

# Single hidden layer feedforward neural networks for indoor air quality prediction

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## ABSTRACT

Indoor air quality (IAQ) has become a problem because it affects human health, comfort, and productivity. Predicting air quality is a complex task due to the dynamic nature of IAQ variable values simultaneously. In this study, the single hidden layer feedforward neural networks model is used, namely radial basis function (RBF), self-organizing maps (SOM)-RBF, and extreme learning machine (ELM) to classify IAQ. This study also observed the effect of the number of neurons in the hidden layer on the model accuracy and overfitting of each network. The experimental results show that the number of neurons in the hidden layer can affect the accuracy of the RBF and SOM-RBF models. Among the three models used, RBF produces very good training data accuracy but also the most significant overfitting value. The largest overall accuracy was obtained using SOM-RBF, with a value of 86.37%.

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## 1. INTRODUCTION

Indoor air pollution is a pressing issue and seriously threatens the health of indoor workers and occupants [1]. Indoor air quality (IAQ) is among the top five environmental risks to global health and well-being [2]. IAQ has become a widely recognized issue, drawing the attention of researchers and citizens to improve air quality in schools and other educational facilities. Air quality can be assessed based on its impact on health, comfort, and productivity. Air quality is essential for improving learning ability and achievement [3]. Predicting air quality is complex due to the dynamic nature, volatility, and high variability in space and time of pollutants and particulates [4]. Among the pollutants that pose a severe threat is PM<sub>10</sub>. PM<sub>10</sub> has been closely associated with adverse health impacts such as respiratory and cardiovascular diseases [5]. In the guidelines for indoor air sanitation of homes issued by the Regulation of the Ministry of Health of the Republic of Indonesia, the IAQ level for PM<sub>10</sub> is  $\leq 70 \mu\text{g}/\text{m}^3$  in 24 hours [6]. It is known that PM<sub>10</sub> concentrations can fluctuate significantly with anomalies detected in the study area [7].

IAQ determined by the concentration of indoor air pollutants, can be predicted using physically based mechanistic models or statistical models based on measured data [8]. Artificial neural networks (ANN) are one of the statistical methods that can be applied to IAQ prediction. 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 [9]. ANN is used for IAQ prediction based on PM<sub>10</sub> values, including radial basis function neural network (RBFNN) [10].

Broomhead and Lowe [11] introduced the RBFNN in multivariable functional interpolation and adaptive networks. Radial basis function (RBF) has good accuracy with a limited number of sensors [12]. In several cases, RBF has good accuracy [13]–[15] and can estimate nonlinear functions [16]. A clustering method can be used to determine the center value in RBF, one of which is self-organizing maps (SOM). Incremental learning of a single SOM with RBF performs better generalization than traditional RBF networks [17]. Integrating the SOM clustering algorithm and RBFNN is suggested to make the network more effective and efficient [18].

RBFNN is one of the single hidden layer feedforward neural networks (SLFNs) methods. Another SLFNs method is extreme learning machine (ELM). ELM was developed by Huang *et al.* [19] as an algorithm that provides good generalization performance at very fast learning rates. The use of ELM produces high accuracy [20], its simple structure, no parameter adaptation, shorter processing time, and lower computational complexity [21], reducing training time costs because it does not have iterative tuning parameters as a substitute for traditional deep learning algorithms [22].

The main objective of this paper is to propose RBF, SOM-RBF, and ELM models to predict IAQ. RBF, SOM-RBF, and ELM models will be investigated to determine IAQ based on temperature, humidity, and PM<sub>10</sub> inputs. The following section will present the algorithms used in this research. Section 2 describes the proposed model and dataset. Experimental results are covered in section 3. Finally, the conclusion and future work of this paper are mentioned in section 4.

## 2. METHOD

The suggested method steps are included in this section. The suggested procedure starts with requirements analysis, data acquisition, data collection, data labeling, building the ANN model, testing model, and performance analysis. Figure 1 shows the working process of this study.



Figure 1. Overall working process

### 2.1. Requirement analysis

At this stage, functional and non-functional needs analysis is carried out. For functional needs, IAQ parameters such as PM<sub>10</sub>, temperature, and humidity are needed, and the room will be used as the object of research. DHT22 sensor is used to measure temperature and humidity, ESP32 is used as a microcontroller module, and the dust sensor is used as a PM<sub>10</sub> counter. The feedforward ANN model used in this study for non-functional needs is RBF, SOM-RBF, and ELM.

### 2.2. Data acquisition

At this stage, data generated by the DHT22 sensor and the GP2Y1010AU0F dust sensor connected to the ESP32 microcontroller is sent to the server. From the server, the data is displayed on the website. This data transmission depends on the Wi-Fi connectivity in the vicinity of the ESP32 microcontroller. After the data is collected, data cleaning and filtering are performed to prepare the data for use in the next stage.

### 2.3. Data labeling

In this study, the inputs used are temperature, humidity, and PM<sub>10</sub>. The output used is the prediction of PM<sub>10</sub> categories for the next 24 hours. Based on the guidelines for indoor air sanitation issued by the Ministry of Health of the Republic of Indonesia, the required level for PM<sub>10</sub> is  $\leq 70$  in 24 hours. Therefore, we created two prediction classes: if the PM<sub>10</sub> value  $\leq 70$ , then the class is not dangerous, and if PM<sub>10</sub>  $\geq 70$ , the class is dangerous.

### 2.4. Artificial neural networks model

ANN are an information processing paradigm inspired by how biological nervous systems, such as the brain, process information [23]. The number of neurons in the hidden layer, learning rate, network weights, threshold, and activation function are some of the parameters that can affect the output value of the network. Specifically, for data sets with sample sizes under 10,000, the total number of hidden neurons is

selected from {10, 15, 20, ..., 540, 545, 550}; for data sets with sample sizes above 10,000, the total number of hidden neurons is selected from {50, 60, 70, ..., 880, 890, 900} [24]. Goni *et al.* [21] used a hidden layer of the ELM model with 700 neurons.

Network weights can be chosen randomly. Neural networks with random weights (NNRW) have significant training time reduction while maintaining high prediction accuracy [25], effectiveness in handling concept shifts [26], and the use of NNRW in ELM can produce high accuracy rates [27]. This study uses three models, namely RBF, SOM-RBF, and ELM. The network model is a SLFNs network model. The network architecture can be seen in Figure 2.

This study uses three input nodes: temperature, humidity, and PM<sub>10</sub>, one hidden layer, and two output nodes. Normalization in RBF and SOM uses min-max normalization [28]–[31] with a range of [0,1]. For the ELM model, we use min-max normalization with a range of [-1 1], as done in the studies [32], [33]. The formula for min-max normalization is as shown in (1) [28].

$$v_{normalization} = \frac{v_i - v_{min}}{v_{max} - v_{min}} \tag{1}$$

The SoftMax activation function is applied to the output value. This function makes it easier to determine the class of the output value. The SoftMax activation function is defined as (2) and (3) [34].

$$\hat{y}_v = softmax(h_v^{(k)}) \tag{2}$$

$$Softmax(h_{v,c}) = \frac{\exp(h_{v,c})}{\sum_{i \in C} \exp(h_{v,i})} \tag{3}$$

Where  $h_{v,c}$  is a scalar value for each class  $c$  in the output vector  $h_v$  of the last layer, and the SoftMax activation function is computed for each class. Model testing is conducted after the optimal ANN model has been derived from the training data. Training data is used as much as 70% of the total data, and test data is used as much as 30%. Performance analysis is conducted to assess the efficacy of the ANN model. Mean squared error (MSE) is used to determine the error of training data so that the best model from training data can be selected for testing test data. Confusion matrix is used to determine the overall performance analysis as in the study [35].

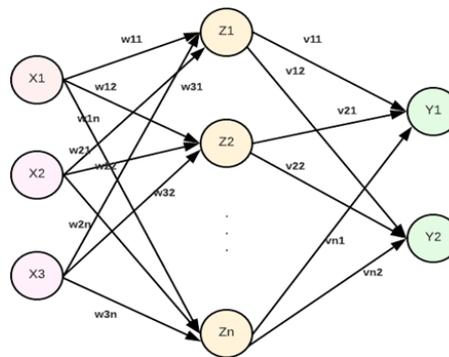


Figure 2. Neural network architecture

### 3. RESULTS AND DISCUSSION

#### 3.1. Result of artificial neural network

This study used 910 data, divided into 637 data for training data and 273 for test data. The parameters used are the number of input neurons of 3 neurons, one hidden layer, and one output. Observations were made on the number of neurons in the hidden layer from 50-700 neurons with multiples of 50 {50, 100, 150, ..., 700}. We also considered the overfitting value of the training model obtained against the test data. Each time the network was trained with a certain number of neurons in 1 hidden layer, 40 trials were carried out to get the best weight and bias values from each model that produced the highest accuracy. From the 40 trials, 1 data with the highest accuracy value or the lowest MSE was selected. The weight value of the training data with the highest accuracy was used to conduct the data test. Figure 3 is the result of training data using a different number of neurons. Figure 3 shows that the number of neurons in the hidden layer affects the MSE value in the RBF and SOM-RBF model. In the RBF and SOM-RBF models, the higher the number of neurons in 1 hidden layer, the lower the resulting MSE value. In the ELM model, the number of neurons has a low effect on the MSE value of the network.

We observe the overfitting value produced by each model. Figure 4 shows the overfitting model that RBF, SOM-RBF, and ELM produced. In Figure 4(a), the smallest overfitting is produced by RBF when using 200 neurons in the hidden layer, with an accuracy difference of 0.120879. In Figure 4(b), the largest overfitting is produced by SOM-RBF when using 550 neurons in the hidden layer, with an accuracy difference of 0.019885. In Figure 4(c), the largest overfitting is produced by ELM when using 600 neurons in the hidden layer, with an accuracy difference of 0.049189. Figure 4 shows that the greater the number of neurons in the RBF hidden layer, the greater the overfitting value. Meanwhile, for the SOM-RBF model, the greater the number of neurons in the hidden layer used, the smaller the overfitting value produced. In the ELM model, changes in the number of neurons in the hidden layer do not significantly affect the overfitting value created by the model. This can happen because the data used is not varied or there is no data balance between classes. The minimum overfitting of the RBF model is obtained by using 200 neurons in the hidden layer. The minimum overfitting of the SOM-RBF model is obtained by using 550 neurons in the hidden layer. The minimum overfitting of the ELM model is obtained by using 600 neurons in the hidden layer.

Table 1 shows that the highest training data accuracy is achieved using the RBF method. For the test data, the best accuracy is obtained with the SOM-RBF method. Overall, using 910 data, the best accuracy is achieved using the SOM-RBF method, with an overall accuracy of 86.37%.

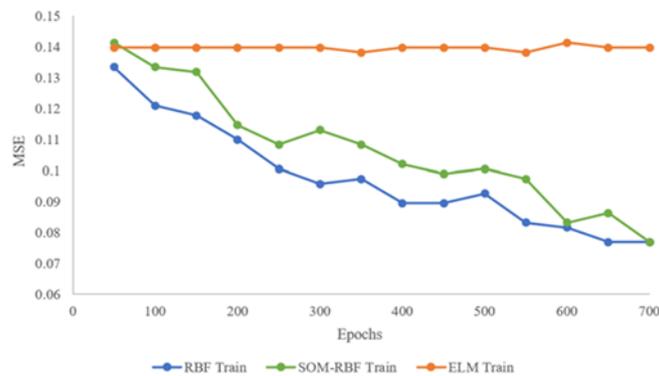


Figure 3. Training data result

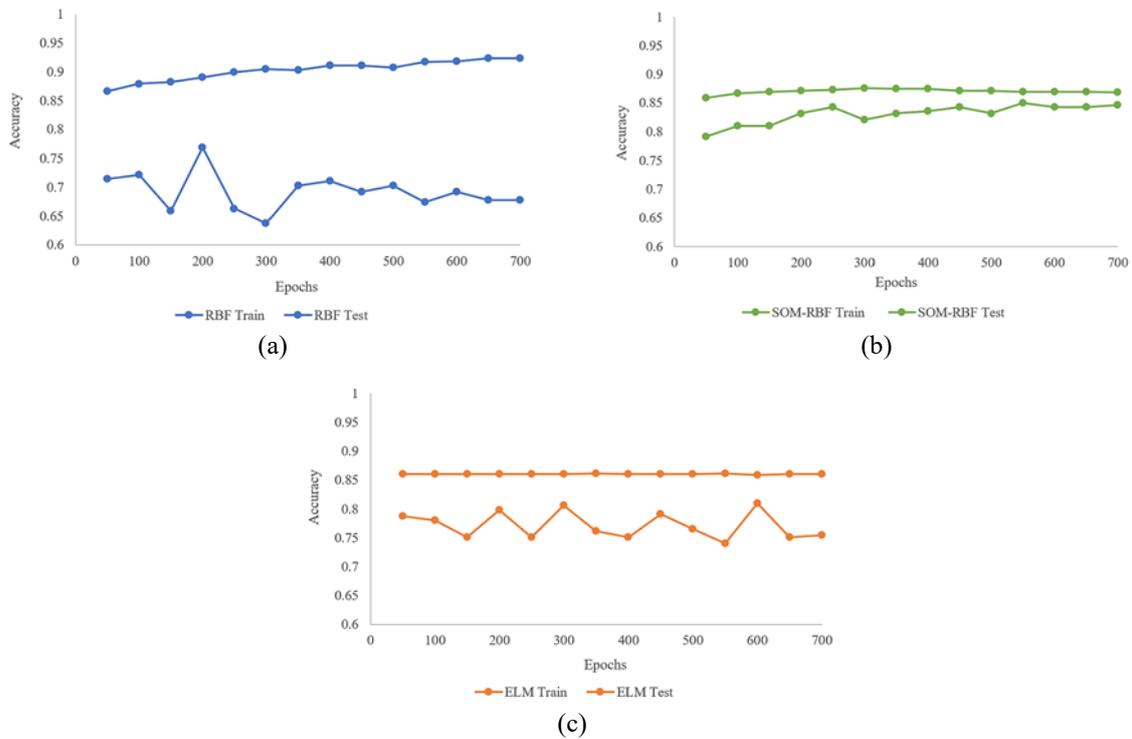


Figure 4. Overfitting model for (a) RBF, (b) SOM-RBF, and (c) ELM

Table 1. Performance comparison

Model	TP	FN	TN	FP	Total	Precision (%)	Recall (%)	Specificity	F1-score	Accuracy (%)
RBF training set	44	55	535	3	637	93.62	44.44	0.99	60.27	90.89
RBF testing set	19	23	187	44	273	30.16	45.24	0.81	36.19	75.46
Overall	63	78	722	47	910	57.27	44.68	0.94	50.20	86.26
SOM-RBF training set	18	81	538	0	637	100	18.18	1	30.77	87.28
SOM-RBF testing set	2	40	228	3	273	40	4.76	0.99	8.51	84.25
Overall	20	121	766	3	910	86.96	14.18	1	24.39	86.37
ELM training set	9	90	537	1	637	90	9.09	1	16.51	85.71
ELM testing set	1	41	224	7	273	12.50	2.38	0.97	4	82.42
Overall	10	131	761	8	910	55.56	7.09	0.99	12.58	84.73

#### 4. CONCLUSION

IAQ has become a problem because it affects health, comfort, and productivity. Predicting air quality is a complex task due to the dynamic nature of IAQ variable values simultaneously. RBF, SOM-RBF, and ELM are proposed to help predict IAQ. The IAQ variables used are temperature, humidity, and PM<sub>10</sub>. The number of neurons in one hidden layer and overfitting in this study are also considered. The experiment was conducted 40 times using random values for each number of neurons to obtain the smallest MSE value on the training data. The results of the experiment show that RBF has a higher F1-score value than SOM-RBF and ELM. RBF has the largest accuracy on training data but has large overfitting when compared to other models. Overall, SOM-RBF has the highest accuracy of 86.37%, RBF at 86.26%, and ELM at 84.73%.

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#### AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Syamsul Bahri	✓		✓		✓	✓	✓	✓	✓					✓
Ilhamsyah				✓	✓				✓					
Zalikhah Khairunnisa					✓				✓		✓		✓	
Hafizhah Insani Midyanti				✓	✓				✓				✓	

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ditting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

#### CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

#### INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

#### DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author, [DMM], on request.

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