurate synaptic plasticity rules.

Hopping from one neuron to the next with spikes must be managed by the synapses, the most intricate part of the neuron, consisting of:the axon's termination, a synaptic gap, and the first segment of the dendrite. The synapse functions as a highly complex signal pre-processor that is essential for learning and adaptation. Some vesicles fuse with the cell membrane when a spike reaches the axonal (presynaptic) side of the synapses, releasing their neurotransmitter contents into the extracellular fluid that fills the synaptic gap.

The initial concepts and models for artificial neural networks extend back more than fifty years, making them a relatively dated computer science technique. The initial generation of artificial neural networks used McCulloch-Pitts threshold neurons, a conceptually straightforward model in which a neuron sends a binary "high" signal if the sum of its weighted incoming inputs exceeds a threshold value.

Despite the fact that they can only produce digital output, these neurons have been used in sophisticated artificial neural networks such as Hopfield nets and multi-layer perceptrons. Since they can compute any function with a Boolean output, such as a multilayer perceptron with a single hidden layer, these networks are known as universal for digital calculations.

Second-generation neurons are suitable for analogue input and output because they compute their output signals using a continuous activation function rather than a step- or threshold function. Examples of frequently used activation functions include the sigmoid and hyperbolic tangent.

3. Applications of SNN

The industry has seen the strength of SNN since its inception. SNN has guaranteed its significance and multifacetedness, whether it be through architectural improvement or use in various fields to address challenges in the real world. The analysis of several SNN applications and how they have demonstrated to provide the best outcome is the focus of the study.Very common applications of SNN include:

Applications Of SNN include pattern recognition, logic gate implementation , image and sound processing, computer vision and robotics etc. The paper here discusses some of its applications:

3.1. Pattern Recognition

Everything around in this digital world is a pattern that can either be noticed physically or it can be observed mathematically by applying algorithms.The technique of identifying patterns with the aid of a machine learning algorithm is known as pattern recognition. The classification of data based on

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previously acquired knowledge or on statistical data extrapolated from patterns and/or their representation is the key over here.

The raw data is processed and transformed into a form that is suitable for a machine to employ in a typical pattern recognition application. Classification and clustering of patterns are involved in pattern recognition.As mentioned previously,in classification, a pattern is given the proper class label based on an abstraction created using a collection of training patterns or subject-matter expertise.A data split created by clustering facilitates decision-making, the particular decision-making process that interests us.

Researchers have found that employing Spiking Neural Networks data, a convolutional layer produces the best results. However, employing a fully connected layer, does not yield good precision. Very fast, the model became over-fitted. Accuracy of above 80%. is achieved after experimenting with convolutional layers.

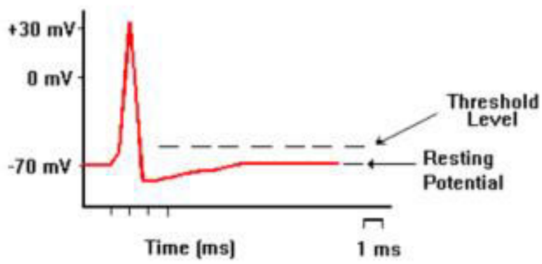
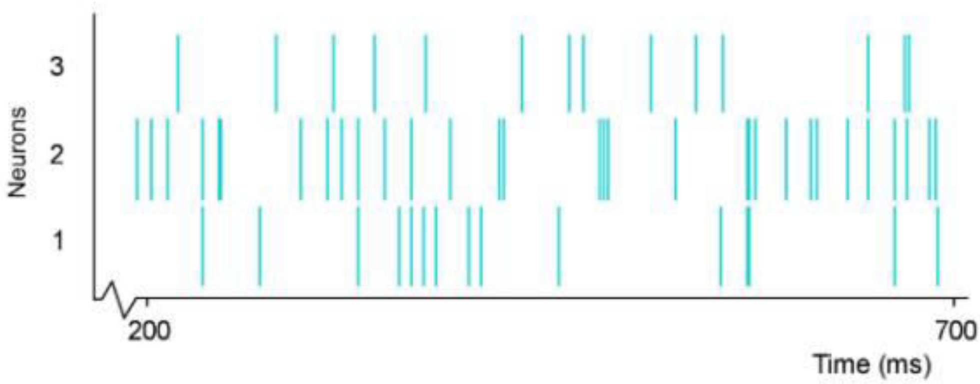


Fig [3.1]: Membrane potential



The time spike implemented by the researcher is 25ms, and it has been noted that a larger timestamp would enhance accuracy. In a typical computer architecture, training spiking neural network models is computationally intensive. Additionally, the SLAYER developers posted a successful performance on Loihi.

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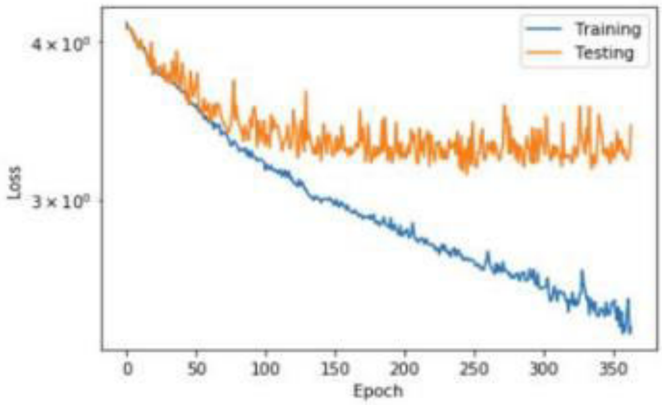

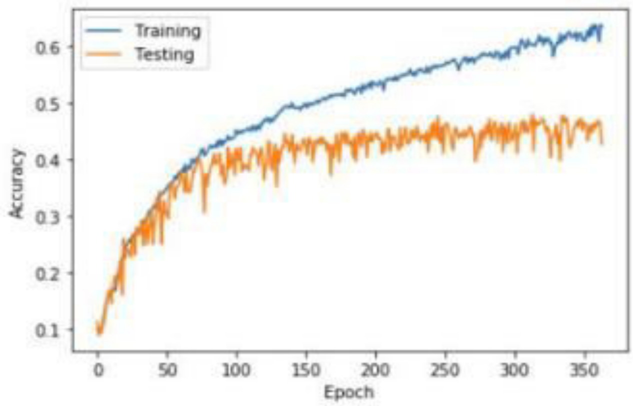

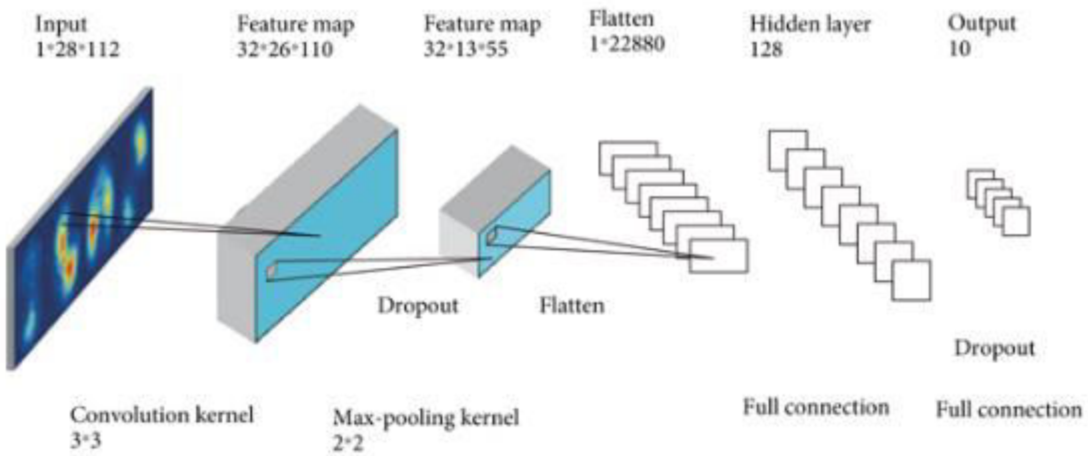

Thus, findings also indicate that the weight matrix between the V2 layer and output layer may be effectively trained using the tempotron supervised learning method, which increases recognition accuracy. The method requires substantially less data samples to obtain great classification performance compared to classification methods. Also, findings point to a new computational model inspired by the brain that uses the visual cortex's image processing system to achieve high-precision image recognition with sparse input. This work could serve as a foundation for spiking neural networks' widespread use in the field of intelligent computing, which would be beneficial and significant for both theoretical and practical research.

3.2. Logic Gate Functionality

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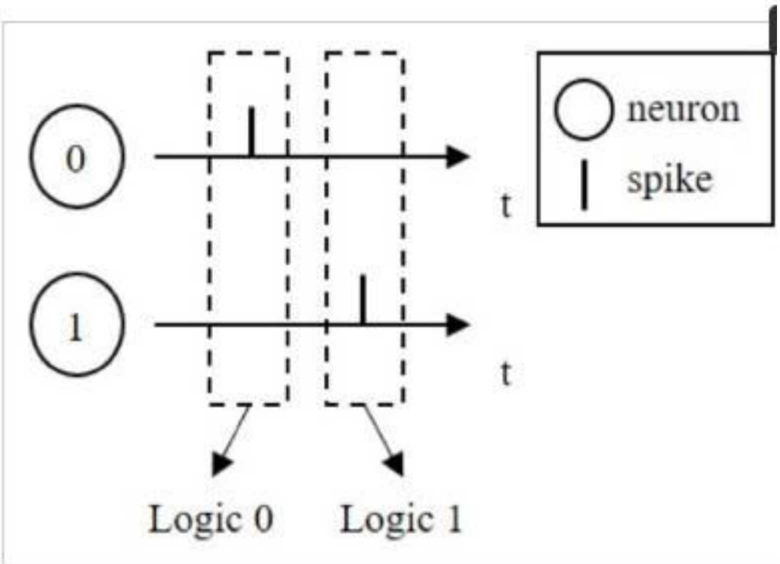
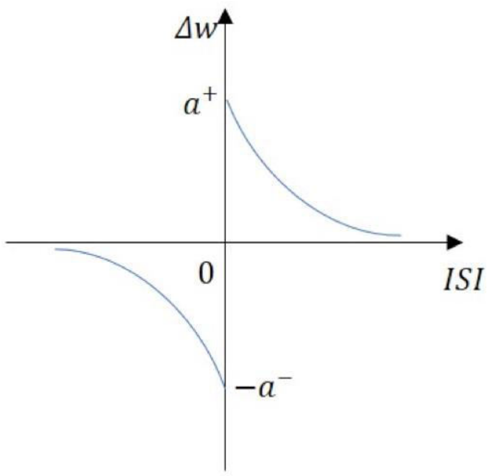
The fundamental element in a digital circuit, logic gates such as AND, OR, NOT gates, etc. Every small digital circuit uses logic gates. Artificial spiking neural networks can be used to enhance logic gates' functionality. A spiking neural network is substantially more effective than a perceptron neural network since it is a massively parallel distributed processor. They are helpful in applications like pattern recognition, robotics, prediction challenges, system identification, and control issues because they have a natural predisposition for accumulating experiential information and making it accessible for usage. Neuronal logic is the realisation of boolean logic using artificial spike-producing neural networks.



In their study ,researchers have developed and established SN P systems with astrocyte-like control to simulate logic AND, OR, NOT, NOR, XOR, and NAND gates. Each neuron in the systems has its own distinct spiking rule, the resultant SN P systems are straightforward and homogeneous. The SN P systems construct a Boolean circuit using logic gates, and synchronisation modules are used to control how synchronously distinct logic gates' outputs enter one another.The implementation of Logic gates using SNN involves focusing on the neuron model, its structure and learning strategy.We further discuss each one of them.



3.2.1. Spike Neuron Model

A popular model in SNN research that partially mimics the properties of biological neurons is the leaky-integrate-and-fire (LIF) neuron model. As implied by its name, its traits are mostly related to three processes: leakage, integration, and firing spike. The integrate-and-fire (IF) process without the

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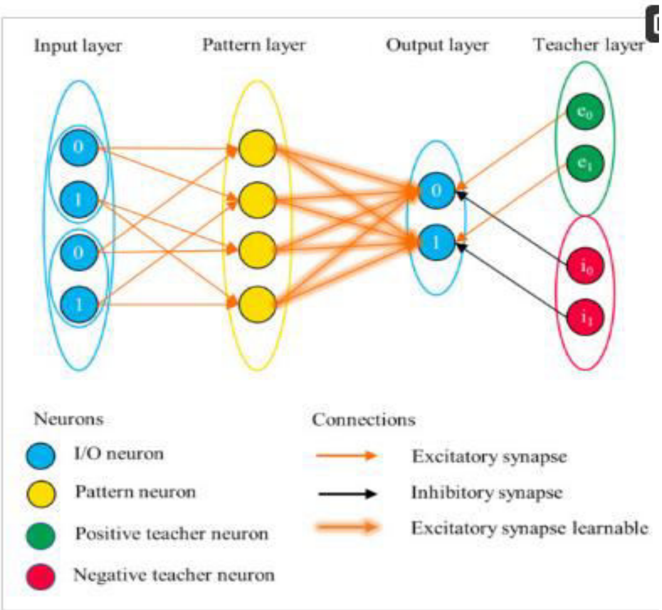
leaking process can be used to represent the LIF neuron model more simply, nevertheless it reduces the dynamic range of the neurons and eliminates their capacity for memory, which is unacceptable for this study. In order to construct the network, the LIF neuron model is used as the spike neuron model.

3.2.2.Network Structure

The network structure of the SNN logical operation moduleThe input layer, the pattern layer, the output layer, and the teacher layer are the four layers that make up the SNN logical operation module. One of these, the instructor layer, shown in Figure 2's dotted box, only exists during training and is eliminated afterward to enable the cascade between modules. The final trained and used logical operation module has a three-layer structure.

There are twice as many input layer neurons as logical variables. The input layer is made up of 2N neurons, generating N input logical neurons groups, which represent N logical variables, for N-ary logical operations. The pattern layer's design makes use of certain past knowledge.



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In most cases, the output layer has just one logical variable, which is made up of two neurons, output Neuron 0 and output Neuro 1, collectively known as the output logical neuron group. The structure and properties of the input and output logical neuron groups are identical. The only distinction is that they are situated in various locations inside the same module. By cascading modules—connecting the output of one module to the input of another—it is simple to create a network structure with a higher degree of complexity. There is complete connectivity between the synapses in the pattern layer and the output layer. The weights of these synapses, which are based on the STDP rule, change as learning progresses. These synapses are malleable, in other words.

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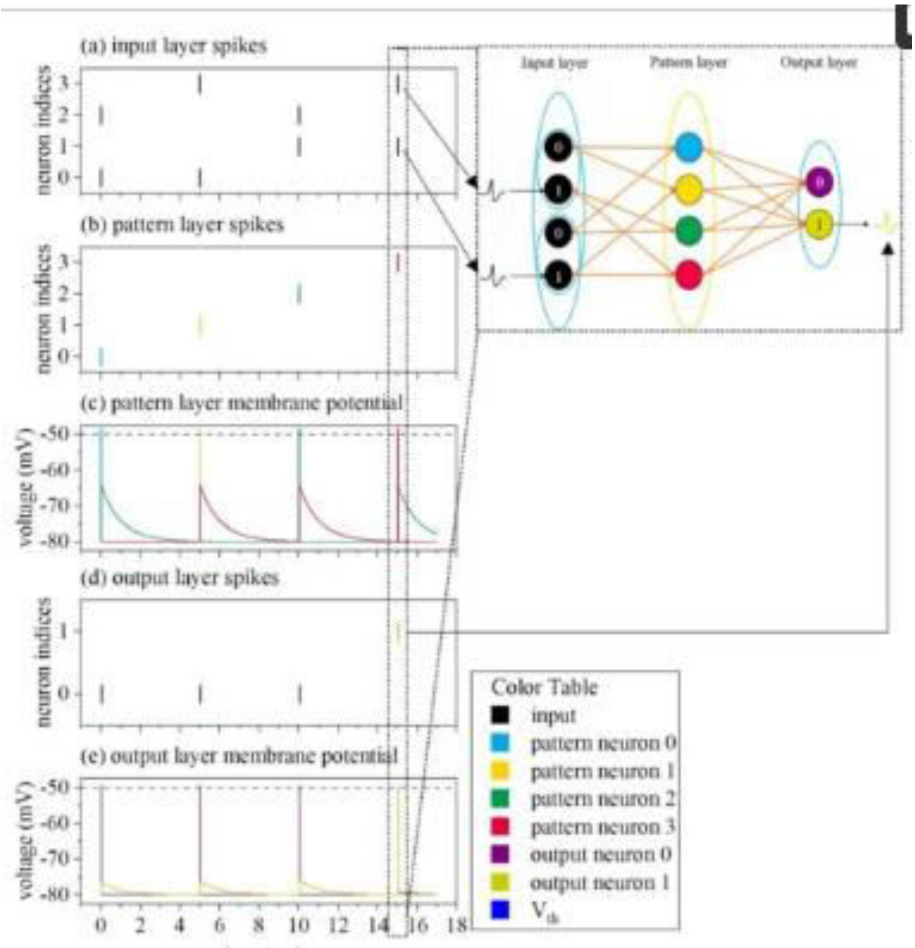
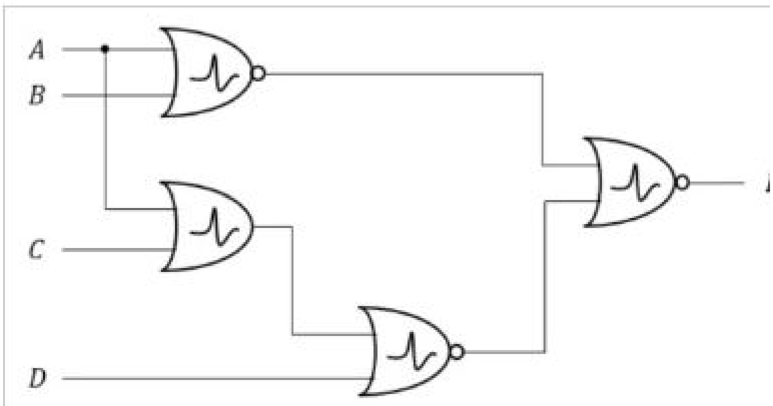


3.2.3 Training Method

Cells that fire together wire together' is the essence of the Hebb rule, and STDP is a charming learning rule that captures this. The close temporal connection between the spikes of pre- and post-synaptic neurons affects STDP.



In the framework of SNN, logical variables and operations are initially defined. The network structure is designed and constructed using LIF neurons in accordance with the traits of logical operation and SNN. STDP is employed for training, and experiments using fundamental SNN logical operation modules and combinatorial logic networks are used to demonstrate the viability and development potential of this paradigm. There is a lot of uniformity in this paradigm. The sole structural difference

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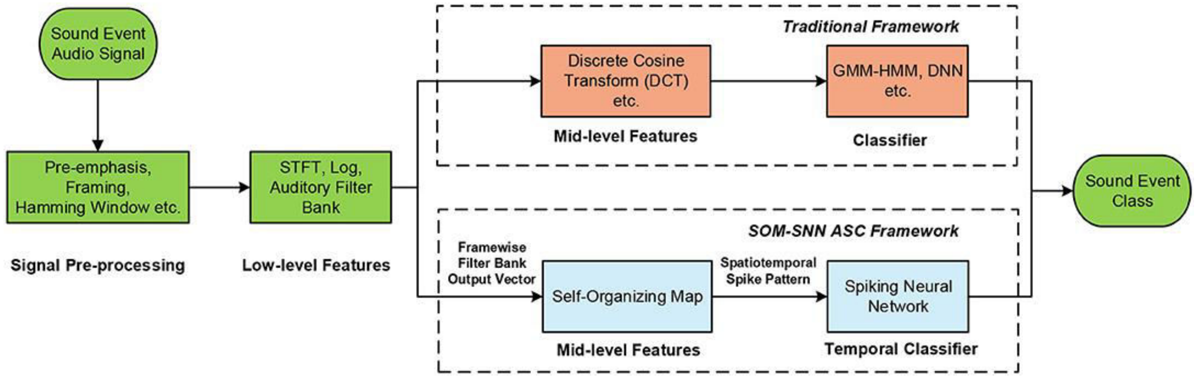
between logical operation modules is the weight of the synapses. It could make "small network, multi-function" a reality. The input layer and output layer adopt the same interface simultaneously, and the "building block" form encourages cascading between modules, making it simple to develop and assemble a large-scale network. This paper fills in the gaps regarding SNN's logical operation, establishes the groundwork for future research in this area, and investigates how computing systems might be built using SNN.

3.3. Image and Sound Processing

The automatic recognition of background noise in the environment is referred to as automatic sound classification. Environmental sounds help us understand our surroundings and are an important aspect of daily living, complementing visual clues. Applications for content-based sound categorization and retrieval, audio surveillance, sound event classification, and disease diagnosis, among others, are made possible by ASC technology .The traditional ASC systems are modelled after automatic speech recognition systems, which typically involve feature extraction, categorization, and pre-processing of acoustic signals.



Although deep learning models and a wealth of training data have significantly improved performance in recent years, two important obstacles still stand in the way of the widespread implementation of such frame-based autonomous systems on ever changing mobile and devices. First off, such devices frequently lack the ability to execute high-performance computation, which normally requires a lot of power. Second, with more background noise, the performance of cutting-edge GMM-HMM and deep learning models, using MFCC or GTCC features as input, drastically declines.

In order to efficiently encode and transfer information, event-based computation, Lological systems represent and process information in a way that is far more energy efficient than classic frame-based machine vision and hearing systems, where energy is only used during spike generation and transmission. One such class of neural networks driven by event-based computing is the spiking neural network (SNN). Many temporal learning rules have been developed for training the SNN on a temporal pattern categorization job.

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Model	Accuracy (%)
MLP	99.45
CNN	99.85
RNN	95.35
LSTM	98.40
SOM-RNN	97.20
SOM-LSTM	98.15
LSF-SNN (Dennis et al., 2013)	98.50
LTF-SNN (Xiao et al., 2017)	97.50
SOM-SNN (ReSuMe)	97.00
SOM-SNN (Maximum-Margin Tempotron)	99.60

The average results over 10 experimental runs with random weight initialization are reported.

When compared to other deep learning and SNN-based models, the SOM-SNN model's test accuracy of 99.60% is competitive.Once sufficient amounts of discriminative information have been gathered, the SNN-based classifier may recognise temporal aspects within the spatiotemporal spike pattern and produce an output spike.

Low-level spatiotemporal spike patterns cannot be classified by the SNN classifier, which only achieves 10.2 and 46.5% classification accuracy for latency- and population-encoded spike patterns, respectively. Since all encoding neurons fire during every sound frame, albeit at different times, for both latency- and population-encoded spike patterns, the synaptic weights either all increase or all decrease in the event of executing systems crash.

4. CONCLUSION

In this paper, we find an overview of the foundations of spiking neural networks (SNNs) and a literature review on their use in pattern recognition, logic gate implementation and image and sound processing application, highlighting the SNNs' enormous promise in the research community. SNNs have drawn a lot of interest in recent years and demonstrated that they are promising in terms of their ability to process temporal information, low power requirements, and great biological plausibility. However, there are still a number of problems that need to be resolved before SNNs can reach their full potential.

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