ENHANCING IMAGE RECOGNITION PATTERNS WITH HOPFIELD NEURAL NETWORKS

Batiuk Taras[1]

---

1. PhD student of Computer sciences and Information technologies
Lviv Polytechnic National University, UKRAINE
ORCID ID: 0000-0001-5797-594X

In 1982, John Hopfield introduced his associative network during a presentation at the National Academy of Sciences. To pay homage to Hopfield and this innovative modeling approach, this network paradigm is commonly known as the Hopfield network. This network concept draws inspiration from the principles of dynamic systems in physics. Initially, it found applications in associative memory and problem optimization.

A Hopfield network [1] comprises three layers: an input layer, a Hopfield layer, and an output layer, with each layer containing an equal number of neurons. The Hopfield layer's input connections link to the corresponding neurons in the input layer via adjustable connection weights. Its output connections link to the input neurons within the Hopfield layer (excluding itself) and to the corresponding elements in the output layer.

During operation, the network transmits data from the input layer to the Hopfield layer using fixed connection weights. The Hopfield layer [2] oscillates until a specific number of cycles are completed, at which point the current state of the layer is transferred to the output layer.

Training a Hopfield network necessitates the simultaneous presentation of training images to both the input and output layers. The recursive nature of the Hopfield layer provides a mechanism to adjust all connection weights. For non-binary network implementations, a threshold mechanism in the transfer function is essential. Effective network training mandates that the input-output pairs differ from each other.

The Hopfield network faces two primary limitations. Firstly, the number of images that can be stored and accurately retrieved is severely restricted. Training a Hopfield network involves a process known as associative or content-addressable memory. Unlike training [3] in traditional neural networks where you adjust weights using techniques like backpropagation, Hopfield networks have a unique

method for learning patterns. The training process aims to store specific patterns in the network's synaptic connections so that it can later recall them when presented with a partial or noisy input.

To train a Hopfield network, you start by presenting the pattern or image you want to store to both the input and output layers simultaneously. These patterns can be binary representations, such as 0s and 1s. During the presentation of the pattern, the network updates its connection weights iteratively. The network uses a Hebbian learning rule, which states that if two neurons are firing simultaneously, the connection weight between them should be increased. If they are not firing together, the weight is decreased. This process is repeated [4] until the network converges. Once the training process is complete, the network should be able to recall and reconstruct the stored pattern when given partial or noisy input.

You can do this by partially presenting the pattern to the network and allowing it to self-organize to retrieve the closest stored pattern. It's important to note that Hopfield networks have some limitations. They can store a limited number of patterns due to their capacity constraints. Also, the network might not always converge to the desired pattern, especially if the input is too similar to multiple stored patterns. To mitigate these issues, techniques like energy minimization are often used to fine-tune pattern retrieval.

In summary, training a Hopfield network relies on Hebbian learning [5], where the network learns to store and recall patterns through iterative weight adjustments. While they have their limitations, Hopfield networks remain a valuable tool for associative memory and solving optimization problems.

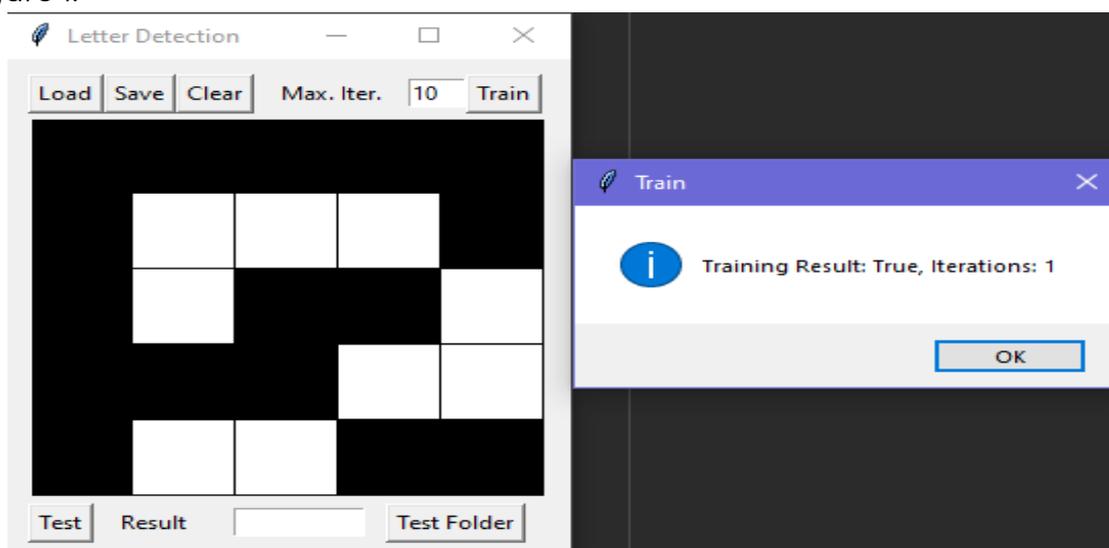Neural network training on the example of reference image "R" is shown in Figure 1.

Fig. 1. **Neural network training on the example of reference image "R"**

The matrix of connection weights is a fundamental component of Hopfield networks and plays a central role in their operation. Hopfield networks use this weight matrix to store and recall patterns or information. The matrix of connection weights in a Hopfield network is typically represented as a symmetric matrix. The size of the matrix depends on the number of neurons in the network. If there are "n" neurons, the weight matrix will be an "n x n" square matrix. This symmetric structure ensures that the connection weights between neuron "i" and neuron "j" are the same as the weights between neuron "j" and neuron "i."

The values in the weight matrix represent the synaptic connection strengths between neurons. Each element of the matrix (i, j) holds the weight associated with the connection from neuron "i" to neuron "j." These weights are real numbers or binary values (typically +1 or -1 in binary Hopfield networks).During the training phase of a Hopfield network, the weight matrix is adjusted to store patterns or information. Saving all reference and test images are shown in Figure 2.

a.txt	27.10.2020 17:41	Текстовый докум...	1 КБ
r.txt	08.11.2020 11:49	Текстовый докум...	1 КБ
t.txt	27.10.2020 17:40	Текстовый докум...	1 КБ
a1.txt	27.10.2020 17:46	Текстовый докум...	1 КБ
r1.txt	08.11.2020 11:51	Текстовый докум...	1 КБ
t1.txt	27.10.2020 17:48	Текстовый докум...	1 КБ

Fig. 2. **Saving all reference and test images**

As patterns are presented to the network, the connection weights are updated using a Hebbian learning rule. The rule states that if two neurons are firing simultaneously, the connection weight between them should be increased. If they are not firing together, the weight is decreased. This process continues until the network converges to the stored patterns. When you present a partial or noisy input pattern to the network, it initiates a recall process. The network tries to reach a stable state by iteratively updating neuron states based on the connection weights.

The network self-organizes to reach a state that is closest to one of the stored patterns in the weight matrix. The symmetric weight matrix allows Hopfield networks to perform associative memory tasks. It can recall complete patterns from partial or corrupted inputs, making it useful for content-addressable memory. Hopfield networks have limitations, including capacity constraints. The number of patterns that can be accurately stored is limited, and the network might fail to converge to a stored pattern if the input is too similar to multiple stored patterns.

The results of calculations of network output signals in a Hopfield network after presenting an image depend on the network's recall process. Hopfield networks are capable of pattern recall, and the process involves updating neuron states based on the connection weights in the matrix. The process starts with the presentation of an input pattern to the network. This input can be a complete pattern or a partial pattern. Determination of the letters of the test images and the current obtained weights during the main training of the neural network are shown in Figure 3.
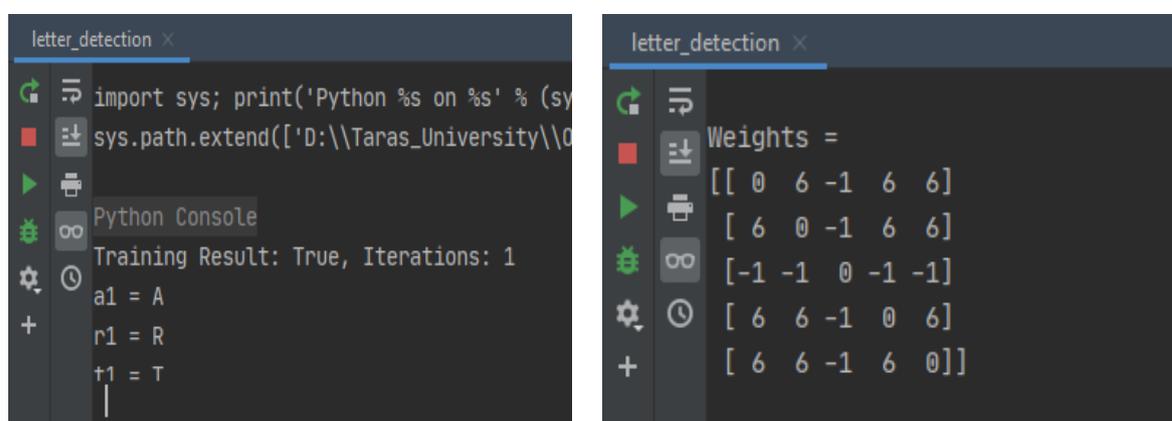

Fig. 3. **Determination of the letters of the test images and the obtained weights during the training of the neural network**

Upon receiving the input pattern, the Hopfield network begins the activation process. The network updates the states of its neurons iteratively based on the presented input and the weight matrix. Neurons can be binary, often with states +1 or -1. Neurons in the Hopfield network converge toward stable states during the recall process. They do so by continuously updating their states according to a set of activation rules and the connection weights. The network strives to minimize the energy function. At each step, the energy decreases, and this process continues until the network reaches a stable state. The energy function is defined based on the current network state, the connection weights, and the input pattern.

In conclusion, Hopfield neural networks have proven their mettle in image recognition tasks, offering a unique and effective approach to associative memory and pattern recognition. This study contributes to the understanding and application of Hopfield networks and paves the way for further exploration of this intriguing field. As technology advances, the potential for Hopfield networks to play an integral role in solving complex image recognition challenges becomes increasingly evident.

REFERENCES:

[1] Corti L., Zanetti M., Tricella G., Bonati M. Social media analysis of Twitter tweets related to ASD in 2019–2020, with particular attention to COVID-19: topic modelling and sentiment analysis. *Journal of Big Data.* 2022. № 9 (1). P. 1–17.

[2] Liu H. Online review analysis on various networks' consumer feedback using deep learning. *IET networks.* 2022. № 11 (6). P. 234–244.

[3] Wang Y., Chen Z., Fu C. Synergy Masks of Domain Attribute Model DaBERT: Emotional Tracking on Time-Varying Virtual Space Communication. *Sensors.* 2022. № 22 (21). P. 450–471.

[4] Wang Y., Guo J., Yuan C., Li B. Sentiment Analysis of Twitter Data. *Applied Sciences.* 2022. № 12 (8). P. 157–189.

[5] Albahli S., Irtaza A., Nazir T., Mehmood A., Ali A., Waleed Albattah W. A Machine Learning Method for Prediction of Stock Market Using Real-Time Twitter Data. *Electronics.* 2022. № 11 (20). P. 341–363.