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Research paper

Cautionary Sign Analysis of Traffic Sign Data-Set Using Supervised Spiking Neuron Technique

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Abstract

In this paper, 19 cautionary traffic signs were selected as a database and 3 types of conditions have been proposed. The conditions are 5 different time of image taken; hidden region and anticlockwise rotation are all the experiments design that will shows all the errors in producing the it's mean value and the performance of traffic sign recognition. Initial hypothesis was made as the error will become larger as the interruption getting bigger. Based on the results of the five-different time of image taken, the error gives the best performance; less error when time is between 8am to 12am due to the brightness factors and the sign can be recognize clearly during noon session. The hidden region conditions show good performances of the detection and recognition of the system depend on the lesser coverage of the hidden region introduce on traffic sign because if the hidden region coverage is huge the database will get confuse and take a longer time to do the recognition process. Lastly, in anticlockwise rotation shows that 90^{o} gave large value of error causing the system unable to recognize sign perfectly rather than 135^{o} angle. To sum-up, detection and recognition process are not depending on higher number of angle but the process solely depending on their value of sample for each traffic signs. The error will give the impact towards traffic sign recognition and detection process. In conclusion, SNN can perform the detection and recognition process to all objects as in the future the system will become more stable with the right technique on spiking models and well-developed technology in this field.

Keywords: *SNN; traffic sign; hidden region; rotational; five-different-time image taken; mean error; detection; recognition.*

1. Introduction

The artificial neuron network has been separated into three phases of era or stages of generation [1-5]. The first generation of neuron network comprised on McCulloch-Pitts neuron known as a threshold-neuron. It was as a theoretical fundamental computation unit. The input and output of the model utilized digital and typically bipolar or binary. Multi-layer perceptron is an example that utilized as a part of first stage. The multi-layer perceptron can process a Boolean function with a single hidden layer.
Neurons of the second generation is a conceivable output values that used an initiation function of a continuous set in light of computation units (neurons) that making them reasonable analog input and output. This generation resembles the first generation that in the wake of utilizing a threshold then it can figure discretionary Boolean functions. This stage can register certain Boolean functions with less neurons and estimated any analog function well with one hidden layer and making these networks widespread for analog computation. Learning algorithm based on gradient descent is the reality of the implementation at this generation can bolster such as blunder back-propagation [6-15].
The third stage of artificial neuron network's generation is spiking neuron. Late bits of knowledge from neurophysiology are utilized for these neurons. To pass the data or information between neurons is particularly by utilizing fleeting coding. The generation additionally same with the second generation that can well approximate continuous arbitrary. It runs admirably with transiently encoded input and output [9-10]. In this way, these three generation are rearrangement of physiology of biological neurons and the third generation of artificial neuron network is a model with the most elevated loyalty.

1.1 Spiking Neural Network

Spiking neural Network (SNN) are portrayed as the third generation of neural network and exceptional propelled by natural computing in the mind and late progress in neurosciences that turning out to be essential in light of the fact that the displayed on an indistinguishable principle as the biological neurons. The SNN is flexible and powerful that being fit in finishing extensive variety of tasks traditionally developed by other framework and a lot of work so far has concentrated on fundamental issues like biologically plausible models, computational complexity and biological learning rules effects and so on [11].
The Spiking neural Network (SNN) is getting attention because it is biologically more sensible model and computationally capable of machine learning method. Biological neurons send the data by expanding the voltage and these signals ordinarily known as action potential and spikes. There are some application has been

utilized the method of spiking neuron such as how to make use of networks of spiking neurons has been the Liquid State Machine (LSM) by [1]. The LSM is a late computational model that comprise of an intermittent network of non-linear associating computational nodes with an inside state. In the paper "Isolated Word Recognition with the Liquid State Machine" that exploration discourse recognition in the Liquid State Machine. This experiment is to test an assortment of temporal encoding that are nourish to LSM and a consequent simple linear decoder categorize of every specific particular pattern. From the experiment shows that spiking neural network was used the same rule with the LSM after created an incredible response as the conventional or traditional neural network by utilizing this technique. It had shown that spiking neural network and conventional neural network capable in practice compute non-linearly separable function.

The most important issue is the reality of application by utilizing spiking neural network that they are regularly computationally more escalated than traditional neural network. It was at that point has proved that the communication load between neuron definitely reduce of time spikes and permitting the principle for implementation in efficient parallel. Some research shows there are different ways of performing Bayesian inference in spiking neural network that are papers by [2-4]. With that, we trust that the papers "Applications of Spiking Neural Networks" by [5] indicate astounding advancement is being made towards the application of spiking neural network. Consequently, the spiking neuron will use to a venture traffic sign recognition since it is more proper and compelling than other neural system method.

2. Model

A model equation of simple spiking (1) and (2) are presented as biologically plausible as the Hodgkin–Huxley model [4], yet as computationally efficient as the integrate-and-fire model by the combination experimental studies of animal and human nervous systems with numerical simulation of huge scale brain models relying on four parameters a, b, c and d. The model produced spiking and bursting behavior of known types of cortical neurons, as illustrated in Figure 1.

The derivation of first (1) equation is based on bifurcation theory and ordinary form reduction [4]. Here, v and u are dimensionless variables and a, b, c and d are dimensionless parameter and '= d/dt, where t is the time. The variable v represents the membrane potential of the neuron and u represents a membrane recovery parameter, which accounts for the activation of K+ ionic currents and inactivation of Na+ ionic currents and it provides negative feedback to v. After the spike reaches its apex (+30 mV), the membrane voltage and the recovery variable are reset according to equation (3). Synaptic currents or injected dc-currents are delivered to variable I. Value of I currently were set with each output data values of each image. Figure 1 shows sample of output spikes type where the FS is the most compatible reaction concomitant with the project objectives.

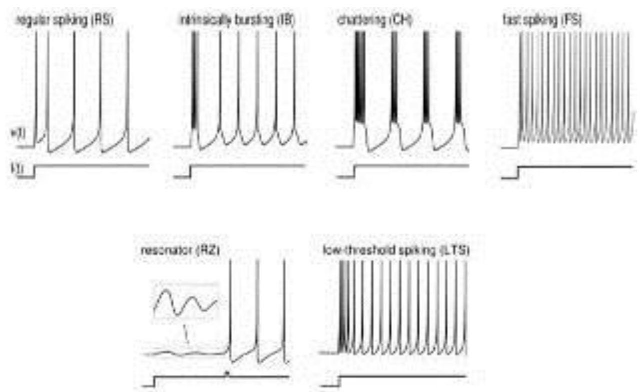


Fig. 1: Type of dynamic response [4]

Euler's Method of 2-D system with first order differential equation:

$$v' = 0.04v^2 + 5v + 140 - u + I \tag{1}$$

$$u' = a * (bv - u) \tag{2}$$

After spike-reset:

$$v \geq 30 = \begin{cases} v = c \\ u = u + d \end{cases} \tag{3}$$

where a-time scale for recovery variable u, b-Sensitivity for recovery variable v, c-After spikes reset value of membrane potential v and d-After spikes reset value of membrane potential u.

3. Architecture

The neurons on the system architecture comprise in a feed forward network of spiking neuron create spikes or action potentials with multiple delayed synaptic terminal as shown in Figure 2. It was happened when the internal neuron state variable crosses a threshold ϑ. Spike Response Model (SRM) is describe the relationship between information spikes and the inner state variable [11]. The reflection dynamic of an expansive assortment of various spiking neuron is rely on upon the decision of reasonable spike-response functions.

Figure 3 shows different delay and weight as a sub-connection that is related every terminal that consist a fixed number of m synaptic terminals for an individual connection. The difference between time the post-synaptic potential start rising and the firing time of the pre-synaptic neuron is defined by the delay, d^k of a synaptic terminal k. A presynaptic spike at a synaptic terminal k as a Post-Synaptic Potential (PSP) was described. The standard height with delay, d^k.

Three vital issues need to explore for the operation of image processing before building a Spiking Network (SNN), which are information coding, learning method and system architecture. Then, SNN will used to cluster images, segment images and detect edges.

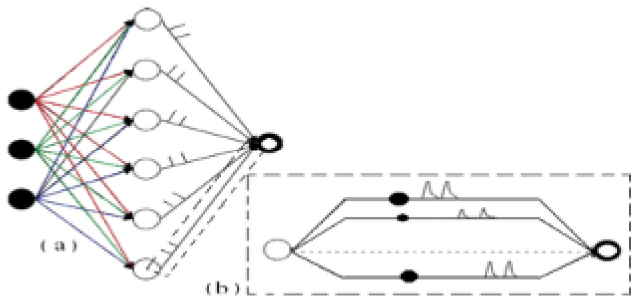


Fig. 2: (a) Spiking neural network architecture (b) Multiple synapses transmitting multiple spikes [5]

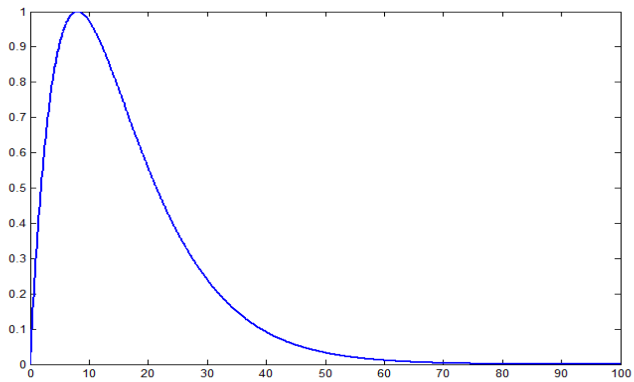


Fig. 3: Spike response Function, Postsynaptic Potential is Excitatory (EPSP), τ = 8

3.1. SNN Architecture for Clustering Images

Spike response with fleeting memory is a model that used for a spiking neuron. Figure 4 shows spiking architecture network in a fully connected feed forward with multiple delayed synaptic terminals of connection implemented. A hidden layer, an input and output layer are consist in the network. The first layer is shows the input neuron that is RGB (red, green, blue) values of pixel. Hidden layer has a confined activation $\emptyset^2 = \emptyset(||X - C_n||, \sigma_n)$ where a Radial Basis Function located around C_n for each node. The localization's degree parameterized by σ_n and Gaussian RBF produced by choosing $\emptyset\ (Z,\sigma) = \exp\frac{z^2}{2\sigma^2}$. This synapse model has their own specific delay and weight comprise of a lot of sub-synapses as shown in Figure 4. This will transform real data to temporal data.

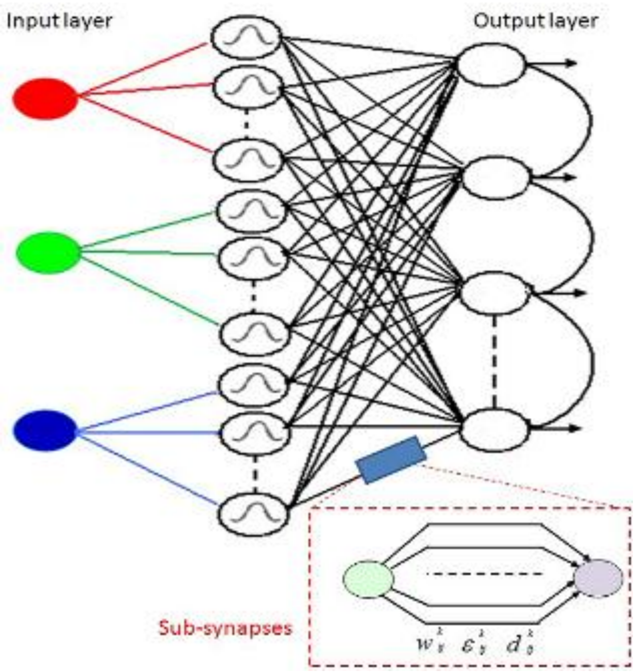


Fig. 4: Network topology for clustering and segmentation images

3.2. SNN Architecture for Cell Segmentation

The techniques uses in this design are watershed, edge based and area based strategies. This method likewise applying completely associated feed-forward as numerous deferred synaptic terminals, however, by executing two techniques which are unsupervised and directed learning.

The cellular segmentation methods are an image analysis of cancer screening. It is a significant tool for cytopathology [12]. In this segment, there are two principles reason might be elaborated. The first is the quantitative analysis of shape and structure of nuclei. For diagnosis assistance is coming from microscopic colour images that bring the information of pathologist valuable. Secondly, when the number of screening increase, the pathologist should be deal in largest of quantity information. Instead, it must be correctly reliable analysis. The watershed [13], threshold-based [14] and region-based [15] are the methods used for this architecture.

The cell segmentation categorizes three classes of the colour pixel that are background, cytoplasm (nucleus) [16]. The same colour of a fraction on nuclei because of the variability on it. It relies on the type of the cells and the chromatin distribution. Out of sight has an indistinguishable shade of mucus from a few cells for cytopathologies. This segment also applying fully connected feed forward as multiple delayed synaptic terminals by implementing two different topology that are unsupervised and supervised learning.

For supervised learning, different images are used for a reference data set of pixel. For unsupervised learning, spiking neuron perform its learning directly on the pixels of the image to classify.

3.3. SNN Architecture for Edge Detection

Spiking Neural Network is used for the first image of segmentation process. The data activity each of output neuron will record once the segmentation is done. When neuron is active, the output binary is 1 for each input pixel and 0 if the neuron is inactive. The binary images that containing edge detected by these neuron represent the result of binary matrices activation of output neuron their category. Figure 5 shows the edge image with color segmentation.

Fig. 5: Edge image with color segmentation

3.4. Spiking Neuron Implementation

In order to developed process of the spike response, the equation on spiking neural needed to insert in the MATLAB coding. The equation was obtained by fitting the spike initiation, so that the membrane potential v has mV scale and the time t has ms scale. Load image from folder and convert the image file onto numeric array using command in MATLAB. Some perimeters need to adjust such as step of training equal to 0.35 and the base of training equal to -5%. Initialize the receptor variables for the cell voltage, membrane potential and recovery variable. Search the indices of receptor neurons for spikes by seeing whether it has crossed the threshold of 30mV and extract feature after it crossed the threshold of 30Mv. The value of area, major axis and saved for each classification of traffic sign.

3.4.1. Training with Neural Network Toolbox

The recognition need to be done by supervised learning algorithm such as training data of spiking neural using MATLAB. 19 numbers of traffic sign were implemented in this project presenting the most appeared cautionary sign around Malacca area and the output data of its own classes were done by spiking coding. All the traffic sign in uses in this project were shown in Table 1. All the sign is referred to cautionary sign, which is red color of traffic sign. The spiking neural training was done in order to analyze the output error each of the image.

Table 1: Image classes

1) Slippery Road	11) No Motorcycle
2) No Entry	12) Obstacle
3) Yield	13) Accident Area
4) No Truck	14) Stop
5) No U-turn	15) No Parking
6) No Left Turn	16) Wide Limit
7) No Right Turn	17) Height Limit
8) No Overtaking	18) Weight Limit
9) No Hooting	19) Speed Limit (80km/h)
10) No Buses	

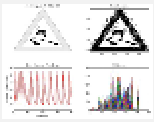
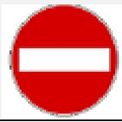
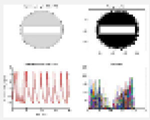
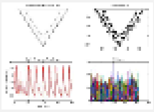
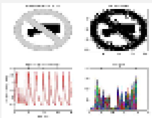
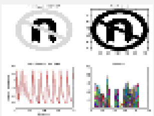
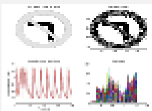
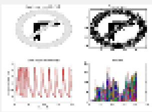
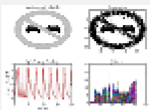
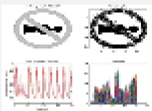
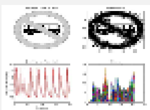
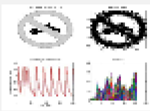
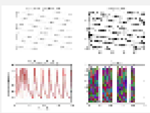
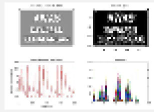
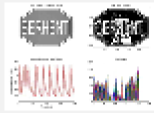
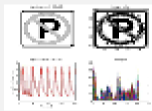
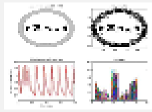
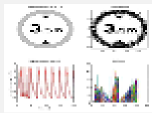
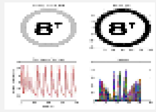
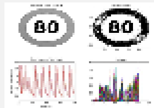
3.4.2. Detection and Recognition

The trained data from previous step is used for detection and recognition. By using MATLAB function block, the trained are loaded to the real time Simulink model. The detection is on real time video and the output is display by using video viewer block. The image recognition is depending on the trained data in the system that stored in block diagram.

3.5. Spike Response Output

This is the 19 graph of spike response to time and histogram of each of the traffic sign. To resulting graph of spike time is when it crossed the threshold of 30mv. Histogram graph is produced from the input image after receptor spike.

Table 2: Image perform spike response

1 	
2 	
3 	
4 	
5 	
6 	
7 	
8 	
9 	
10 	
11 	
12 	
13 	
14 	
15 	
16 	
17 	
18 	
19 	

Based on Table 2, each of the image traffic sign have their own data by refers the histogram. Histogram shows the pixel of intensity grayscale level for an input image. The histogram of an image was analyzed after complete spike response. Then, extract feature of the image for classification in the system. So, it shows that the system of detection and recognition will perfectly recognize if the input image on camera have a same data that stored in the system as sample of image [17-20].

3.6. Mean Error Recognition

This section will discuss the results throughout completing the project from software simulation. The simulation is done and result was established using MATLAB. The task only covered cautionary sign for red traffic sign color observation based on real time taken, hidden region and anticlockwise rotation. Analyses were conducted to compare each image error based on their specific condition and the mean value stated in part A, B and C below.

3.6.1. Experiment 1: Five Different Time of Image Taken

In this part A, the values of error for image taken in five different times are plotted into a graph. The system will detect and recognize the error values gained and these traffic signs are selected for real time analysis.

Based on the mean graph error for real time taken in Figure 6, the lowest value of error for detection presented at 12pm because the traffic sign can be seen clearly during noon. So, during this time, the recognition process will produces a lesser value of error. The graph also shows the good performance of the recognition system during 8am to 12pm because the brightness factors, which give big impact towards the recognition process.

Fig. 6: Mean error for five different times

3.6.2. Experiment 1: Hidden Region

Part B shows the value of error in twelve type percentage of hidden region which is 3.15%, 6.25%, 12.5%, 25%, 37.5%, 43.75%, 46.8745%, 50%, 56.255%, 62.55%, 68.755% and 75.5% for the traffic sign. This error is generated from the non-real time experiment to enable exact error value to be obtained and was plotted in graph.

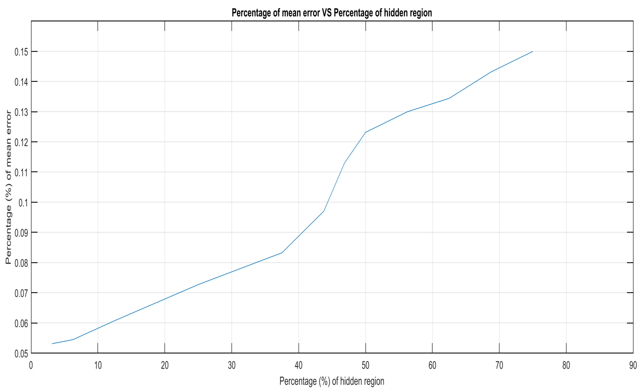


Fig. 7: Mean error for hidden region

Based on Figure 7, it shows that the lesser of hidden region on traffic sign will give a better performance of the detection and recognition system. The graph shows the increasing number of the error value are causing by increment number of hidden region percentage. This phenomenon happened if some region of the image is hidden, the value of extract feature for training the data is gone and surely confuse for the input trained image and the value of the sample in the system. For the extracting feature process, it considered on the perimeter of the image such as area of the image, major and minor axis, the total of pixel for black and white and so on. When the system is doing a recognition process, it will produce a higher value of error when the number of feature of the image observed is less than the trained template. So, the increasing percentage of hidden region will increase recognition error and produce a bad performance for the system.

3.6.3. Experiment 3: Anticlockwise Rotation (Degree)

This section shows the value of error in nine type degree of rotation which is 15^o, 30^o, 45^o, 60^o, 75^o, 90^o, 105^o, 120^o and 135^o for the traffic sign. This error is generated from the non-real time experiment to enable exact error value to be obtained and was plotted in graph.

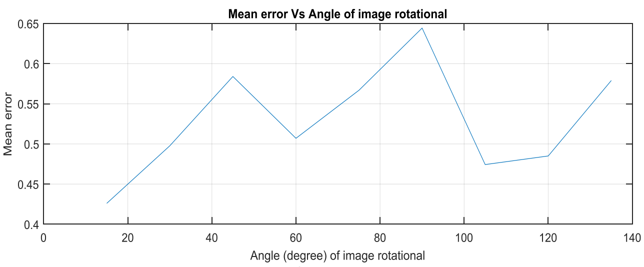


Fig. 8: Mean error for anticlockwise rotation

Nine types of angle in degree were selected in this experiment. Based on Figure 8, the lowest value of error occurs at rotation of 15 degree while at, 90 degree of rotation, it gives a highest one. The experiment shows that at 90 degree, most of the selected traffic signs in this system cannot recognize perfectly. From the graph, it can be conclude that the higher value of error is not depending on the higher angle of rotation. As shown in Figure 8, the system still can recognize the traffic sign at 135 degree of rotation and at 75 degree the system failed to recognize it. So, the system can detect the traffic sign is due to the feature trained that is almost to the value of sample present.

3.7. Output Image Recognition

Table 3: Table time taken for traffic sign recognition

Traffic Sign	Time Taken for Recognition (s)
Slippery Road	2.02
No Entry	1.78
Yield	2.53
No Trucks	0.78
No U-turn	0.52
No Left Turn	1.05
No Right Turn	0.97
No Overtaking	1.63
No Hooting	1.89
No Buses	1.98
No Motorcycles	2.79
Obstacle	2.05
Accident Area	2.94
Stop Sign	1.82
No Parking	1.79
Wide Limit	2.07
Height Limit	2.68
Weight Limit	2.58
Speed Limit (80km/h)	1.83

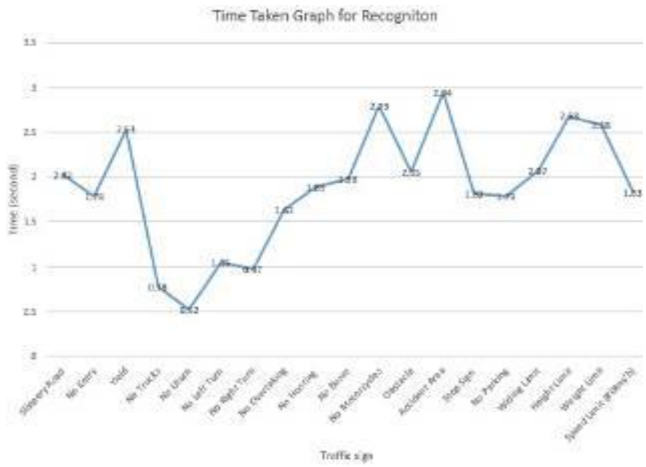


Fig. 9: Graph of time taken for recognition

This part has shown an analysis of time taken for traffic sign recognition of all 19 dataset shown in Table 3. Based on Figure 9, time taken for the system to recognize a traffic sign is around 0.52s to 2.94s. The time taken for the image recognition is depending on the camera used. A good camera can recognize the image recognition faster. For this experiment, the time taken as shown in graph is used webcam camera.

To get the correct or shape analysis of displaying image for all the 19 data, all the condition of each image as hidden region and rotational were recorded. The output estimation and error of each image need to be total up in order to recognize each image contribution of its output. Figure 8 and Figure 9 are utilized to compare between image output and input for hidden region and rotational effect [21-23].

3.7.1. Hidden Region

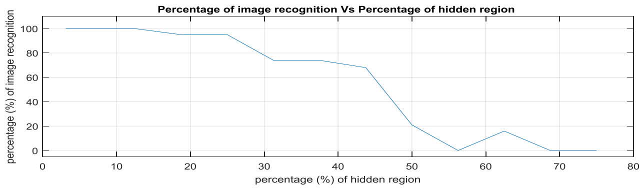


Fig. 9: Comparison image output and input for hidden region

From Figure 10, the image is perfectly recognized when the percentages of hidden region is 2.3%. At 50% of hidden region, the image that able to recognize only about 20% and there is no recognition process when the percentages at 68.5% until 75.5%.

3.7.2. Rotational Effect

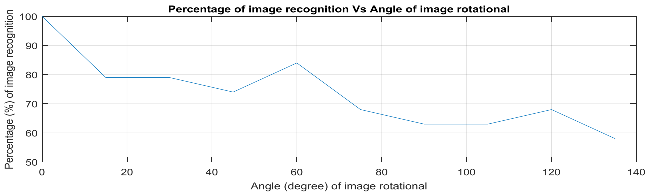


Fig. 10: Comparison image output and input for rotation

The image are 78.9% recognized when the angle of image rotational is at 18˚. While at 60%, there is 82% of image that able to recognize. The image is in the lowest percentages recognition, which is 50% when the angle of image rotational at 138.9%.

4. Conclusion and Recommendations

In conclusion, this project is traffic sign detection and recognition using Spiking Neural Network (SNN). This method is applying SNN to image segmentation. At first, the network is build, a subset of the image pixel is taken to be learned by the network and finally the SNN process the rest of the image to classify the image. The image analysis will give a spike response time graph and histogram for an image of traffic sign. In learning of spiking neuron network, some key parameters need to be considering such as for network architecture is number of sub-synapses receptive field and output neuron. The other perimeters that need to be consider is step of training, the base of training, training step, peak of the learning function and so on. This technique also needs to use supervised learning neural network because there are data-set to be stored in the system. The detection and recognition based on the data-set that had trained and if no data-set stored in the system, the system will failed to detect and recognize. The image of cautionary traffic sign was analyses in MATLAB. It can be said that this project can help the driver to detect Cautionary traffic sign without any disturbance. At the same time, it will give a benefit to all users and can decrease the road accident [24-28].

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