Classifying Patient General Health Using Elman Recurrent Neural Network Method

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Abstract. This research aims to improve the accuracy and efficiency of patient health classification using the Elman Recurrent Neural Network (ERNN) method. This research utilizes medical data such as blood pressure, heart rate, body temperature, blood sugar levels, cholesterol levels, oxygen levels, and uric acid as parameters in the classification model. The model is trained to classify health categories into "Low," "Medium," "High," and "Very High" disease risk. The data classification results show that the training and testing data achieved an accuracy of 98.49%.
The ERNN method has the potential to help health professionals diagnose diseases more accurately and quickly, thereby allowing patients to receive appropriate and specific treatment for their condition. The research results show the potential of the ERNN method in improving the accuracy and efficiency of patient health classification. However, further research is needed to enhance the model's generalizability and validate its effectiveness in real-world healthcare settings. This research provides a promising approach to improve patient health classification using the ERNN method. The findings of this study have significant implications for the healthcare sector, as accurate and efficient diagnosis of disease is essential for timely and appropriate treatment.

Keywords: Patient General Health Classification, Elman Recurrent Neural Network (ERNN), Health Prediction.

1 Introduction

Health is a crucial need for all living creatures in this world. A sick body can make a person unproductive and at risk of death. Improving disease diagnostic capabilities in healthcare significantly impacts patient care and overall health outcomes [1]. However, the similarity of symptoms between diseases often makes obtaining a medical history or provisional diagnosis difficult. This is due to the long waiting time and limited speed in diagnosing the disease, which can result in patients receiving inadequate initial treatment and worsening their health condition [2].

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A classification model is needed to diagnose disease and accurately differentiate the patient's health condition. Good classification plays a vital role in speeding up the medical history process, which is very important to avoid delays in treatment and prevent the worsening of the patient's condition [3]. In the healthcare field, significant advances in artificial intelligence and machine learning have introduced new solutions to address health classification problems. One method that stands out is the Elman Recurrent Neural Network (ERNN).

ERNN, or Elman Recurrent Neural Network, is an Artificial Neural Network method that includes an additional context layer. The context layer functions to remember the state of the previously hidden layer so that it can be used with input in training function calculations to speed up the acquisition of training data results. With a context layer, ERNN can improve its ability to perform health classification more accurately and efficiently [4]–[6].

As an East Denpasar Community Health Center community health center, I face challenges in accurately classifying patients' health conditions. This is due to the large number of patients who come with various complaints and symptoms and the many health parameters that need to be considered. ERNN can help address this problem by performing deeper analysis and more accurate classification for early detection and timely treatment. For example, research conducted by Mao et al. [7] showed that ERNN achieved a classification accuracy rate of 92% in detecting breast cancer. Thus, ERNN can be an effective solution to help health professionals diagnose diseases more accurately and quickly, allowing patients to receive appropriate and specific treatment.

The research entitled "Patient Health Classification Using the Elman Recurrent Neural Network (ERNN) Method" was motivated by the above background. This research utilizes medical data such as blood pressure, heart rate, body temperature, blood sugar levels, cholesterol levels, oxygen levels, and uric acid as parameters in the classification model. The model will be trained to classify health categories into "Low," "Medium," "High," and "Very High" disease risks. Using the ERNN method, the classification model can provide more accurate and efficient results in diagnosing patient health conditions.

2 Relate Works

The first research was conducted by Abdulloh dan Wutsqa [8], titled "Brain Cancer Classification using Elman Recurrent Neural Network with Genetic Algorithm Optimization." This research aimed to classify brain cancer from brain Magnetic Resonance Imaging (MRI) using the ERNN model. The classification results were evaluated using accuracy, sensitivity, and specificity on training and testing data. This research had perfect results on the training data with no classification errors. In contrast, on the testing data, the results were also very satisfactory, with a sensitivity value of 100%, specificity of 93.33%, and accuracy of 96.43%.

The second research was conducted by Butarbutar et al [4], titled "Implementation of Artificial Neural Network using Elman Recurrent Neural Network Method for Coronary Heart Disease Prediction." This research created a system to predict coronary heart disease using the Elman Recurrent Neural Network (ERNN) algorithm. The result of the training process produced an MSE of 0.00959216. The result of the testing process had the highest accuracy value of 96.667% by recognizing 87 out of 90 test data at a learning rate of 0.1.

The third research was conducted by Jumhuriyah [9], titled "Tuberculosis Disease Classification Based on X-Ray Images Using Elman Recurrent Neural Network Method." In this research, tuberculosis disease classification will be based on chest X-rays using ERNN to determine whether someone is normal or detected with tuberculosis. The best model from the classification results was obtained at an orientation angle of 45◦ with 20 and 50 hidden layer nodes, at a learning rate of 0.5, resulting in an accuracy of 95.4773%, sensitivity of 97.9591%, and specificity of 97.9591%.

Research conducted by Kusnanti [10], titled "Cancer Classification Based on RNA Data Using Elman Recurrent Neural Network," aimed to determine the results of cancer classification based on RNA data. In her study, Eka Alifia Kusnanti utilized the ERNN method to classify cancer based on RNA data. The research findings indicated that ERNN can be used for cancer classification with a relatively high level of accuracy. This study has the potential to contribute to the healthcare field, particularly in the diagnosis and treatment of cancer.

The fifth research was conducted by Pakan [11], titled "Cancer Data Classification Based on Gene Microarray using Elman Recurrent Neural Network." This research aimed to classify cancer using gene expression as a feature trained on an artificial neural network. The results obtained during testing showed that the system could type 10 cancer classes with a training MSE of 1.38526e-11 and a testing/validation MSE of 0.15. This indicates that the ERNN ANN architecture is quite reliable in classifying cancer data based on microarray.

3 Method

This study aims to evaluate the accuracy level in assessing a patient's health using the Elman Recurrent Neural Network (ERNN) method. The process of creating the classification model involves several essential steps, namely:

1. Phase 1: Data Representation with a Value Range between 0 and 1.
   Patient health data is transformed into representations suitable within a value range between 0 and 1 to facilitate processing by the model.
2. Phase 2: Model Training using Elman Recurrent Neural Network (ERNN).
   The classification model utilizes the ERNN method and is trained with patient data. The training aims to enable the model to understand patterns and relationships within the health data to perform more accurate classification.
3. Phase 3: Model Testing using Elman Recurrent Neural Network (ERNN).
   After the training process, the trained model is tested using unseen data. This is done to assess the model's ability to generalize and make accurate predictions on new data. The testing results are then calculated using the Elman Recurrent Neural Network (ERNN) method. Upon completion of the calculation process, the output is obtained in the form of patient health classification with risk

categories of "Low," "Moderate," "High," and "Very High" based on the previously processed and analyzed data.

Thus, this research is expected to improve accuracy and efficiency in diagnosing patients' health conditions.

3.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is an artificial intelligence technology inspired by the human nervous system and is often abbreviated as a neural network. ANN is used to model and optimize complex phenomena involving many process variables [12]. Each neural network consists of switching units divided into three layers: the input, hidden, and output. Input data is stored in the input layer and forwarded with certain weights through the hidden layer before being produced as output in the output layer. Although the hidden layer neurons are not visible, using additional hidden layer neurons can increase flexibility and more accurate processing [13]. However, there may be better ways than many hidden layers if only a few neurons can solve the problem, as many hidden layers can add a computer load.

According to Mikami [14], a neural network is a machine-learning technique inspired by the neuron structure, which is the basic unit of the brain. Each neuron receives a set of inputs, and each input is given a certain weight. The neuron then calculates some input weight functions. Neurons perform linear and nonlinear functions throughout the network. A neural network's basic structure consists of three layers: the input layer, the hidden layer, and the output layer. Figure 1 is an example of an artificial neural network structure. In its use, ANN can help solve complex problems and improve accuracy in various fields, including healthcare [15].

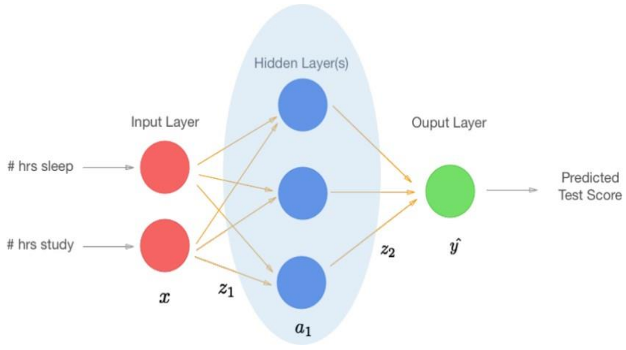

Fig. 1 Artificial Neural Network (ANN). (Source: Mikami, 2016)

3.2 Elman Recurrent Neural Network

ERNN, or Elman Recurrent Neural Network, is a recurrent network that utilizes contextual layers for reference. In its application, ERNN uses the backpropagation algorithm for guided training based on input and target input. Several parameters that affect the training process include initial weights, input types, the number of hidden neurons, learning rate, and spike factor. However, the training process can be time-consuming if these parameters are misconfigured. In its use, ERNN can help improve accuracy in patient health classification more efficiently and accurately.

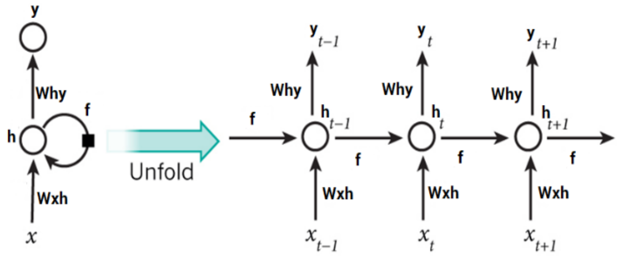

Fig. 2 Elman Recurrent Neural Network (ERNN). (Source: Mikami, 2016)

3.3 Algorithm Elman Recurrent Neural Network (ERNN)

The following are the steps of the Elman Recurrent Neural Network algorithm:

1) Enter the initial weight values, learning rate, error tolerance, and maximum epoch between the input hidden layer and the hidden output layer.
2) Each input device xi receives input signals, then sends these input signals to all units in the hidden layer.
3) Each unit netj(t) in the hidden layer adds the input value xi, which is multiplied by vji and combined.
   Multiply the context layer yh(t-1) by the weight uji with bias netj plus equation (1).

   $$\boldsymbol{net}\mathbf{j}=(\textstyle\sum^{n}\boldsymbol{x}\mathbf{i}(\boldsymbol{t})\boldsymbol{v}\mathbf{ji} + \sum^{m}\boldsymbol{yh}(\boldsymbol{t}-\mathbf{1})\,\boldsymbol{u}\mathbf{j}\boldsymbol{h} + \boldsymbol{\theta}\mathbf{j}) \quad (1)$$

   For neurons, the activation function used is the binary sigmoid with equation (2).

   $$\boldsymbol{y_j} = \boldsymbol{f}\left(\boldsymbol{net_j}(\boldsymbol{t})\right) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{net_j}}} \quad (2)$$

4) with the context layer yh(t-1) multiplied by the testing weight and added with bias netj using Equation (2.1).

   $$\boldsymbol{net}\mathbf{j}=(\textstyle\sum^{n}\boldsymbol{x}\mathbf{i}(\boldsymbol{t})\boldsymbol{v}\mathbf{ji} + \sum^{m}\boldsymbol{yh}(\boldsymbol{t}-\mathbf{1})\,\boldsymbol{u}\mathbf{j}\boldsymbol{h} + \boldsymbol{\theta}\mathbf{j}) \quad (3)$$

   The activation function used for the neuron is binary sigmoid with Equation (3).

   $$\boldsymbol{y_j} = \boldsymbol{f}\left(\boldsymbol{net_j}(\boldsymbol{t})\right) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{net_j}}} \quad (4)$$

5) The output yj from the hidden layer is multiplied by the weight wkj and added to the hidden layer bias to obtain the output, netk is calculated as yk in the activation function, formulas (5) and (6).

   $$\boldsymbol{net_k}(\boldsymbol{t}) = \left(\textstyle\sum_{j}^{m}\boldsymbol{y_j}(\boldsymbol{t})\boldsymbol{w_{kj}}\right) + \boldsymbol{\theta_k} \quad (5)$$

   $$\boldsymbol{y_k} = \boldsymbol{g}(\boldsymbol{net_k}) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{net_j}}} \quad (6)$$

6) Each output part will receive the target pattern tk according to the input pattern during the training process, as well as calculate the error value and correct its

weight. The process of calculating the error value derivative of the activation function is shown in equation (5).

$$\delta_k = (t_k - y_k)\, g'(net_k) = y_k (1 - y_k)(t_k - y_k) \quad (5)$$

Use equation (6) to calculate the corrected weight values.

$$\Delta wk_j = a\delta_k y_j \quad (6)$$

Use equation (7) to calculate the corrected bias values.

$$\Delta\theta_k = a\delta_k \quad (7)$$

Then, the generated δ_k value will be used for all previous layer units.

7) Each output from the connected output unit and hidden layer unit will be multiplied by δ_k and summed using Equation (8) as the next input unit.

$$\delta\_net_j \textstyle\sum \delta_k wk_j \quad (8)$$

Next, use equation (9) to correct and calculate the δ error factor of the hidden layer unit.

$$\delta j = \delta\_net \quad f'(net j) = \delta j\_net \; zj\; (1\text{-}zj) \quad (9)$$

Next, use equation (10) to correct and calculate the weight values.

$$\Delta v_{kj} = \alpha\delta_j x_i \quad (10)$$

Use equation (11) to calculate the corrected bias values.

$$\Delta\theta j = \alpha\delta j \quad (11)$$

8) Each output unit will correct the weight and bias values according to equation (12).

$$w_{kj}(new) = w_{kj}(old) + \Delta w_{kj} \quad (12)$$

9) Each output will be compared to the desired target tk to obtain the overall error value (E) through equation (13).

$$E(t) = \frac{1}{2}^{k} \textstyle\sum_{i=1}(t_k - y_k)\, 2 \quad (13)$$

10) Check the termination condition (active iteration).

The training process is successful if the error value consistently decreases during the training iterations until the training data given to each neuron obtains good weights. The training process is considered unsuccessful if the error value during the training iterations does not tend to decrease.

3.4 Accuracy

Accuracy is an evaluation metric that measures how well a classification or predictive model can accurately estimate data [16]. This metric shows how well the model can make accurate predictions based on the given data. Accuracy is calculated by measuring the percentage of correct predictions from the total sample data. Data is divided into two parts to calculate accuracy: training data and test data. The model is trained using the training data and then tested using the test data. To calculate the number of correct predictions, the model's predictions are compared to the actual values of the experimental data. Accuracy is crucial in diagnosing patients' health conditions and providing appropriate and effective treatment. Therefore, using technologies such as ERNN can help improve accuracy in patient health classification more efficiently and accurately.

$$\textbf{Accuracy} = \frac{\textit{Number of Correct Predictions}}{\textit{Total Number of Data}}\ x\ 100\% \tag{14}$$

3.5 Patient Health Classification

Patient health classification is a system that categorizes health information and data based on the type of disease, disease status, and specific risk factors. It aims to facilitate analysis and decision-making in more effective and efficient treatment, care, and disease prevention [17]. Additionally, a health classification system can assist healthcare professionals in understanding and further studying disease epidemiology, risk factors, and patient health patterns. Therefore, patient health classification is crucial in improving the quality of healthcare services and providing appropriate solutions for patients.

4 Results and Discussion

This research uses training data that has gone through a data representation process. The data used consists of 1,000 data points, which are then divided into two parts: training and testing. This data includes parameters such as Systolic Blood Pressure, Diastolic Blood Pressure, Heart Rate, Body Temperature, Blood Sugar Levels, Cholesterol, Uric Acid, and Oxygen Levels. The training and testing process uses the Keras library in Google Colab. Before the data is divided into training and testing data, it is necessary to create a class for each data obtained from medical records. The data is divided into four categories:w, medium, high, and very high disease risk.

	id	resiko	sistolik	diastolik	denyut_jantung	suhu_tubuh	kadar_gula	kolesterol	asam_urat	kadar_oksigen
0	88345	S	0.4	0.444444	0.20	0.2	0.615385	0.222222	0.394737	0.857143
1	92473	R	0.2	0.074074	0.00	0.5	0.153846	0.055556	0.210526	0.714286
2	60815	T	0.6	0.629630	0.60	0.0	0.307692	0.611111	0.578947	0.571429
3	35792	S	0.3	0.259259	0.40	0.7	0.000000	0.166667	0.131579	0.857143
4	48106	S	0.5	0.444444	0.28	0.4	0.230769	0.277778	0.473684	1.000000

Fig. 3 First 5 rows the DataFrame

	id	resiko	sistolik	diastolik	denyut_jantung	suhu_tubuh	kadar_gula	kolesterol	asam_urat	kadar_oksigen
995	58976	R	105	68	65	36.5	80	160	3.2	99
996	30467	ST	138	88	83	37.4	125	260	5.5	95
997	65789	S	115	72	70	36.9	90	170	3.8	97
998	41327	T	133	86	80	37.2	108	230	4.6	96
999	92684	S	123	80	75	37.1	98	190	4.2	98

Fig. 4 Last 5 rows of DataFrame

The results of model training for each epoch show the training loss and test loss values for 2000 epochs. Each epoch includes one time sending the entire training dataset.

Table 1. Model Training Results at Each Epoch

Epoch	Training Loss	Test Loss
50/2000	0.4898	0.4824
100/2000	0.3913	0.3892
150/2000	0.3273	0.3300
200/2000	0.2820	0.2888
...	...	...
1950/2000	0.0724	0.1019
2000/2000	0.0714	0.1011

Epoch 50/2000 to Epoch 2000/2000 shows the evolution of the model during training. Initially, training loss and test loss had relatively high values, namely at Epoch 50/2000, with values of 0.4898 and 0.4824, respectively. However, as time goes by, there is a significant decrease in both losses.
At Epoch 100/2000, there was a reasonably significant decline, where training loss fell to 0.3913 and test loss to 0.3892. This decrease shows that the model successfully learned patterns in the training data and could generalize them to the test data.
The decline continued in each subsequent epoch, reaching a training loss value of 0.0714 and a test loss of 0.1011 in the 2000/2000 Epoch. These values indicate that the model has converged and got a good level of performance.

The graph below shows the development of training loss and test loss throughout the training process:

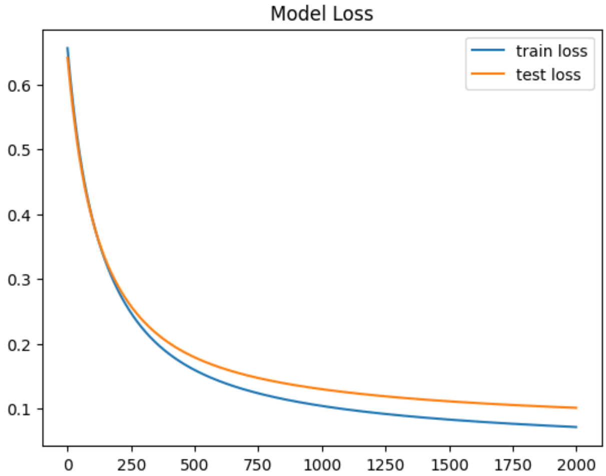

Fig. 5 Last 5 rows of DataFrame

This graph shows that the model has improved performance over time, and test loss has been successfully reduced to a low level.

At the end of training with 2000 epochs, we get the following accuracy results:

Table 2. Accuracy Results of Training Data and Test Data

Data	Accuracy
Training Data	98.49%
Testing Data	98.49%

The high accuracy values on both data sets indicate that the model succeeded in learning well and could generalize well on data that had never been seen before (test set). This phenomenon reflects the optimal performance of the model and its ability to identify patterns in the data.

5 Conclusion

In this journal, researchers aim to improve the accuracy and efficiency of patient health classification using the Elman Recurrent Neural Network (ERNN) method. This research utilizes medical data such as blood pressure, heart rate, body temperature, blood sugar levels, cholesterol levels, oxygen levels, and uric acid as parameters in the classification model. The model is trained to classify health categories into "Low," "Medium," "High," and "Very High" disease risk.

The data classification results show that the model works well, with an accuracy value on training and testing data of 98.49%. The model training results at each epoch show the training loss and test loss values for 2000 epochs. From Epoch 50/2000 to Epoch 2000/2000, the model evolved during the training process. Initially, training loss and test loss had relatively high values, namely at Epoch 50/2000, with values of 0.4898 and 0.4824, respectively. However, as time went by, there was a significant decrease in both losses.

There was a significant decline at Epoch 100/2000, where training loss fell to 0.3913 and test loss to 0.3892. This decrease indicates that the model successfully learned patterns in the training data and was able to generalize them to the test data.

This decline continued in each subsequent epoch, reaching a training loss value of 0.0714 and a test loss of 0.1011 in the 2000/2000 Epoch. These values indicate that the model has converged and got a good level of performance.

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