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Semaphore letter code recognition system using wavelet method and back propagation neural network

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Abstract

Semaphore is a means of long-distance communication using semaphore flags as tools. This communication method has been used since ancient times to convey information. In Indonesia, semaphore communication is practiced in scouting activities and by mariners to convey specific messages. In these activities, communication using semaphores involves transmitting important information through specific gestures performed by demonstrators. Transmitting messages using semaphore letter codes can be challenging for beginners. With the increasing use of semaphores in specific fields, there is a need for a system that can automatically recognize semaphore letter gestures in real-time. The designed system can be used in learning processes and implementing semaphore letter code in reading devices. This research aims to design a real-time semaphore letter code recognition system using soft computing methods. Digital image processing is chosen for image recognition in the designed system. Image segmentation is employed to obtain the object parts of the image, followed by wavelet as a feature extraction method. Back propagation neural network (BPNN) is used for semaphore gesture classification. 910 image data were used to design the semaphore gesture recognition system. The success rate in sequential recognition is 94% at a distance of 3 meters, 90% at 4 meters, 88% at 5 meters, 86% at 6 meters, and 83% at 7 meters. The test results demonstrate the positive potential of the system for use in learning processes and the implementation of semaphore letter code reading devices.

Keywords

Semaphore code, Digital image processing, Image segmentation, Wavelet extraction, Back propagation neural networks.

1.Introduction

The semaphore is one method of communication that can be used for long distances [1]. This method is a way to convey information non-verbally with the help of additional signaling tools. This step is taken because there is a relatively long distance between the information giver and receiver. The message is conveyed using this method with the help of two semaphore flags, colored red and yellow, tied to a pole approximately 60cm long and held by the right and left hands, as shown in *Figure 1*. In Indonesia, semaphore usage as a communication tool is still implemented by the Marines [2] and is part of basic training for scout members.

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Communication is conducted to convey messages that the recipient must correctly understand. Semaphore flags are not only limited to alphabet recognition but is also employed to translate characters and other languages [3].

The sender and receiver of messages in the semaphore system are expected to have special abilities to interpret the messages conveyed through semaphore flag movements. Despite this knowledge being attainable through self-learning, currently, no system can provide correction and assistance to learners in understanding hand movements corresponding to semaphore signals, as illustrated in *Figure 1*.

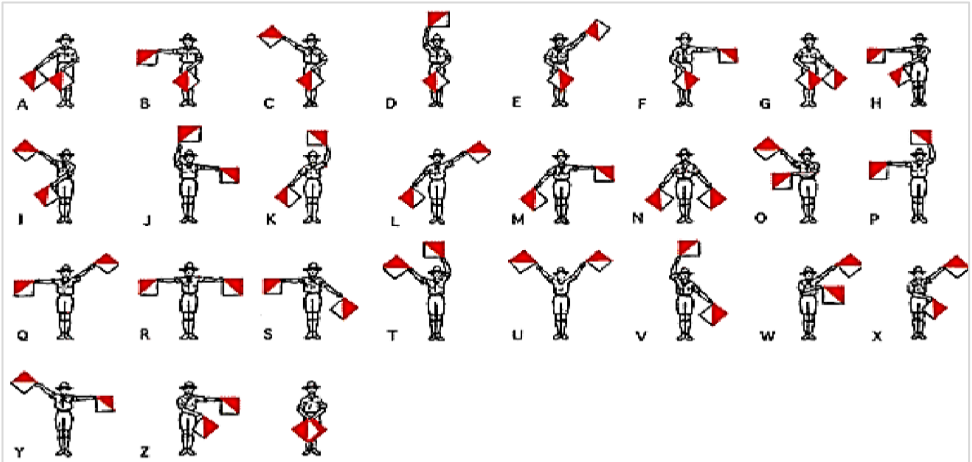


Figure 1 Illustration of semaphore movement in the alphabet [4]

Currently, the introduction of semaphore code letters mainly still relies on a simple method: direct observation by the human eye. Researchers argue that this observation is a traditional method that requires more time and energy without the assistance of technology in today's era. There have been studies that have attempted recognition using technology, but still with a low recognition distance, less than 2 meters between the signaller and the recognition camera and require considerable expenses [5]. These considerable expenses make the application of technology in semaphore motion recognition inaccessible to every social stratum.

Therefore, the recognition of semaphore code letters using a technological approach is an important matter that needs to be further researched in order to create a recognition system with longer distances and lower costs. Special attention is given to developing real-time semaphore motion reading with high accuracy rates for universal application in daily life. By designing semaphore recognition and learning models, the system can automatically recognize and be integrated with other technologies, such as marine systems, in the current technological advancements.
The main objective of this research is to design a semaphore letter recognition system using digital image processing [6], which contributes significantly to designing recognition models and systems for use in marine environments and other technologies. Several studies have designed semaphore recognition systems with high costs and a maximum distance of less than 3 meters [7]. Based on the literature review discussions, we are motivated to develop a recognition system with lower costs and a distance of more than 3 meters as an improvement over previous researchers. Testing this system involves using signallers with different types and physical conditions to determine the system's reliability in the recognition process. The researchers understand that the cost of knowledge and innovation significantly contributes to the success of achievement, making it a challenge to design a system with reliable programming to advance semaphore letter recognition that various groups can use.

This research employs a feature extraction method using wavelet with a combination of coefficient decomposition [8], which ideally can be used to obtain the core parts of the image [9], subsequently combined with a classification method using back propagation neural network (BPNN) [10]. Modifications to BPNN parameters can be made by determining the number of nodes [11] and hidden layers, which function as one of the sensitive parameters in forming the recognition architecture model. Other parameters can be adjusted, such as the weighting part [12] in backpropagation to strengthen the multiplier weights for better classification of the process data, aiming to enhance image recognition according to the semaphore letters transmitted by the signaller. This research contributes to developing an automatic semaphore letter recognition system with high accuracy rates [13], potentially providing positive impacts in utilizing such technology in various contexts, including maritime applications [14].

The arrangement of this manuscript is as follows: Section 1 discusses the background of semaphore, challenges from previous literature, semaphore code model, work motivation, manuscript objectives, and manuscript contributions. Section 2 explains the literature review with the background of research related to wavelet, BPNN, and digital image processing. Section 3 discusses the image acquisition method, pre-processing of semaphore images, segmentation process, wavelet feature extraction, and BPNN architecture. Section 4 elaborates on the research results, explaining the BPNN architecture and the semaphore motion image extraction process. These results are demonstrated by comparing distances to classification outcomes, displaying decimated images of letters A – Z. Section 5 covers the discussion. Section 6 concludes the research results with a statement on the success percentage of semaphore letter code recognition with varying distances and specified decimation extraction.

2.Literature review

A similar study on semaphore reading using arm position detection to determine semaphore movement has been carried out by Iwane [7]. The task hits the Japanese semaphore letters using the Kinect as an arm detection device. Research has succeeded in reading arm movements in semaphore transmission approximately 2 meters between the model and the camera. The introduction of the Semaphore to recognize the letters A to Z has been carried out by Rachmad and Fuad [5], with a success rate of 90.76%. This study uses the limitation of gesture recognition from 1.2 meters to a maximum of 3.5 meters. Based on research, Kinect often experiences errors in determining the left and right arm.

Semaphore motion recognition is also done using the Wavelet Haar method by combining the Euclidean method for classification [15]. The recognition rate reached 95.4% by utilizing the decimation variation in the extraction feature. This study uses a maximum distance of 5 meters which can be used to recognize semaphore objects [4]. Tian et al. [16] use semaphores in the robot's world to carry out the mirroring process of the semaphore movement by demonstrating to the imitating robot. The mirroring process accuracy reached 90% and 76.7%, respectively. The imitating robot is given seven essential points to follow the demonstration in moving the arm.

Ren and Meng [17] proposed the use of multi-level discrete wavelet transform (DWT) to determine the first-order curvature before and after damage in wooden beams or wooden frameworks of ancient Chinese structures. The research results indicated that the differences in wavelet coefficients could determine the location of structural damage and estimate the level of damage by adjusting the relationship equation between the coefficient difference indices and the damage level.

Deb et al. [18] suggested the use of a graph neural network combined with wavelet in the node classification process. This research attempted to address the problem through wavelet transformation by modifying the graph topology and eliminating inappropriate wavelet filters. The research scheme, utilizing high-pass and low-pass frequency components to enhance feature representation, resulted in the effectiveness of the proposed method.
Shi et al. [19] suggested the use of wavelet analysis to build a model for thermal conductivity and radiation properties recognition using wavelet decomposition coefficients, comparing it with traditional methods. Wavelet, as a signal analysis on the temperature field decomposition parameters operating in the frequency band of 4-8, can separate from the random error of the wavelet frequency band 1-3. The test results have shown that the significant impact of wave shape and amplitude coefficients, and the approximation coefficients of the wavelet decomposition parameters, works in the frequency band 5-7 with higher accuracy.

Volvach et al. [20] explored the use of wavelet in the spectral composition analysis and the relationship between local surface air temperature and solar activity from the displacement of the Earth's North Pole. Prediction models were designed and compared with various wavelet decomposition data. Based on the average annual surface air temperature data in Yalta (44.48o, 34.17o = 72.0m) for the period from 1869 to 2022, it was found that localized similarities were found in the surface air temperature data in Yalta and the average Earth pole displacement data relative to the conventional onset over the 30-70 year period.

Qiu et al. [21] conducted research to improve the accuracy of electrocardiogram (ECG) classification. The classification method for ECG has limitations in signal processing and manual feature selection, as well as difficulties in extracting relationships between time series features and high-level time series features. This research utilized continuous wavelet transform (CWT) and converted the ECG signal, obtaining experimental results showing F1-Scores of 97.57% and 98.65%, which outperformed most existing methods and demonstrated excellent performance.

Zhang et al. [22] proposed the use of a BPNN to design a predictive model for the thermal management system of electric vehicles. This study combined particle swarm optimization (PSO) and BPNN. Simulation results showed that the PSO-BPNN prediction method could reduce predictions by 66%, 75%, and 25%.

Aswathy et al. [23] conducted research in the context of the coronavirus disease of 2019 (COVID-19) pandemic, utilizing transfer learning and BPNN for extracting features from COVID-19 computer tomography (CT) images. BPNN aimed to enhance the classification of patient severity levels with a detection rate of 97.84% and an area under the curve of 99.19%, indicating excellent performance in diagnosis and severity assessment.

Feng et al. [24] utilized BPNN to establish the relationship between urban river flow and various parameters. The proposed BPNN framework must be integrated with principal component analysis (PCA) and genetic algorithm (GA), abbreviated as PCA-GA-BPNN. This combination proved effective for calibration, resulting in a 90% prediction parameter and PCA usage, reducing training time by up to 64%. The training time is decreased from 18,142 seconds to 4.5 seconds.

Xiong et al. [25] researched improving the crashworthiness performance of composite tubes. The research method involved the development of finite element models to multi-objective optimization using BPNN to enhance knowledge of crushing forces and energy absorption in the tubes. The results of using BPNN comprised a composite tube framework that enhances crashworthiness performance with precise structural design and lightweight energy absorption systems.

Wang et al. [26] proposed the use of a BPNN to optimize sample data in the nitrite prediction process in water. The PSO algorithm was also used to optimize the initialization weights and biases in the BP neural network. The results showed that the r-squared (R2), root mean squared error (RMSE), and mean absolute error (MAE) values were 0.976290, 0.008626, and 0.006617, indicating a promising model for predicting nitrite concentrations in water.

Tian and Chang [27] designed a method for adequate circuit protection in industrial design. Testing on 40 resistors connected in parallel resulted in an algorithm utilizing the PSO-BPNN method. The time obtained using PSO-BPNN was 0.28 seconds with a stable current. It indicates that the prediction rate in testing reached 0.9903 with optimal performance.

Artificial intelligence technology has been used to complete and define a model [28], using a neural network [29], to detect vibrations that appear and become a forecasting model for future events. The use of artificial neural networks in predicting future events has been carried out by Khan et al. [30] in predicting behavior and changes in the stock market using variations of levenberg-marquardt (LM), Bayesian regularization (BR), scaled conjugate gradient (SCG), and quasi-newton (QN), with the highest accuracy value being 95.64% when using the LM method.

The literature review above indicates that semaphore letter recognition can be achieved through semaphore motion image processing, feature extraction, and letter classification techniques. However, most researchers utilize image recognition technology with other non-specific research subjects unrelated to information transmission via semaphore. Similar studies on letter recognition have higher costs and limitations on recognition distance of less than 2 meters [7]. Therefore, there is a need for a breakthrough in semaphore letter recognition as a method of information transmission that incorporates an automatic recognition system utilizing digital image processing.

In this research, the solution adopted to design the recognition system is to develop a semaphore motion image extraction process that identifies colors and gestures classified step by step using BPNN. The outcomes of this system are designed to provide information on letter recognition as performed by the signaler, comparing it against the system's database. Therefore, it can be employed in learning semaphore motions and reading information conveyed through these signals.

3.Methods

Research conducted to recognize semaphore movements has variations in the distance in the recognition process. The distance used in this study has five variations, each being 3m, 4m, 5m, 6m, and 7m. The entire data will be processed by image recognition, feature extraction, and classification to determine the level of accuracy in reading the correctness of semaphore movement. The success of semaphore code reading can be determined through a classification process compared to a training database. In this process, the system will compare the semaphore code movements received from the demonstrator with the training database that has been processed previously. One parameter for success is to recognize that the acquired semaphore code movements by the system match the semaphore code movements in the training database, so the reading of the semaphore code movements is considered successful. However, if there is a mismatch between the received semaphore code movements and the semaphore code movements in the training database, reading the semaphore code movements is considered a failure. Therefore, paying attention to the quality of the training database used in the classification process is essential to improve the success of semaphore code reading.

3.1Image acquisition

Image acquisition is a process of taking image objects to produce digital images [31]. This research uses primary data obtained by researchers by taking pictures using a webcam camera connected directly to the Matrix Laboratory (MATLAB) software on the computer. The researcher used seven demonstrators tasked with carrying out semaphore movements of the letters A – Z with five distance variations of 3m, 4m, 5m, 6m, and 7m. This process is illustrated in below Diagram, of the seven demonstrators, the researcher divided them into two groups consisting of 5 demonstrators as the first group (training data) and two as the second group (test data). Each model performs the letter movements according to *Figure 2* by holding a pair of semaphore flags. In collecting training data, the first group of demonstrators carried out movements of the letters A to Z alternately at each distance variation to obtain 130 digital image data. The results of the letter movements carried out by the first group obtained 650 images, which will later be used as training data for the classification system. Then, testing of the system was carried out by a second group consisting of 2 demonstrators. The test was carried out by moving each letter A – Z over five variations in distance. From the second group, 260 image data were obtained from testing.

The demonstrators for data collection consisted of 7 individuals, each with distinct characteristics. These differences included height and body posture variations, ranging from overweight to slim. Data collection occurred under varying lighting conditions, including natural sunlight and artificial lighting during nighttime, with an open background. The demonstrators wore both scout uniforms and shirt attire. *Figure 2* illustrates a hand motion position in semaphore code. There are eight conditions (0 – 7) for hand movements in semaphore. The image depicts the semaphore hand motions, with each condition corresponding to specific positions for the right hand (colored red) and the left hand (colored yellow). For each semaphore letter the demonstrators convey, attention is paid to the eight directions and their respective hand positions. For example, when a demonstrator sends the letter "O," the left hand is positioned at 2, and the right hand is positioned at 3."

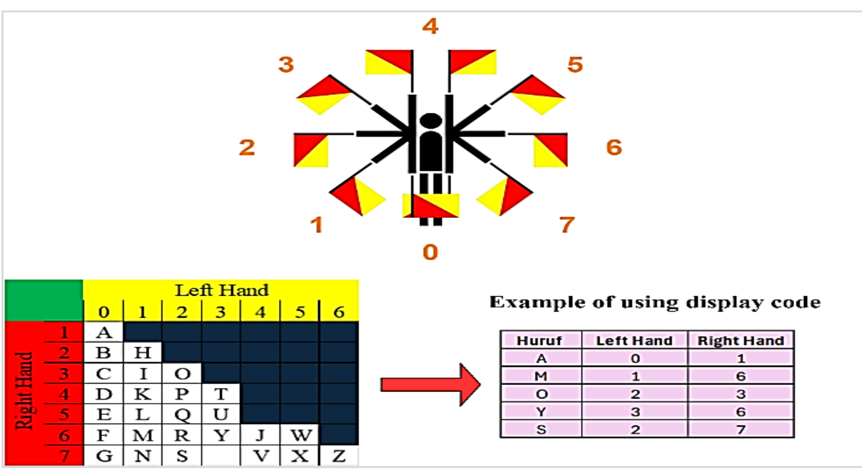


Figure 2 The hand motion positions in semaphore code

3.2Pre-processing

Image acquisition is a process of capturing image objects that produce a digital image [32]. Pre-processing is the initial stage in processing digital images obtained in the previous step. In this process, the digital image will be color segmented [33] to get the color of the Semaphore and the model's movement. The method of detecting the motion of the semaphore part is adjusted to each letter that is demonstrated [34]. The semaphore image obtained is converted from red, green, blue (RGB) to hue, saturation, value (HSV) color model [35]. The brightness value in the brighter image can be changed to become darker or vice versa. This value is helpful in image normalization as it can help eliminate brightness differences and enhance the contrast between the flag and the background [36]. For semaphore flag detection, image normalization aims to eradicate light or brightness differences in the image to detect the semaphore flag more accurately. After normalization, the next step is to crop the painting according to the recognized semaphore flag parts. Image cropping is done by cutting out the unnecessary parts of the image and leaving only the relevant details. The process of pre-processing is broadly shown in *Figure 3.*

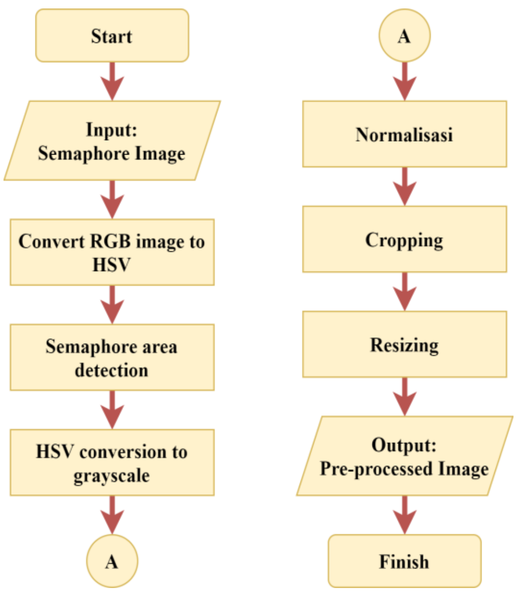


Figure 3 Pre-processing process diagram

The cropping process can be done using various techniques, such as image segmentation or thresholding. After the image is cropped, the next step is to resize the pixels to match other images. Pixel resizing is usually done by resampling the image, which changes the image resolution by adding or reducing the number of pixels in the image. The purpose of pixel resizing is to standardize the image size and resolve to be processed more efficiently and accurately. The cropping and pixel resizing processes are essential parts of image processing, especially in applications that require real-time image processing, such as object recognition systems, face recognition, or motion detection. By performing accurate cropping and pixel resizing, the image can be processed more effectively and efficiently, resulting in better results [37, 38].

3.3Image segmentation

Image segmentation is an important image processing technique because it can help us understand an image's structure and essential information [39–41]. The main goal of image segmentation is to group pixels into several groups or objects with the same characteristics [42, 43].

Several image segmentation methods can be used in digital image processing. Each segmentation method has its advantages and disadvantages. Some popular image segmentation methods are as follows [44, 45]:

1. Edge detection method: This method searches for intensity differences between surrounding pixels to find the edges of objects in the image.
2. Statistical-based method: This method uses statistical analysis to group pixels in the image into groups with similar intensity distributions.
3. Area-based method: This method divides the image into several regions based on a specific size or area.
4. Histogram-based method: This method uses a histogram to separate pixels in the image into several groups based on similar intensities.
5. Machine learning-based method: This method uses machine learning techniques to classify pixels in the image into several groups.

Each image segmentation method has advantages and disadvantages, and the appropriate selection depends on the image's characteristics to be segmented and the goal of the image analysis [46].

The approach using edge detection and object area methods helps to determine the parts of the image that belong to the orange and red semaphore objects. Color separation techniques are used to obtain information about the object's color, while shape techniques are used to get information about the object's shape. In the initial stage, the edge detection method determines the object's contour in the image. Then, the desired object area is calculated using image processing techniques. After that, color separation techniques are used to separate the orange and red objects from the background and other things.

The final step is to use object shape detection techniques to strengthen the recognition of the semaphore object through color. This technique allows for a more accurate determination of the object's shape so that object recognition can be done better. Overall, this study uses several image processing techniques to improve the recognition of the image's orange and red semaphore objects.

3.4Wavelet feature extraction

Feature extraction is the process of obtaining vital information contained in each digital image. This information is used to distinguish it from other digital images. Data from an image can be used by utilizing wavelet feature extraction [6]. Wavelet feature extraction can group the energy in the image and then be concentrated into coefficient values in each grouping [47, 48]. Each coefficient is set to distinguish between parts of the image with complete information and those with less essential data. Each set of this information contains a small amount of energy that can eliminate certain parts of the group without reducing the critical value of identifying information in the image.

The wavelet transformation used is a 2-dimensional wavelet transform or DWT [49, 50]. This method is the development of a 1-dimensional wavelet transform. DWT using 2-dimensions has the same x(m,n) value as the 1-dimension shown in *Figure 4* but has different results with the 1-dimensional transformation; the output image is grouped into sub-fields with 4 different sections, such as low-low (LL), low-high (LH), high-low (HL), and high-high (HH). The LL subsection is the rough part with approximate coefficient values. The LH and HL sub-sections record image changes along with the horizontal and vertical directions, respectively, as shown in *Figure 5*. In comparison, the HH sub-section shows the high-frequency components of a digital image.

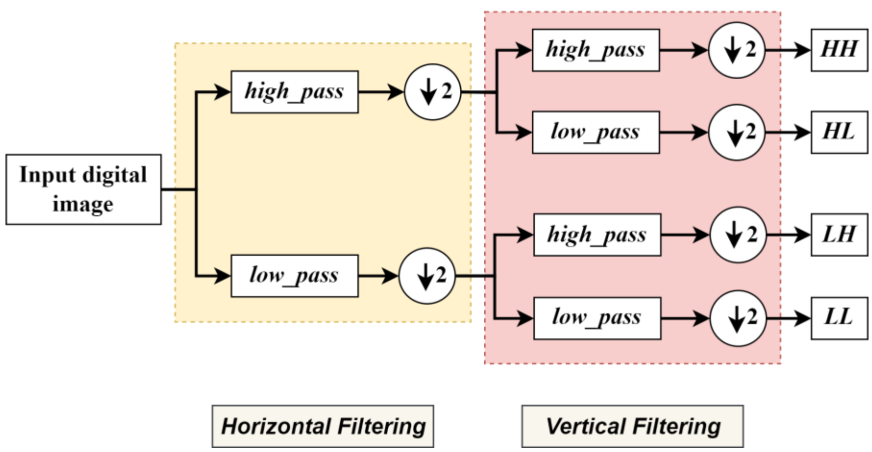


Figure 4 Illustration of 1-dimensional wavelet transform

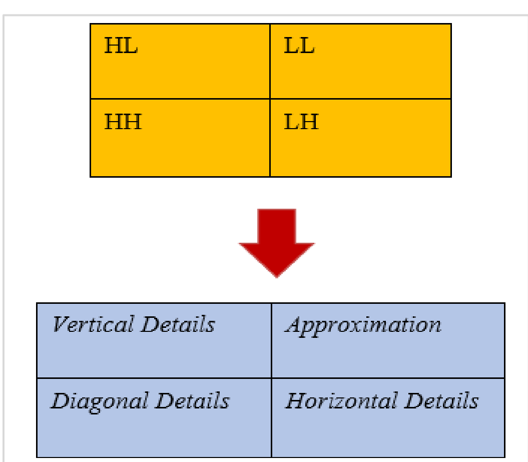


Figure 5 Schematic of 2-dimensional wavelet transform

This study extracts results from the segmentation process, specifically color extraction and semaphore flag shape extraction. By employing DWT, the dimensionality of the extraction process in dimension one can be enhanced by recognizing values in a higher dimension, namely dimension 2. The input data for this process consists of color extraction data for red and orange semaphore flags. Each data point with these colors has been identified to demonstrate letters A – Z within a frame of image data.

Subsequently, the color extraction data is used for recognition in the shape extraction, distinguishing between the shape of the flag in the right hand and the shape of the flag in the left hand. The difference in positions between the right hand and the left hand affects the shape of the flag pattern. Thus, this difference can be utilized to deepen the recognition of a semaphore motion position for each reflected letter demonstrated by the performer. Both the results of color extraction and shape extraction serve as primary data in the training and testing processes of the semaphore letter code recognition system.

3.5BPNN

Neural Network is a classification method utilizing a learning model from previous training data [51]. The training data is used to build an appropriate model to recognize objects in the training process [52]. This method uses a systems approach with capabilities like human thinking patterns or artificial intelligence [29]. This study uses a BPNN that allows for learning with the concept of a feed-forward artificial neural network (FFANN) [31, 53]. The weighting used will be adjusted to the gradient descent value and the derivative of the error function using the previous weight. The weighting update occurs after the forward, and backward transmission phases occur. The system works to correct the error value of the output in the onward transmission in the previous stage. BNN is one of the algorithms that can solve complex problems using 3 layers of architecture consisting of an input layer, a hidden layer, and an output layer. The architecture of the BPNN can be shown in *Figure 6*.

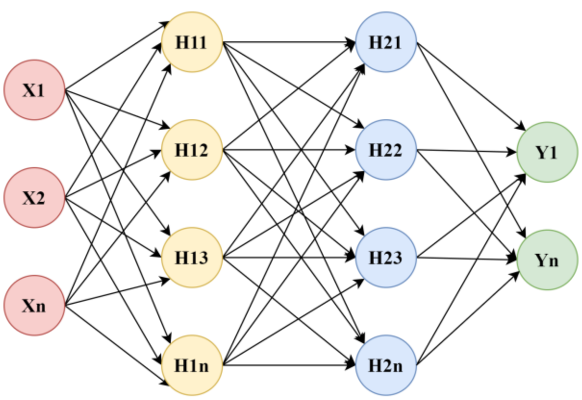


Figure 6 BPNN architecture

The use of BPNN involves adjusting parameters to achieve optimal recognition results. The input data consists of 40 values obtained from feature extraction. This data is connected to each network weight in the hidden layer and is given an activation function. The results are then compared with target data to measure the error rate.

Table 1 displays the parameters used in the artificial neural network to classify semaphore letters. There are 11 parameters representing the training model of the network. After training, the researcher uses mean squared error (MSE) as an indicator to measure the accuracy of the regression model in predicting numerical values. MSE calculates the difference between the model's predicted and actual values in the test data, then squares the differences to ensure non-negativity. The total squared differences are summed and averaged across all data samples. Mathematically, MSE can be calculated using Equation 1[54].

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2 \quad (1)$$

where N is the number of data samples, y_n is the actual value of the nth data, and $\hat{y}_n$ is the predicted value from the model for the nth data.

Table 1 Parameter for the BPNN

Parameter	Specification
Input	40
Number of Layers	(15 10 1)
Output	26
Activation function for the hidden layer	Log – Sigmoid
Activation function for the output layer	Linear
Learning Function	Sigmoid biner
Initialization of Weights	Random
Numbrt of maximum epoch	1000
Error Goal	10e-6
Learning Rate	0.1
Momentum Constant	0.95

4.Results

Figure 7 is an illustration of the process of collecting data from a demonstration model. This study uses variations in distance from 3 meters to 7 meters with a range of 1 meter to take images of the semaphore movement. This study used 7 demonstrators who had different physical conditions between heights, gender, and other physical conditions, which were designed to determine the reliability of the test if different visualizers carried out the sending of the code.

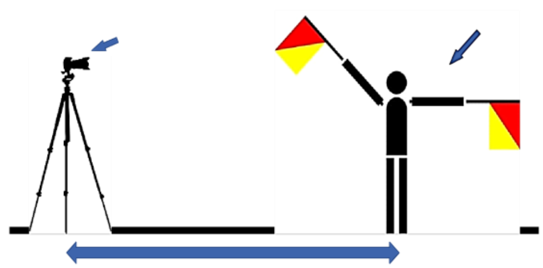


Figure 7 Semaphore on a model image capture illustration

Using the designed system, a model uses a semaphore to provide information by sending letter by letter for recognition.

4.1Digital image segmentation

Segmentation is a process to obtain the essential part of a digital image. This process is carried out to distinguish the foreground and background areas [55]. The most important part of the image is the foreground area, as the core part of the image, while the background area is an area that needs to be removed as a part that does not have information. *Figure 8* shows the process of segmenting a semaphore motion image carried out by a model. The image captured using a webcam has a RGB format, so it is necessary to convert it into a HSV format image.

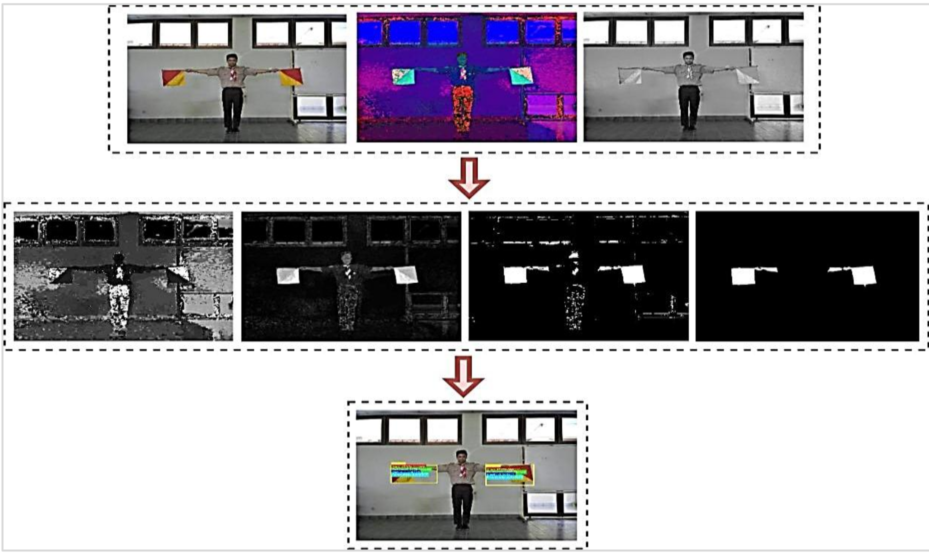
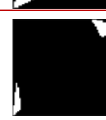
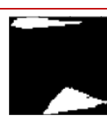


Figure 8 Semaphore movement digital image segmentation

4.2Feature extraction

Tests on the semaphore image were performed on each letter from A to Z with 26 movements to represent the correct sending motion. Each motion image has undergone a pre-processing process so that only the semaphore part has been segmented according to the color and characteristics of the semaphore. The extracted images are shown in *Table 2.*

Table 2 Semaphore movement and wavelet extraction results

Letter	Semaphore movement	Extraction	Letter	Semaphore movement	Extraction	Letter	Semaphore movement	Extraction
A			J			S		
B			K			T		
C			L			U		
D			M			V		

Letter	Semaphore movement	Extraction	Letter	Semaphore movement	Extraction	Letter	Semaphore movement	Extraction
E			N			W		
F			O			X		
G			P			Y		
H			Q			Z		
I			R					

Each movement of alphabet letters A to Z has a different Movement model, which is used as an initial condition in introducing semaphore codes. A visualizer that sends semaphore code uses flags as props. Using flags, researchers can extract the image results obtained from the capture. The image above shows the extraction results pre-processed from the 26 letters of the semaphore movement.

It can be seen from the extraction results that each semaphore movement has different characteristics between one image and another. The effects of wavelet extraction have significant differences, but there are also differences in parts that must be recognized in more detail through computer system processing.

4.3Training results

The extracted image then needs to be separated for each letter A to Z according to its characteristic value. There are four main characteristics that can be used as characteristics that represent the letters of the alphabet, including area, perimeter, metric, and eccentricity. The parameters used are additional information in shape extraction that helps in recognizing semaphore letters. The parameter values obtained from the letters A–Z are shown in *Table 3.*

Table 3 The average value of the semaphore letter perimeter

Letter	Area	Perimeter	Metric	Eccentricity
A	2635	212.87	0.864	0.2546
B	2765	211.87	0.768	0.1650
C	2732	198.64	0.955	0.1984
D	2888	213.24	0.856	0.0250
E	2485	199.25	0.789	0.0984
F	2702	185.36	0.898	0.0217
G	2358	195.35	0.986	0.1264
H	2768	215.50	0.885	0.0156
I	2712	221.32	0.858	0.2722
J	2665	186.25	0.958	0.2640
K	2808	254.26	0.858	0.0454
L	2755	202.15	0.870	0.2670
M	2738	200.87	0.895	0.3499
N	3024	175.27	0.896	0.0490
O	2699	228.75	0.947	0.0947
P	3014	224.36	0.765	0.1267
Q	2934	224.69	0.698	0.0967

Letter	Area	Perimeter	Metric	Eccentricity
R	2569	218.27	0.846	0.2564
S	2120	199.85	0.946	0.2334
T	2914	206.75	0.857	0.2673
U	3125	201.25	0.689	0.2546
V	3186	199.98	0.984	0.1597
W	2368	212.56	0.493	0.0785
X	3254	210.67	0.897	0.0437
Y	2946	208.71	0.986	0.3464
Z	2969	223.71	0.857	0.1567

The parameter values are then entered into the BPNN as training data, a design in the system's introduction to each letter's characteristics. A total of 650 data were trained to obtain a network that can classify data according to letter groups. Classification using a BPNN can help group letters according to 26 different characteristics. The results of the classification process are shown in *Figure 9.*

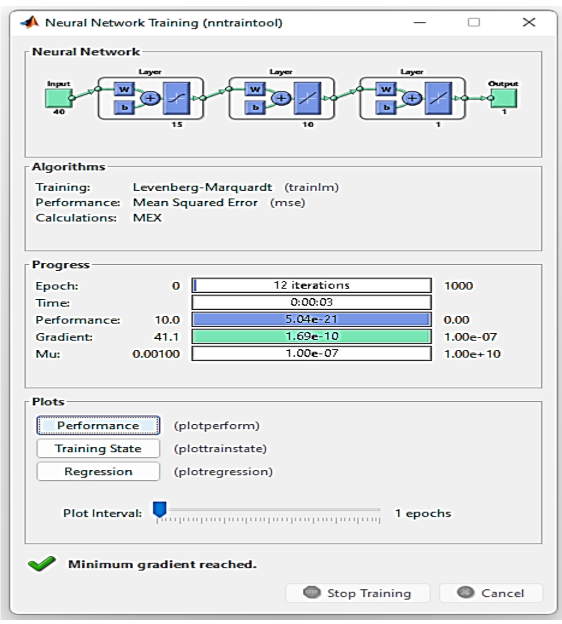
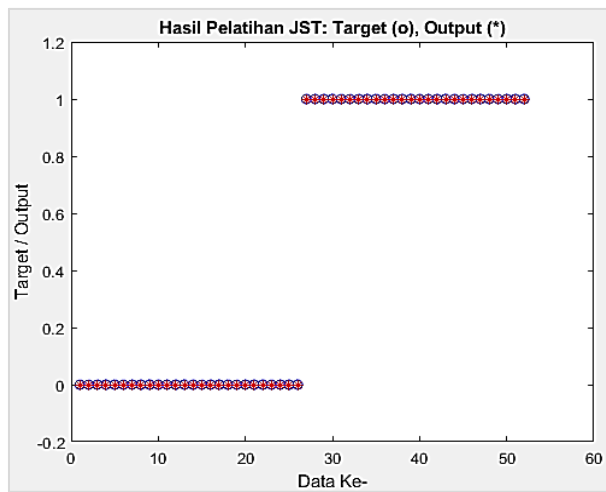


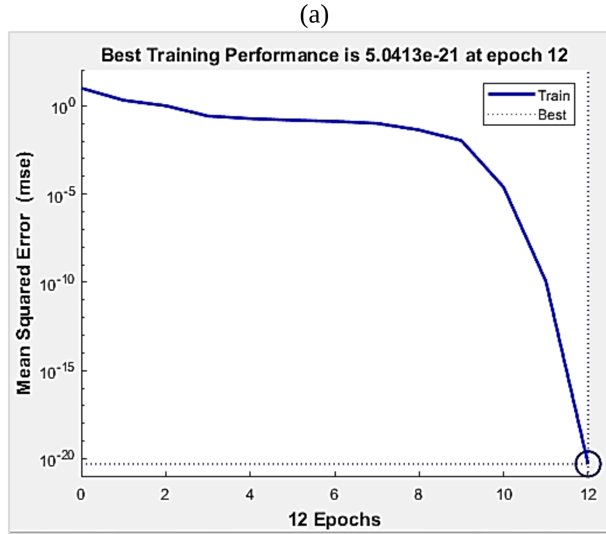
Figure 9 The process of training data using a BPNN

The results of training with artificial neural networks require 12 iterations to achieve the desired output target. The use of 3 layers on the network with a combination of 15 hidden layers on the first layer network, then 10 hidden layers on the second layer network, and 1 layer on the third layer network has been used to build a semaphore letter recognition system.

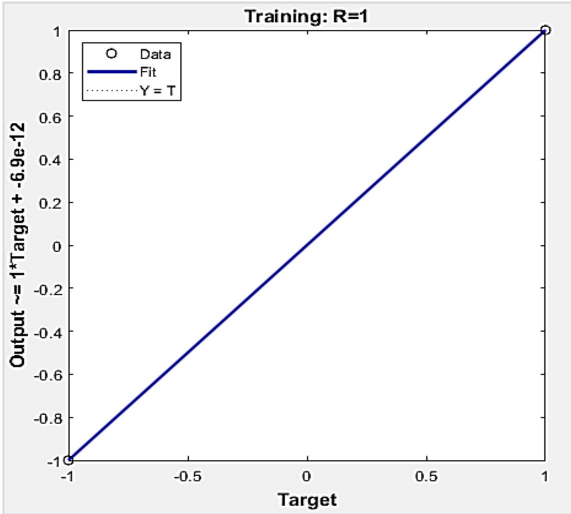
Figure 10 (a) shows training results on the test targets for each image. There are 26 data groups used to obtain the target value. Then *Figure 10(b)* shows the resulting difference between the output target value and the actual value at the output. MSE results reaching 5.0413e-21 indicate that this test achieved the optimal target. While in *Figure 10(c)* shows an output graph of the product to achieve the optimal value and the resulting R=1, which states that the training data has reached the optimal output.



(a)



(b)



(c)

Figure 10 The results of target testing against the target output were obtained, a) the results of testing on 26 targets; b) the MSE value obtained; c) target data on training values

5.Discussions

The test was carried out on 260 semaphore movement-image data showing the movement of the letters A to Z, which went through the process of segmentation, extraction, and classification, then compared with the previous training data to obtain the percentage level of success in recognizing the movement of the semaphore letters. In the recognition process, this study uses 5 variations of distance for all signs of the semaphore letters, and the test results are classified into two parts. The correct test states that the movement follows the semaphore movement, and the incorrect test states that the movement data has failed to be identified. The results of the recognition of semaphore letters are shown in *Table 4.*

Table 4 Semaphore movements test results based on distances variations

Letter	**Variations of distances (meter)**				
	3	**4**	**5**	**6**	**7**
A	✓			✓	
B	✓	✓	✓		✓
C	✓	✓	✓	✓	✓
D	✓	✓	✓		
E	✓	✓	✓	✓	✓
F	✓	✓	✓	✓	✓
G	✓	✓	✓	✓	✓
H	✓	✓	✓	✓	✓
I	✓	✓	✓	✓	
J			✓		✓
K	✓	✓	✓		✓
L	✓	✓	✓	✓	✓
M	✓	✓	✓	✓	✓
N	✓			✓	
O	✓	✓	✓	✓	
P	✓	✓	✓		✓
Q	✓	✓	✓	✓	✓
R	✓	✓	✓	✓	✓
S				✓	
T	✓	✓	✓	✓	✓
U	✓	✓		✓	
V	✓	✓		✓	✓
W	✓		✓	✓	✓
X	✓	✓	✓		
Y	✓	✓	✓	✓	✓
Z		✓			

The success percentage of semaphore movement recognition is shown in *Figure 11*. The recognition at 3 meters obtained the highest success percentage of 94%. At 4 meters, obtained a percentage value of 90%, at 5 meters, got an 88% success rate, at 6 meters, a success rate of 86% was achieved, and at 7 meters, the success rate was 83%.

From the test results under various physical conditions of demonstrators, it is evident that the semaphore motion can be well recognized by the system. The differences in the physical conditions of demonstrators do not significantly affect the accuracy of recognition; instead, factors such as distance and the precision of movements influence the system's recognition.

The highest semaphore letter recognition results were obtained using 3 meters, and the percentage of readings decreased significantly with distance variation with the model. The highest recognition at a closer distance is achieved because the semaphore movement has a better and sharper image quality for recognizing moving objects. The closer distance between the camera and the model significantly influences the recognition process. With the distance variation used, the system has recognized every movement of the Semaphore with a success rate of above 83%.

At a long distance between the demonstrator and the recognition camera, it affects the image quality, resulting in poorer processing in the recognition system. In this test, demonstrators conducted recognition under different conditions and lighting, so the lighting factor during data collection influenced recognition. Not only the distance factor explained above causes a decrease in recognition accuracy, but also the lighting can introduce bias to the color of semaphore flags or alter the HSV values in image data. The limitations in this research are related to distances greater than 7 meters and lighting conditions that introduce color bias in semaphore flags.

Accuracy in recognition is also impacted if the demonstrator does not position the semaphore flags correctly according to the instructions in *Figure 2*. In these instructions, both the right and left hands have specific conditions for transmitting a letter code. Hand shifts significantly affect the code angle and recognition in the system. In line with the goal of this research that the designed system serves as an aid in learning semaphore code there is a correction process between the correct hand positions that produce a specific letter and incorrect positions that result in semaphore code transmission errors.

Therefore, this research sets limitations for better use of the recognition system, such as demonstrators being required to use standard-sized semaphore flags, flags in red and yellow, conducting tests within the range of 3 – 7 meters with movements entering the camera frame, and ensuring that hand positions align with the correct semaphore code delivery guidelines.

A complete list of abbreviations is summarized in *Appendix I.*

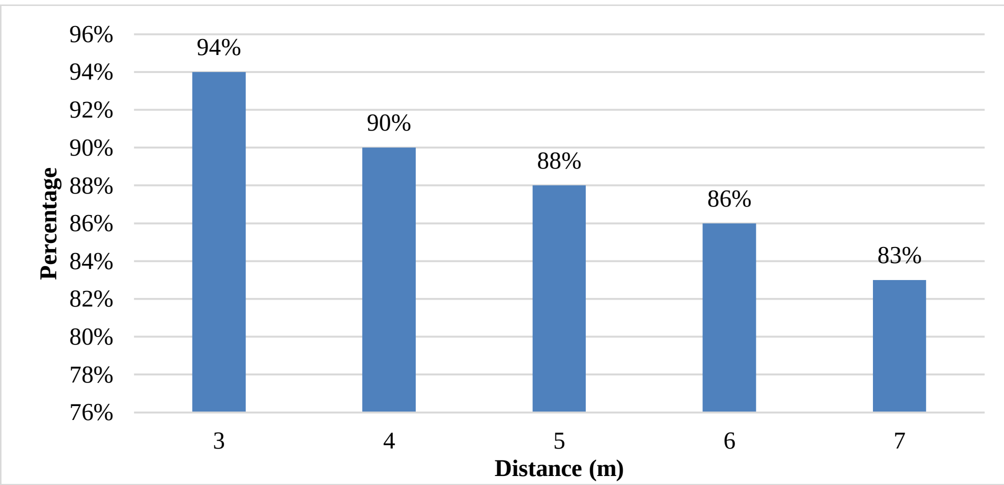


Figure 11 The percentage of success in recognizing semaphore letters to variations in distance

6.Conclusion and future work

This study uses distance variation to determine the system's effectiveness in recognizing semaphore movements. The recognition success rates were measured at distances ranging from 3 to 7 meters, with percentages of 94%, 90%, 88%, 86%, and 83%, respectively. From the recognition percentage results, the distance variation affects the process of recognizing the object of the semaphore movement. The further away the moving object is from the camera, the more recognition accuracy decreases.

The system designed by combining the feature extraction process using the wavelet method and classification using a BPNN has been successfully used to recognize the movement of the semaphore letter code. Six hundred fifty motion image data were successfully modeled in the classification process. In comparison, 260 image data as training data were recognized in the BPNN modeling, with the highest percentage reaching 94%.

Future research is being carried out on developing semaphore letter code recognition by utilizing cloud computing, which allows letter recognition to be carried out using a mobile application. This use can be modified to recognize letters and characters using the video processing method. To realize this, researchers use the basis of current research as an initial reference in determining the quality of image processing at varying distances.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The data and images used in this research were collected and processed directly by researchers to be used as primary research data. We may share data upon reasonable requests made to the research team.

Author's contributions statement

Leonardus Sandy Ade Putra: Conceptualization of research, writing research draft, review, and editing. **F. Trias Pontia Wigyarinto:** Conceptualization of data collection, design study, and draft manuscript preparation. **Eka Kusumawardhani:** Data collection, manuscript review, and editing. **Vincentius Abdi Gunawan:** Data curation, data testing, analysis, and interpretation.

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Appendix I

S. No.	Abbreviation	Description
1	BR	Bayesian Regularization
2	BPNN	Back Propagation Neural Network
3	Covid-19	Coronavirus Disease of 2019
4	CT	Computer Tomography
5	CWT	Continuous Wavelet Transform
6	DWT	Discrete Wavelet Transform
7	ECG	Electrocardiogram
8	FFANN	Feed-Forward Artificial Neural Network
9	GA	Genetic Algorithm
10	HH	High-High
11	HL	High-Low
12	HSV	Hue, Saturation, Value
13	LH	Low-High
14	LL	Low-Low
15	LM	Levenberg-Marquardt
16	MAE	Mean Absolute Error
17	MATLAB	Matrix Laboratory
18	MSE	Mean Squared Error
19	PCA	Principal Component Analysis
20	PSO	Particle Swarm Optimization
21	QN	Quasi-Newton
22	R2	R-Squared
23	RGB	Red, Green, Blue
24	RMSE	Root Mean Squared Error
25	SCG	Scaled Conjugate Gradient