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Image Completion using Spiking Neural Networks

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***Abstract:** In this paper, we are showing how spiking neural networks are applied in image repainting, and its results are outstanding compared with other machine learning techniques. Spiking Neural Networks uses the shape of patterns and shifting distortion on images and positions to retrieve the original picture. Thus, Spiking Neural Networks is one of the advanced generations and third generation of machine learning techniques, and is an extension to the concept of Neural Networks and Convolutional Neural Networks. Spiking Neural Networks (SNN) is biologically plausible, computationally more powerful, and is considerably faster. The proposed algorithm is tested on different sized digital images over which free form masks are applied. The performance of the algorithm is examined to find the PSNR, QF and SSIM. The model has an effective and fast to complete the image by filling the gaps (holes).*

***Keywords:** Biological Neuron Model, image inpainting, Machine Learning, response entropy, spiking neural networks, STDP rule.*

I. INTRODUCTION

Spiking neural networks is a machine learning technique that has involved in all domains including optimal pathfinding and security domains. From the past four years, SNN is purely involved in all aspects and solving many problems, as it has an excellent scope and powerful algorithm with spikes, the performance, and accuracy calculated using SNN is outstanding. Because of the close representation of the concept on the human brain, spiking neural networks is the most advanced version of neural networks, currently. In the workflow of SNN, it has got a Synaptic, neural state and included the idea of time. SNN is purely based on the activity of neurons.

In SNN's, neurons are active only if the electrical potential difference between two neurons exceeds the predetermined value. Once the neurons are activated, then the generated spikes reach other neurons, and neurons potential gets changed in favor of received value, i.e. the potential value gets either increased or decreased. Depending on the interval between spikes and frequency of the spikes, the number of coding methods are used for interpreting the outgoing spike as a real-valued number or not. The network consists of spiking neurons, and each neuron is randomly connected with each other with axonal conduction delays. The network has spike timing-dependent plasticity (STDP). Synaptic connections among neurons have a fixed conduction delay which are expected as a random integer that could vary between 1ms and 20ms.

The advantage of the spiking network is that the output can be represented in sparse in time. SNN conquers the energy consumption compared to the biological system for the spikes, which have high information[24].

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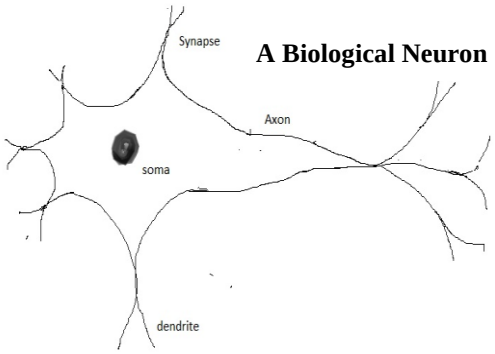
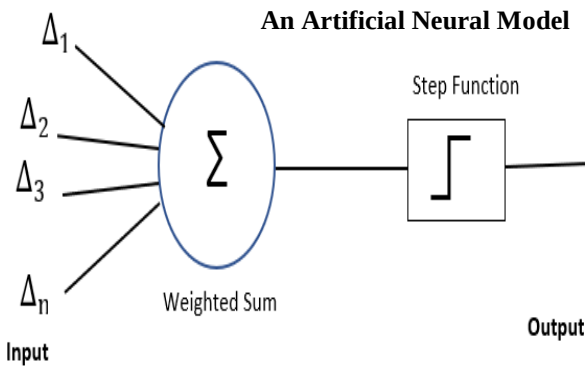
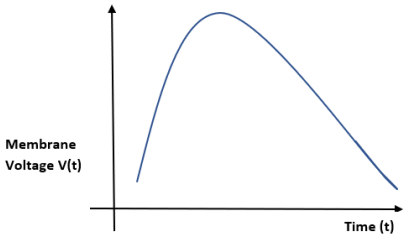
II. LITERATURE SURVEY

It is important to classify the objects in an image so that, the process solves many issues related to image processing and computer vision. Generally, the image classification problems are mostly affected due to the factors like noise, poor quality of the image, and occlusion. Then IoT becomes difficult to categorize what exactly the object becomes more difficult as the object count increases. Most of the image classification techniques are based on the features that are extracted from an existing image. Thus, image classification techniques have their own role, which is categorized as supervised and unsupervised.







(c)

Fig1. (a) Biological representation of Neuron. (b) An Artificial Neuron Model. (c) Graphical Presentation of Spike in response to Inputs when a neuron is integrated and triggered.

If the learning process of an image is designed to form a mapping from one set of data say features to another set of data which could be information classes, under human intervention is called supervised classification. Unsupervised classification is the same as supervised classification, but it does not require any human intervention. For assigning pixels to informational classes, some of the supervised classifications techniques are Artificial Neural Networks (ANN), Support Vector Machine (SVM), Minimum Distance from Mean (MDM), Maximum Likelihood (ML).

The Support Vector Machine (SVM) [4] is applicable to pattern recognition as well as regression. It is a new universal machine. Generally, in supervised classification, there is a human intervention due to which, if errors are made, those could be detected and corrected during training. But this classification deals with high costs and consumes more time. No prior information is required in unsupervised classification since it is free from human intervention. Using statistical methods such as clustering algorithms; it is possible to understand the structure of the data when reliable training data are absent.

K-means and ISODATA are popular clustering algorithms that are faster and errors free, and it is not necessary to have detailed prior knowledge. Major drawbacks are due to maximally separable clusters in this technique [3].

Soft classifications are Maximum Likelihood (ML), Subpixel Classifier, Classifier-NN Classifier, fuzzy –set classifiers which are pixel-based. Everything currently, is upgraded with machine learning, artificial neural network and deep learning in many sectors like health monitoring, speech recognition, object detection, marketing, behavioral analysis, etc. Thus, ANN has its key role everywhere because of its advantages such as fault tolerance, working with incomplete data as it gets trained for once. But the main drawback is, it takes more time for training the sets which contain millions of patterns and many features. That is the reason, It is important to have limited important features from every layer which can be processed by the next layer which makes the classification better. Vectorization, which played an important role in scaling up the neural network model is a process of transforming the actual data structure into a vector form.

It has introduced deep learning which is a part of machine learning, which generally works on various layers. Here, the output of every layer acts as an input of other layers. This is how; it helps both supervised and unsupervised learning. Some of the deep learning networks are CNN (Convolutional Neural Network) [4], SAE (Stacked Auto Encoder) [6] and RBM's(Restricted Boltzman Machines) [5] which helps in extracting useful data from digital images.

Among all, CNN is mostly used for several applications like speech recognition, image recognition, object detection [7], and image inpainting. CNN uses several layers like input, output layers and hidden layers like pooling, fully connected layer, convolution layer, and normalization layer.

CNN is a hierarchical structured artificial neural network and was the first one, which is based on neural connectivity. It was found in the mid-1980. The algorithm which was proposed was a multi-layered network made up of neurons that deal with a problem with shifts in distortion in images and positions in shape of patterns. Later Artificial Neural Network was introduced, which can be used in daily life problems [9]. David Rumel Hart, Geoffery Hinton, and Ronald Williams published a backpropagation algorithm in 1985, which was used for determining the error gradient [10]. In 1990, backpropagation algorithm was used in the CNN model [11] for training, when the hand-written digital identification is studied by then and MNSIT [12]. By fusing convolution and pooling operation, CNN was made simpler by Simard et al. in 2003 which improved the document and network analysis.

In 2006, Chellapilla et al. [14] converted the architecture of convolution layers into a matrix-matrix product which is a faster recognition algorithm. But the computing result is very smaller compared to deep CNN's because of low computing power available during that time. A multi-layered generative model of natural images used in CIFAR-10 was trained by A krizhevsky, G Hinton [15] in 2009.

III. METHODOLOGY

Spiking Neural Networks as a tool:

A spiking neural network is used as an intention to replicate the human brain. It happens by implementing individual spike, and it includes spatial, temporal information in cross-layer connection. Neurons use pulse coding, which means they process individual pulses that allow image multiplexing.

In spiking models, spiking artificial neural networks have the internals which is the same as a biological analogy. It receives information coming from many inputs and produces them as a single spike response. As the excitatory inputs increases, the probability of spike generation increases, and it decreases by inhibitory inputs. When neurons get activated by reaching the threshold value, spikes are generated as a response.

$$y_j = \begin{cases} 1, & if \ \sum_{i=1}^{n} w_{ji} x_i \geq \theta \\ 0, & if \ \sum_{i=1}^{n} w_{ji} x_i < \theta \end{cases} \quad (1)$$

Where x_i is input, w_{ji} is weight which denotes the synaptic energy, and y_j is spike response

Spike Timing Dependent Plasticity (STDP) Rule: STDP is a biological process that adjusts the strength of connections between neurons in the brain. The process adjusts the connection strengths based on the relative timing of a particular neuron's output and input action potentials (or spikes) [16].

Neurons fire stochastically as a function of membrane potential.

S (neuron j spikes at time t) = $k^{e^{(\gamma i(t)-T)/m}}$ (2)

Where k is constant, t is the time taken, and T is total time taken yi is neurotransmitter concentration.

Good idea to minimize response variability: -

Response entropy:

$$H(\Omega i) = -\int_{\Omega i}^{n} G(£) log(G(£)) d£ \quad (3)$$

$G(£)$ is defect identified and $log(G(£))d£$ gives the border of the defected image

Gradient:

$$\frac{\partial H(\Omega i)}{\partial \omega ij} = -\int_{\Omega i}^{n} G(£) \frac{\partial log(G(£))}{\partial \omega ij} (log(G(£)) + 1)\, d£ \quad (4)$$

This equation shows how the mask of the image is in painting the defected image using train data [17].

DBN's (Deep Belief Networks) [18] is considered as a traditional network since it was created by stacking RBM's (Restricted Boltzmann Machine).

It looks like:

The visual input layer has 784 neurons because of the input vector, which is equal to 28x28 pixel image data set. Visual abstraction and associative layers, each have 50 neurons. This is not an optimal or perfect amount but is given for an assumption. The label layer has 10 neurons which resemble the digits from 0 to 9. The total picture is converted into 0-9.

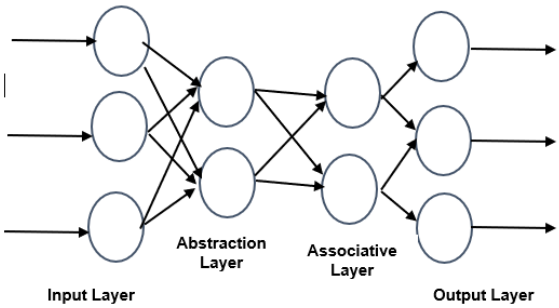


Fig 2. The architecture of Spike Neural Network.

Training the system:

The spiking neural network training process is generally divided into a few steps [19,20]. Since our model consists of many RBM's, they should be trained individually.

An independent RBM determines the weight of the coefficients within the input and abstract layers.

Later, supervised learning between the Associative and Label layer is established. But as input, previously trained RBM (Input and Abstract) are used in the Associative layer. Every RBM must be trained for predefined epoch times.

IV. RESULTS AND ANALYSIS

Spike Neural Network performance is tested by providing the input image with the same sized masked image. This mask image will overlap on the original image and the outer line is going be framed once the neural network is trained. The network first detects the edges and hole exist in the images. These holes are filled by finding the best suitable pixel from the boundary of the hole. The best suitable pixel is selected based on the proposed model.

For the for proposed SNN model, we are making the given set of datasets into train and test by the general division ratio either 80:20. To test the logic we are going to use 20% of data, and that will be given as input to the network, based on the train data the image is going to be Inpainted the missing pixels[20-22].

Proposed algorithm performance is evaluated on the three parameter PSNR, QF and SSIM. PSNR is a peak signal noise ratio which measure the correctness against the noise, Quality factor correlates the pixel of of input image and generated output image, while Structure similarity finds the similarity of images.

Table1. Performance comparison of existing model and proposed SNN Model

Techniques	Type of Data	Complex images	Learning capability	Power consumption
Feed Forward Neural Network	Recognition	Less resolution image with less noise	Training	1.0
Neuro fuzzy network	Recognition	Live image	Training	1.3
Hierarchical temporary memory	Recognition	Live image	Training	1.6
Spiking neural networks	Recognition	Live image	Predicting the learning process	0.9

Sample results of other images are as follows

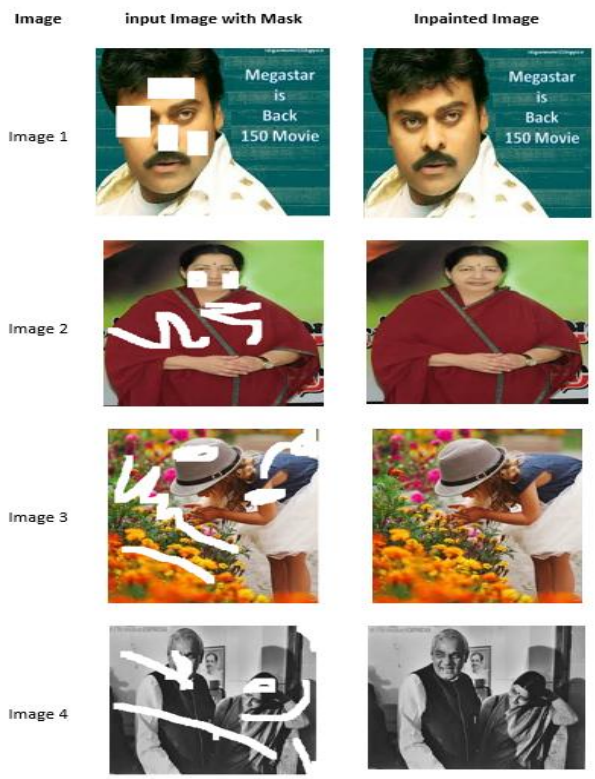


Fig 4. Sample Results of different images using SNN.

V. CONCLUSION

In this paper, we have used the Spiking Neural network technique for image inpainting as so far no researcher has used this technique in the image processing field. It has proved that it is giving better results compared with existing techniques called Graphical neural network, convolutional neural network and so on. So we are suggesting the modern developers and researchers to use this technique to corrupted or spoiled images rectification. The future scope is as we are unable to extend it for large resolution images; when it applied for large resolution images, we are unable to receive exact image what we are expected, received blur image as an output. Future researches is a challenging task to extend our work for large resolutions images also [23].

VI. FUTURE SCOPE

Further our work can be extended with ensemble machine learning techniques or bio-inspired techniques to get cent percent accurate results. So we are suggesting the modern developers and researchers to use this technique to corrupted or spoiled images rectification. Future scope is as we are unable to extend it for large resolution images, when it applied for large resolution images, we are unable to receive exact image what we are expected, received blur image as an output. Future researches it is a challenging task to extend our work for large resolutions image also.

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Vineet Kumar is an associate professor in the department of Computer Science & engineering in NIET Greater Noida. He has done B.Tech In CSE from GBPUAT Pantnagar and MTech in CSE from AKTU Lucknow. He is Pursuing his PhD in CSE from AKTU Lucknow. He has published 4 research paper in International Journal and 6 research paper in national and international conference. He is life time member of ISTE.

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