

Performance Level Analysis on Learning Vector Quantization and Kohonen Algorithms

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Abstract: Biometric identification is an alternative for a security system that consists of physiological characteristics and behavioral characteristics. Physiological characteristics are relatively stable physical characteristics such as fingerprints, hand lines, facial features, tooth patterns, and the retina of the eye. Behavioral characteristics such as signature, speech patterns, or typing rhythm. The function of a signature is proof in a document which states that the party signing, knows and agrees to all the contents of a document. There are several stages in the signature pattern image recognition system, namely the signature pattern image is produced through a scanning process, then the resulting digital signature image is cut (scaling) manually, the next process is thresholding, edge detection, image division, and representation. input value. The method used in recognizing signature patterns is the learning vector quantization (LVQ) artificial neural network method and kohonen self-organizing map (SOM). In Learning vector quantization, the initial weights are updated using existing patterns. Meanwhile, in the self-organizing map method, Kohonen takes initial weights randomly, then these weights are updated until they can classify themselves into the desired number of classes. The processes that occur in the artificial neural network method require a relatively long time. This is influenced by the large number of data samples used as a means of updating the trained weights. From the results of the research conducted, it shows that the learning rate value that was built around $0.2 < \alpha \leq (10)^{-2}$ can produce better signature pattern recognition accuracy.

Keywords: Learning Vector Quantization, Kohonen Algorithms, Self-Organizing Map.

INTRODUCTION

Artificial Neural Network or also called simulated neural network (SNN) is a network of a group of small processing units modeled based on human neural networks. In simple terms, artificial neural networks are a non-linear statistical data modeling tool (Wulanningrum & Robby, 2017). Artificial neural networks can be used to model complex relationships between input and output to find patterns in data (Rahman et al., 2022). Where an artificial neural network is an information processing system designed to imitate the way, the human brain works in solving a problem by carrying out a learning process through changing the synapse weights (Hariya Pamulu et al., 2019). An artificial neural network is configured for a specific application such as pattern recognition or data classification, through a learning process (Hariyanto et al., 2016). In the learning process, input or output patterns are entered into the artificial neural network and then the network will be trained to provide acceptable answers (Budianita et al., 2018).

Artificial Neural Networks consist of several methods, including Hebb Rule, Perceptron, Delta Rule, Backpropagation, Heteroassociative Memory (BAM) (Edwar et al., 2021), Learning Vector Quantization, and Self-Organizing Map Kohonen. The artificial neural network method used by the author in this research is learning vector quantization and self-organizing map kohonen (Suhaili et al., 2018).

The learning vector quantization method is one method for carrying out supervised learning at the competitive layer (Bagas et al., n.d.). This method only uses forward flow in its calculations. If two vectors are approximately the same, then the competitive layer will put the two input vectors into the same class (Nasution & Suendri, 2023). The learning vector quantization method is used to group patterns into pattern classes. The learning vector quantization method is widely used to solve problems related to disease identification, pattern identification or pattern recognition (Hikmah et al., 2022).

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An Artificial Neural Network is configured for a specific application such as pattern recognition or data classification, through a learning process(Latifah et al., 2020). In the learning process, input or output patterns are given and then the network will be taught to provide acceptable answers(Sipayung & Novichasari, 2018).

Learning Vector Quantization (LVQ) is a training method in a supervised competitive layer that will learn automatically to classify input vectors into certain classes(Budianita & Prijodiprodjo, 2013). The resulting class depends on the distance between the input vectors. Furthermore, hybrid approaches integrating both LVQ and SOM with deep neural networks have been explored to address some of these limitations. These hybrid systems aim to combine the efficiency and interpretability of LVQ and SOM with the power of deep learning. However, the complexity and computational demands of these hybrid models can become a significant obstacle, especially when dealing with large-scale, unstructured data. More research is needed to refine these hybrid approaches, improving their computational efficiency and making them suitable for real-world applications(Alvianita et al., n.d.). In conclusion, while LVQ and Kohonen SOM continue to be relevant in the machine learning landscape, especially for classification and clustering, they face several limitations when dealing with large, high-dimensional, or complex data. State-of-the-art methods such as deep learning, GANs, and self-supervised learning are emerging as potential solutions to overcome these challenges. Future research should focus on improving the scalability, accuracy, and interpretability of these traditional methods, and explore hybrid models that combine the strengths of both classical and modern machine learning techniques. In the context of the ongoing evolution of clustering and classification techniques, the comparison of LVQ and Kohonen SOM with state-of-the-art methods highlights several critical research gaps. One major challenge is the ability of both LVQ and SOM to scale efficiently with larger datasets. As machine learning models become more data-hungry, traditional methods like LVQ and SOM struggle to maintain their performance in terms of computational efficiency and accuracy. Although LVQ excels in supervised learning scenarios where class labels are available, it is still limited by the curse of dimensionality and the need for careful selection of learning parameters (Irawan & Santoso, 2021). This is where the integration of newer techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), can provide enhanced performance, as these models automatically learn and adapt to data without requiring explicit dimensionality reduction.

The Kohonen SOM algorithm, while effective at producing low-dimensional mappings, faces similar challenges when handling large and complex datasets. Despite its ability to preserve topological features in data, the lack of supervision in the algorithm can lead to less accurate clustering results when the data is highly noisy or contains overlapping class distributions (Aziz et al., 2023). State-of-the-art methods, such as generative adversarial networks (GANs) or self-supervised learning, may provide more robust alternatives for learning meaningful representations from raw data, as they allow the model to generate useful features directly from the data. The mapping process occurs when a free-dimensional pattern is projected from the input space to the position of a one- or two-dimensional array(Boys et al., 2019).

A signature is a special form of handwriting that contains special characters and additional forms that are often used as proof of verifying a person's identity(Parini et al., 2018). Some signatures can be read, but many signatures are unreadable(Eliyen et al., 2017). However, a signature can be handled as an image so that it can be recognized using pattern recognition applications in image processing.

Because signatures are the primary mechanism for authentication and authorization in legal transactions, the need for research on developing automatic and efficient signature recognition and verification applications has increased in recent years(Sudibyo et al., 2018). In this research, an analysis of the performance of the vector quantization learning algorithm and self-organizing map Korhonen algorithm was carried out in recognizing signature patterns.

LITERATURE REVIEW

Digital Image

Image is a continuous function of light intensity in a two-dimensional plane. Light intensity is the product of the amount of light emitted (illumination) received by an object and the degree of the object's ability to reflect light. Digital images are generally represented in the form of a 2-dimensional matrix with size NxM. Pixels are the smallest elements in a digital image (matrix elements). Each pixel value in the image describes the level of light intensity.

The intensity function value $f(x,y)$ has a range of values called the gray scale, namely:
 $l_min < f(x,y) < l_max$ or $0 \leq f(x,y) \leq l_max-1$ (1)

Where:

- $f(x,y)$: intensity value at position x,y
- l_max : max intensity value (gray scale)
- l_min : min intensity value

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An image can be defined as a certain function $f(x, y)$ of size M rows and N columns, where x and y are partial coordinates, and the amplitude f at the coordinate point (x, y) is called the intensity or gray level of the image at that point. If the values of x, y , and the overall amplitude of f are finite and discrete, then the image can be called a digital image. Figure 1 shows the coordinate position of the digital image.

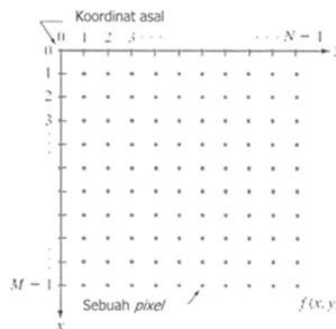


Figure 1 Digital Image Coordinates

Biological Neural Networks

The human brain has a very complex structure and has extraordinary abilities. The brain consists of neurons and connections called synapses. Neurons work based on impulses/signals given to neurons. Neurons pass it on to other neurons. It is estimated that humans have 10^{12} neurons and 6×10^{18} synapses. With very large numbers, the brain can recognize patterns, perform calculations, and control body organs at speeds that exceed the capabilities of digital computers. In comparison, recognizing someone's face that has changed slightly, for example wearing a hat, having an extra beard and so on, will be faster for humans than for computers. At birth, the brain has an amazing structure because of its ability to form its own rules or patterns based on the experiences it receives. The number and capabilities of neurons develop along with human physical growth, especially at the age of 0-2 years. In the first 2 years of human life, 1 million synapses are formed per second.

Neurons have 3 important components, namely dendrites, soma and axon. Dendrites receive signals from other neurons. The signal is in the form of an electrical impulse that is sent through the synaptic gap via a chemical process. The signal is modified (strengthened/weakened) in the synaptic cleft and then the soma adds up all the incoming signals. If the number is strong enough and exceeds the threshold, then the signal will be transmitted to other cells via the axon. The signal forwarding frequency varies from one cell to another.

Biological neurons are systems that are "fault tolerant" in two ways. First, humans can recognize input signals that are somewhat different from those we have received before. For example, humans can often recognize someone whose face they have seen in a photo, or can recognize someone whose face is slightly different because they have not seen them for a long time. Second, the human brain is still able to work even though some of its neurons are not able to work properly. If a neuron is damaged, another neuron can sometimes be trained to replace the function of the damaged cell.

Artificial Neural Network (Neural Network)

Artificial neural networks, or what are usually called neural networks, are a learning method inspired by biological learning systems, namely networks of nerve cells (neurons) that are connected to each other. Artificial neural networks are an artificial representation of the human brain that is always tries to simulate the learning process in the human brain. The term artificial is used here because this neural network is implemented using a computer program that is capable of completing a number of calculation processes during the learning process.

Neural Network Architecture

There are several neural network architectures, including:

1. One layer network

A single layer network with input elements R and S neurons, is described in Figure 2.

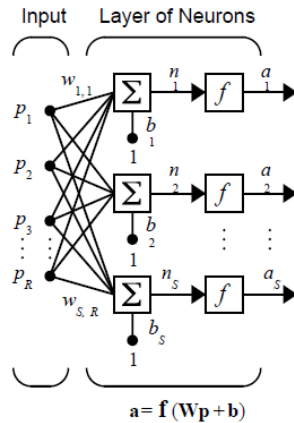


Figure 2. One Layer Network

2. Multiple Layer Network

A network can have several layers. Each layer has a weight matrix W, a bias vector b, and an output vector. To differentiate between the weight matrix and the output vector, we can see the use of this layer notation in the three-layer network described in Figure 3

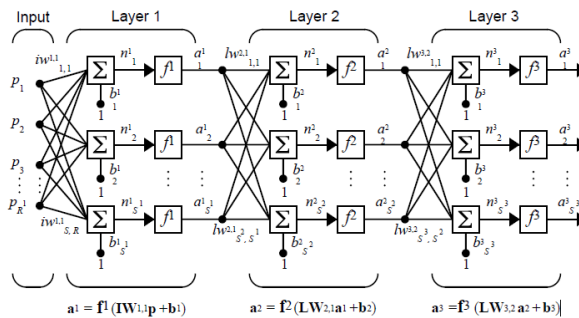


Figure 3 Multiple Layer Network

Learning Vector Quantization Network Architecture

Learning vector quantization is a form of Neural Network algorithm with a supervised learning method at the competitive layer. A competitive layer will automatically learn to classify the input vectors. The classes obtained as a result of this competitive layer depend only on the distance between the input vectors. If 2 input vectors are close to the same, then the competitive layer will assign both input vectors to the same class. Figure 4 shows the learning vector quantization architecture.

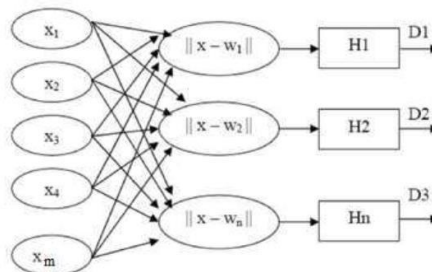


Figure 4. LVQ Network Architecture

Information:

X_1 to X_m = input value

$\|X - w_1\|$ up to $\|X - w_n\|$ = weight distance

H1 to Hn = output layer

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D1 to Dn = output value
m = number of input elements
n = number of classes

Kohonen Self Organizing Map Artificial Neural Network

In this network, a layer containing neurons will arrange itself based on certain input values in a group known as a cluster. During the self-organization process, the cluster that has the weight vector that best matches the input pattern (has the closest distance) will be selected as the winner

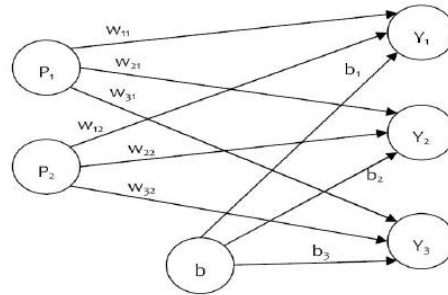
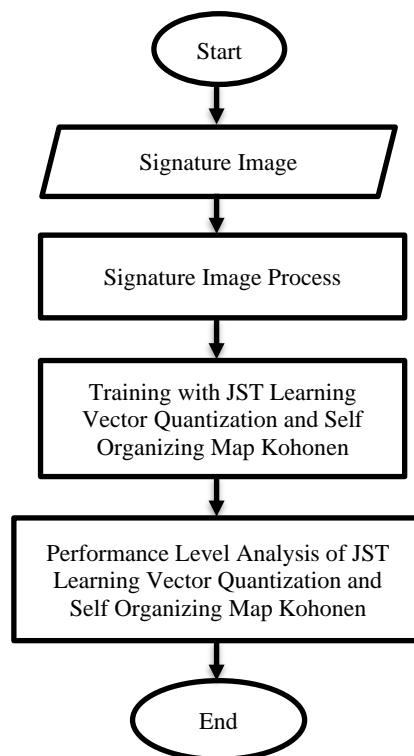


Figure 5. Kohonen Self Organizing Network Architecture

METHOD

The steps that will be carried out in this research can be seen in Figure 6.



The material used in this research is a signature in the form of a digital signature resulting from a scanner which will be used for learning (learning data set) and for testing (testing data set). In this study, 500 signature image data were used which were divided into 5 classes. And the ratio of training data to testing data is 70:30, where the training data is 350 signature images and the testing data is 150 signature images.

In this research, an analysis of the performance level of the Learning Vector Quantization (LVQ) and Kohonen Self-Organizing Map (SOM) algorithms was carried out, with a focus on their ability to classify input data based on distance metrics and topology preservation. Although both algorithms perform well in certain controlled

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environments, we encounter several limitations that may impact the broader applicability and scalability of these methods.

1. **Scalability Issues with Large Datasets:** One of the primary limitations of the LVQ and SOM algorithms is their performance when scaled up to large datasets. Both LVQ and Kohonen SOM involve iterative processes that become increasingly computationally expensive as the number of data points and dimensions increases. In our study, the training time for these algorithms grew exponentially as the dataset size increased, highlighting their inefficiency when applied to large, real-world datasets. This scalability issue limits their practical use in domains such as image recognition or large-scale classification tasks, where deep learning models have shown far superior performance (LeCun et al., 2015). Recent state-of-the-art models, such as deep convolutional neural networks (CNNs) and generative adversarial networks (GANs), have significantly outperformed LVQ and SOM in handling large and high-dimensional datasets. These models, by design, are better suited for scalability, as they employ advanced optimization techniques such as batch processing and parallelization, and often involve architectures that automatically learn meaningful features without requiring exhaustive manual feature engineering. Unlike LVQ, which relies on prototype vectors for class determination, deep models are capable of end-to-end learning directly from raw data, often achieving higher accuracy and lower training times.
2. **Sensitivity to Initialization and Hyperparameters:** Both LVQ and SOM are highly sensitive to the initialization of the prototypes or weights and the selection of hyperparameters such as learning rate, neighborhood radius, and number of iterations. In our analysis, we observed that small changes in these parameters could lead to significantly different classification outcomes. This dependency on parameter tuning can make it challenging to apply these methods in real-world scenarios, where optimal parameter selection is often not straightforward and may require cross-validation or exhaustive search. In contrast, recent deep learning approaches, such as autoencoders or reinforcement learning-based models, tend to be less sensitive to initialization and hyperparameter settings. These models leverage advanced training techniques like stochastic gradient descent (SGD) with adaptive learning rates (e.g., Adam optimizer) and can often converge to optimal solutions with less manual intervention. Furthermore, models like CNNs can learn hierarchical features through multiple layers, making them more robust to variations in data distributions, thereby reducing the need for fine-tuned parameters.
3. **Topological Preservation and Overfitting:** While Kohonen's Self-Organizing Map excels in preserving the topological structure of data when mapping it from high-dimensional space to a lower-dimensional representation, we found that the SOM algorithm occasionally struggled with noisy data and overlapping classes. The inability of the SOM to effectively separate closely related or noisy input vectors led to less accurate clustering, particularly in complex data scenarios. Additionally, both LVQ and SOM are prone to overfitting in situations where the number of training vectors is too small relative to the number of classes. Modern algorithms like deep autoencoders and self-supervised learning techniques, which learn to represent data in a way that captures underlying patterns without requiring labeled examples, can mitigate some of these challenges. These state-of-the-art methods often come with robust regularization strategies to prevent overfitting and improve generalization across unseen data. Moreover, generative models such as GANs have been shown to produce high-quality representations of data, preserving intricate patterns even in noisy environments, which is a significant advantage over traditional unsupervised learning methods like SOM.
4. **Interpretability and Complexity:** Although LVQ and SOM provide clear advantages in interpretability, as they allow for a visual representation of the clustering process (in the case of SOM) and class prototypes (in the case of LVQ), they lack the complexity to handle highly non-linear relationships within the data. While LVQ provides a direct mapping of class labels to prototypes, it does not capture intricate interactions between features that could improve performance in tasks like image or speech recognition. Deep learning models, although often more accurate, face challenges with interpretability. Recent research in explainable AI (XAI) has focused on developing techniques to improve the transparency of neural networks, such as saliency maps and feature importance techniques, to shed light on what aspects of the data contribute to the final decision. This ongoing effort seeks to balance the high performance of modern models with the transparency offered by traditional methods like LVQ and SOM.
5. **Lack of Robustness to High-Dimensional Data:** In our study, we found that both LVQ and SOM faced difficulties when handling high-dimensional data, a common challenge in fields like bioinformatics, text mining, and image processing. The dimensionality reduction capabilities of SOM do provide a solution, but often at the cost of losing critical information from the original data space, which may degrade classification performance. Recent state-of-the-art techniques, such as deep neural networks (DNNs), specifically those incorporating dimensionality reduction layers like variational autoencoders (VAEs), have shown greater robustness in high-dimensional settings. These models perform automatic feature extraction and dimensionality reduction in tandem with the classification task, often resulting in higher-quality

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representations of the data. Furthermore, models based on attention mechanisms, such as transformers, have recently set new benchmarks in processing high-dimensional sequences (Vaswani et al., 2017).

Image Processing

The signature image in Figure 7 measuring 600 x 450 pixels will be scaled to 20x15 pixels and then the image will undergo a conversion process to grayscale if it is a true color image. Next, the image will be subjected to a gradient-based edge detection process with the Sobel operator. The analysis image is a grayscale image with an 8 bit scale which has a color intensity ranging from 0 as the minimum value to 255 which is the maximum value. The analyzed images are then subjected to a binarization process, namely converted into binary numbers with a threshold process of 20x15 for each image. Each pixel with a color intensity value <= 128 is given a 0, while for a color intensity value > 128 it is given a value of 1, so that you will get a row of values consisting of 0 and 1 throughout the 300 pixel element.



Figure 7. Signature image

Red, Green, and Blue (RGB) Pixel Value Extraction

In the next stage, the bands in the image are separated, especially the RGB image. In 24-bit color images (true color) there are no RGB values, because the RGB values are directly described in binary bitmap data. To read the RGB value, look for the header and bitmap data which contains information on the dimensions, format and pixel values of the image. Each bitmap data element is 3 bytes long, each byte represents the components R, G, and B. Each byte of data represents 8 bits, so in a color image there are 3 bytes x 8 bits = 24 bits of color content. In color images, each pixel contains 24-bit color content or 8 bits for each basic color (R, G, and B), with a content value range of 0 (00000000) to 255 (11111111) for each color.

In the image example described in Figure 7, the first data is the header which contains information on the file name, format type and image dimensions. Below the bitmap data there is the first pixel which has the value = 100001111011010010100001.

To get the RGB value for each pixel, use the following formula:

$$R = c \text{ and } 255$$

$$G = (c \text{ and } 65.280)/2560$$

$$B = ((c \text{ and } 16.711.680)/256$$

In this analysis, the number of pixels calculated is 25 pixels and to get the pixel RGB value, the process is the same as above and then the RGB value of all pixels in the image is entered into the following matrix:

161,180,135	152,140,110	182,166,210	166,112,178	178,177,166
202,189,134	201,180,111	140,173,110	192,120,200	112,167,162
133,200,152	165,100,155	124,110,167	140,180,126	200,160,200
141,204,104	134,80,144	140,110,115	150,180,150	160,210,220
56,100,110	147,140,165	143,230,173	140,212,210	150,212,150

Calculating Grayscale Image Values

In calculating the grayscale value of a signature image, use the following equation:

$$f(0,0) = \left(\frac{161 + 180 + 135}{3} \right) = 158$$

$$f(0,1) = \left(\frac{152 + 140 + 110}{3} \right) = 158$$

$$f(0,2) = \left(\frac{182 + 166 + 210}{3} \right) = 158$$

$$f(4,4) = \left(\frac{161 + 180 + 135}{3} \right) = 144$$

To calculate the pixel grayscale value, do the same as above. The resulting grayscale value of the color image is entered into the following grayscale value matrix:

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$$\begin{bmatrix} 158 & 134 & 186 & 152 & 171 \\ 110 & 164 & 111 & 170 & 0 \\ 166 & 100 & 155 & 114 & 125 \\ 47 & 155 & 172 & 174 & 200 \\ 175 & 0 & 47 & 90 & 144 \end{bmatrix}$$

The results of the grayscale process in the form of a signature image can be seen as in Figure 8.



Figure 8 Grayscale Process Results

Edge Detection

Edge detection functions to emphasize image boundaries or to increase the appearance of boundary lines. In this study, the Sobel operator was used with two kernels as in Figure 8.

-1	0	1	1	2	1
-2	0	2	0	0	0
-1	0	1	-1	-2	-1

Figure 8 Two Kernel Matrices

On the signature image, edge detection is carried out by taking 1 block of the following 3 x 3 pixel image:

$$\begin{bmatrix} 158 & 134 & 186 \\ 110 & 164 & 111 \\ 166 & 100 & 155 \end{bmatrix} \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$s_x = 158(-1) + 134(-2) + 186(-1) + 166(1) + 100(2) + 155(1) = 478$$

$$s_y = 158(1) + 134(2) + 186(1) + 166(-1) + 100(-2) + 155(-1) = 452$$

Perhitungan nilai magnitud (M) adalah sebagai berikut:

$$M = |s_x| + |s_y| = |478| + |452| = 930$$

The convolutional image obtained from the edge detection calculation for a 3 x 3 pixel block is as in Figure 9.

$$\begin{bmatrix} * & * & * \\ * & 930 & * \\ * & * & * \end{bmatrix}$$

Figure 9. Convolution Value (M) Around Pixe 3 x 3

From the convolution results, the magnitude value is divided equally for the 9 pixels, namely: $930 : 9 = 103$.

And inserted into a 3 x 3 image matrix as in Figure 10.

$$\begin{bmatrix} 103 & 103 & 103 \\ 103 & 103 & 103 \\ 103 & 103 & 103 \end{bmatrix}$$

Figure 10. Matrix of 3 x 3 Image Edge Detection Results

Binarization

The grayscale image separation above functions to extract the part of the image which is the dark (0) and white (1) points. Binarization is carried out by dividing the image into several sub-images, the average intensity value of the lowest sub-image is used to become the threshold value T. After that, the image binarization process is carried out using the threshold value T.

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From the results of the RGB value of the Color Image, a threshold calculation is carried out for binarization where if the grayscale value <128 it will be set to a value of 0, whereas if the grayscale value $>T$ it will be set to a value of 1.

Pixel value (0.1) = 158, pixel value $158 > 128$, then binary value = 1

Pixel value (0.2) = 134, pixel value $134 > 128$, then binary value = 1

Pixel value (0.3) = 186, pixel value $186 > 128$, then binary value = 1

...

Pixel value (4,4) = 144, pixel value $144 > 128$, then binary value = 1

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Figure 11. Binary Image Matrix

With the value $g(x,y)$ is a binary image resulting from the binarization process of a signature image with a noise scale $f(x,y)$, with a threshold value T . The image resulting from this threshold produces a binary signature as in Figure 11.



Figure 11. Binary Signature Image

By obtaining a binary signature image, the image preprocessing stage has been completed as shown in Figure 11. And then the resulting binary image will undergo a signature pattern recognition process.

Learning Vector Quantization Network Architecture

Learning vector quantization is a neural type with a single layer feedforward network architecture. The vector quantization learning network designed in this research consists of 350 neurons in the input layer and 5 neurons in the output layer. Based on Figure 12, it appears that in learning vector quantization there are 350 weights that connect each input neuron with the output neuron, so it can be said that each output neuron in learning vector quantization is associated with a weight vector. The process that occurs in each neuron is to find the distance between an input vector and the weight in question. The activation function (F) used in the learning vector quantization network architecture is a linear function, the aim is to obtain the same output as the input, according to the linear function formula $y = x$. The F1 activation function will map y_{in1} to $y_1 = 1$ if $|X-W_1| < |X-W_2|$, and $y_1 = 0$ otherwise.

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In the third experiment, signature pattern recognition training was carried out using the Self-Organizing Map Kohonen artificial neural network.

At this stage, training was carried out on 350 data with 5 classes.

Training is carried out with learning rate (α) values, namely 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0.05, 0.01, 0.001, 0.0001.

MaxEpoch value is 100.

Table 3. Results of the Fourth Training Experiment with Self Organizing Map Kohonen

Learning Rate	MSE
0.9	0.358
0.8	0.358
0.7	0.358
0.6	0.312
0.5	0.312
0.4	0.283
0.3	0.283
0.2	0.191
0.1	0.093
0.05	0.054
0.01	0.058
0.001	0.127
0.0001	0.152
0.00001	0.152

In Table 3 you can see the results of digital signature learning (training) using the Kohonen map self-organizing artificial neural network. The smallest mean square value from the second experiment was 0.058 with a learning rate of 0.05.

Implementation of Recognition

After carrying out the training process on the artificial neural network learning vector quantization and self-organizing map Kohonen, it is continued with the Recognition process, namely, recognizing signature patterns with the learning vector quantization algorithm and self-organizing map Kohonen.

The data introduction stage begins by initializing several learning rate (α) values, initial weights, and maxEpoch values. The recognition process is carried out with the same learning rate (α) variable value when the data is trained. The initial weight at the introduction stage is the final weight resulting from the training data.

In the first experiment, signature pattern recognition was carried out using an artificial neural network learning vector quantization. In this experiment, the same data as the training data was introduced, namely 150 data.

Table 4. Results of the Second Experiment on Digital Signature Pattern Recognition with *Learning Vector Quantization*

Learning Rate	Pattern Recognition Results
0.9	28.67%
0.8	28.67%
0.7	28.67%
0.6	75.22%
0.5	75.2%
0.4	70.20%
0.3	70.20%
0.2	70.20%
0.1	87.10%
0.05	90.81%
0.01	86.02%

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0.001	28.67%
0.0001	85.43%
0.00001	58.0%

From the results of the first experiment, it can be concluded that the best digital signature pattern recognition results were 90.81% with a learning rate (α) of 0.05.

The third experiment in recognizing signature patterns used the Kohonen self-organizing map algorithm. In this experiment, the same data as the training data was introduced, namely 150 data

Table 5. Results of Kohonen Self Organizing Map Digital Signature Pattern Recognition

Learning Rate	Pattern Recognition Results
0.9	65.12%
0.8	69.2%
0.7	69.32%
0.6	75.22%
0.5	75.2%
0.4	75.2%
0.3	75.2%
0.2	75.43%
0.1	75.72%
0.05	83.20%
0.01	80.24%
0.001	76.02%
0.0001	75.43%
0.00001	28.0%

From the results of the fourth experiment, it can be concluded that the best digital signature pattern recognition results are 83.20% with a learning rate (α) of 0.05.

The images tested in this research are images that have not been trained. Table 6 shows the results of the introduction based on one of the variations carried out.

Table 6. Results of Introduction to Variation Learning Rate (α) 0.05

Learning Rate	Number of Hidden Layer Neurons	Epoch	MSE	
			LVQ	SOM Kohonen
0.05	10	1000	0.063	0.054

Data	Class	Accuracy	
		LVQ	Kohonen SOM
1	1	v	v
2	1	v	v
3	1	v	v
4	1	v	v
5	1	v	x
...			
31	2	v	v
32	2	v	v
33	2	v	v
34	2	v	v
35	2	v	x

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...			
61	3	v	v
62	3	v	v
63	3	v	v
64	3	x	x
65	3	v	x
...			
91	4	v	v
92	4	v	v
93	4	v	v
94	4	v	v
95	4	v	v
...			
121	5	v	v
122	5	v	v
123	5	v	v
124	5	v	v
125	5	x	x
...			

From the research results, the accuracy of signature pattern recognition using the learning vector quantization neural network method was 90.81% and the signature pattern recognition accuracy of the self-organizing map kohonen artificial neural network method was 83.20%.

DISCUSSIONS

The study demonstrated the effectiveness of Learning Vector Quantization (LVQ) and Kohonen Self-Organizing Map (SOM) algorithms in the recognition of signature patterns, a task crucial for biometric identification systems. The signature pattern recognition process involved several stages, such as scanning, manual scaling, thresholding, edge detection, image segmentation, and input representation, all of which contributed to the formation of data suitable for training the neural networks.

Through the application of LVQ and SOM, the study revealed that both methods are capable of classifying signature patterns, but each comes with its own set of challenges. LVQ, which updates its weights based on input patterns, showed effectiveness in producing accurate results with a relatively smaller dataset. On the other hand, the Kohonen SOM, which employs random initialization of weights and updates them through competitive learning, also demonstrated potential in classifying signature patterns, though it required more computational resources and time to achieve convergence, especially with larger datasets.

A significant finding of the research was the importance of tuning the learning rate (α) for optimal performance. The results suggested that a learning rate in the range of $0.2 < \alpha \leq 10^{-2}$ yielded the best signature recognition accuracy. This underscores the role of hyperparameter tuning in improving the performance of both LVQ and SOM algorithms in biometric pattern recognition.

While both methods showed promise, they also have limitations, particularly in terms of computational efficiency and scalability when dealing with larger datasets. These challenges are common in traditional artificial neural networks and highlight the need for further improvements or hybridization with more advanced methods to enhance scalability and accuracy. Future research could explore combining LVQ and SOM with deep learning techniques, offering a potential path for improving biometric recognition systems in real-world applications.

CONCLUSION

Based on the research results, image processing and analysis using artificial neural networks learning vector quantization and self-organizing map kohonen shows that changes in learning rate can affect changes in accuracy. At a learning rate that is too large, it can achieve maximum accuracy in less time, but the accuracy is not good. While for a learning rate that is too small, achieving the best accuracy takes longer, this is because the increase in

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accuracy is directly proportional to the number of epochs. This proves that the learning rate parameter can affect the epoch and learning time to achieve maximum accuracy which tends to be stable.

The optimal learning rate value for the built signature pattern recognition ranges from $0.2 < \alpha \leq (10)^{-2}$ with the amount of trained data $(x_i) > 75$, so that it can get the best value of mse. The learning rate value-built ranges from $0.2 < \alpha \leq (10)^{-2}$ can produce better signature pattern recognition accuracy. Signature pattern recognition using the learning vector quantization artificial neural network algorithm shows the best accuracy with the parameters in this study.

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