A Comprehensive Comparison of Artificial and Spiking Neural Networks

Abstract—In this paper, we discuss available artificial neural networks and Spiking Neural Networks and their ways of solving the problem of Handwritten character recognition by using the MNIST dataset which is an open-source dataset.MNIST is a subset of NSIT dataset and has a set of over 60000 images of handwritten numbers. There is a pursuit to build something similar to the human brain. The human brain is the best computer there isand very energy efficient too. Attempts and various frameworks have been introduced to mimic the human brain but there is still a worthy mile to be covered before we build a computer as wonderful as the human brain. We compare the Convolution Neural Network, Self Organizing Maps, and Supervised and Unsupervised Spiking neural networks which classify the MNIST dataset and also give an overview of their efficiencies.

Index Terms—Index - Convolution Neural Networks, Spiking Neural Networks, Hebbian learning, Spiking Neural Networks.

I. INTRODUCTION

Artificial Neural Networks (ANN) are inspired by the way human brain works. An ANN is a highly interconnected network with neurons. Every neuron has a weight and a bias. These attributes determine if a particular neuron fires based on the given input. Just like the human brain a neural network needs examples to learn from. The learning can be either supervised or unsupervised. But the main drawback of a neural net is that, it is not very closer to the human brain as human brain doesn't need thousands of labeled examples to detect handwritten digits. We also have another unsupervised learning network called self-organizing map which was introduced by Kohonen, the network forms cluster by themselves based on the input data. However these networks are deterministic and synchronous, which is not how the human brain works. Human brain works asynchronously and also is non-deterministic and also it does not separate the memory and the processing where as all the computing that currently exist do separate the memory and the processing. This gave a way for developing the hardware which is similar to human brain and does not separate the working memory and the processing. This led to development of a field called Neuromorphic computing and there was a breakthrough when the design of memristor was put forth.Spiking neural networks is a one such network which generates spike trains based and the neuron fires if the spike is greater than the threshold. The spikes are asynchronous and aims at making the model a step closer to human brain. But training a spiking is difficult but it has a few methods for supervised and unsupervised learning and also often a trained Convolutional neural network can be converted to Spiking Neural Networks. We will discuss the advantages and disadvantages of these techniques and comment on what might the future hold for these domains.

II. METHODOLOGIES

In this section we will review each of the methods which solve MNIST handwritten digits classification problem. Be fore proceeding, we would like to outline the features of the MNIST dataset which we will be using to compare the approaches and the models.MNIST handwritten digit database can be taken from the page of Yann LeCun (Yann.lecun.com, n.d.). It has become a standard for fast-testing theories of pattern recognition and machine learning algorithms. The MNIST database was constructed out of the original NIST database; hence, modified NIST or MNIST. It contains 60,000 handwritten digit images for the classifier training and 10,000 handwritten digit images for the classifier testing, both drawn from the same distribution. All these black and white digits are size normalized, and centered in a fixed-size image where the center of the intensity lies at the center of the image with 28×28 pixels. The dimensionality of each image sample vector is $28 \times 28 = 784$, where each element is binary [2].

A. Convolution Neural Networks

A Convolution Neural Network (CNN) is a deep Learning algorithm which takes an input image which is a matrix with the values of pixels of the image.It starts with random weights and biases and then it optimizes the weights and biases of the neurons to minimize a loss function based on the training image input.We will be using the convolution neural network called LeNet-5 which was designed by Y. LeCun .LeNet-5 comprises 7 layers, not counting the input, all of which contain trainable parameters (weights). Layer C1 is a convolutional layer with 6 feature maps. Each unit in each feature map is connected to a 5×5 neighborhood in the input. Layer S2 is a sub-sampling layer with 6 feature maps of size 14 × 14. Each unit in each feature map is connected to a 2 × 2 neighborhood in the corresponding feature map in C1. Layer C3 is a convolutional layer with 16 feature maps. Each unit in each feature map is connected to several 5 × 5 neighborhood at identical locations in a subset of S2's feature maps. Layer S4 is a sub-sampling layer with 16 feature maps of size 5 × 5. Each unit in each feature map is connected to a 2 × 2 neighborhood in the corresponding feature map in C3, in a similar way as C1 and S2. Layer C5 is a convolutional layer with 120 feature maps. Each unit is connected to a 5 × 5 neighborhood on all 16 of S4's feature maps. Layer F6 contains 84 units and is fully connected to C5. Finally, the output layer contains 10 units with 84 inputs each, one for each class [8].

We use the Tensorflow [9] to build such network and then train it over MNIST dataset. We pad zeros to the image,since the MNIST dataset all the images have a dimension of 28 × 28 and the LeNet-5 expects an image of 32 × 32.

1) Limitations of CNN:

- Training the neural network takes considerable amount of time and energy.It is also synchronous which is not the way a human brain works.
- It is not very often do human babies need a 60000 labeled examples to learn to classify the symbols.In humans mostly the learning is unsupervised.

B. Self-organizing Maps

Self-organizing maps were first introduced by T.Kohonen, a Finnish Professor back in 1990.It is a sheet-like artificial neural network, the cells of which become specifically tuned to various input signal patterns or classes of patterns through an unsupervised learning process. In the basic version, only one cell or local group of cells at a time gives the active response to the current input. The locations of the responses tend to become ordered as if some meaningful coordinate system for different input features were being created over the network. The spatial location or coordinates of a cell in the network then correspond to a particular domain of input signal patterns. Each cell or local cell group acts like a separate decoder for the same input. It is thus the presence or absence of an active response at that location, and not so much the exact input output signal transformation or magnitude of the response, that provides an interpretation of the input information [7]. The map has nodes who have weights and with each training input the winning node (node whichever is closer to the features of the current input) and the nodes in its locality changes their weight closer to the current input based on the learning rate. The learning is unsupervised which a step forward in a neurobiological aspect of developing a classifier.

1) Limitations of Self-organizing maps:

- The learning is stochastic and takes a very long time to train the map.
- Since it takes a very long time for learning , the energy efficiency of the self-organizing maps is very low.

C. Spiking Neural Networks(SNN)

Even though the neural network and the self organizing maps have achieved a very good accuracy in classifying the data, they do not encode the temporal information, as in the time of spike of a particular neuron is not a matter of significance.A spiking neuron is a building block of the Spiking Neural Network.Spiking neurons act as integrate-and fire units and have an all or none response. The spiking neuron, however, has an inherent dynamic nature characterized by an internal state which changes with time. Each postsynaptic neuron fires an action potential or spike at the time instance its internal state exceeds the neuron threshold. Similar to biological neurons, the magnitude of the spikes (input or output) contains no information. Rather, all information is encoded in the timing of the spikes [5]. The learning process of the spiking neural networks can either be supervised or unsupervised. We will go over each of these in the next section.

1) Unsupervised Learning for SNN: The rationale of unsu pervised learning is that data that are close or similar to each other in terms of the selected property should be clustered together. One advantage of unsupervised clustering is the lower computational burden because the process eliminates the need for multiple iterations through a training data set, which is typically required for supervised learning algorithms such as gradient descent and its variants. As a result, it is not surprising that most initial applications of SNNs were restricted to applications of unsupervised learning [5]. The labels are not used for the training , it is only used to label a cluster. We will discuss two such networks.

Diehl And Cook Network :

This is an unsupervised learning spiking neural network which was introduced by Diehl and Cook.Their network con sists of two layers. The first layer is the input layer,containing 28 × 28 neurons(one neuron per image pixel),and the second layer is the processing layer,containing a variable number of excitatory neurons and as many inhibitory neurons.Each input is a Poisson spike-train,which is fed to the excitatory neurons of the second layer.The rates of each neuron are proportional to the intensity of the corresponding pixel in the example image. The excitatory neurons of the second layer are connected in a one-to-one fashion to inhibitory neurons,i.e.,each spike in an excitatory neuron will trigger a spike in its corresponding inhibitory neuron.Each of the inhibitory neurons is connected to all excitatory ones,except for the one from which it receives a connection.This con nectivity provides lateral inhibition and leads to competition among excitatory neurons.The maximum conductance of an inhibitory to excitatory synapse is fixed at 10nS.However,the exact value did not have a big influence on the results of the simulation,instead the ratio between inhibitory and excitatory synaptic conductance has to be balanced to ensure that lateral inhibition is neither too weak,which would mean that it does not have any influence,nor too strong,which would mean that once a winner was chosen that winner prevents other neurons from firing [3]. This network learns by encoding the information by the timing of the spikes. A particular class is encoded in a particular neuron by inhibition of the other neurons which do not represent the class. However this can be improved, by inhibiting all the other neurons , we may train the neuron to be overfitting or the neuron would be more specific than generic.

Self-Organizing Spiking Neural Networks: This is a spik ing version of the Kohonen's SOM [7]. The spiking neural network has a multi-layer architecture, including input layer, excitatory layer, and inhibitory layer. The input layer is an array of N × N neurons, which correspond to the pixel of the input images in an image processing application. The excitatory and inhibitory layers have size of K × K. Each input pixel projects to each of the excitatory nodes through modifiable synapses. Spikes are generated in the input neurons using Poisson spiking neurons, with average firing rate λ proportional to pixel intensity [4]. The [6] paper made an improvement over the basic architecture of the spiking neural network by taking the inspiration from Kohonen's model of Self-organizing maps.we increase the level of inhibition with the distance between neurons. Inhibition level is increased in proportion to the square root of the Euclidean distance, similar to the SOM learning algorithm. This requires a pa rameter c_{inhib} which is multiplied by the distance to compute inhibition levels, as well as a parameter c_{max} that gives the maximum allowed inhibition (see Figure 3). With proper choice of c_{inhib}, when a neuron exceeds its firing threshold $v_{threshold}$, instead of inhibiting all other neurons from firing for the rest of the iteration, a neighborhood of nearby neurons will be weakly inhibited and may have the chance to fire. This encourages neighborhoods of neurons to fire for the same inputs and learn similar filters [6]. The overall idea is similar to Kohonen's as by inhibiting only those neurons which are neighbouring to the spiked neuron makes the formation of the clusters faster.

2) Supervised Learning for SNN: Although unsupervised learning was demonstrated in SNNs with a recurrent ar chitecture, until recently, spiking neurons were considered to be incompatible with the error backpropagation required for supervised learning in purely feedforward networks. This incompatibility was due to the lack of a continuous and differentiable activation function that could relate the internal state of the neuron to the output spike times [5] In the paper [10] they mention a way of training the SNN by optimizing the least square error function, where the error is calculated between the generated and target spike train. We mention this way of learning for the sake of completeness.

III. CONCLUSION

The unsupervised learning seems more human-like since development of human brain doesn't require a huge number of labeled data to classify it. Supervised learning functions with really good accuracy, however the paradigm is more similar to curve fitting, which is statistic tool and not to how human brain works. The convolution neural network is not very energy efficient compared to the Spiking neural networks. Spiking neural networks also encode temporal data , which a step forward. With IBM Truenorth [1] and other neuromorphic chips being introduced, spiking neural networks can be a really energy efficient problem solver.We would like to conclude with saying that the Spiking neural networks are a better in both energy and mimicking the human brain with only limitation being it needs specific hardware.

REFERENCES

[1] Filipp Akopyan. "Design and Tool Flow of IBM's TrueNorth: An Ultra-Low Power Programmable Neu rosynaptic Chip with 1 Million Neurons". In: *Pro ceedings of the 2016 on International Symposium on Physical Design*. ISPD '16. Santa Rosa, California, USA: Association for Computing Machinery, 2016, pp. 59–60. ISBN: 9781450340397. DOI: 10 . 1145 / 2872334 . 2878629. URL: https : / / doi . org / 10 . 1145 / 2872334.2878629.

[2] Li Deng. "The MNIST Database of Handwritten Digit Images for Machine Learning Research [Best of the Web]". In: *IEEE Signal Processing Magazine* 29.6 (2012), pp. 141–142. DOI: 10.1109/MSP.2012.2211477.

[3] Peter Diehl and Matthew Cook. "Unsupervised learning of digit recognition using spike-timing-dependent plas ticity". In: *Frontiers in Computational Neuroscience* 9 (2015), p. 99. ISSN: 1662-5188. DOI: 10.3389/fncom. 2015.00099. URL: https://www.frontiersin.org/article/ 10.3389/fncom.2015.00099.

[4] Wulfram Gerstner and Werner M. Kistler. *Spiking Neu ron Models: Single Neurons, Populations, Plasticity*. Cambridge University Press, 2002. DOI: 10 . 1017 / CBO9780511815706.

[5] SAMANWOY GHOSH-DASTIDAR and HOJJAT ADELI. "SPIKING NEURAL NETWORKS". In: *International Journal of Neural Systems* 19.04 (2009). PMID: 19731402, pp. 295–308. DOI: 10 . 1142 / S0129065709002002. eprint: https : / / doi . org / 10 . 1142 / S0129065709002002. URL: https://doi.org/10.1142/S0129065709002002.

[6] Hananel Hazan et al. “BindsNET: A Machine Learning Oriented Spiking Neural Networks Library in Python”. In: *Frontiers in Neuroinformatics* 12 (2018), p. 89. ISSN: 1662-5196. DOI: 10.3389/fninf.2018.00089. URL: https://www.frontiersin.org/article/10.3389/fninf.2018. 00089.

[7] T. Kohonen. “The self-organizing map”. In: *Proceed ings of the IEEE* 78.9 (1990), pp. 1464–1480. DOI: 10.1109/5.58325.

[8] Y. LeCun et al. “Gradient-Based Learning Applied to Document Recognition”. In: *Intelligent Signal Process ing*. IEEE Press, 2001, pp. 306–351.

[9] Martın Abadi et al. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. Software avail able from tensorflow.org. 2015. URL: https : / / www . tensorflow.org/.

[10] Jianguo Xin and M.J. Embrechts. “Supervised learning with spiking neural networks”. In: *IJCNN’01. Interna tional Joint Conference on Neural Networks. Proceed ings (Cat. No.01CH37222)*. Vol. 3. 2001, 1772–1777 vol.3. DOI: 10.1109/IJCNN.2001.938430.