



## **SPIKING NEURAL NETWORK: BRIDGING THE GAP BETWEEN BIOLOGICAL BRAIN AND AI**

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### **ABSTRACT**

*Spiking neural network is a new method of artificial neural network, which is more aligned with the human brain. It considered more with neural processing and brain like intelligence. SNN is a hardware friendly and energy saving tool, which works on sparse event driven model. SNN is a powerful tool for deep learning, gradient learning, and reinforcement learning. Neural networks in AI includes interconnected artificial neurons or nodes structure, which helps further improvement in energy efficiency and processing speed of transforming information. SNN applied time series prediction and showcasing their potential in forecasting and predictive analytics. In this paper, we will review the mechanism, training process and its algorithms for today's high demanding applications like image recognition, video recognition, natural language processing and speech recognition etc.*

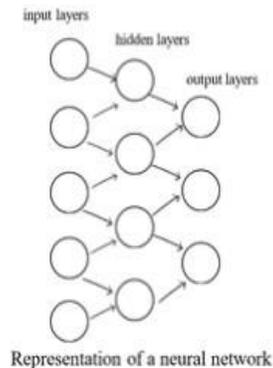
*We will know about synaptic plasticity, approximate Backpropagation through time (BPTT). This paper establish a precise mapping between the biological parameters of SNN and parameters of Deep neural network (DNN), we will talk about advantages, opportunities, challenges and its key concepts in between. Finally this paper look out for the future development of SNN in the direction of biological mechanism, network training, network designing, computing platform, and communications.*

**Keywords-** Neuron, Neural Network, SNNs, Supervised learning, unsupervised learning, reinforcement learning, algorithms.

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### **[1] INTRODUCTION**

Neural Network is a computational model which is inspired by the structure and functioning of human brain. It is made up of interconnected units called neurons. [1]



## [2] TYPES OF LAYERS IN NEURAL NETWORK :-

1. **Input layer:-** This layer takes inputs through bunch of neurons, where each neurons is connect to a input point like pixel input, numerical data.
2. **Hidden layer(s):-** This layer is the intermediate layer which process the input information and process the information in the output. This layer is responsible for learning and giving the structure to the data.
3. **Output layer :-** This layer is final layer where we get the prediction of the situation. It has its own set of output and bias where the final output or predicted output we can get.[2]

Neurons are the basic units of human nervous system which process information by propagating electrochemical signals. In nervous system there is presence of  $\text{Na}^+$ ,  $\text{K}^+$ , and  $\text{cl}^-$  ions. The human brain consists of neuron in such a way to form complex nervous system which encodes and process the information. A SNN model is based on the spiking behave of neuron, here a neurons fire a pulse/spike when their membrane potential crosses the threshold point, this model is trained by tweaking the synapticweights which is based on the timing of spikes, this helps the neurons to learn any new pattern, whereas anANN model processes the data by mathematical functions and weights.[3]

SNN models are used more in current scenario is just because of its energy efficiency, real time processingand temporal nature(brain like processing) some big challenges in SNN is that, it is complex to train, un-mature frameworks, computationally intensive means require more computational power and powerful GPU.

Lets get deep into SNN models, there are three commonly used neuron models here:-

1. Leaky integrate-and-fire (LIF) model
2. Hodgkin-huxley (HH) model
3. Izhikevich Model

**1) Leaky integrate-and-fire (LIF) model :-** It is the simplest model in SNN, lets first understand the Membrane potential equation of this model

$$\tau_m \cdot dV(t) = -V(t) + R \cdot I(t)$$

Here  $V(t)$  is membrane potential,  $R$  is resistance,  $I(t)$  is input current and  $\tau_m$  is membrane's time constant when the  $V(t)$  cross the  $V_{th}$  (threshold) then the neuron fires the spike, and after that  $V(t)$  got reset to  $V(\text{reset})$ .[\[4\]](#)

### Spiking mechanism-

First input spikes got received by neuron and its membrane potential get increase, then due to multiple input spikes at the input, the membrane potential of all these get integrated, and the moment this integrated membrane potential crosses the threshold then the neuron fire out the spike to the next neuron.

**Synaptic weights:-** Synaptic weight decides the influence of an spike on the receiving neuron, and this weight gets adjusted during the training process.[\[5\]](#)

### Learning Algorithms:-

$$\Delta w = \begin{cases} A^+ e^{-\Delta t / \tau^+} & \text{if } \Delta t > 0 \\ A^- e^{\Delta t / \tau^-} & \text{if } \Delta t \leq 0 \end{cases}$$

1. **Spike-Timing-Dependent Plasticity (STDP):** In this algorithm synaptic weight gets adjusted on basis of timing difference between presynaptic and post-synaptic spikes. Here  $\Delta w$  is the weight change,  $\Delta t$  is the time difference,  $A^+$  and  $A^-$  are learning rates and  $\tau^+$ ,  $\tau^-$  are time constants for these rates[\[13\]](#)
2. **Approximate backpropagation:** In this algorithm traditional back propagation (of NN) is adapted in the context of SNN, in which gradient descent is used to minimize errors.

### Training techniques:-

1. Supervised learning: SNN get trained by label data
2. Unsupervised learning: SNN identifies the structures and patterns without labels, like clustering. [\[18\]](#)
3. Reinforcement learning: SNN interact with the environment and learns by rewards.

## Simulation tools

-NEST: a widely used SNN simulation tool

-BindsNET: python library for simulating SNNs.

Example of workflow:-

Initialize network: Defining of neuron models ,layers and synaptic connections.

1. Input encoding: converting input data into spikes by rate or temporal coding techniques.
2. Training: updating the synaptic weights by applying learning rules.
3. Evaluation: evaluating the network performance by accuracy and energy efficiency metrices.[\[15\]](#)

## 2.) Hodgkin - Huxley (HH) Model:

This model has been conducted in the axon of a squid in which has two types of channels which are  $k^+$  channel and  $Na^+$  channel which involves in potential actions .These channels are responsible for behaviour . Structure change of protein results in permeability which results in opening and closing of gates. It's a detailed neuron mode which accurately simulate the electrical nature of biological neurons. This model describes the changes in membrane potential ,and it has included the dynamics of ion channels.[\[14\]](#)

$$C_m \frac{dv_m(t)}{dt} = I_{ion}(t) + I_{syn}(t)$$

where  $C(m)$  is membrane capacitance,  $V(m)$  is potential ,  $I(syn)$  is synaptic input current ,  $G(k)$  represents conductance of  $k^+$  ion ,  $E(k)$  represents reversal potential of  $k^+$ ,  $G(na)$  represents conductance of  $Na^+$  ion,  $G(l)$  is leak conductance ,  $E_l$  is leak reverse potential and  $n$ ,  $m$  and  $h$  are dimensional quantities between 0 & 1.[\[12\]](#) Membrane potential represents the difference of potential between outside and inside, this change is represented in terms of membrane current and conductance of ion channels. This model is computationally expensive it involves many differential equations and parameters, so its quite challenging for large scale applications. HH model is used extensively for neuroscience research for understanding neuron behaviour and action potential generation.[\[10\]](#)

### 3.) Izhikevich Model :

This model is simple and very efficient, which stimulates the spiking behaviour of neuron. This model was introduced in 2003 by Eugene Izhikevich. This model can't give the detailed explanation like Hodgkin - Huxley (HH) Model but this is more realistic spiking pattern for replication. [17]

This model uses two basic differential equations :

1) Membrane Potential Equation (v):

$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I$ ; where v is the membrane potential of neuron and I is the input current .

\*Recovery Variable Equation (u):

$\frac{du}{dt} = a(bv - u)$ , where u is the recovery membrane potential and I is input current. [11]# parameters :

- a. : time scale of the recovery variable of u.
- b. : sensitivity of recovery variable u to the subthreshold fluctuations of v .
- c. : membrane potential reset value after a spike
- d. : reset value of recovery variable u after a spike.

\*Model Dynamics : when membrane potential (v) exceeds the threshold (usually 30 mV) then neuron spikes.

At that moment : If  $v \geq 30$  mV, then  $v \leftarrow -c$  {  $u \leftarrow u + d$

We can simulate the neuron type by using different parameters of Izhievich model, like ;  
 Regular Spiking (RS) Neuron :

$a=0.02, nb=0.2, c = -65, 8d=8$

Intrinsically Bursting (IB) Neurons:

$a=0.02, b=0.2, c = -55, d=4$  Chattering (CH) Neurons:  $a=0.02, b=0.2, c = -50, d=2$  [21]

**Izhikevich model** is very powerful for neuroscience research because this is computationally efficient and it can accurately produce the complex spiking patterns . This model has the

capability to simulate various neuron behavior and making it ideal for large - scale network simulations. [14]

### **Difference between SNN and ANN:-**

#### **Spiking Neural Network (SNN)**

-Low precision, low power consumption, high efficiency performance

-Suitable for simpler tasks-Suitable for many of complex learning tasks like-tasks pattern recognition

-Deep SNN models are difficult to train, because the ,due to the availability

theory of SNN is not mature yet ,less tools and training

#### **Artificial Neural Network (ANN)**

- High precision and good

- ANN used for many machine classification, regression,

- ANN models are easier to train

of mature training techniques

### **[3] HISTORY OF SNN:-**

**1990s:** SNN developed by neuroscience and cognitive science researchers, where they wanted to understand the functioning and information processing of brain. [10] They studied the spiking behaviour of biological neurons and developed a model. [20]

**Early 2000s:** During this, researchers of computational neuroscience and artificial intelligence adopted this developed SNN model. They seen that SNN has capabilities of real time processing and energy efficiency, which was absent in the traditional ANN models. So during this SNN got promising response for cognitive computing and neuromorphic engineering applications. [22]

**2010s:** In recent years, SNN got more promising interest, specially with advancements of neuromorphic hardware and deep learning techniques. Researchers and industries are interested in applications like robotics, sensory processing and neuromorphic computing. Due to the development of neuromorphic hardware, SNN got a clear path way to integrate in real world applications. [25]

**Present and Future:** As history of SNN is evolving, researchers and developers are exploring its potential and capabilities further. for future its moreover visible that SNN will grow

extensively, because of specialities like cognitive computing, real time processing and energy efficiency.[28]

#### **[4] Advantages:-**

Biological realism: Closely mimic spiking behaviour of biological neuron.

Temporal dynamics: SNN model effectively processes time based information, like how neuron encodes and decodes

#### **The temporal patterns Energy efficiency:**

- i. Sparse Activation: SNN only fires the input signal when it crosses the threshold,[11] so its overall reduces the energy consumption.
- ii. Event-driven processing: SNN is based on event driven processing means the processing and computation only gets done when a spike gets at input.[8]

Low latency: SNN gives immediate response when it detects a spike.

Asynchronous operation: Asynchronous nature of SNN model reduces the latency[5] of it in real world applications.

Specialized hardware: SNN is compatible with neuromorphic hardware,[27] which is specially design to run SNN algorithms efficiently.

Scalability: By using neuromorphic hardware, large scale models[4] can be easily scaled.Noise robustness: SNN inherently tolerant-noise.

Fault Tolerance: SNN's distributed architecture makes it fault-Tolerant. individual neuron failures significantly affect the network performance

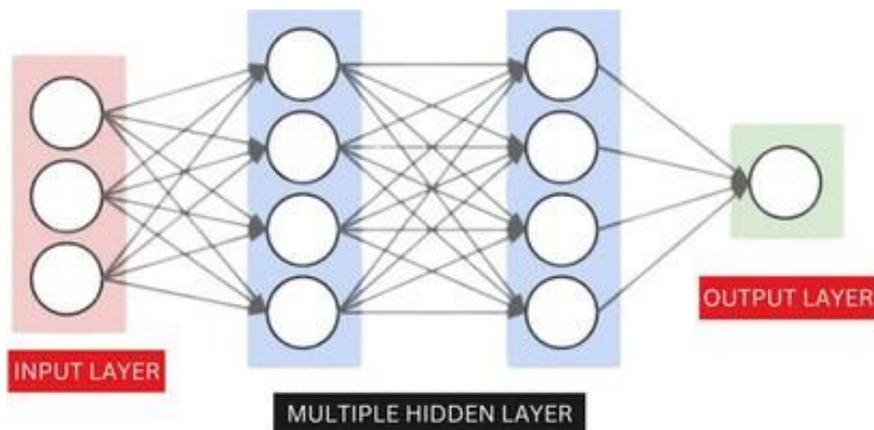
#### **[5] BIOLOGICAL NEURONS:-**

Neurons are the basic working units that process the information from electrochemical signals to in action potential.  $\text{Na}^+$   $\text{k}^+$  and  $\text{cl}^-$  are the basic working ion which exhibit in the cell and helps the information to process.[1] A neuron has four main component dendrites, soma, axon and synapse[21]. Dendrites are the part of cell body, which is a tree like structure. The structures can extend for collecting more and more information. Their main function is to receive the information and further transfer the information to another neuron and the other neuron which receives the information and signals from the dendrites. When dendrites receives a signal then cell transform the signals from body, where the body

further records the process in transmit through the axon.[27] Let's see an example just think a friend calls, our phone receive signals that is dendrites and further the signals reach to our cell body and we make the decision or react the situation like we receive or ignore the call. This complete process of neuron helps to maintain the communication between the nervous system and this function helps the nervous system smoothly.

Soma is the body of neuron.[5] It has a central part which plays very important role for the functioning of neurons. Soma is a part of neuron which has nucleus and cytoplasm nucleus has DNA that maintains the functioning of neuron.

Soma help then you to live and to do proper functioning . It transmits the signals which which helps to process the information.

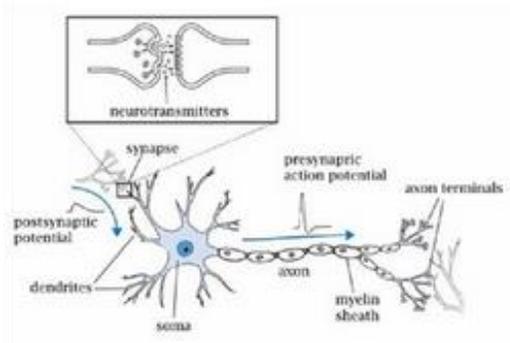


When signals are transmitted through dendrites then signals are analysed and processed by Soma then, it decides whether the signals are strong or weak and then decide whether the signals can be transmitted or not. Soma contains ribosomes and endoplasmic reticulum which has lots of protein, these proteins help in body growth preparing and communication. [13] Axon is a part of neuron which is very large and cylindrical in shape which transmits the signals

to cell body, other neuron, muscle, gland. It's a tube-like structure which comes from cell body. In the end of the axon there are terminals which transmit the signals from one neuron to other that combine with target cell with synapse. Axons are covered with myelin sheath,

which is a fatty layer. Myelin sheath enhance the conductance and makes it faster and more efficient.

Axon help the neuron to communicate more efficiency and had the body to co-ordinate with the different parts of body.[31]



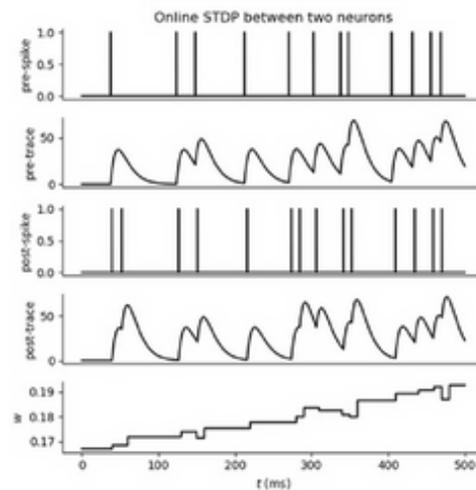
Synapse is a complex structure which facilitates the communication between the neurons. Synapse[13] has basically made up of three parts.

Presynaptic neuron- Basically this type of neuron transmit the signal from Axon terminal synaptic[33] vesicles through neurotransmitter.

Synaptic cleft- This is very short gap between the presynaptic neuron and postsynaptic neuron. Postsynaptic neuron this neuron receive the signal . This neuron then try have receptors or cell body have receptors which detects the neurotransmitter.

Basically the main function of synapse is to deliver the information from one neuron to another neuron, this transferred the electrical signals or action potential[19] and convert the neurotransmitters. When action potential presynaptic[28] neuron reaches to the exact terminal then synaptic vesicles activities.

Synaptic vesicles are used with free and Patrick membrane[29] and release the neurotransmitter synaptic cleft.[33] When neurotransmitters and receptors bind for postsynaptic neuron[41] to response or journey the information for a new action. Basically in this process the new rules are effectively communicate with each other and coordinates with the nervous system.



Artificial neural networks ANN and spiking neural networks SNN both are neural network models which mimic biological brain[45]. But their functioning and implementations are very different from each other let's see how:

In ANN the neuron layers are arranged which typically have input layer hidden layer and output layer. In the flow of value process to activation function of neurons[51] are continuous and transmit the information is also continuous. Basically ANN is train with back propagation algorithm which uses the gradient decent method. In Spiking neural system (SNN) neurons are also arranged but neuron spikes are discrete instead of continuous values.

#### [6] APPLICATIONS:-

SNN in computer vision- SNN have very unique and exciting applications in the computer vision. Here are few:-

**Object recognition** : SNN is trained in object recognition task [1]. Traditionally neural network are mutable and uses brain inspired approach so that they work on real time processing which make them very efficient.

**Image classifications** : SNN is used in image classification task. In this classification packing behaviour is used in which power consumption are reduced and processing is faster.

**Edge detection**: SNN is implemented in edge detection algorithm [12]. These algorithms are very efficiently used in lowpower devices just like a mobile devices or iot sensor.

**Motion detection** : In motion detection, SNN is also used temporal dynamics of SNN is

suitable for detection of real time motion which are very useful in autonomous driving system.[55]

**Pattern recognition :** SNN is very helpful in pattern recognition [10] their ability of processing and recognition complex and very beneficial in the field to robotics and AI applications.

### [7] CHALLENGES:-

**Training complexity :** SNN is very complex to train. Traditional neural network are mutable so that the we have to take care between the time and spiking pattern.[53] That's make it more time consuming and challenging.

**High power CPU and GPU requirements :** For training and simulation in SNN we need high computational power consumption. CPU and GPU[35] are very heavy and high demand so that the power consumption between them is also high so if we use them in practical applications they are very costly which makes it inefficient.

**Scalability:** It is very challenging to convert SNN into a large scale system.[15] For their large architecture and computation requirements it's very difficult to implement them in large networks. So there scalability issue their adoption in real world applications is slow.[16]

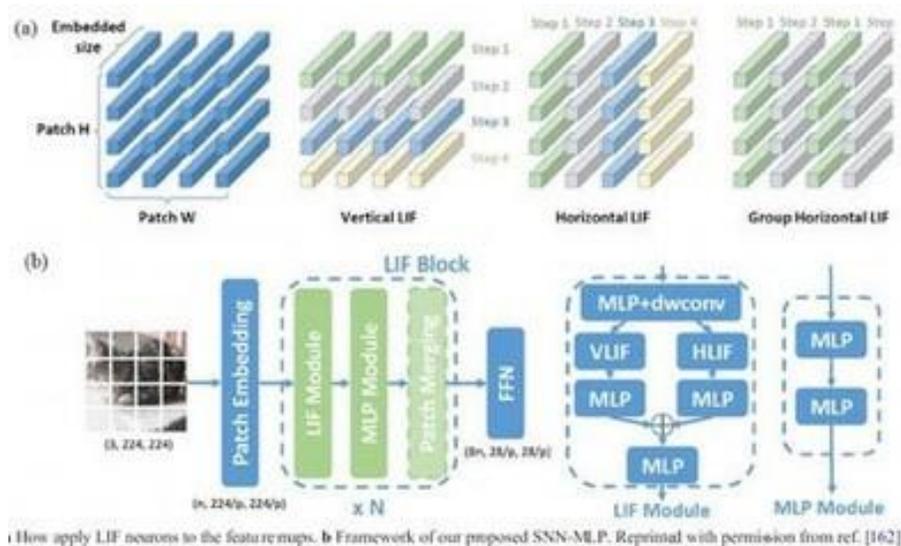
**Interference with the traditional system :** Traditional networks and SNN integration they have many compatibility issues. The implementation of SNN [19] into the existing systems are very difficult because both have different working mechanisms. This will create the interference problem which affects the overall performance of the system. [60]

### [8] CONCLUSION:-

In this tribute first be introduced the development of the mirror network describe the background of the SN n and analyse it's processing mechanism in detail after that we introduced the layers of the neural network. We also introduced the http rules that stimulate the biological synthetic behaviour and commonly used coding methods of SNN, after that we studied the models of the accident that are LIF model assess model and Izhikevich model.

We conduct an in-depth analysis and detail comparison of common algorithms of SNN and clarify the advantage and disadvantage of different algorithms.

This paper can enable readers to fully understand the learning algorithm of SNN. Our work provide the comparison between the SNN and ANN, history of ascendant advantages and disadvantages of SNN its applications in the field of object recognition image classification h detection motion detection and pattern recognition. Hopefully this review and attract researchers from different discipline and more the different development of artificial intelligence through communication and cooperation.



The SNN algorithm based on STDP and spike focus on learning shallow networks its challenging to train the large scale definite works the method of ANN and SNN source the technical problems for training deep SNN to a certain exchange. The SNN model is a new generation of neural networks with more biological interpretability. At present there was not sufficient technology and we give limitations to SNN, we we believe that researchers need to make more immacible progress and breakdown through the following aspect:

1. **Biological mechanism** : Correct understanding for actual biological neural coding in the brain function andhow to abstract the spiking neural model and good learning ability according to the brain science researchthat help us to solve the real large scale deep level SNN.
2. **Design and train SNN** : SNN supervisor learning algorithm is a new research field the key to research is to design a journal modelling and learn framework for SNN based

on supervised and unsupervised learning algorithm.

3. **Computing Platforms** : Bing of its advantage of low power consumption SNN based on heart chip design can realize a deep and large scale network therefore building a neural computing platform which is highly efficient and strong universality can promote the development of SNN.
4. **Neuroscience research** : Synonyms to meet the parallel information processing mechanism of the brain to the variant degree because of the high complexity it cannot be completely determine into the real world. Plural computing science is based on the research result of the biological neural system and the user computer simulation to complete the process of the complex task is a multi level system with a high complex structure and function the current level of the computerize the accurate simulation of the nervous system.

Based on the specific information of ANN and processing model of SNN can be used in a biological nervous system modelling tool for the simulation and quantitative analysis. The advantage of assignment are emboid in a system with sensor chips and powerful essential algorithms. It's a power consumption and running speeds are unmatched by ANN therefore the research on models with more biological authenticity and good learning ability. It still the main work of ascendant research research of biological system is the foundation for promoting the development of the SNN and the result of brain like chip in is the key to the application of SNN. Therefore the development of SNN needs multi faceted coordination.

**[9] REFERENCES:-**

- [1]. Azevedo FA et al (2009) Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled- up primate brain. *J Comp Neurol*.
- [2]. Maass W (1997) Networks of spiking neurons: the third generation of neural network models. *Neural Netw* 10(9):1659– 1671.
- [3]. Hodgkin AL, Huxley AF (1952) A quantitative description of membrane current and its application to conduction and excitation in nerve. *Journal of Physiology*, vol. 117.
- [4]. Hubel DH, Wiesel TN (1959) Receptive fields of single neurones in the cat's striate cortex. *The Journal of Physiology*, vol. 148.es.
- [5]. Taherkhani A, Belatreche A, Li Y, Cosma G, Maguire LP, McGinnity TM (2020) A review of learning in biologically plausible spiking neural networks. *Neural Netw* 122:253–272.
- [6]. Tan C, Šarlija M, Kasabov N (2020) Spiking neural networks: background, recent development and the NeuCube architecture. *Neural Process Lett* 52(2):1675–1701.
- [7]. Diehl PU, Cook M (2015) Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Front Comput Neurosci* 9:99.
- [8]. Legenstein R, Pecevski D, Maass W (2008) A learning theory for reward-modulated spike-timing-dependent plasticity with application to biofeedback. *PLoS Comput Biol* 4(10)
- [9]. Esser SK et al (2016) Convolutional networks for fast, energy-efficient neuromorphic computing. *Proc Natl Acad Sci U S A* 113(41):11441–11446.
- [10]. Mozafari M, Ganjtabesh M, Nowzari-Dalini A, Thorpe SJ, Masquelier T (2019) Bio-inspired digit recognition using reward-modulated spike-timing-dependent plasticity in deep convolutional networks. *Pattern Recogn* 94:87– 95.
- [11]. Falez P, Tirilly P, Bilasco IM, Devienne P, Boulet P (2019) Multi-layered spiking neural network with target timestamp threshold adaptation and STDP
- [12]. Khacef L, Miramond B, Barrientos D, Upegui A (2019) Self-organizing neurons: toward brain-inspired unsupervised learning," in *IEEE International Joint Conference on Neural Networks (IJCNN) 2019 Research Progress of Spiking Neural Network in Image Classification: A Review*
- [13]. Xiang S, Ren Z, Song Z, Zhang Y, Hao Y (2020) Computing Primitive of Fully VCSEL-Based

All-Optical Spiking Neural Network for Supervised Learning and Pattern Classification. *IEEE Trans Neural Netw Learn Syst* PP(99):1–12

[14]. Wu J, Chua Y, Li H (2018) A biologically plausible speech recognition framework based on spiking neural networks. In: 2018 International Joint Conference on Neural Networks (IJCNN)

[15]. Yang Y, Ren J, Duan F (2022) The spiking rates inspired encoder and decoder for spiking neural networks: an illustration of hand gesture recognition. *Cogn Comput*:1–16

[16]. Yao Y, Yu Q, Wang L, Dang J (2019) A spiking neural network with distributed Keypoint encoding for robust sound recognition. In: 2019 International Joint Conference on Neural Networks (IJCNN)

[17]. Mansouri-Benssassi E, Ye J (2019) Speech emotion recognition with early visual cross-modal enhancement using spiking neural networks," in 2019 International Joint Conference on Neural Networks (IJCNN).

[18]. Zhu L, Dong S, Li J, Huang T, Tian Y (2020) Retina-Like Visual Image Reconstruction via Spiking Neural Model. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)

[19]. Maass W, Markram H (2004) On the computational power of circuits of spiking neurons. *J Comput SystSci* 69(4):593–616

[20]. O'Connor P, Neil D, Liu SC, Delbruck T, Pfeiffer M (2013) Real-time classification and sensor fusion with a spiking deep belief network. *Front Neurosci* 7:178

[21]. Perez-Carrasco JA, Bo Zhao, Serrano C, Acha B, Serrano-Gotarredona T, Shouchun Chen, LinaresBarranco B (Nov 2013) Mapping from frame-driven to frame-free event-driven vision systems by low-rate rate coding and coincidence processing–application to feedforward ConvNets. *IEEE Trans Pattern Anal Mach Intell* 35(11):2706–2719

[22]. Esser SK et al (2016) Convolutional networks for fast, energy-efficient neuromorphic computing. *Proc Natl Acad Sci U S A* 113(41):11441–11446

[23]. Hunsberger E, Eliasmith C (2016) Training spiking deep networks for neuromorphic hardware

[24]. Cao Y, Chen Y, Khosla D (2014) Spiking deep convolutional neural networks for energy-efficient object recognition. *Int J Comput Vis* 113(1):54–66

[25]. Diehl PU, Neil D, Binas J, Liu M, Liu SC (2015) Fast-classifying, high-accuracy spiking deep networks [26.] Hubel DH,

Wiesel TN (1959) Receptive fields of single neurones in the cat's striate cortex. *The Journal of Physiology*, vol. 148

- [27]. Bing Z, Meschede C, Rohrbein F, Huang K, Knoll AC (2018) A survey of robotics control based on learning-inspired spiking neural networks. *IEEE Trans Robot* 34(1):1–13
- [28]. Immunity to device variations in a spiking neural network with Memristive Nanodevices. *IEEE Trans Nanotechnol* 12(3):288–295
- [29]. Brader JM, Senn W, Fusi S (2007) Learning real-world stimuli in a neural network with spike-driven synaptic dynamics. *Neural Comput* 19(11):2881–2912
- [30]. Moraitis T, Sebastian A, Eleftheriou E (2018) Spiking neural networks enable two-dimensional neurons and unsupervised multitimescale learning. In: 2018 International Joint Conference on Neural Networks (IJCNN)
- [31]. Luke R, McAlpine D (2019) A Spiking Neural Network Approach to Auditory Source Lateralisation. In: ICASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2019)
- [32]. Qiao GC, Ning N, Zuo Y, Hu SG, Yu Q, Liu Y (Oct 7 2021) Direct training of hardware-friendly weight binarized spiking neural network with surrogate gradient learning towards spatiotemporal event-based dynamic data recognition. *Neural Comput & Applic* 33(19):12317–12332
- [33]. Yu Q, Shen J, Wang Y, Tang H, Gang P (2018) Jointly learning network connections and link weights in spiking neural networks. In: Twenty-Seventh International Joint Conference on Artificial Intelligence {IJCAI-18}
- [34]. Tavanaei A, Kirby Z, Maida AS (2018) "Training spiking ConvNets by STDP and gradient descent," in 2018 International Joint Conference on Neural Networks (IJCNN)
- [35]. Lee C, Panda P, Srinivasan G, Roy K (2018) Training deep spiking convolutional neural networks with STDP-based unsupervised pre-training followed by supervised fine-tuning. *Front Neurosci* 12:435
- [36]. Tavanaei A, Maida A (2019) BP-STDP: approximating backpropagation using spike timing dependent plasticity. *Neurocomputing* 330:39–47
- [37]. Bellec G, Scherr F, Hajek E, Salaj D, Legenstein R, Maass W (2019) Biologically inspired alternatives to backpropagation through time for learning in recurrent neural nets
- [38]. Zheng H, Wu Y, Deng L, Hu Y, Li G (2020) Going deeper with directly-trained larger spiking neural networks
- [39]. Mostafa H (Jul 2018) Supervised learning based on temporal coding in spiking neural networks. *IEEE Trans Neural Netw Learn Syst* 29(7):3227–3235
- [40]. Mesnard T, Gerstner W, Brea J (2016) Towards deep learning with spiking neurons in energy

based models with contrastive Hebbian plasticity

[41]. Querlioz D, Bichler O, Gamrat C (2018) Simulation of a memristor-based spiking neural network immune to device variations. In: IEEE

[42]. Shrestha A, Ahmed K, Wang Y, Qiu Q (2017) Stable spike-timing dependent plasticity rule for multilayer unsupervised and supervised learning: In: 2017 International Joint Conference on Neural Networks (IJCNN)

[43]. Tavanaei A, Masquelier T, Maida AS (2016) Acquisition of Visual Features through Probabilistic SpikeTiming-Dependent Plasticity

[44]. Nessler B, Pfeiffer M, Buesing L, Maass W (2013) Bayesian computation emerges in generic cortical microcircuits through spike-timing-dependent plasticity. PLoS Comput Biol 9(4)

[45]. Tavanaei A, Maida AS (2017) Multi-layer unsupervised learning in a spiking convolutional neural network. In:

International Joint Conference on Neural Networks

[46]. Thiele JC, Bichler O, Dupret A (2018) A timescale invariant STDP-based spiking deep network for unsupervised online feature extraction from event-based sensor data," in 2018 International Joint Conference on Neural Networks (IJCNN)

[47]. Yu M, Tang H, Gang P (2018) A supervised multi-spike learning algorithm for spiking neural networks. In: 2018 International Joint Conference on Neural Networks (IJCNN)

[48]. Morrison A, Aertsen A, Diesmann M (2007) Spike-timing-dependent plasticity in balanced random networks. NeuralComput 19(6):1437–1467

[49]. Diehl PU, Cook M (2015) Unsupervised learning of digit recognition using spike-timing-dependent plasticity.

Front Comput Neurosci 9:99

[50]. Iyer LR, Basu A (2017) Unsupervised learning of event-based image recordings using spike-timingdependent plasticity. In:  
International Joint Conference on Neural Network

[51]. Xiao R, Yu Q, Yan R, Tang H (2019) Fast and accurate classification with a multi-spike learning algorithm for spiking neurons," In: Twenty-Eighth International Joint Conference on Artificial Intelligence {IJCAI-19} [52]. Srinivasan G, Roy S, Raghunathan V, Roy K (2017) Spike timing dependent plasticity based enhanced selflearning for efficient pattern recognition in spiking neural networks. In: 2017 International Joint Conference on Neural Networks (IJCNN)

[53]. Liu D, Yue S (2018) Video-based disguise face recognition based on deep spiking neural network. In: 2018 International Joint Conference on Neural Networks (IJCNN)

[54]. Saunders DJ, Siegelmann HT, Kozma R, Ruzinkao M (2018) STDP learning of image patches with convolutional spiking neural networks. In: 2018 International Joint Conference on Neural

- Networks (IJCNN) [55]. Hazan H, Saunders D, Sanghavi DT, Siegelmann H, Kozma H (2018) Unsupervised Learning with SelfOrganizing Spiking Neural Networks. pp. 1–6
- [56]. Legenstein R, Pecevski D, Maass W (2008) A learning theory for reward-modulated spike-timing-dependent plasticity with application to biofeedback. *PLoS Comput Biol* 4(10)
- [57]. Legenstein R, Chase SM, Schwartz AB, Maass W (2010) A reward-modulated Hebbian learning rule can explain experimentally observed network reorganization in a brain control task. *J Neurosci* 30(25):8400–8410
- [58]. Liu J, Zhao G (2018) A bio-inspired SOSNN model for object recognition. pp. 1–8
- [59]. Mozafari M, Ganjtabesh M, Nowzari-Dalini A, Thorpe SJ, Masquelier T (2019) Bio-inspired digit recognition using reward-modulated spike-timing-dependent plasticity in deep convolutional networks. *Pattern Recogn* 94:87–95
- [60]. Falez P, Tirilly P, Bilasco IM, Devienne P, Boulet P (2019) Multi-layered spiking neural network with target timestamp threshold adaptation and STDP