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Performance Evaluation of Neural Networks in Road Sign Recognition

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***Abstract*— *This paper presents an in-depth study of road sign recognition techniques leveraging neural networks. Road sign recognition stands as a critical component of intelligent transportation systems, contributing to enhanced road safety and efficient traffic management. The paper focuses on exploring various neural network architectures for example, backpropagation neural network and hybrid neural network which is a combination of two neural network (backpropagation neural network and bidirectional associative memory), training methodologies, dataset considerations, and performance evaluations for accurate and real-time recognition of road signs. The experimental result shows that the hybrid neural network is faster than the backpropagation neural network in the completion of the training process with higher recognition accuracy.*

I. INTRODUCTION

In today's dynamic and interconnected world, the safety and efficiency of transportation systems stand as paramount concerns. Road sign recognition, a fundamental component of intelligent transportation systems, plays a pivotal role in enhancing road safety, facilitating efficient traffic management, and enabling the progression towards autonomous driving. Recognizing and interpreting road signs is crucial for providing timely and accurate information to drivers and autonomous vehicles, aiding in adherence to traffic regulations, and ensuring safe navigation on roadways.

Road signs convey essential messages to drivers, alerting them to speed limits, warnings about hazards, providing directions, and communicating regulatory instructions. The ability to recognize these signs accurately and swiftly is imperative, as it directly influences driver decision-making, reduces accident risks, and contributes significantly to the overall efficiency of transportation networks.

Traditionally, road sign recognition relied on manual interpretation by human drivers. However, advancements in computer vision, machine learning, and neural network-based approaches have revolutionized this field. These technologies enable automated recognition and interpretation of road signs from images or video streams captured by cameras mounted on vehicles or infrastructure.

The complexity of road sign recognition arises from various factors, including diverse environmental conditions, variations in sign appearances due to aging, damage, or regional differences in designs and symbols, as well as the need for real-time processing to ensure timely responses. Overcoming these challenges requires sophisticated algorithms, robust training methodologies, and extensive datasets that encompass the diversity of road signs encountered in different geographical locations and environmental conditions.

In recent years, there has been notable research advancement in the domain of road sign recognition. Namyang and Phimoltares [1] utilized a combination of Support Vector Machines (SVM) and Random Forest algorithms, along with HOG and the Color Layout Descriptor (CLD), for traffic sign classification. Soni et al. [2] employed HOG and LBP descriptors with Principal Component Analysis (PCA) and Support Vector Machines (SVM) for traffic sign classification. Sapijaszko et al. [3]

proposed a traffic sign recognition system encompassing stages such as normalization, feature extraction, compression, and classification. Aziz and Youssef [4] proposed a traffic sign recognition system utilizing feature extraction and the Extreme Learning Machine (ELM) algorithm. Wang [5] introduced a traffic sign classification system employing three machine learning classifiers: Logistic Regression (LR), Multilayer Perceptron (MLP), and SVM.

But, neural networks, particularly Backpropagation Neural Network, have demonstrated remarkable capabilities in image recognition tasks, making them a promising approach for road sign recognition. This paper outlines the performance evaluation of the backpropagation neural network and the hybrid neural network.

II. PRELIMINARIES

A. Road Signs

Road signs serve as crucial elements of traffic control and safety, providing essential information to drivers, pedestrians, and other road users. These signs are standardized visual cues that communicate various instructions, warnings, regulations, and guidance about road conditions. Figure 1 shows some road signs with their corresponding meanings.

Signs	Meaning
	No parking
	School zone
	Crossroad ahead
	Gas
	No U turn
	No pedestrians

Fig. 1 Road signs

B. Neural Networks

A neural network is characterized as a reasoning model inspired by the human brain's structure. The brain is composed of a highly interconnected network of nerve cells known as neurons, which serve as the fundamental units for processing information. Human brains encompass nearly 10 billion neurons and an extensive network of 60 trillion synapses interconnecting them, as documented by Shepherd and Koch [6] Leveraging the simultaneous activation of multiple neurons enables the brain to execute tasks at a considerably higher speed compared to today's fastest computers.

Despite their straightforward architecture, a collection of neurons yields remarkable computational capabilities. Each neuron comprises a cell body, a multitude of dendrites (fiber-like structures), and a solitary elongated fiber identified as the axon. Dendrites form an intricate network surrounding the cell body, while the axon extends towards other neurons' dendrites and cell bodies. Refer to Figure 2 for an illustrative representation of a biological neuron.

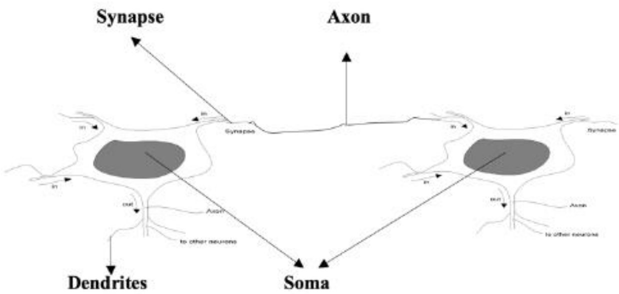

Fig. 2 Biological neuron

Our brain functions as an intricate and sophisticated information-processing system that operates in a highly complex, nonlinear, and parallel manner. Unlike traditional systems where data processing occurs in specific areas, in neural networks, information is stored and processed simultaneously across the entire network. This global approach to both data and its processing distinguishes neural networks by their widespread rather than localized functionality. The adaptability of connections between neurons, causing variations that contribute to arriving at the 'correct' outcome, highlights the plasticity of neural networks. Consequently, these networks possess the capacity to learn from experiences, marking learning as a foundational and vital attribute of biological neural networks. The innate ability to learn effortlessly prompted endeavors to replicate a biological neural network's functionality within a computer environment.

C. Backpropagation Neural Network

The backpropagation neural network (BPNN) architecture comprises an input layer, an output layer, and one or more hidden layers. The number of input units corresponds to the quantity of bits or values representing the input pattern, accommodating these n bits or values. Similarly, the count of output units is determined by the bits or values associated with the output pattern. Conventionally, the network establishes complete connectivity exclusively between adjacent layers, forming fully connected pathways throughout the network as shown in Figure 3.

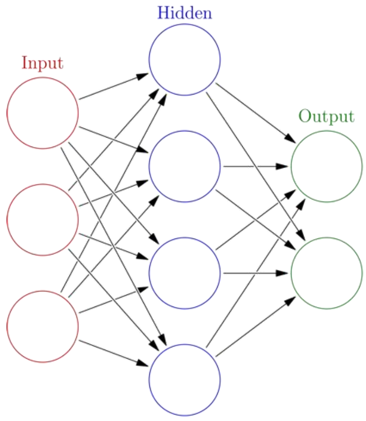

Fig. 3 Backpropagation Neural Network

The backpropagation method uses two steps:

1. In the 'forward step', the input is applied and allowed to propagate to the output. The error values of the output units are calculated by subtracting output value from target value for each unit.
2. In the 'backward step', errors are propagated backwards, and weights are modified.

The network's training objective involves refining the weights to ensure that a given set of inputs yields the intended set of outputs. For conciseness, these input-output combinations are often denoted as vectors. Training operates on the premise that each input vector aligns with a target vector, symbolizing the anticipated output; collectively, these form a training pair. Typically, a network undergoes training with multiple such pairs. For instance, an input pair might encompass a sequence of ones and zeros representing a binary image corresponding to an alphabet letter. The compilation of these training pairs constitutes a training set.

D. Bidirectional Associative Memory

Bart Kosko [7] introduced Bidirectional Associative Memory (BAM) as a heteroassociative neural network as shown in Figure 4. It operates by receiving an input pattern represented as a vector across one group of neurons and generates a correlated yet distinct output vector across another set, and conversely does the same in reverse.

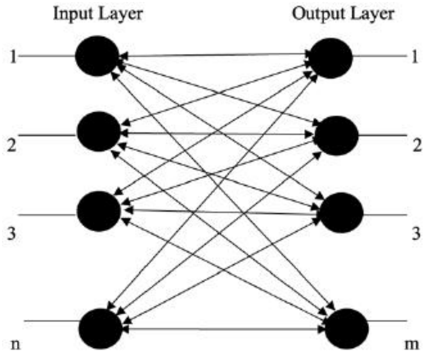

Fig. 4 BAM Network Architecture

The main features of a BAM are given below:

- A BAM comprises two layers of interconnected neurons.
- Neurons within one layer establish complete connections with neurons in the other layer.
- There are no interconnections among neurons within the same layer.
- The storage capacity and reliability of recall hinge on the network architecture and the algorithms used for both recalling and learning.
- Enhancing performance can be achieved by introducing additional layers or establishing more interconnections among neurons.

The input to a BAM network is a vector of real number, usually in the set $\{-1, +1\}$. The output is also a vector in the set $\{-1, +1\}$ with the same or different dimension. These vectors can be considered as patterns, and the network makes heteroassociation of patterns. If the output is required to be the same as input, then the network is said to make auto-association.

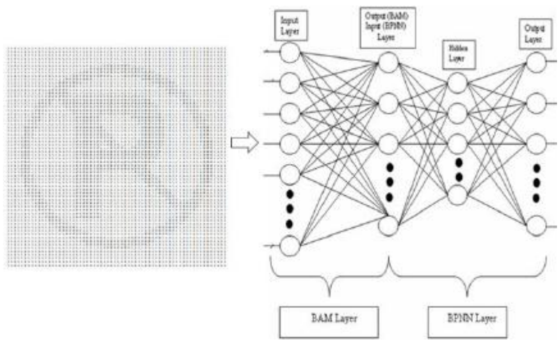

Fig. 5 Hybrid neural network

E. Hybrid Neural Network

A hybrid neural network consists of two distinct neural networks: the BAM neural network and the Bidirectional neural network. BAM is employed to reduce the dimensions of the feature matrix, thereby enhancing the speed and efficiency of recognition. Figure 5 illustrates the network architecture for this hybrid neural network.

III. EXPERIMENTS AND PERFORMANCE EVALUATION

Recognition of Road Sign is a step-by-step processing of road sign. These processes include:

- Preprocessing
- Recognition of sign
- Performance evaluation

The effectiveness of the algorithm has been justified for different Road Sign images of different resolutions. The algorithm is capable of preprocessing and recognizing signs of any grayscale images. The implementation of the algorithm was carried out using the C programming language.

At the beginning, a sign is chosen. The sign is a grayscale image. Whole of the task is done by the following way:

A. Preprocessing

Road signs are being preprocessed by following a sequence of operations: Capturing, Binary image conversion.

Capturing: Road sign acquisition involves utilizing a camera for capturing purposes. For this study, specific obligatory road signs were utilized to create an image database stored as BMP type files. As part of the capturing process, standardization, and geometric normalization, involving adjustments in size and direction, were applied to the images. For analysis purposes, the images were resized to a resolution of 64×64 pixels, as depicted in Figure 6.

Fig. 6 Road sign image

Binary Image Conversion: The initial image was notably in color. It underwent a transformation into a grayscale image and subsequently underwent binarization, a process chosen for its simplicity in pattern matching during sign recognition. Each sign is represented as a matrix of numerical values, ranging from 0 to 255, which can be further translated into binary format (0s and 1s). The conversion sequence is demonstrated in Figure 7.

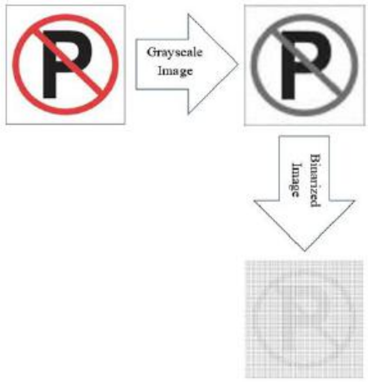

Fig. 7 Image conversion

The road signs are arranged within a 64×64 grid and inputted into the neural network's input layer as feature vectors or training patterns. Consequently, the grid configurations are depicted as vectors comprising 4096 components (where each vector component is 1 if the pixel in the grid is shaded, otherwise it is 0). The hidden layers encompass 60 neurons each, which account for 60% of the input layer. Considering a total of 64 signs, inclusive of both mandatory and other signs, the output layer comprises 64 neurons. Having 64 neurons in the output layer enables the representation of a 6-bit code ($2^6 = 64$) for classifying each target output. Hence, the target outputs range from 000000 to 111111, aligning with each distinct sign.

B. Recognition of sign

The road sign recognition phase is most important and complicated phase. Hence, the sign is 64×64 pixels image. Each sign has a feature matrix of 4096 elements in it. Each element is nothing but binary values (0 and 1).

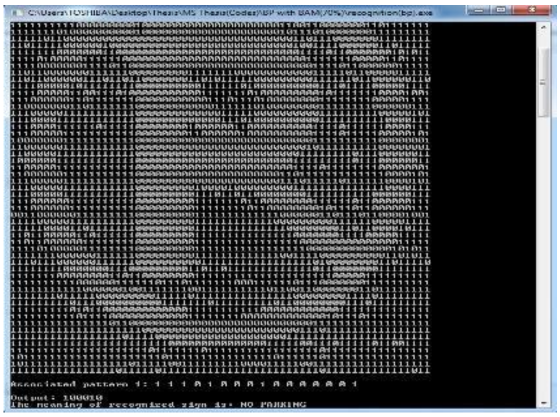

Fig. 8 Recognition of a sign "NO PARKING"

Hence, in this experiment the number of neurons in input layer is 4096, neurons in input layer for BPNN and output layer for BAM is 16, number of neurons in hidden layer is 10, and finally the neurons in output layer is 6. The number of neurons in hidden layer can vary from 50% to 70% of its input neurons.

Figure 8 shows the snapshot of the program output of a normal image.

C. Performance evaluation

To assess the neural network's performance, a series of experiments were conducted, employing separate training and test image sets for each sign without any overlap between them. The back-propagation neural network underwent training utilizing default learning parameters (learning rate 0.3, threshold 1) over 75 epochs. Subsequently, the network was employed to recognize individual signs.

Throughout the training process, the program continued execution until the error reached a minimum threshold level, illustrating the error reduction per iteration in a graphical representation. Initially, the task was implemented using the BPNN algorithm alone, followed by merging the BAM and BPNN algorithms to train and recognize road signs. Upon analysis, it was observed that employing the hybrid network (BAM and BPNN) required fewer iterations for training and less time for sign recognition compared to BPNN alone.

Table 1 Iteration Vs. Error (70%)

Iteration	BP (70%)	BP With BAM (70%)
2	3,866509	1,959864
5	3,858203	1,894699
10	3,503066	1,881338
100	3,435648	1,702669
500	3,217658	1,119279
1000	3,095643	0,612061
1500	2,943532	0,575292
2000	2,873423	0,554884
2500	2,806753	0,543144
3000	2,645987	0,53713
3500	2,546534	0,531881
4000	2,513423	0,492877
4500	2,485645	0,315097
5000	2,437864	0,293473
6000	2,376588	0,278986
7000	2,238757	0,272395
8000	2,187658	0,268759
9000	2,074542	0,266053
10000	1,984532	0,264022
15000	1,912328	0,258816
20000	1,813421	0,256447
25000	1,746574	0,255095
30000	1,698342	0,25338
34075	1,607801	0,009981
40000	1,576457	
45000	1,53768	
50000	1,457854	
55000	1,356245	
60000	1,247856	
65000	1,109854	
70000	1,065242	
75000	0,176542	
80000	0,039947	
85000	0,017469	
88043	0,009997	

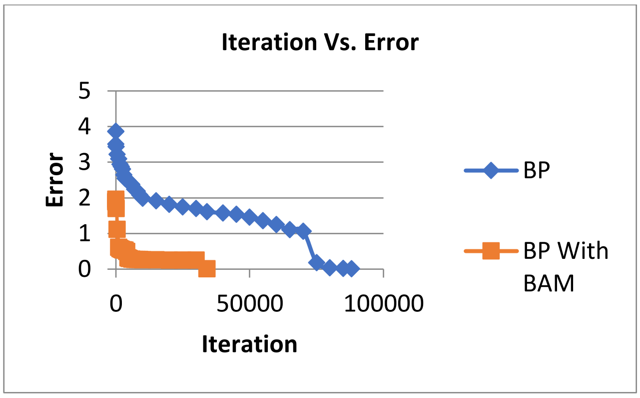

Fig. 9 Iterations Vs. Error (70%)

The training process involved eight training input patterns and employed an error threshold (e.g., 0.001) to halt training. The number of iterations was contingent upon the percentage of the hidden layer and the algorithm utilized during training. For instance, setting the hidden layer to 70% of the input layer resulted in 88043 iterations, while reducing the hidden layer to 50% led to 43067 iterations.

Upon adopting the hybrid network with the same percentage of the hidden layer, the iteration count decreased further. Specifically, it decreased from 34075 to 14977, illustrating an even more pronounced reduction in iterations compared to previous results.

Table 2 Iteration Vs. Error (50%)

Iteration	BP (50%)	BP With BAM (50%)
2	6,933186	3,07014
5	5,694922	3,055324
10	4,678283	3,025566
100	4,333929	1,374816
500	4,045357	0,567401
1000	3,874532	0,316263
1500	3,523548	0,134039
2000	3,223324	0,077653
2500	2,963092	0,057539
3000	2,927669	0,04723
3500	2,906451	0,040717
4000	2,566751	0,035315
4500	2,550943	0,031443
5000	2,539485	0,028615
6000	2,530225	0,023834
7000	2,522263	0,020596
8000	2,515119	0,018211
9000	2,502996	0,016202
10000	2,448071	0,014673
14977	2,056355	0,01
20000	1,800224	
25000	1,034644	
30000	0,176542	
35000	0,039947	
40000	0,017469	
43067	0,009997	

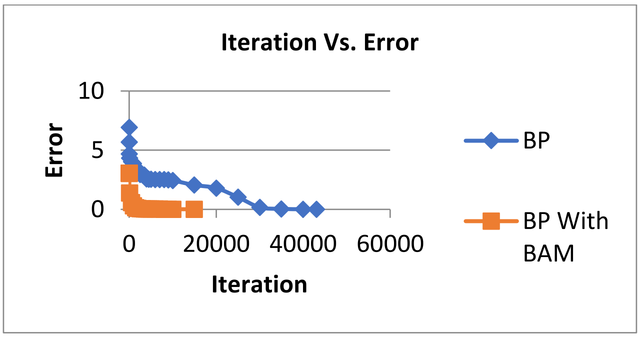

Fig. 10 Iterations Vs. Error (50%)

Comparing the performance of two networks as BPNN and hybrid neural network a decision had been taken that the hybrid neural network takes less iteration than BPNN in completion of the training process.

IV. CONCLUSION

Neural network-based road sign recognition holds immense potential in revolutionizing transportation systems by enhancing road safety and traffic management. The paper underscores the significance of neural networks in this domain and outlines the performances of BPNN and hybrid neural networks with experimental results. And the result shows that the hybrid neural network performs faster than BPNN with high recognition accuracy.

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