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Classification Of Temanggung Coffee Plants Using Deep Learning

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Abstract:
Deep learning is a part of machine learning that allows an algorithm to understand patterns with high accuracy based on very large data through various types of complex variables, DNN (Deep Neural Network) is one of the techniques that can be used to process these data. DNN (Deep Neural Network) is a neural network-based algorithm used in decision making. In addition, DNN is a method that can solve classification problems, but the classification performance with ordinary deep neural networks is still relatively slow in some cases, so a method is needed that can improve data classification. One optimization technique is the use of adaptive learning rate technique. Adaptive Learning Rate is an approach or method that aims to increase the efficiency of the learning rate parameter, where the learning rate is a parameter that helps to increase the learning speed of the backpropagation network. Root Mean Square Propagation (RMSProp) is an algorithm that adjusts the learning rate based on the average weight. RMSProp uses the first value of the gradient to determine the average weight value. This research analyzes conventional deep neural network methods and deep neural with adaptive learning rate RMSProp in the classification of coffee plant data. The results of the research conducted are the Deep Neural Network (DNN) method, where RMSProp (Root Mean Square Propagation) gets an error value of 0.0824 and an accuracy of 98.30% in the 100th epoch training process, and data testing. The accuracy score is 98.00% at the 100th epoch. Standard Deep Neural Network (DNN) research results achieved an error value of 0.1027 and an accuracy of 97.80% in the 1000th training period and a testing accuracy value of 97.70% at the 1000th epoch.
Key Word*: Deep Learning, Deep Neural Network, Adaptive Learning Rate, RMSProp*

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I. Introduction

Deep learning is the key to the development of Artificial Intelligence (AI) methods that enable computers to process data in a way inspired by the human brain network. Deep learning is an element of machine learning that has its own network capable of detecting patterns and information without the supervision of unstructured or unlabeled data. The emergence of deep learning has had a significant impact on the field of artificial intelligence. Deep learning was first published by the father of neural networks, Professor Dr. Geoffrey Hinton of the University of Toronto, in his paper 'A fast learning algorithm for deep belief nets'. From the perspective of deep learning, there are several architectures: Deep Neural Network (DNN), Deep Believe Network (DBN), Deep Convolutional Neural Network (DCNN), and Deep Recurrent Neural Network (DRNN). DNN is very suitable for multivariate data types with many input neurons, where the DBN process is usually performed in a one-way feed-forward manner. DBN itself is a neural network with hidden layers consisting of Restricted Boltzmann Machine (RBM). On the other hand, DCNN uses max and pool layers as well as dense layers which are more suitable for image classification. Conversely, DRNN is more suitable when using speech data, text, language, or time series data.

In general, the improvement and optimization of the training process in deep learning architecture also depend on the learning rate. Learning rate is the most important parameter in training artificial neural networks to increase learning efficiency. The higher the learning rate value, the higher the learning rate. The lower the learning rate, the longer it takes for learning to reach a local optimum. Therefore, the right value for the learning rate needs to be chosen. One optimization technique used is adaptive learning rate technique. Optimization of the training process also applies to several deep learning architectures. Some examples of the use of adaptive learning rate in deep learning are ADAGRAD, RMSProp, and Cyclical Learning Rate.

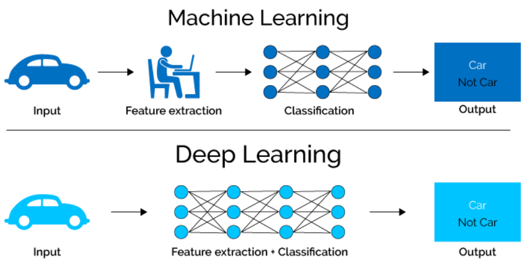
Coffee is a favorite beverage loved by many due to its unique aroma and flavor. Coffea spp is a flowering plant genus in the Rubiaceae family. Research on coffee plants related to classification is more commonly used in mapping coffee plant diseases through images rather than using real value data such as morphological data. Some research includes image information extraction using joint sparse representation, non-linear unmixing, pure pixel extraction, CART Decision Tree, and Decision Tree.

In this study, the author will analyze the performance of coffee plant classification using deep learning with the addition of adaptive learning rate. The desired results include performance analysis such as speed and accuracy in the classification of coffee plant morphological data.

II. Material And Methods

Deep Learning

Deep learning is the key to the development of Artificial Intelligence (AI) methods that teach computers to process data in a way inspired by the human brain network. Deep learning models can detect complex patterns in images, text, audio, and other data to produce accurate insights and predictions. Deep learning is a machine learning technique that has a 'deeper' architecture for solving prediction and classification problems compared to other machine learning techniques. Figure 2.1 shows the difference between deep learning and machine learning.



"Figure 2.1 The difference between deep learning and machine learning."

From the perspective of deep learning, there are several architectures, namely Deep Neural Network (DNN), Deep Belief Network (DBN), Deep Convolutional Neural Network (DCNN), and Deep Recurrent Neural Network (DRNN). DNN is well-suited for multivariate data types with many input neurons, where the DBN process is usually carried out unidirectionally by passing through the DBN. DBN itself is a neural network with hidden layers represented by Restricted Boltzmann Machine (RBM). On the other hand, DCNN uses max and pool layers as well as dense layers that are more suitable for image classification. Conversely, DRNN is more suitable when using language data, text, speech, or data with time series types [2].

Deep Neural Network

Basically, the architecture of a deep neural network still follows the architecture of FFNN (Feed Forward Neural Network) or MLP (Multi-Layer Perceptron); the difference lies in the depth level of the architecture in Deep Neural Network (Bengio, 2009). With the same structure as MLP, another difference between DNN and MLP is in their training phase; while MLP uses direct training, DNN uses a Generative Deep Belief Network (DBN), which is a stack of Restricted Boltzmann Machines (RBM) or sometimes Autoencoders, where each RBM has 2 layers: visible layer and hidden layer, which are trained first and then transformed into DNN [2].

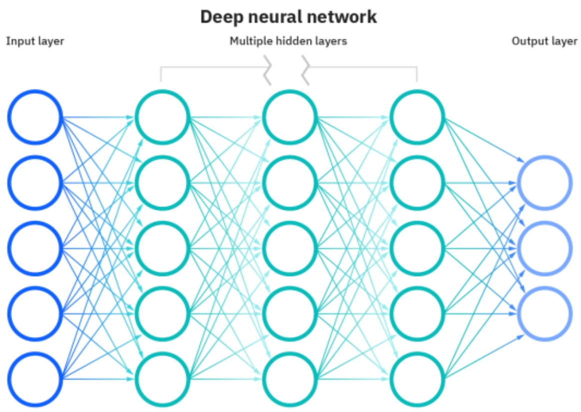


Figure 2.2 Deep Neural Network (DNN) Architecture

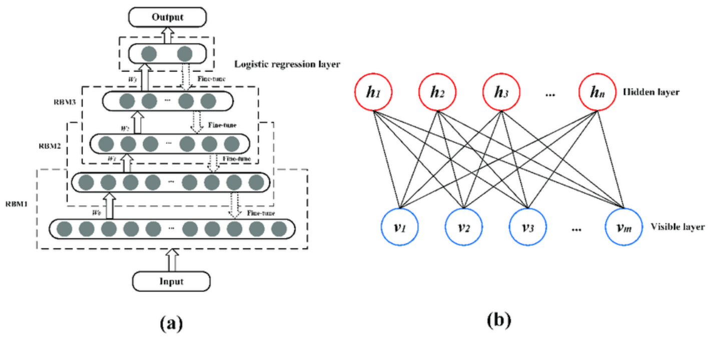


Figure 2.3 Architecture of (a) Deep Belief Networks (DBN) and (b) Restricted Boltzmann Machines (RBM).

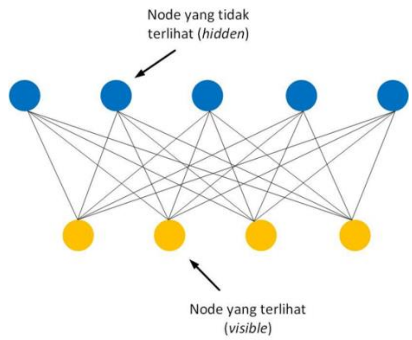


Figure 2.4 Architecture of Restricted Boltzmann Machine (RBM)

Training in Deep Neural Networks

The training process in a deep neural network (DNN) is divided into two phases. The first phase involves unsupervised learning using the generative pretraining algorithm of the deep belief network (DBN) from the lowest layer to the highest layer. In this phase, weights are initialized for use in the second phase. The second phase involves fine-tuning the parameters using supervised learning across the entire DBN to adjust the weights from the top layer to the bottom layer [14].

The Sigmoid Activation Function

The selection of activation functions is crucial in neural networks as it affects the format of input data. The sigmoid activation function is commonly used in feed-forward neural networks that require positive outputs. The equation of the activation function and its derivative can be seen as follows, and Figure 2.5 shows the plot of the sigmoid activation function.

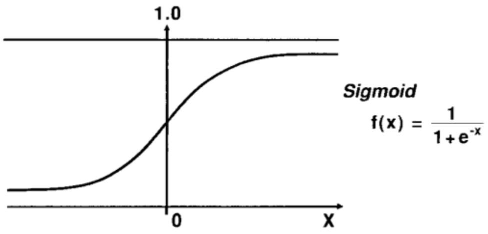


Figure 2.5 Graph of the sigmoid activation function.

The Softmax Activation Function

The softmax activation function can be found in the output layer, which typically has more than two output units. The softmax activation function is also commonly used in classification tasks to provide output values ranging between 0 and 1 [15].

Learning rate, Momentum, and Epoch

Learning rate, also known as the learning rate, significantly impacts training. The higher the value of the learning rate, the larger the learning step, and the algorithm becomes unstable. Conversely, the lower the learning rate, the longer it takes to reach a local optimum. Therefore, it is essential to choose the right value for the learning rate [18].

Momentum is the change in weights based on the gradient direction of the last pattern and the previous pattern. The magnitude of momentum is between 0 and 1. The hyperparameter that determines how many times the deep learning algorithm works through the entire dataset, both forward and backward, is called an epoch.

Coffee Plants

The morphology of coffee plants can be grouped into several parts: roots, stems, leaves, flowers, fruits, and seeds. The location of coffee plant growth depends greatly on several parameters: soil, rainfall, temperature, wind, and altitude. The types of coffee plants used in this research are Arabica coffee, Robusta coffee, and Liberica coffee.

III. Research Methodology

This study was conducted to obtain good performance or high accuracy in classifying coffee plants. Classification was done using the Deep Neural Network (DNN) method and the Adaptive Learning Rate-RMSProp method. The research methodology began with the data used, the general research architecture, the classification process, and the analysis of classification performance.

Dataset

The data used consists of morphological measurements of coffee plants filtered to obtain suitable data. The total number of data used is 2000 samples. There are three types of coffee plants to be studied: 680 data for robusta coffee plants, 660 data for arabica coffee plants, and 660 data for liberica coffee plants. The coffee plant data used includes morphological data of coffee plants aged between three to six months. Morphological data generally consist of measurements of the plant's shape, and each type of plant has different measurements. This data will be divided into two parts: 1400 data for training and 600 data for testing.

The General Architecture

The general architecture of the research for improving performance in classifying coffee plant data using a deep neural network with adaptive learning rate can be seen in Figure 3.1.

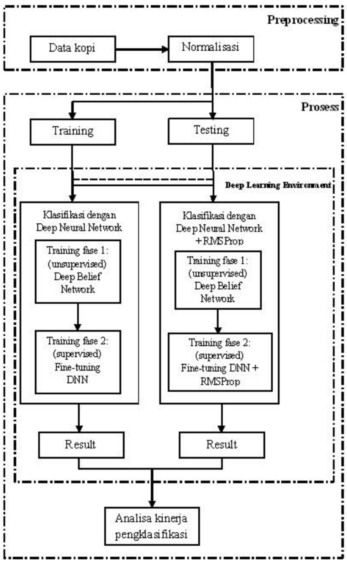


Figure 3.1 The general architecture

Figure 3.1 depicts the general architecture of the classification research using deep learning with adaptive learning rate - RMSProp. In the initial phase, information about the investigated data is gathered, followed by data normalization and transformation into test-ready data. Subsequently, the data is divided into two parts: training data and testing data. The classification process utilizes a standard deep neural network on one side and, on the other side, a deep neural network with adaptive learning rate. The training process in the deep neural network consists of 2 training phases: the first phase being unsupervised learning using deep belief network, and the second phase being supervised learning fine-tuning of the deep neural network. The final evaluation results are analyzed for each stage.

Data Preprocessing

The data preprocessing stage is a data selection stage aimed at obtaining usable data. In raw data, missing values or misrecorded values are often found, as well as inadequate data sampling and other issues. Therefore, steps such as removing some records that will not be analyzed or are not determinants in classification, and data transformation, are needed.

Data Processing

The normalized and transformed data will be divided into two parts: training dataset and testing dataset. The testing/training stage in this research is divided into two phases. The first phase is unsupervised training with a deep belief network (DBN) consisting of stacked restricted Boltzmann machines (RBMs), which will then be transformed into a deep neural network (DNN) by applying the backpropagation method (supervised learning). Subsequently, the constructed deep learning model will be tested using the testing dataset. The classification process is conducted twice: first, classification using the deep neural network method, and second, classification using the deep neural network with the addition of adaptive learning rate-RMSProp, with weight updates in each training phase using the Stochastic Gradient Descent method.

Performance Evaluation

The quality of the standard deep neural network training results and the deep neural network with the addition of adaptive learning rate-RMSProp will be evaluated using Cross Entropy Error. Cross entropy error is commonly used to calculate errors in data classification. According to McCaffrey (2013), in some cases, cross entropy error is better at evaluating the quality of a neural network compared to mean squared error [20]. Cross entropy error can also provide steeper gradient results for errors compared to mean square error [15]. This cross entropy error is also used in neural networks that use the softmax activation function in the output layer, which has more than two neurons or classes in classification (Sadowski, 2016). The calculation of cross entropy error can be seen in the following equation [15].

$$CE = -\frac{1}{n}\sum_{i}^{n\ class}[yln\, a + (1-y)\ln(1-a)$$

Where \(n \) is the target vector and \(y \) is the output vector.

IV. Results and Discussion

The results of data pre-processing, training, and testing in classification using the Deep Neural Network (DNN) technique with adaptive learning rate - RMSProp will be discussed in this chapter. Simulation analysis was conducted twice with different methods, the first with the standard deep neural network technique, and the second with the deep neural network technique using adaptive learning rate - RMSProp.

Results

The data used is morphological field data of coffee seedlings, totaling 2000 data points, divided into 1600 data points for the training process and 400 data points for testing. Before analysis, the data was normalized by transforming it to a scale of 0-1 to facilitate processing. Originating from the available test data, the data is highly diverse and dispersed. The distribution of data based on 3 variables can be seen in Figure 4.1.

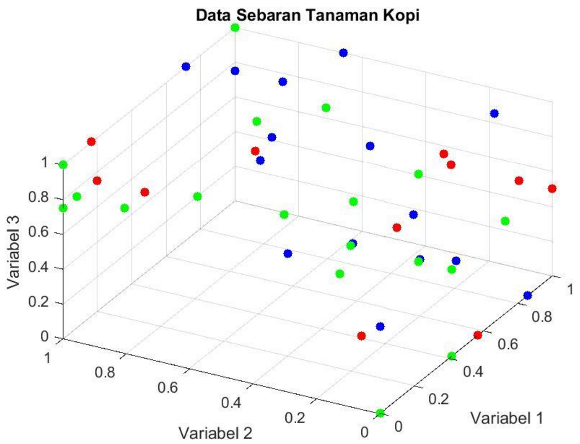


Figure 4.1 Data Distribution

In Figure 4.1, the data distribution based on three initial variables (x, y, z), namely soil acidity (soil pH), height, and number of leaves, is illustrated. Red color indicates seedlings of robusta coffee plants, blue color indicates seedlings of arabica coffee plants, and green color indicates seedlings of liberica coffee plants.

Data Processing Results

In this subsection, the results of data processing, training data, and testing data from classification with a maximum epoch of 1000 using standard deep neural network and classification using RMSProp will be presented.

Training Results of Deep Neural Network

The training process with the deep neural network technique used 1600 seedling data of coffee plants and employed network specifications as discussed in the previous subsection. The training data error results using the deep neural network technique can be seen in Table 4.1.

Table 4.1 Training Error Results of Deep Neural Network

***Epoch* ke-**	**Cross Entropy Error**
5	1.0770
10	1.0159
50	0.7700
100	0.5620
150	0.4194
200	0.3275
250	0.2727
300	0.2312
350	0.2088
400	0.1912
450	0.1682
500	0.1582
550	0.1454
600	0.1376
650	0.1291
700	0.1246
750	0.1203
800	0.1136
850	0.1091
900	0.1060
950	0.1041
1000	0.1027

From Table 4.1, it can be observed that as the number of epochs increases, the error value decreases. For instance, at epoch 5, the error is 1.0770, at epoch 10, the error is 1.0159, at epoch 50, the error is 0.7700, at epoch 100, the error is 0.5620, and so on until reaching the maximum epoch (epoch 1000) where the error is 0.1027. The change in error from epoch 5 to epoch 1000 can be visualized in the graph displayed in Figure 4.2.

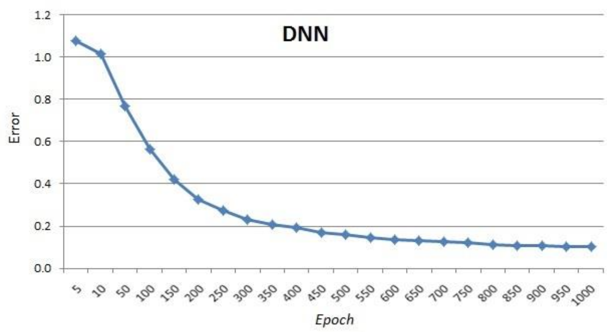


Figure 4.2 depicts the error graph resulting from training the Deep Neural Network (DNN).

In Figure 4.2, it can be observed that the error value decreases as the epoch increases. This indicates that training with the standard Deep Neural Network is capable of recognizing data with the smallest error of 0.1027 at epoch 1000. Furthermore, from the error results, the training accuracy level can be calculated. The training accuracy results of the Deep Neural Network can be seen in Table 4.2.

Table 4.2 Training Accuracy Results of Deep Neural Network

***Epoch* ke-**	**Accuracy**
5	48.75%
10	53.25%
50	66.07%
100	82.48%
150	86.19%
200	89.19%
250	91.29%
300	92.69%
350	94.59%
400	94.69%
450	95.90%
500	96.50%
550	96.70%
600	96.90%
650	97.00%
700	96.90%
750	96.90%
800	97.40%
850	97.50%
900	97.70%
950	97.90%
1000	97.90%

From Table 4.2, it can be seen that at epoch 5, the training accuracy is still 48.75%, at epoch 10 the accuracy is 53.25%, at epoch 50 the accuracy is 66.07%, at epoch 100 the accuracy is 82.48%, and at the maximum epoch (epoch 1000), the training accuracy is 97.90%. This indicates that the accuracy value increases continuously with further training. The change in accuracy percentage from epoch 5 to epoch 1000 can be visualized in the graph that will be displayed in Figure 4.3.

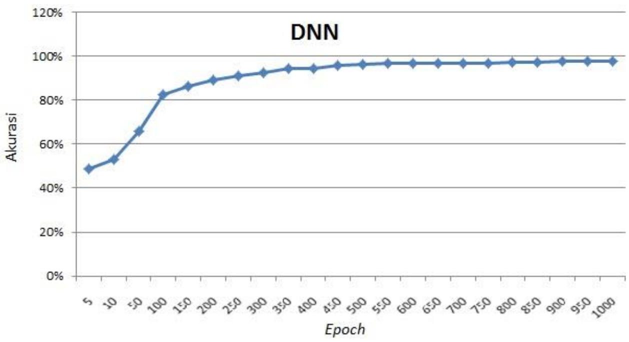


Figure 4.3 shows the accuracy graph resulting from training the Deep Neural Network (DNN).

From the above graph, it can be observed that the accuracy value increases as the number of epochs increases, approaching 100%. This indicates that training with the standard Deep Neural Network can achieve an accuracy of 97.90% at epoch 1000.

Training Results of Deep Neural Network with RMSProp

The subsequent training process uses the deep neural network technique with the addition of adaptive learning rate-RMSProp, also using 1600 data, the same as the data used in the previous standard deep neural network training. The training data results using the deep neural network technique with RMSProp can be seen in Table 4.3.

Table 4.3 Training Error Results of Deep Neural Network + RMSProp

***Epoch* ke-**	**Cross Entropy Error**
5	0.2987
10	0.2147
50	0.1301
100	0.0824
150	0.1083
200	0.0782
250	0,1106
300	0.0891

350	0.0672
400	0.0760
450	0.0545
500	0.0541
550	0.0650
600	0.0934
650	0.0648
700	0.0439
750	0.0378
800	0.0706
850	0.0734
900	0.0838
950	0.0769
1000	0.0460

From the error results of DNN with RMSProp in Table 4.4, the error at epoch 5 is 0.2987, which decreases to 0.2147 at epoch 10. At epoch 50, the error is 0.1301, and at epoch 100, the error further decreases to 0.0824. At epoch 150, the error slightly increases to 0.1083, then decreases again to 0.0782 at epoch 200. At epoch 250, the error increases slightly to 0.1106, then decreases again until epoch 350. The error values fluctuate between epochs 400 and 1000 but remain relatively stable. The change in training error results of Deep Neural Network (DNN) with RMSProp from epoch 5 to epoch 1000 can be seen in Figure 4.4.

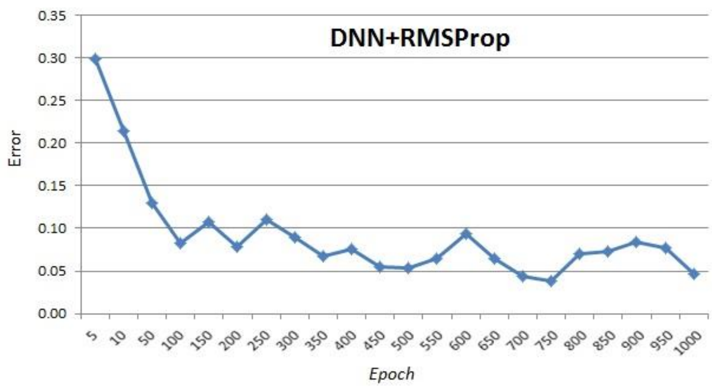


Figure 4.4 depicts the error graph resulting from training the Deep Neural Network with RMSProp.

From the graph above, it can be observed that there is a decrease in error values from epoch 5 to epoch 100, indicating optimal performance of the RMSProp process. However, from epoch 100 to epoch 150, there is an increase in error values from 0.0824 to 0.1083, and from epoch 200 to epoch 250, there is an increase from 0.0782 to 0.1106. Furthermore, from epoch 400 to epoch 1000, there are fluctuations in error values, which is reasonable as RMSProp is an adaptive learning rate method. When entering the optimal zone, adaptive processes may cause fluctuations, although they remain within the optimal zone. This indicates that the training of the Deep Neural Network with RMSProp is capable of recognizing data with the lowest error value of 0.0378 at epoch 750. The training accuracy level can be calculated from these error results, which can be seen in Table 4.4.

Table 4.4 Training Accuracy Results of Deep Neural Network + RMSProp

***Epoch* ke-**	**Accuracy**
5	90.69%
10	94.69%
50	97.30%
100	98.30%
150	98.10%
200	98.80%
250	98.80%
300	98.50%
350	99.20%
400	99.00%
450	99.20%
500	99.50%
550	98.80%
600	98.70%
650	99.10%
700	99.20%

750	99.60%
800	99.30%
850	99.20%
900	99.00%
950	98.90%
1000	99.50%

From the table above, the training accuracy at epoch 5 is 90.69%, at epoch 10 it is 94.69%, at epoch 50 it is 97.3%, and by epoch 250, the accuracy reaches 98.80%. However, from epoch 300 to epoch 1000, the accuracy fluctuates slightly, such as at epoch 300 where the accuracy decreases to 98.50%, but then increases again to 99.20% at epoch 350. The accuracy fluctuates until epoch 500, where it reaches 98.80% at epoch 550. The accuracy peaks at epoch 750 with the highest value of 99.60%, but then decreases to 98.90% at epoch 950. Finally, at the maximum epoch of 1000, the accuracy rises again to 99.50%. These accuracy results are consistent with the error values in the previous table.

It can be observed that the optimization process occurs mainly in the early epochs, from epoch 5 to epoch 100. This indicates that RMSProp performs very well in finding the best values during this period. Furthermore, from epoch 150 to epoch 1000, there is also improvement, although not as significant, as it has already reached the optimal zone around 98%. The change in accuracy percentage from epoch 5 to epoch 1000 can also be visualized in the form of a graph. The accuracy graph resulting from the training of the Deep Neural Network with the addition of RMSProp can be seen in Figure 4.5.

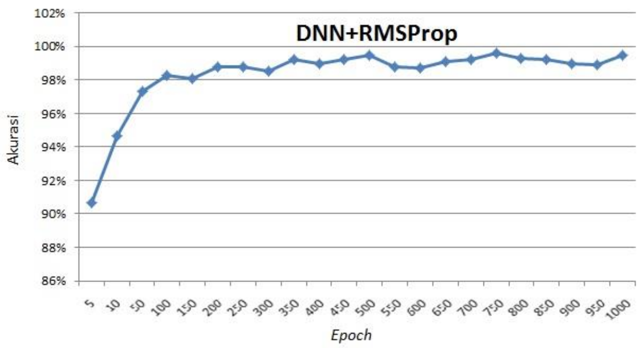


Figure 4.5 depicts the accuracy graph resulting from training the DNN with RMSProp.

From Figure 4.5, it can be observed that the training accuracy changes over epochs. It starts at 90.69% at epoch 5, then increases to 94.69% at epoch 10, and further increases to 97.3% at epoch 50. From epoch 100 to epoch 1000, the accuracy remains around 98%, reaching a local optimum, although there are slight fluctuations in some epochs, which is expected in the adaptive and optimization process.

Testing Results of Deep Neural Network

After the training process is completed, testing is conducted to measure how well the classifier from the training process performs in classifying correctly. This testing process uses 400 different data points from the data used in the previous training process. The testing results of the deep neural network are conducted with a maximum epoch of 1000, and the results can be seen in Table 4.5.

Table 4.5 Testing Accuracy Results of Deep Neural Network

***Epoch* ke-**	**Accuracy**
5	41.40%
10	46.30%
50	75.60%
100	81.20%
150	88.20%
200	91.00%
250	89.70%
300	94.60%
350	95.30%
400	95.90%
450	94.30%
500	95.30%

550	96.10%
600	95.50%
650	95.90%
700	96.60%
750	96.40%
800	97.10%
850	97.10%
900	97.00%
950	96.50%
1000	97.70%

From the table above, it can be observed that the standard deep neural network can classify data with an accuracy of 41.40% at epoch 5, which increases to 46.30% at epoch 10. At epoch 50, the accuracy rises to 75.60%, reaching 81.20% at epoch 100. As the iterations continue, the accuracy improves, reaching 91.00% at epoch 200. However, at epoch 250, the accuracy decreases to 89.70% and further decreases in subsequent epochs. At epoch 750, the accuracy rises to 96.40%, reaching 97.10% at epochs 800 and 850. At epochs 900 and 950, there is a slight decrease to 97.00% and 96.50%, respectively. However, at the maximum epoch of 1000, the accuracy increases again to 97.70%. These accuracy results are visualized in the graph in Figure 4.6.

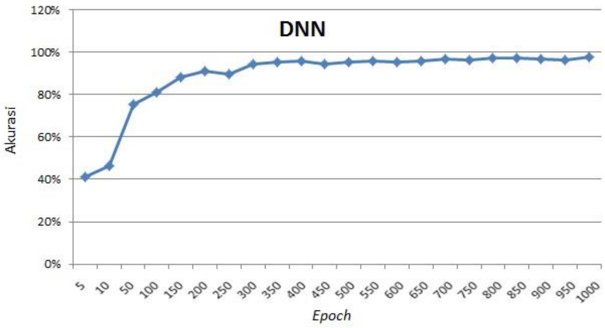


Figure 4.6 depicts the accuracy results of testing the deep neural network.

From the accuracy graph above, it can be observed that there is an increase in accuracy from epoch 5 to the maximum epoch of 1000. Although there are some decreases in accuracy between certain epochs, such as from epoch 200 with an accuracy of 91.00% to epoch 250 with an accuracy of 89.70%, and from epoch 400 to epoch 450 with an accuracy of 94.30%, from epoch 550 to epoch 600 with an accuracy of 95.50%, and from epoch 900 with an accuracy of 97% to epoch 950 with an accuracy of 96.50%. This graph also shows that from epoch 500 to epoch 1000, the accuracy results have entered the optimal zone of 95%. Furthermore, it indicates that as the number of epochs increases, the accuracy approaches 100%.

Testing Results of Deep Neural Network with RMSProp

After testing the standard DNN, the DNN with the addition of adaptive learning rate - RMSProp is tested. This testing process is also conducted to measure how well the classifier from the testing process performs in classification. The testing process is also tested with a maximum epoch of 1000, as shown in Table 4.6.

Table 4.6 Testing Accuracy Results of Deep Neural Network + RMSProp

***Epoch* ke-**	**Accuracy**
5	90.10%
10	93.40%
50	97.00%
100	98.00%
150	98.10%
200	97.00%
250	98.90%
300	97.90%
350	99.00%
400	97.10%
450	98.80%
500	97.60%
550	98.70%

600	97.30%
650	98.70%
700	97.90%
750	98.60%
800	99.30%
850	98.20%
900	99.10%
950	97.10%
1000	98.50%

From the table above, the accuracy results in classification using DNN with the addition of adaptive learning rate-RMSProp at epoch 5 achieved an accuracy of 90.10%, and at epoch 10, the accuracy reached 93.40%. From epoch 50 to epoch maximum 1000, the accuracy results of testing experienced both increases and decreases, but the accuracy values remained above 97%. This indicates that as the number of epochs increases, the testing results obtained become larger. These accuracy results can be visualized in the graph in Figure 4.7.

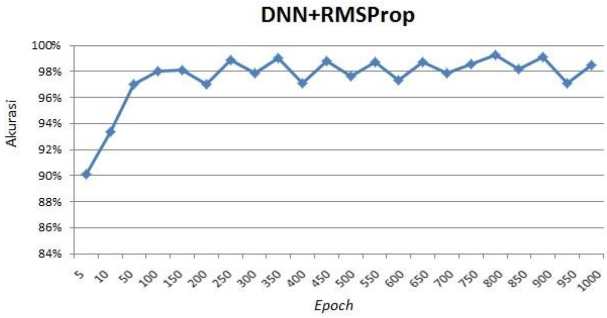


Figure 4.7 Graph of accuracy results of testing deep neural network + RMSProp

From the graph of the accuracy results of the deep neural network (DNN) + RMSProp above, it can be observed that the accuracy increases from epoch 5 to epoch 50. The rate of achieving this accuracy is influenced by the optimization factor of the learning rate from RMSProp. Furthermore, from epoch 50 to the maximum epoch (epoch 1000), the accuracy experiences fluctuations but remains above 97%.

Comparison of DNN Performance with DNN+RMSProp

After performing classification using both the standard DNN and DNN with RMSProp, the results obtained, such as error and accuracy during the training process, as well as accuracy during the testing process, will be presented in graphical form to facilitate analysis of both approaches.

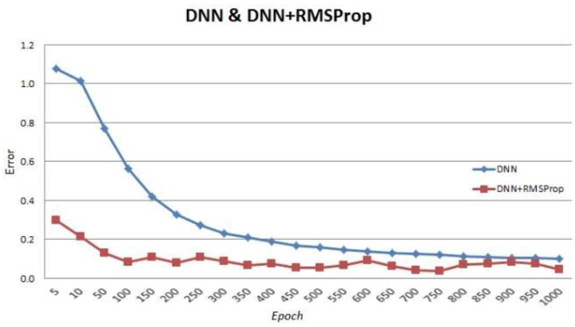


Figure 4.8 Graph of comparison of training error between DNN and DNN+RMSProp

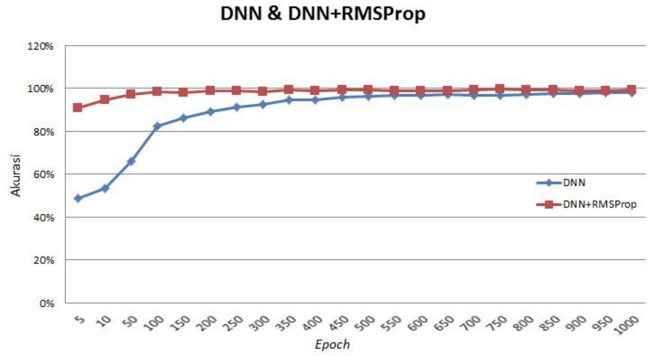


Figure 4.9 Graph of comparison of training accuracy between DNN and DNN+RMSProp

In addition to the analysis of training performance, there is also an analysis of testing performance. Based on the graph of the testing results, the comparison of error and accuracy can be seen in Figure 4.10.

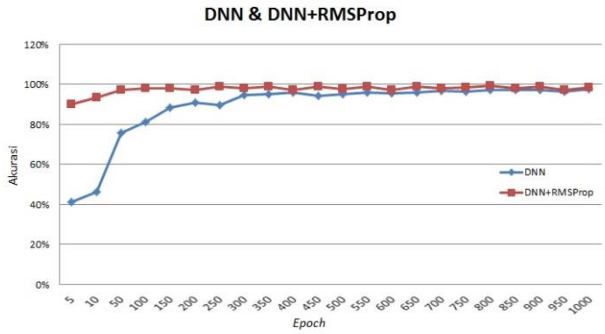


Figure 4.10: Comparison graphic of testing accuracy between DNN and DNN + RMSProp

From the comparison chart above, both standard DNN and DNN+RMSProp techniques exhibit increasing data classification accuracy when observed from the 5th epoch up to the maximum 1000 epochs. However, from the rate of classification accuracy above, the testing results of DNN+RMSProp reach 100% faster. It can be seen that at the 5th epoch, the accuracy of standard DNN is still 41.40%, whereas with RMSProp, the accuracy has reached 90.10%. This trend continues in subsequent epochs from the 10th to the 1000th. In the graph, it can be observed that at the 400th epoch, the accuracy values of standard DNN and DNN+RMSProp are almost approaching, at 95.90% and 97.10%, respectively. Furthermore, at the 850th epoch, the accuracy of standard DNN is 97.10%, while DNN+RMSProp reaches 98.20%. At the 950th epoch, the accuracy of standard DNN is 96.50%, whereas DNN+RMSProp achieves 97.10%. From the information above, it can be concluded that data classification using DNN+RMSProp is faster compared to standard DNN, even though the accuracy values of DNN+RMSProp sometimes experience fluctuations.

Discussion

In the previous subsection, errors and accuracies during training, as well as the accuracy of testing results, were discussed, resulting in the finding that the RMSProp algorithm can improve the performance of deep neural networks (DNNs), where RMSProp (Root Mean Square Propagation) adjusts the learning rate value to be used for parameter changes such as weights and biases in each iteration. This is evidenced by the research results of Deep Neural Network (DNN) with RMSProp obtaining a low error value of 0.0824 and an accuracy of 98.30% in the training process of the 100th epoch, and a testing data accuracy of 98% in the 100th epoch. Meanwhile, the standard Deep Neural Network (DNN) research obtained the lowest error of 0.1027 and an accuracy of 97.80% in the training process of the 1000th epoch, and a testing accuracy of 97.70% in the 1000th epoch.

V. Conclusion

The RMSProp (Root Mean Square Propagation) technique has successfully improved the performance of the Deep Neural Network in terms of speed towards the global optimum, where RMSProp adjusts the learning rate value to be used for parameter changes such as weights and biases in each iteration. The research results indicate that the Deep Neural Network method using RMSProp obtained a low error value of 0.0824 and an accuracy of 98.30% in the training process of the 100th epoch, and a testing data accuracy of 98.00% in the 100th epoch. Meanwhile, the standard DNN research results obtained the lowest error of 0.1027 and an accuracy of 97.80% in the training process of the 1000th epoch, and a testing accuracy of 97.70% in the 1000th epoch. The convergence rate of the Deep Neural Network method using RMSProp is faster towards the global optimum compared to the standard deep neural network method, but the resulting values are less stable compared to the standard deep neural network method.

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