Eligibility of village fund direct cash assistance recipients using artificial neural network

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ABSTRACT

Bantuan Langsung Tunai Dana Desa (BLT-DD), or known as Village Fund Direct Cash Assistance is assistance from the Indonesian government which causes problems and conflicts in the community when the assistance is not on target. The classification algorithm is proven to use in determining BLT-DD recipients. In this study, the radial basis function (RBF) and elman recurrent neural network (ERNN) models compare to classify the eligibility of BLT-DD recipients. In the experiment, the optimal performance of the RBF and ERNN compare in determining the eligibility of BLT-DD recipients. Also, it's compared with the classification algorithm that implements the same data, namely BLT-DD data for Kubu Raya District. The experimental results show the effectiveness of the RBF model in recognizing test data, while the ERNN model is effective in identifying test data. The RBF and ERNN models can achieve the same total accuracy of 98.10%.

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1. INTRODUCTION

Bantuan Langsung Tunai Dana Desa (BLT-DD), or known as Village Fund Direct Cash Assistance is assistance from the Indonesian government which provides to reduce the impact of the Covid-19 pandemic on villages in the form of financial assistance originating from village funds [1]. This assistance is only given to the poor and vulnerable who have not received assistance from other social welfare insurance schemes such as *Program Keluarga Harapan* (PKH) or known as Hope Family Program, staple food cards, pre-employment cards, cash social assistance (BST). There are problems in implementing BLT-DD; the target of BLT-DD beneficiaries has yet to be fully achieved or is not on target [2]. Another problem is that in the implementation of data collection on Village Fund Direct Cash Assistance recipients, there is a lack of coordination between the village government and the community, so the community does not know the criteria for beneficiaries or the mechanism for recipients of direct cash assistance recipients, and the existence of a list of recipients of direct cash assistance does not match the criteria set by the government, giving rise to conflict in society [3]. Rustan [4] used the Mamdani fuzzy in determining the eligibility of candidate BLT-DD recipients.

Fuzzy set theory is often applied in ambiguous multi-criteria decision-making environments when there is ambiguity and uncertainty in the information. Besides fuzzy, another method used when there is ambiguity for the assessment is an artificial neural network (ANN). ANN is an artificial intelligence model that tries to imitate how the human brain works and is better at managing complexity and uncertainty than traditional methods [5]. This study proposes ANN radial basis function (RBF) and ERNN to determine the feasibility of candidate BLT-DD recipients.

Broomhead and Lowe introduced the radial basis function neural network (RBF) in multivariable functional interpolation and adaptive networks [6]. RBF has adaptability [7]–[10], an efficient and practical approach [11], less dependence on the number of sensors [12], and, combined with CNN, can perform image classification [13]. RBF is a multilayer neural network with a supervised learning model.

ERNN is a distinct feedback network, and a dynamic recurrent neural network with additional advanced layers added to the hidden layers. ERNN has higher computational power than ordinary feed-forward neural networks and can be used to solve fast optimization problems. ERNN is used for the prediction of vehicle interior noise [14]. ERNN describes powerful learning techniques such as uncertainty estimation [15], environmental adaptability [16], increasing the amount and accuracy of forecast data [17], improving the accuracy of time series forecasting [18], [19], early detection of circuit failures by combining with cuckoo search [20], improvement of accuracy of identification processing by combining with the Kalman filter [21], face recognition possible by connecting with principal component analysis (PCA) [22].

The main objective of this paper is to propose the RBF and ERNN models to determine the eligibility of prospective BLT-DD recipients. We will look for the optimal RBF and ERNN models and compare the performance of the RBF and ERNN models with other studies. Section 2 will present the ANN, RBF, ERNN algorithms, and feature data. Section 3 describes the proposed model and experimental results. Finally, the conclusions of this paper are mentioned in section 4.

2. METHOD

2.1. Artificial neural networks

Artificial neural networks are an information processing paradigm inspired by how biological nervous systems, such as the brain, process information [23]. ANN has several parameters that can affect the network output value, including the number of neurons in the hidden layer, learning rate, network weight, threshold, and activation function. The learning model of ANN is supervised learning, unsupervised learning, and hybrid learning.

The number of hidden layer neurons is 2/3 (or 70% to 90%) of the input layer size. If this is insufficient, the number of output layer neurons can be added later [24], [25]. ANN can use random network weight values for each network. Neural networks with random weights (NNRW) have much lower training complexity compared to traditional feed-forward neural network training [26], fast learning speed, and good generalization performance [27].

2.2. Radial basis function algorithm (RBF)

RBF is a neural network method with supervised learning. RBF architecture consists of an input layer, a hidden layer, and an output layer. RBF uses the Gaussian function as the kernel function of the hidden unit using [28],

$$G(\|x-t_i\|^2) = exp\left(-\frac{m_1}{d_{max}^2}\|x-t_i\|^2\right), i = 1,2,\dots,m_1 \tag{1}$$

where *m1* is the number of centers, *dmax* is the maximum distance between the chosen centers. The width of all the Gaussian RBF fix in fixes in,

$$\sigma = \frac{d_{max}}{\sqrt{2m_1}} \tag{2}$$

the linear weights in the output layer of the networks use the pseudoinverse method in the following,

$$w = G^+ d \tag{3}$$

where d is the desired response vector in the training set of the ANN. The matrix G^+ is the pseudoinverse of matrix G. For the centers of the networks, we chose randomly from np.random.rand.
The network output uses [29].

$$F(x) = \sum_{i=1}^{N} w_i \varphi(\|x - x_i\|) \tag{4}$$

Where {φ(||x – xi||) | i = 1, 2,… ,N} is a set of N arbitrary (generally nonlinear) functions.
For output binary classification, uses binary step function with threshold [30].

$$f(x) = \begin{cases} 1 \; if \; x \; \geq \; \theta \\ 0 \; if \; x \; < \theta \end{cases} \quad (5)$$

Threshold value used = 0.5.
Normalization data RBF in this study uses min-max normalization as in [31],

$$X^*_{mm} = \frac{X - \min(X)}{range\,(X)} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (6)$$

network error using mean squared error (MSE) as in [32],

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Desired - Actual)^2 \quad (7)$$

where, *Desired r*epresent target class value and *Actual* represent real class value generated by network.

The pseudo code-1. RBF algorithm for train data:

```
Normalization data training (6)
Determine the number of clusters
While stop criteria is not met do
        randomly generate weights
        For each data train, do
                Calculate width (2)
                Calculate Gaussian (1)
                Calculate pseudoinverse (3)
        End for
        For each data train, do
                Calculate Output (4)
                Calculate output with activation function (5)
                Calcutate error network (7)
        End for
End while
Output the global best RBF classification.
```

2.3. Elman neural network algorithm

ERNN is a recurrent neural network where the network is given memory before entering into the hidden layer [33]. The memory is called the context layer. Figure 1 is the ERNN architecture.

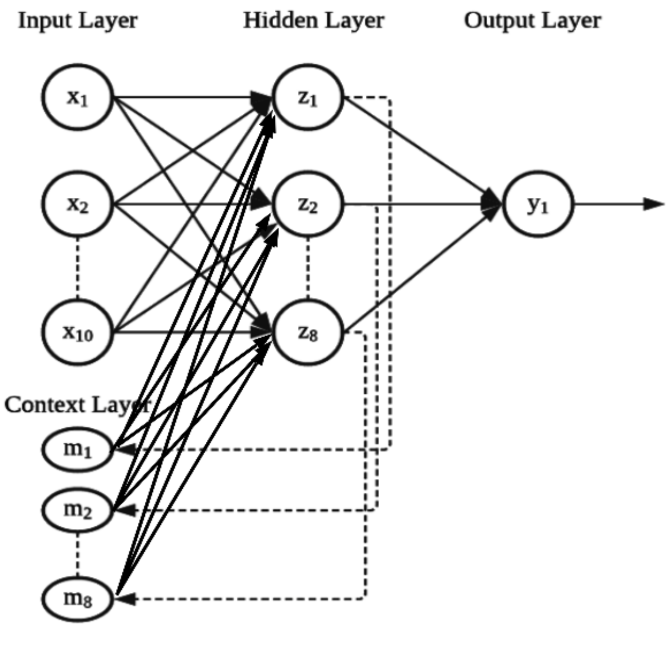

Figure 1. ERNN architecture

Normalization data ERNN in this study uses Normalization between 1 and -1, as in (8) [34]. Normalization between -1 and 1 was used because, in the different experiments, this normalization allowed us to identify ERNN patterns from the data quickly. The normalization uses,

$$\left(2 * \frac{\max value - sample_i}{\max value - \min value}\right) - 1 \quad (8)$$

we used Elman's algorithm from research [19]. We use the two-condition criterion to stop iterating over the training data. These two conditions are, using a small MSE value or the number of iterations has reached.

The pseudo code-1. ERNN algorithm for train data:

```
randomly generate weights w and zeros weight bias w
randomly generate weights v and zeros weight bias v
Normalization data training (8)
Determine the number of clusters
While stop criteria is not met do
        For each data train, do
                Calculate hidden layer Z, sigmoid activation for Z
                Calculate output Y, sigmoid activation for Y
                Update weights v and bias v
                Update weights w and bias w
        End for
        For each data train, do
                Calculate hidden layer Z, sigmoid activation for Z
                Calculate output Y, sigmoid activation for Y
Calcutate output Y use binary step function with threshold (5)
Calcutate error network (7)
        End for
End while
Output the global best Elman classification.
```

2.4. Data set

The data in this study uses research [4]. The data set consists of 158 with ten input features and two output classes. Input features can see in Table 1. To calculate the accuracy of the network, we used a confusion matrix from [35].

Table 1. Feature data

Feature input	Feature name
1	Last education of family head
2	Residential building control status
3	Floor area
4	The widest type of floor
5	State of the building
6	Family members with chronic diseases
7	Source of income
8	Source of clean water for drinking
9	Source of clean water for bathing or washing
10	Number of vehicles
Class	1 if worthy, 0 or -1 if not worthy

3. RESULTS AND DISCUSSION

3.1. Result of artificial neural network

In this study, 158 data were used, divided into 111 data for training data and 47 for test data. The parameters used are the number of input neurons of ten neurons, one hidden layer, eight neurons in the hidden layer, and one output. In ERNN, the learning rate parameter is 0.5. We also consider the value of overfitting in the training model to the test data. The training is carried out several times using normalized and different random weight values for the RBF and ERNN networks to get optimal results. Each experiment stores the random weight and network bias values to be selected and reused in training data, test data, and Graphical User Interface applications. Figures 2 to 5 show the results of the RBF and ERNN training and testing.

Figures 2 to 5 compares predicted and actual data for data training and testing using RBF and ERNN. It can see that RBF does not recognize two training data and one testing data, while ERNN recognizes all training data but does not recognize 3 data testing. The results of the confusion matrix can see in Table 2.

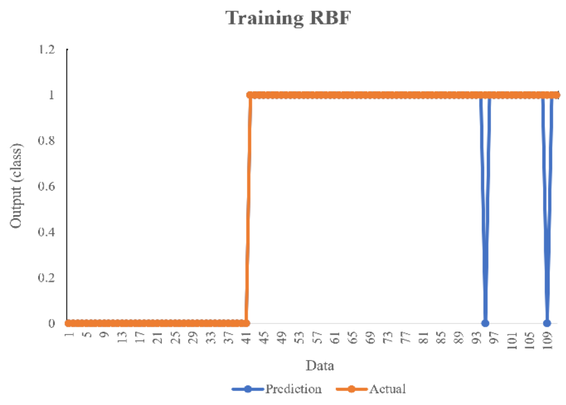

Figure 2. Results of RBF training

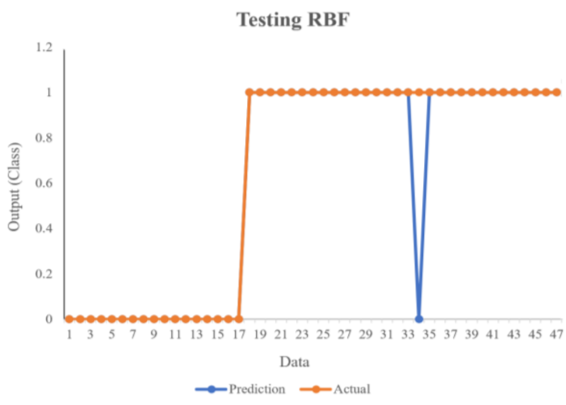

Figure 3. Results of RBF testing

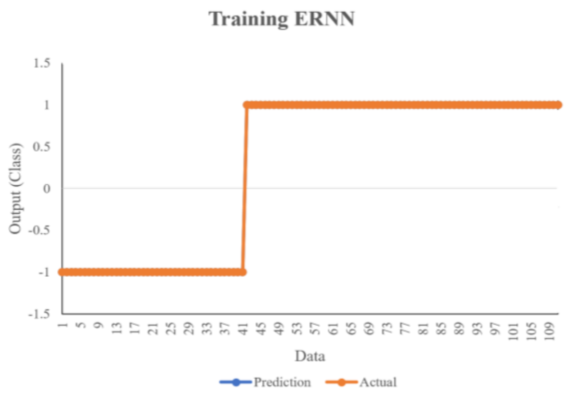

Figure 4. Results of ERNN training

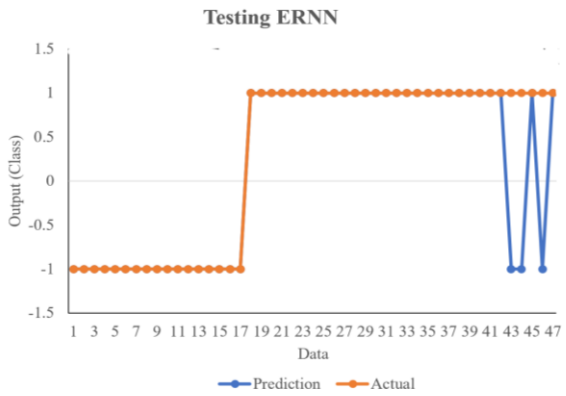

Figure 5. Results of ERNN testing

Table 2 shows performance comparison results between RBF, ERNN, and Fuzzy. Fuzzy has been carried out by [4]. The table shows that, in this case, RBF and ERNN overall have higher accuracy than Fuzzy research.

Table 2. Performance comparison

	TP	FN	TN	FP	Total	MSE	Precision (%)	Recall (%)	F-Score	Accuracy (%)
RBF Training set	68	2	41	0	111	0.02	100	97.14	98.55	98.20
RBF Testing set	29	1	17	0	47	0.02	100	96.67	98.31	97.87
Overall	97	3	58	0	158	0.02	100	97.00	98.48	98.10
ERNN Training set	70	0	41	0	111	0.00	100	100.00	100.00	100.00
ERNN Testing set	27	3	17	0	47	0.06	100	90.00	94.74	93.62
Overall	97	3	58	0	158	0.02	100	97.00	98.48	98.10
Fuzzy Overall [4]	90	12	52	4	158	0.10	95.74	88.24	91.84	89.87

3.2. Result of application development

An application was developed to make it easier for users to determine the eligibility of Kubu Raya Regency BLT-DD recipients. The application interface develops using python, flask, HTML, and Cascading Style sheet (CSS). The initial appearance of the application is in the form of categories that the user can select. There are ten categories along with answer choices that can be selected by the user, as shown in Figure 6 and Figure 7.

After selecting the answers for each category, the user clicks Run. The results of the application using the RBF algorithm can see in Figure 8 and Figure 9. On the results tab, the user can see the results menu and the variable & value menu from the categories and options entered by the user from the initial display tab. Results can be in the form of eligible or not-eligible classes. The interface application using ERNN has the same appearance as RBF. The difference is in the algorithm used in the application.

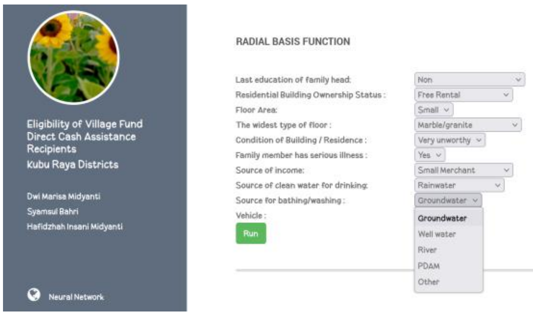

Figure 6. RBF data input application

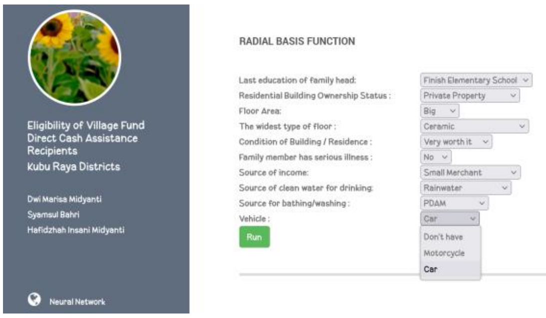

Figure 7. RBF data input application

Figure 8. Eligible RBF result application

Figure 9. Not Eligible RBF result application

4. CONCLUSION

The determination of BLT-DD beneficiaries has yet to be fully achieved or is not on target. Therefore, it's proposed that the RBF and ERNN help decision-makers determine which communities will receive BLT-DD funds so that they are more objective and on target. The RBF and ERNN networks use parameters, namely the number of input neurons of 10 neurons, one hidden layer, eight neurons in the hidden layer, and one output, and a learning rate of 0.5 on ERNN. Trial and error are used on random values of artificial neural networks to get the optimal value. The experimental results found that RBF had a higher F-Score testing data value than ERNN, while in the training data, ERNN had a higher F-Score value than RBF. Overall, RBF and ERNN produce an accuracy of 98.10%. In addition, a web-based application develops in this case. The application has an interface for category forms and an interface for the results of using the RBF and ERNN methods. Besides being easy to use, the application works well by implementing RBF and ERNN algorithms.

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