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ADALINE Neural Network For Early Detection Of Cervical Cancer Based On Behavior Determinant

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Abstract.
Purpose: Cervical cancer is one of the most common types of cancer that kills women worldwide. One way for early detection of cervical cancer risk is by looking at human behavior determinants. Detection of cervical cancer based on behavior determinants has been researched before using Naïve Bayes and Logistic Regression but has never using ADALINE Neural Network.
Methods: In this paper, ADALINE proposes to detect early cervical cancer based on the behavior on the UCI dataset. The data used are 72 data, consisting of 21 cervical cancer patients and 51 non-cervical cancer patients. The dataset is divided 70% for training data and 30% for testing data. The learning parameters used are maximum epoch, learning rate, and MSE.
Result: MSE generated from ADALINE training process is 0.02 using a learning rate of 0.006 with a maximum epoch of 19. Twenty-two test data obtained an accuracy of 95.5%, and overall data got an accuracy value of 97.2%.
Novelty: One alternative method for early detection of cervical cancer based on behavior is ADALINE Neural Network.

Keywords: Cervical Cancer, ADALINE, Early Detection
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INTRODUCTION

Cervical cancer is a malignant tumor that grows in the cervix [1]. According to Andrijono in Fitrisia et al., [2], the oncogenic type of HPV (Human Papilloma Virus) is the cause of cervical cancer. It significantly affects women who are active in sexual activity or married women.

Cervical cancer is one of the most common types of cancer that kills women in all corners of the world. In Indonesia, every year, there are about 15,000 cases of cervical cancer. Unfortunately, early detection, such as routine Pap Smear tests, is still not a common concern.

Besides the Pap smear test, behavior determinants can be considered to detect cervical cancer risk early. It is based on the research of Sobar et al. [3], which uses eight variables of behavior for conducting early detection of cervical cancer risk by using two machine learning methods, Nave Bayes (NB) and Logistic Regression (LR). The accuracy of the Machine Learning method obtained in this study was 91.67% using NB and 87.5% using LR.

Another alternative that can solve the early detection of cervical cancer is the Adaptive Linear Neural Network (ADALINE) method. ADALINE is one of the methods in artificial neural networks with a simple network structure that can solve classification problems.

ADALINE has been widely used in research, among others, used to predict output when smart home controllers are in automatic mode [4], for MPPT controllers in photovoltaic systems [5], toddler nutrition

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classification [6], Dynamic Parameter Identification for Reconfigurable Robots [7], Alphabet Pattern Recognition [8], Optimization of Harmonics with Active Power Filter [9], Extraction of the fetal ECG signal (fECG) [10], and Friction Identification and Compensation of a Linear Voice-Coil DC Motor [11].

In this paper, ADALINE Neural Network will use to detect cervical cancer based on human behavior determinants. This paper will observe the effect of the learning rate parameter and MSE on ADALINE on the accuracy value generated using the ADALINE method.

METHODS

ADALINE is one of the methods in the Neural Network developed by Widrow and Hoff, which has two working processes, the training process and the testing process. Figure 1 is the training process, and figure 2 is the testing process from ADALINE.

Figure 1. Training Process

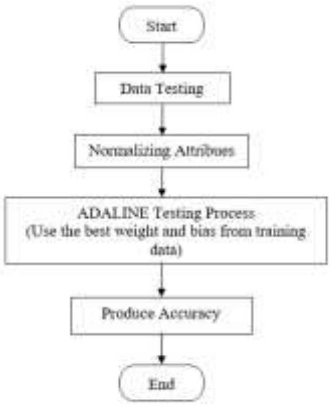

Figure 2. Testing Process

In this paper, a dataset from the UCI Machine Learning Repository on cervical cancer was used based on the journal Sobar et al.,[3]. The dataset consists of 72 data. The dataset is divide into 70% (50 data) for training data and 30% (22 data) for test data. The training and testing data were normalized first using equation 1 [12].

$$nv = f(v) = \frac{v - \min(v)}{\max(v) - \min(v)} \tag{1}$$

ADALINE Neural Networks training algorithm [13]:

1. Initialize weight (not zero but small random values are used). Set learning rate α.
2. While stopping condition is false, do step 3-7.
3. For each bipolar training pair s:t, perform Steps 4-6.
4. Set activations of input units $x_i = s_i$, for i = 1 to n.
5. Compute net input to output unit :

$$y_{\_in} = b - \sum_i x_i w_i \tag{1}$$

6. Update bias and weights, i = 1 to n.

$$w_i\ (new) = w_i\ (old) + \alpha(t - y_{\_in})\ x_i \tag{2}$$

$$b\ (new) = b(old) + \alpha(t - y_{\_in}) \tag{3}$$

7. Test for stopping condition.

The stopping condition may be when the weight change reaches small level or number of epochs etc. We use two conditions for the stop condition, the number of epochs or the Mean Square Error (MSE). MSE using equation 4 [14].

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Desired - Actual)^2 \tag{4}$$

Before testing the data, the test data normalized using equation 1. The min-max value used was the same as the min-max value from the training data.

For the application procedure, which is used for testing data, using bipolar activation with the following steps [13]:

1. Initialize weight obtained from the training algorithm
2. For each bipolar input vector x, perform Steps 3-5.
3. Set activations of input unit.

$$y_{in} = b - \sum_i x_i w_i \tag{5}$$

4. Calculate the net input to output unit.
5. Finally apply the activations to obtain the ouput y.

$$\boldsymbol{y = f(y_{-in}) = \begin{cases} 1 & jika\ y_{-in} \geq 0 \\ -1 & jika\ y_{-in} < 0 \end{cases}} \tag{6}$$

To calculate the accuracy of the network, used confusion matrix [15]:

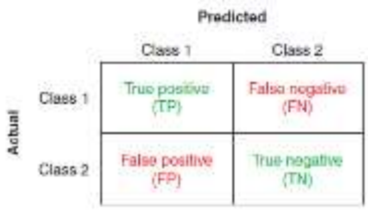

Figure 3. Confusion matrix for a binary class of data [15]

$$\boldsymbol{Accuracy = \left(\frac{TP+TN}{TP+FP+FN+TN}\right) x\ 100\%} \tag{7}$$

$$\boldsymbol{Precision = \left(\frac{TP}{TP+FP}\right) x\ 100\%} \tag{8}$$

$$\textbf{Recall} = \left(\frac{\textbf{TP}}{\textbf{TP+FN}}\right) \textbf{ x } \mathbf{100}\% \tag{9}$$

$$\boldsymbol{F - Score} = \mathbf{2} \textbf{ x } \left(\frac{\boldsymbol{Precision} \textbf{ x } \boldsymbol{Recall}}{\boldsymbol{Precision+Recall}}\right) \tag{10}$$

where :
True positive (TP) : Cases where the actual data belonged to class 1 and the model correctly classified as class 1.
False negative (FN) : Cases where the actual data belonged to class 1 but the model wrongly classified as class -1.
False positive (FP) : Cases where the actual data belonged to class -1 but the model wrongly classified as class 1.
True negative (TN) : Cases where the actual data belonged to class -1 and the model correctly classified as class -1.

RESULT AND DISCUSSION
We observe the effect of learning rate on the accuracy of training data. The observed learning rate is 0.001-0.01.

1. Testing with maximum epochs = 500 or minimum MSE = 0.

Figure 3 shows the results of the 500 epoch test with a minimum MSE = 0. Figure 3 shows that the lower the learning rate, the more epochs needed to achieve MSE = 0. The minimum MSE achieved is 0.02. The network cannot reach MSE=0 using 500 epochs.

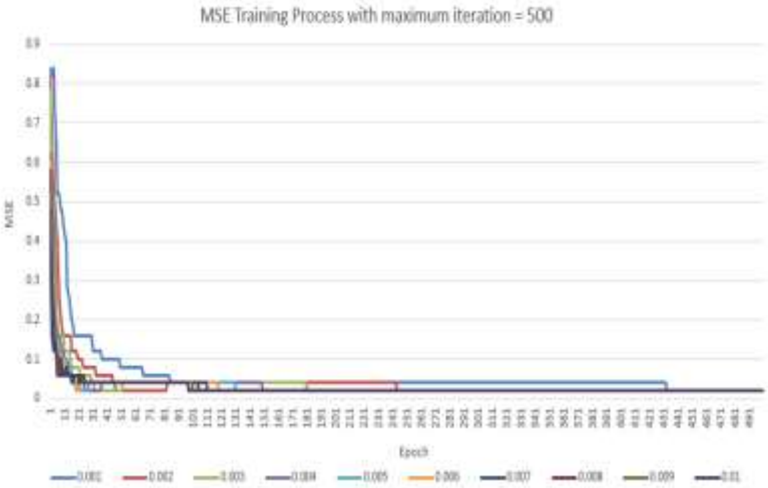

Figure 3. MSE Training Process with Maximum Iteration = 500

2. Testing with minimum MSE = 0.02 or maximum epoch = 500.

The test results with a minimum MSE = 0.02 or a maximum epoch = 500, as shown in Figure 4. Figure 4 shows that the minimum epoch to obtain MSE = 0.02 by using a learning rate of 0.006. Therefore, the final weight and bias values from the 19 epoch of training from a learning rate of 0.006 used as the weight and bias values for the test data.

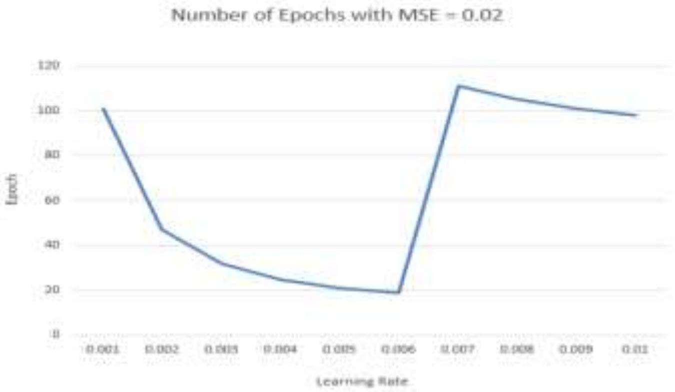

Figure 4. Number of Epochs with MSE = 0.02

3. Testing of the data.

Table 1 presents the performance evaluation of ADALINE Neural Network. The MSE result of the training set is 0.020, the test set result is 0.045, and the overall result is 0.028. The test results with 22 test data show that ADALINE has a precision of 100%, recall of 83.3%, F-Score of 90.9 with an accuracy of 95.5%. All data results have a precision of 100%, recall 90.5%, F-score 95%, and accuracy of 97.2%.

Tabel 1. Result of Cervical Cancer Based On Behavior Determinant using ADALINE

	TP	FN	FP	TN	Total	MSE	Precision (%)	Recall (%)	F-Score	Accuracy (%)
Training set	14	1	0	35	50	0.020	100.0	93.3	96.6	98.0
Testing set	5	1	0	16	22	0.045	100.0	83.3	90.9	95.5
Overall	19	2	0	51	72	0.028	100.0	90.5	95.0	97.2

Sobar et al. [3] compared NB and LR with an accuracy of 91.67% using NB and 87.5% using LR. The comparison of the test set's performance using the ADALINE Neural Network, NB, and LR shows in Table 2. Based on this comparison, the ADALINE Neural Network can have better accuracy than the NB and LR methods by selecting the appropriate initial random values.

Tabel 2. Performance comparison of the testing set

Author	Method	TP	FN	FP	TN	Total	Accuracy (%)
Sobar et al.,[3]	NB	17	2	4	49	72	91.7
	LR	16	4	5	47	72	87.5
Proposed	ADALINE NN	19	2	0	51	72	97.2

CONCLUSION

This study uses ADALINE NN on the UCI Machine Learning Repository dataset for early detection of cervical cancer based on behavior determinants. The approach results are evaluated by MSE, precision, recall, f-score, and accuracy of the training set, testing set, and overall data. The results of this study are the accuracy for the 22 test data is 95.5%, and the accuracy for the whole data is 97.2%. Compared to the NB and LR approaches, ADALINE can have better accuracy.

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