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قسم الرياضيات

Comparison Between Kohonen Neural Network (SOM) and Backpropagation Neural Network

مقارنة بين شبكة كوهنين(خارطة التنظيم الذاتي) وشبكة العصبية للتغذية الخلفية

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بسم الله الرحمن الرحيم

﴿ وَأَن لَّيْسَ لِلْإِنسَانِ إِلَّا مَا سَعَى ﴾

صدق الله العظيم

(سورة النجم: 39)

الإهداء

إلى من كان لهم الفضل في مسيرتي العلمية،

إلى من علموني الصبر والاجتهاد،

إلى من ساندوني في كل خطوة...

إلى والديّ العزيزين...

وإلى كل من كان له أثر في دعمي وتشجيعي...

أهدي هذا العمل المتواضع.

الشكر والتقدير

أتقدم بخالص الشكر والتقدير إلى اللّه سبحانه وتعالى الذي وفقني لإتمام هذا البحث.

كما أتقدم بجزيل الشكر والامتنان إلى أستاذي المشرف

د. اميره فنجان

لما قدمه من توجيهات علمية قيمة ومتابعة مستمرة كان لها الأثر الكبير في إنجاز هذا البحث.

كما أقدم شكري إلى أساتذتي الكرام في جامعة بابل كلية العلوم الصرفه / قسم الرياضيات لما قدموه من علم ومعرفة طوال فترة دراستي.

ولا يفوتني أن أتقدم بالشكر لكل من ساهم في إنجاح هذا العمل.

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Abstract

Artificial Neural Networks (ANNs) have become essential tools in data analysis, pattern recognition, and medical image processing. Among the most widely used paradigms are the Kohonen Neural Network, also known as the Self-Organizing Map (SOM), and the Backpropagation Neural Network (BPNN). This study presents a comparative analysis of these two models in terms of learning strategy, network architecture, performance, and application suitability.

The Self-Organizing Map is an unsupervised learning algorithm that performs dimensionality reduction while preserving the topological structure of input data. It is particularly effective for clustering, visualization, and exploratory data analysis, especially when labeled data is unavailable. In contrast, the Backpropagation Neural Network is a supervised learning approach that utilizes error minimization through gradient descent to iteratively adjust network weights. It is highly effective in tasks requiring precise prediction, classification, and function approximation.

This comparison highlights key differences between the two approaches, including their training mechanisms, convergence behavior, computational complexity, and robustness to noise. SOM demonstrates strengths in discovering inherent data structures and handling high-dimensional data, while BPNN excels in achieving high accuracy when sufficient labeled datasets are available. Additionally, the study discusses their respective advantages and limitations in real-world applications, particularly in medical imaging, where SOM is often used for clustering and segmentation, whereas BPNN is applied for classification and diagnosis.

The findings suggest that the choice between SOM and BPNN depends largely on the nature of the problem, the availability of labeled data, and the desired output. In some cases, hybrid models that integrate both techniques can provide improved performance by leveraging the strengths of each method.

Chapter 1

Theoretical aspect of Artificial Neural Networks

1.1. Introduction

Neural networks can be broadly categorized based on their learning paradigms into supervised and unsupervised models. Among these, the Kohonen Neural Network, also known as the Self-Organizing Map (SOM), represents an unsupervised learning approach, whereas backpropagation is a supervised learning algorithm widely used in multilayer feedforward neural networks. This section presents a comparative analysis of these two approaches in terms of structure, learning mechanism, performance, and applications, particularly in the field of medical image processing. [1][2]

1.2. Aim of Research

The aim of neural networks study and the comparison between some kind of them that have principles and different characteristics in artificial intelligence field and image processing is to show the best performance of these networks, in order to the reader can choose the best one that give optimal results in their works**.**

1.3. Learning Paradigm

The primary distinction between the Kohonen Neural Network and backpropagation lies in their learning strategies. SOM operates under unsupervised learning, meaning it does not require labeled data. It identifies inherent patterns and structures within the input data by grouping similar data points into clusters.

In contrast, backpropagation is a supervised learning algorithm that requires labeled datasets. It learns by minimizing the error between predicted outputs and actual target values through iterative weight adjustments. [1][2]

1.4. Network Architecture

The Kohonen Neural Network typically consists of a single layer of neurons arranged in a two-dimensional grid. Each neuron represents a prototype vector, and the network preserves topological relationships among input data.

On the other hand, backpropagation networks are composed of multiple layers, including input, hidden, and output layers. These multilayer structures allow the network to model complex nonlinear relationships in data. [2]

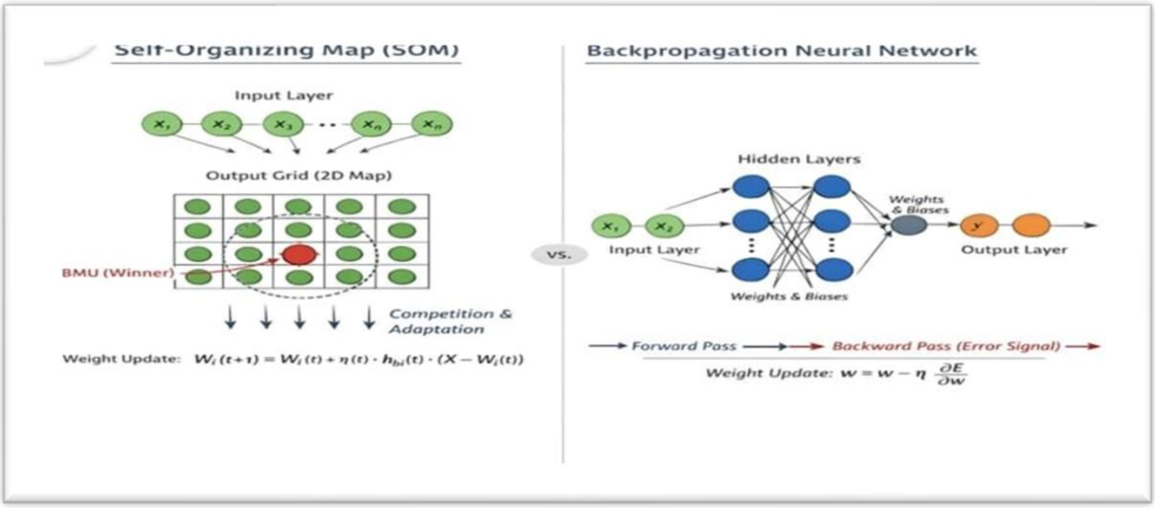

Fig1: Architeature set organization and back progation neural network

1.5. Training Mechanism

SOM uses a competitive learning approach. For each input vector, the neuron with the closest weight (Best Matching Unit, BMU) is identified, and both the BMU and its neighboring neurons are updated. This process enables the network to form organized clusters over time.

Backpropagation relies on gradient descent optimization. The algorithm performs a forward pass to compute the output, calculates the error, and then propagates this error backward through the network to update weights using the chain rule.[3]

1.6. Output Representation

The output of a Kohonen network is typically a map that visualizes clusters of similar data. It is especially useful for data exploration and dimensionality reduction.

In contrast, backpropagation networks produce explicit outputs such as class labels or continuous values, making them suitable for classification and regression tasks.[2]

1.7. Performance and Complexity

SOM is generally simpler and computationally less intensive, as it does not involve complex gradient calculations. However, its performance in predictive tasks is limited compared to supervised models.

Backpropagation networks, while computationally more demanding, provide higher accuracy in prediction and classification tasks due to their ability to learn complex mappings from input to output.[4]

1.8. Applications in Medical Imaging

In medical image processing, SOM is commonly used for image segmentation and clustering, such as grouping tissues in FACES or CT images without prior labeling. Its ability to preserve spatial relationships makes it valuable for exploratory analysis.

Backpropagation-based networks, particularly deep learning models like convolutional neural networks (CNNs), are widely used for tasks such as tumor classification, disease diagnosis, and image recognition, where labeled datasets are available.[5]

1.9. Advantages and Limitations

Kohonen Neural Network (SOM):

Advantages:

Does not require labeled data

Effective for clustering and visualization

Preserves topological relationships

Limitations:

Limited predictive capability

Sensitive to parameter selection (map size, learning rate)

Backpropagation Neural Network:

Advantages:

High accuracy in classification and prediction

Capable of modeling complex nonlinear relationships

Widely applicable in deep learning

Limitations:

Requires labeled data

Computationally intensive

Risk of overfitting. [6]

Chapter 2

Neural Network for faces Image Recognition

2.1 Introduction

The Kohonen Neural Network, also known as the Self-Organizing Map (SOM), is an unsupervised learning algorithm widely applied in medical image analysis. In Magnetic Resonance Imaging (FACES), SOM is particularly effective for tumor detection and tissue segmentation due to its ability to cluster high-dimensional pixel features and provide intuitive visualization.

FACES images contain complex intensity patterns that represent different tissue types such as gray matter, white matter, cerebrospinal fluid, and abnormal tumor regions. SOM helps in grouping similar pixels into clusters without requiring labeled data.

2.2 Methodology

2.2.1 Feature Extraction from FACES Images

Each pixel (or voxel) in the FACES image is represented as a feature vector:

X = [Intensity, Texture, Spatial Coordinates]

Common features include:

- Intensity values (T1, T2, or FLAIR images)
- Texture features (e.g., entropy, contrast)
- Spatial location (x, y coordinates)

2.2.2 SOM Architecture

The SOM consists of a two-dimensional grid of neurons, where each neuron represents a prototype vector:

Wi = [w1, w2, ..., wn]

Each neuron learns to represent a group of similar pixels.

[Figure 3.X: SOM grid mapping FACES pixel features into a 2D lattice]

2.2.3 Training Algorithm

The SOM training for FACES clustering follows these steps:

1. Initialize neuron weights randomly.
2. For each pixel feature vector X:
3.
    - Compute Euclidean distance between X and all neurons.
    - Identify the Best Matching Unit (BMU):

$$BMU = \arg\min ||X - W_i||$$

4. Update BMU and its neighbors:

$$W_i(t+1) = W_i(t) + \alpha(t) * h_{ci}(t) * (X - W_i(t))$$

1. Repeat until convergence. [7][8]

2.3 Self-Organizing Map (KSOM) Method

The Kohonen Self-Organizing Map (KSOM), also known as Kohonen map/network learning method is an unsupervised learning method, so this network structure does not require an output target. It modifies the weight of an ANN without needing to determine the output for a specific input pattern. The advantage is that it enables the network to find solutions, thus making it more effective and efficient with pattern connections. The main disadvantage is that interpreting the output must be done correctly.

The activation function used in KSOM is Sigmoid Binary (Logsig), so before entering the learning process, the input data must be changed so that the value is in the range 0 to 1. All face images will be trained according to the algorithm of this method to update the weights which will be the final weights used for the recognition process.

The initial values needed for entering the KSOM algorithm such as maximum epoch, learning rate/alpha (α), data training matrix, random initial weight matrix and alpha reduction (δ). The algorithm for the KSOM is described as follows:

- Initialization: determine the initial weight random value of Wij
- Do this if the stop condition is FALSE

1. For every j, equation (1) for calculating:

$$D_j = \sum_i \left(W_{ij} - X_i\right)^2$$

(1)

2. Specify j, up to D(j) the smallest/minimum value
3. For unit j, for each i, equation (14) for counting:

$$Wij(new) = Wij(new) + \alpha\ (Xi - Wij(old))$$

(2)

4. Equation (15) for improving learning rate:

$$\alpha(new) = \alpha(old).\delta$$

(3)

- Do this until the epoch value is reached or the condition test stops.

Equation (16) is used for calculating the Euclidean distance, in the matching or recognition process:[7][8]

$$d = \sqrt{\Sigma i^{n}} (Wi - Xi)^2$$

(4)

where d is the Euclidean distance, Wi is the weight of neuron i (final weight), and Xi is the vector input to Xi. The minimum Euclidean distance is the result of recognition that best matches the stored face image. The threshold is used to limit the Euclidean Distance in the matching/recognition process. While the similarity distance serves to limit the iteration of changes in weight so that the best weight is obtained, even though the maximum epoch has not been fulfilled.

2.4 Backpropagation Method

One of the most widely used artificial neural network training algorithms in the field of pattern recognition is Backpropagation. This algorithm is generally used in multi-layer feed-forward neural networks, which are composed of several layers and the signal is flowed in a unidirectional direction from input to output. The Backpropagation training algorithm basically consists of three stages:

a. Input the value of the training data so that the output value is obtained

b. Backpropagation of the error value obtained

c. Weight connection adjustment to minimize error value

These three stages are repeated continuously until the desired error value is achieved. After the training is complete, only the first step is needed to utilize the neural network. Error information is propagated sequentially starting from the output layer and ending at the input layer, so this algorithm is named Backpropagation.

In training artificial neural networks using the backpropagation algorithm, the steps are as follows:

a. Initialize the weights with a random value between -0.5 to 0.5.
b. Determine the learning rate (α).
c. Specify the error tolerance value or threshold value (when using the threshold value as a stop condition) or the maximum set of epochs (when using the number of epochs as a stop condition).
d. Perform the following steps as long as the stop condition has not been met (value FALSE)

1. For each pair of training patterns, do the following.

a) <u>Feedforward</u>

a. Each input unit Xi (from the 1st unit to the nth unit in the input layer, i = 1, ..., n) sends an input signal to all units in the upper layer (to the hidden layer).
b. For each unit in the hidden layer Yj (from the 1st unit to the pth unit; j = 1, ..., p) the hidden layer output signal is calculated by applying the activation function to the sum of the input signals weighs Xi. In this study, the bipolar sigmoid activation function is used (5);

$$Yj = f\,(V_{0j} + \textstyle\sum_{i=1}^{n} XiVij\ ) \qquad (5)$$

then sent to all overlay units.

c. Each unit in the output layer Zk (from the 1st unit to the mth unit, i = 1, ..., n; k = 1, ..., m) is calculated the activation function (6) of the zj-weighted sum of the input signals for this layer:[7][8]

$$Z_k = f\,(W_{0k} + \textstyle\sum_{j=1}^{p} YiWjk) \qquad (6)$$

then sent to all overlay units.

b) <u>Backpropagation</u>

(1) Each unit of output Zk (from 1st unit to mth unit j = 1, ..., p; k = 1, ..., m) receives a target pattern tk and then the output layer error information (δk) is computed by (7). δk is sent to the layer below it and is used to calculate the weight and bias correction (ΔWjk and ΔW0k) between the hidden layer and the output layer. It is shown on (9), (8):

$$\delta_k = (T_k - Z_k)\, f'(W_{0k} + \textstyle\sum_{j=1}^{p} YiWik) \qquad (7)$$

$$\Delta W_{jk} = \alpha.\delta_k.Yj \qquad (8)$$

$$\Delta W_{0k} = \alpha.\delta_k \qquad (9)$$

(2) For each unit in the hidden layer (from 1st unit to pth unit i = 1, ..., n; j = 1, ..., p; k = 1, ..., m) the layer error information is calculated by (10). Hidden (δj), δj is then used to calculate the amount of weight and bias correction (ΔVij and ΔV0j) between the input layer and the hidden layer. It is shown on (10), (11):

$$\delta_j = (\textstyle\sum_{k=1}^{m} \delta kWjk)\, f'(V_{0j} + \textstyle\sum_{i=1}^{p} XiVij) \qquad (10)$$

$$\Delta V_{ij} = \alpha.\delta_j.X_i \qquad (11)$$

$$\Delta V_{0j} = \alpha.\delta_j \qquad (12)$$

c) <u>Weights and Bias Updates</u>

1. For each unit of yk output (from the 1st unit to the m-unit), the bias and weight (j = 0, ..., p; k = 1, ..., m) are corrected so that the new bias and weights become (13):

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} \qquad (13)$$

From the 1st unit to the p-unit in the hidden layer, updates are also made to the bias and the weights (i = 0, ..., n; j = 1, ..., p) by the following formula:

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \qquad (14)$$

2. Calculate the MSE (Mean Squared Error) with the formula (15):

$$MSE = (Tk - Zk)^2 \qquad (15)$$

Difference of squares of Tk Output Target and Zk output value.

3. Stop condition test: stop condition is TRUE, if the MSE value is more than or equal to the error tolerance value, or the number of Epochs has not exceeded the maximum epoch.
   In the matching/recognition process, do the feedforward process using the final weights.

2.5. RESULTS

The process of testing the Kohonen Self Organizing Map (KSOM) Neural Network used training variables as follows: training rate (α) = 0.6; alpha reduction (δ) = 0.5; threshold = 0.02; and similarity distance = 0.00000000000001. The threshold function is to limit the Euclidean distance in the matching/recognition process. While the similarity distance serves to limit the iteration of changes in weight so that the best weight is obtained, even though the maximum epoch has not been fulfilled.

While the Backpropagation Neural Network testing process, used the following training variables: training rate (α) = 0.008, momentum (μ) = 0.02; error tolerance = 0.01; number of hidden layers = 30.

Flowchart

Fig.**1** illustrates the flowchart of the training process and face image recognition system.

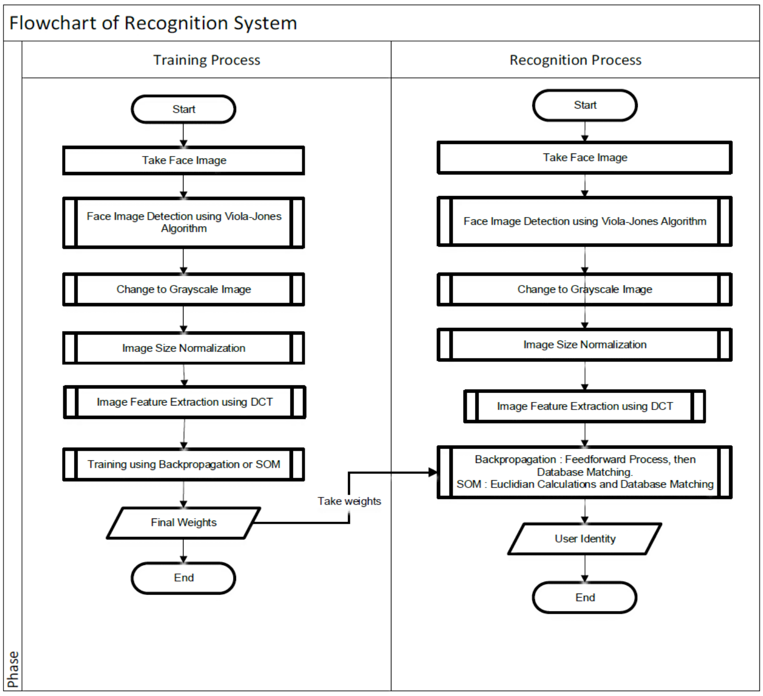

Fig .1 Flowchart of system

B. Data and Training

The face image database used is 500 face images, consisting of 50 identities with 10 face images for each identity. From the 50 identities, 30 identities came from ORL face dataset and 20 identities were taken using a web camera. The 10 face images were taken with several tilt angles and face expressions. These were sample training/learning and testing images that had been cropped and converted to grayscale. Fig. 2 shows the images from ORL database; and Fig. 3 shows sample images taken from a web camera. [7][8]

fig (2) Training and Testing Images taken from The ORL Database

Fig(3) Training and Testing Images taken from Web Camera

C. Application of Face Image Recognition System

Following are the results of the data input form shown in Fig. 4, training form with Backpropagation shown in Fig. 5, training form with KSOM shown in Fig. 6 and face image recognition form shown in Fig. 7.

Fig. 4 Identity and Face Input Form

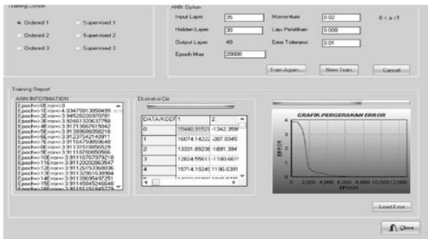

Fig. 5 Backpropagation Training Form

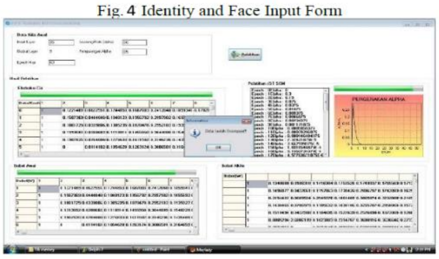

Fig. 6 KSOM Training Form

Fig. 7 Recognition Form

D. Definition of FAR and FRR

In the case of matching or recognition, the accuracy of the system is measured by Accuracy Rate, False Acceptance Rate (FAR) and False Rejection Rate (FRR). False Acceptance (FA) occurs when the system accepts a face image whose identity is not recorded in the database. False Rejection (FR) occurs when the system rejects a face image whose identity is stored in the database. The success rate is the percentage of the system's success in recognizing the right face, namely accepting face images stored in the database, or rejecting face images that are not stored in the database. The rate of Accuracy, FA and FR is calculated using (15), (16) and (17) [25] [26] [27]. Therefore, if the FAR or FRR is lower, then the success rate will be higher.

$$\text{FAR} = \text{number of FA} / \text{number of test} \times 100\% \qquad (15)$$

$$\text{FRR} = \text{number of FR} / \text{number of test} \times 100\% \qquad (16)$$

$$\text{Success Rate} = \frac{\text{the number of system success}}{\textit{number of expreriment}} \times 100\% \qquad (17)$$

E. FAR and FRR of Backpropagation based on the Number of Hidden Layers

In the testing process of determining the best hidden layer on the Backpropagation, the following training variables are used: input layer = 35, training rate (α) = 0.008, momentum (μ) = 0.02, error tolerance = 0.01. The face image used is in accordance with training and testing data. Table 2 shows the comparison of the calculation of the FAR and FRR values of the face image recognition system using the Backpropagation method based on the number of hidden layers. To calculate FAR, 50 face images whose identities were not stored in the database were used; and to calculate

F. Comparison of the Backpropagation and KSOM

The testing used the KSOM method, the training variables were used as follows: training rate (α) = 0.6; alpha reduction (δ) = 0.5; threshold = 0.02 and similarity distance = 0.00000000000001. Table 3 shows a comparison of the FAR and FRR of the face image recognition process using the Backpropagation or KSOM method. In the first experiment, to calculate FAR, 50 face images whose identities were not stored in the database were used; and to calculate different FRRs, 50 face images whose identities were stored in the database were used.

TABLE 3

FAR AND FRR OF BACKPROPAGATION AND KSOM METHOD

Method	FA	FAR	Success Rate	FR	FRR	Success Rate
Backpropagation	14	28%	72%	11	22%	78%
KSOM	18	36%	64%	15	30%	70%

From the test results, it can be seen that the FAR of Backpropagation is 28%, and the FAR of KSOM is 36%., while the FRR of Backpropagation is 22%, and the FRR of KSOM is 30%. The average success rate of the Backpropagation is 75%, and the average success rate of the KSOM is 67%. Because the FAR and FRR of Backpropagation are lower than KSOM, and the success rate of Backpropagation is higher than KSOM, so it can be concluded that the Backpropagation method is better in recognizing face images than the KSOM method. In the second experiment, a recognition test was conducted based on the level of face tilt, such as tilting right, left, up and down. In this experiment, 20 face images were used whose identities were stored in the database. [7][9]

2.6. Conclusion

In summary, the Kohonen Neural Network and backpropagation serve different purposes in machine learning. SOM is more suitable for unsupervised tasks such as clustering and visualization, while backpropagation is ideal for supervised learning tasks requiring high predictive accuracy. In modern research, hybrid approaches that combine both methods are increasingly explored to leverage the strengths of each, particularly in complex domains such as medical image analysis.

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