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# Improved Time Training with Accuracy of Batch Back Propagation Algorithm Via Dynamic Learning Rate and Dynamic Momentum Factor

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**ABSTRACT**

The man problem of batch back propagation (BBP) algorithm is slow training and there are several parameters needs to be adjusted manually, also suffers from saturation training. The learning rate and momentum factor are significant parameters for increasing the efficiency of the (BBP). In this study, we created a new dynamic function of each learning rate and momentum facor. We present the DBBPLM algorithm, which trains with a dynamic function for each the learning rate and momentum factor. A Sigmoid function used as activation function. The XOR problem, balance, breast cancer and iris dataset were used as benchmarks for testing the effects of the dynamic DBBPLM algorithm. All the experiments were performed on Matlab 2012 a. The stop training was determined ten power -5. From the experimental results, the DBBPLM algorithm provides superior performance in terms of training, and faster training with higher accuracy compared to the BBP algorithm and with existing works.



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## 1. INTRODUCTION

The batch BP algorithm is commonly used in many applications including robotics, automation, and weight changes in ANNs [1]. The BP algorithm has led to tremendous breakthroughs in applications involving multilayer perceptions [2]. Gradient descent is commonly used to adjust the weight using a change the error training; however, this approach is not guaranteed to find the global minimum error [3]. The BBP algorithm is accurate in terms of training [4]. The batch BP algorithm is a new style for updating weight, it is widely used in training algorithms as it is accurate for training [5]. It utilizes the gradient descent, which does not ensure to reach the global minimum error because it may result in leading the local minimum [6,7]. Despite the training rate and momentum factor being significant parameters for controlling the updated weight, it is difficult to select the best valueduring training [8]. Generally, there are two techniques for selecting the values for each training rate and momentum factor. The first is set to be a small constant value from interval [1], the second the selected series value from [9]. The learning rate should be sufficiently large to allow for escaping the local minimum [10]. But the biggest value leads to fast training with oscillation error training. To ensure a Suitable learning BP algorithm, the learning rate must be small [11]. Another requirements for speeding up of the batch BBP algorithm is adaptive training rate and momentum factor together [12]. The main problem of BBP algorithm, is slow training, or stuck training around the local minimum and suffers from saturation training [13]. In addition problem of the BP algorithm, several parameters need to be adjusted manually, such as learning rate and momentum factor [14].

Current work for solving the slow training of the BBP algorithm is through adapting of a some significant parameters, such as learning rate and momentum factor. For these cases many studies has been done such as [15] improved the BP algorithm through two techniques, the training rate and momentum factor, the values of training rate were fixed at different values. The idea of this study is to set the value of training, rate to be large initially, and then to look at the value of error training after iteration. If the error (e) training is increased, the fit produced changes the value of training, rate multiplied by less than one and then recalculated in the original direction. If the iteration error can be reduced, the fit produced changes the value of training rate by multiplied by a constant greater than one, the next iteration is calculated continuously. In [16] compare several techniques for improved BP algorithm. The BP algorithm with adaptive learning rate and momentum factor gave superior accuracy training at 1000 epochs. In [17] modifying the training rate and momentum. The value of the training rate selected depends on the ratio between the new error and the previous error training. The simulation results show an optimization of the training speed and an oscillation reduction duration training. In [18], created dynamic training that consists of multi-steps. The value of the learning rate and momentum factor are set as munaule value. From the experimental results, the improved algorithm was overall efficient, both in visual effect and quality.

The remaining portion of this paper is organized as follows: Section 2 is the materials and method; Section 3 is created the dynamic parameters; Section 4, is experimental results; Section 5 discussion to validate the performance of the improved algorithm; Section 6,evaluate the performance of improve DBBP algorithm.Finally, Section 7 the conclusions.

## 2. MATERIALS AND METHOD

This kind of this research belongs to the heuristic method. This method is includes the learning rate and momentum factor. To Investigate the aims of this study there are many steps as follows.

### 2.1. Data set

The data set is very important for verification to improve the BBP algorithm. In this study, all data are taken from UCI Machine Learning Repository through the link https://archive.ics.uci.edu/ml/index.html. All real dataset change to become normization dataset between [0,1]. All data set divided in to two set training set and testing set.

### 2.2. Neural Network Model

We propose an ANN model, which consist of three-layer neural network that has an input, hidden, and output layer. The input layer is considered to be { $x_1$, $x_2$, $x_i$ }, which represents the nodes; the nodes depend on the types or attributes of the data. The hidden layer is made of two layers with four nodes. Whereas the $L_h$ and $LL_k$ are the first and second layer respectively.The output layer $Y_r$ is made of one layer with one neuron. Three basis, two of them are used in the hidden and one in the output layer, which is denoted by $u_{0j}$, $v_{0k}$ and $w_{0r}$ . $v_{hj}$ is the weight between neuron h from hidden layer $L$ and neuron j from the hidden layer $LL$ . $u_{ih}$ is the weight between neuron $i$ in the input layer and neuron h in the hidden layer. Finally, the sigmoid function is employed as an activation function.

## 3. CREATED THE DYNAMIC LEARNING RATE AND MOMENTUM FACTOR

The weight update between neuron k from the output layer and neuron j from the hidden layer is as follows:

$$w_{jk}(t+1) = w_{jk}(t) + \gamma\Delta w_{jk}(t) + \mu\Delta w_{jk}(t-1) \quad (1)$$

Where $\Delta w_{jk}(t)$ is a weight change the weight is updated for each epoch in Equation 1. Speed up training depends on a parameter that affects the updating of the weight. Before going to create the dynamic function for learning rate and momentum factor. The exponential is monotone function, we can create the learning rate as boundary function as follows

$$\gamma_{dmic} = e^{(k+\sin 2E)} \tag{2}$$

from above the dynamic learning rate $\gamma_{dmic}$. In this case the property of function exponential depend on of the value of $k+\sin 2e$. $\sin e$ is the boundary function on defining set of e (error training) also $\sin e$ has a boundary as $-1 \le \sin e \le 1 \ \forall e \in$ [0,1]. The Equation 2, is bounded function. The weight updated under effected boundary of learning rate. To get smooth training and avoid inflation in the gross weight of the added values for momentum factor, the fitting producer through creating dynamic momentum factor and implicate the $\gamma_{dmic}$. Depend above we can created the dynamic momentum factor as follow:

$$\mu_{dmic} = \sin(e[Y_r(1-Y_r)]+\zeta)+\sin(\frac{1}{e^{(k+\sin 2E)}}) \tag{3}$$

Where the $\zeta$ is the penalty, the $\mu_{dmic}$ is boundary funcation. Insert the Equation 2 and 3 into Equation 1, then the weight is updated between any layer as below

$$w_{jk}(t+1) = w_{jk}(t) - e^{(k+\sin 2E)}\Delta w_{jk}(t) + \sin(e[Y_r(1-Y_r)]+\zeta)+\sin(\frac{1}{e^{(k+\sin 2E)}})\Delta w_{jk}(t-1) \tag{4}$$

The weighted updated under effected under dynamic learning rate and momentum factor

### 3.1. Dynamic batch Back propagation (DBBPLM) algorithm

Update Weight Phase, the weights are adjusted simultaneously, as follows

For each output layer $(\text{j}=0,1,2,\ldots \text{ p; r}=1\ldots,\text{m})$, Y, the out put at neuron r, $LL_j$ the second layer

$$w_{jr}(t+1) = \Delta w_{jr}(t) - (e^{(k+\sin 2E)}\ )\delta_r LL_j + [\sin(e(Y_r(1-Y_r)+\varepsilon)+\sin(\frac{1}{e^{(k+\sin 2E)}})\Delta w_{jr}(t-1) \tag{5}$$

For bias

$$w_{0r}(t+1) = w_{0r}(t) - (e^{(k+\sin 2E)}\ )\delta_r + [\sin(e(Y_r(1-Y_r)+\varepsilon)+\sin(\frac{1}{e^{(k+\sin 2E)}})\Delta w_{0r}(t-1) \tag{6}$$

For each hidden layer $L_h$ i=0,…,n; h=1,…,q

$$u_{ih}(t+1) = w_{ih}(t) - (e^{(k+\sin 2E)}\ )\delta_j x_i + [\sin(e(Y_r(1-Y_r)+\varepsilon)+\sin(\frac{1}{e^{(k+\sin 2E)}})\Delta u_{ih}(t-1) \tag{7}$$

For bias

$$u_{0h}(t+1) = u_{0h}(t) - (e^{(k+\sin 2E)}\ )\delta_h + [\sin(e(Y_r(1-Y_r)+\varepsilon)+\sin(\frac{1}{e^{(k+\sin 2E)}})\Delta u_{0h}(t-1) \tag{8}$$

## 4. EXPERIMENTAL RESULTS

We calculate the accuracy of training as follows [19], Accuracy (%) $= \frac{1-\text{absolut}(\text{T}_\text{i}-\text{O}_\text{i}\ )}{\text{UP}-\text{LW}} * 100$ where UP=1 and LW=0 are the upper bound and lower bound of the activation function.

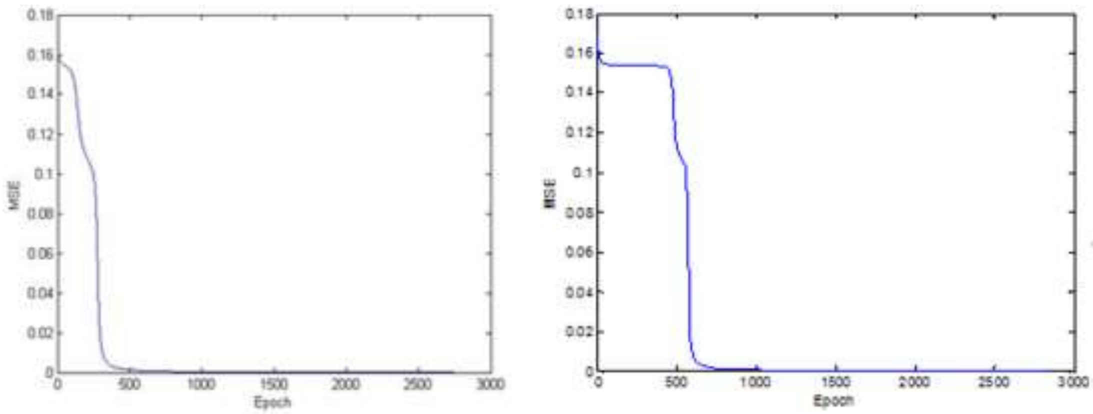
### 4.1. Experiment result of the DBBPLM algorithm with XOR problem

The DBBPLM algorithm is training under effected dynamic learning rate and momentum factor which created in each Equation 2 and 3. Ten experiments has been done and then take the average of time, epoch and accuracy. The result recorded in the Table 1.

Table 1. Average the Performance of DBBPLM algorithm with XOR

| | First structure | | | second structure | | |
|---|---|---|---|---|---|---|
| Ex | Time-sec | Epoch | Accuracy Training | Time-sec | Epoch | Accuracy Training |
| Av | 1.9569 | 2741 | 0.9834 | 1.6267 | 2832 | 0.9858 |
| S.D | 0.19802 | 0 | 0 | 0.120328 | 0 | 0 |

From Table 1, for first structure the average training time is t=1.9569 seconds with 2741 epoch. For second structures the average time training is t=1.6267 seconds, with 2832 epoch. No more different between both structures for accuracy training. The accuracy training is very high for both sturacture. The curve of the training is shown in the following Figure 1.




(a) (b)

Figure 1. Curve Training of Dynamic algorithm with XOR

From Figure 1, the curve (a), is daisy quickly with index epoch to meet global minimum. While the curve (b), the weight training change nearest 1000 epochs, that meaning the DBBPLM algorithm, it has saturation training, but after that, the curve training is converges quickly to obtain the minimum error trianing.

## 4.2. Experiment result of the BBP algorithm with XOR problem

The BBP algorithm is training with munual value for each learning rate and momentum factor from [0,1]. Eight value for each learning rate and momentum factor were used. The experiment results is recorded in the Table 2.

Table 2. Average Performance of BBP algorithm with XOR

| Values of | | First structure | | Second structure | |
|---|---|---|---|---|---|
| $\gamma$ | $\mu$ | Time-sec | Epoch | Time-sec | Epoch |
| Av | | 2351.98525 | 178229 | 2172.49575 | 502622 |
| S.D | | 2472.541353 | 142055.6465 | 2596.868029 | 499421.8464 |

From Table 2, for first structure the average training time is 2351.98525seconds with178229 epoch. For the second structure, the average training time 2172.49575 second with502622 epoch. The S.D for both structure is greater than one.

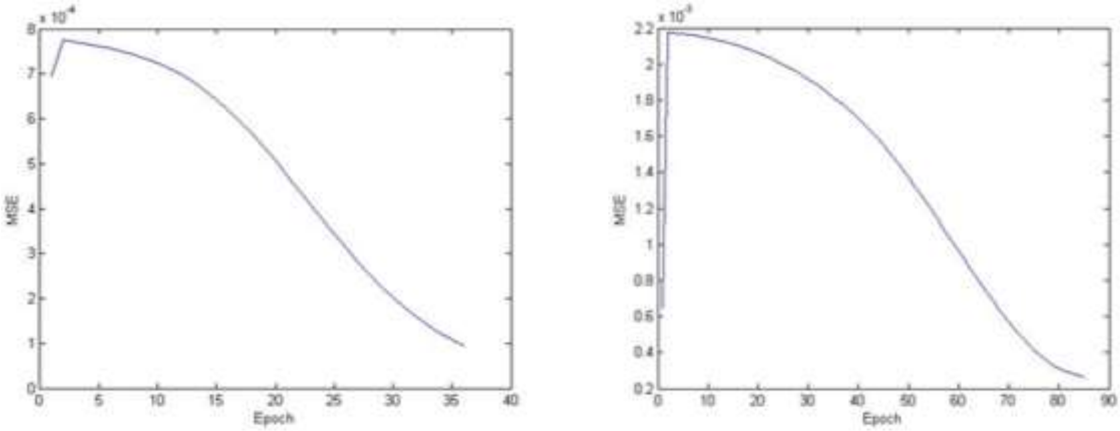
## 4.3. Experiments result of the DBBPLM algorithm with Balance- Training set

We implement the DBBPLM algorithm using balance-training set. The experiments results is tabulation in the Table 3. From Table 3, for first structure the average training time is 2.6034 seconds with 45 epochs. For second structure the average training time is 3.0148 seconds with epoch is 85 epochs. Both structures gave high accuracy training. The average S.D of time for both structures are less than one. The curve of the training is shown in the Figure 2.

The training curve of (b) started with flat -spot training, while the curve of training in (a), started without flat spot. The curve (a) attend to the global minimum around 35 epochs, while the curve (b) attend to the global minimum after spend 80 epochs. Also each curve (a) and (b) have different time for training to reach the global minimum.

Table 3. Average the Performance of DBBPLM algorithm with balance- training set

| | First structure | | | second structure | | |
|---|---|---|---|---|---|---|
| Ex | Time-sec | Epoch | Accuracy Training | Time-sec | Epoch | Accuracy Training |
| Av | 2.6034 | 45 | 0.99996 | 3.0148 | 85 | 0.986 |
| S.D | 0.55041 | -2.842E-14 | 4.898E-05 | 0.67703 | 0 | 0 |




(a) (b)

Figure 2. Training curve of the BP algorithm with balance- train

#### 4.3.1. Experiments of the batch BP algorithm with Balance- Traing set

Several value for each $\gamma$ and $\mu$ were used from ]0,1]. The experiments results are tabulated in Table 4

Table 4. Performance of batch BP algorithm with balance- train set set

| Values of | | First structure | | Second structure | |
|---|---|---|---|---|---|
| $\gamma$ | $\mu$ | Time-sec | Epoch | Time-sec | Epoch |
| Av | | 1066.545 | 3416 | 443.0475 | 4834 |
| S.D | | 2025.956102 | 3577.965095 | 327.7748629 | 3431.437717 |

From Table 4, for first structure, the averge of time is 1066.545 $\approx$ 1067 s with average epoch is 3416, while the second structure the averge of time training is 443.0475 $\approx$ 443 s with 4838 epoch.

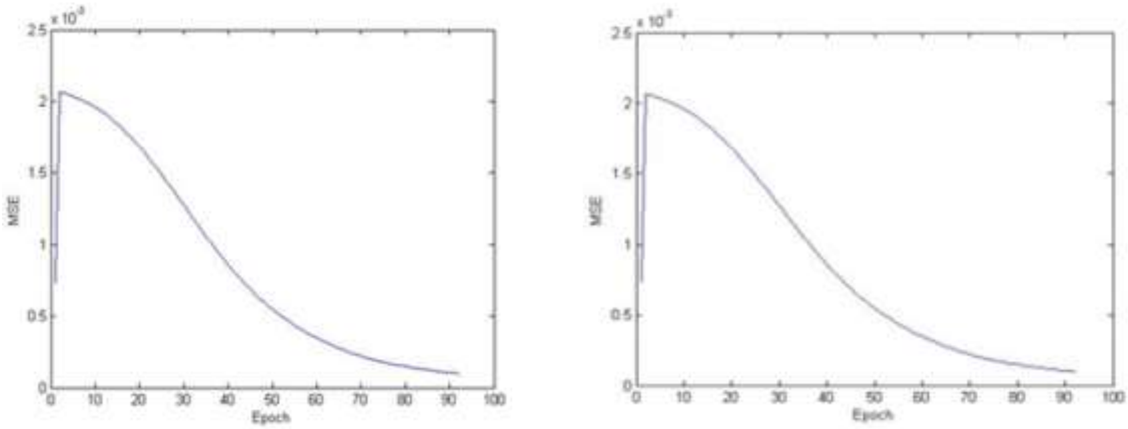
#### 4.3.2. Experiments result of the DBBPLM algorithm with Balance- Testing set

The experiments result is tabulated in the Table 5.

Table 5. Average the Performance of DBBPLM with Balance- Testing set

| | First structure | | | second structure | | |
|---|---|---|---|---|---|---|
| Ex | Time – sec | Epoch | Accuracy Training | Time-sec | Epoch | Accuracy Training |
| Av | 4.6975 | 92 | 0.9908 | 4.5906 | 104 | 0.9860 |
| S.D | 0.7695144 | 0 | 0 | 0.4191749 | 0 | 0 |

From Table 5, for first structure the average training time is 4.6975seconds at an average epoch of is 92epoch. For second structure the average training time is 4.4850 seconds at an average epoch of is 104 epoch. Both structures gave high accuracy training. The average S.D of time for both structures are nearst to zero. Both structures gave high accuracy training. The curve of training shown in Figure 3.




(a) (b)

Figure 3. Curve Training of the DBBLM algorithm for Balance- Testing set

#### 4.3.2. Experiments result of the batch BP algorithm with Balance-Testing set

We run the batch BP algorithm with several munal value, and used the balance-testing set. The experiments result recoded in the Table 6.

Table 6. The performance of the training of batch BP algorithm with Balance-Testing set

| Values of | | First structure | | Second structure | |
|---|---|---|---|---|---|
| $\gamma$ | $\mu$ | Time-sec | Epoch | Time-sec | Epoch |
| Av | | 2351.596 | 8672 | 1811.0055 | 19096 |
| S.D | | 2377.327 | 9175.253381 | 2043.02911 | 17835.4912 |

From Table 6, for first structure the average time training is 2351.596 second with 8672 epoch. For second structure the average time is 1811.0055 seconds with 19096 epoch.

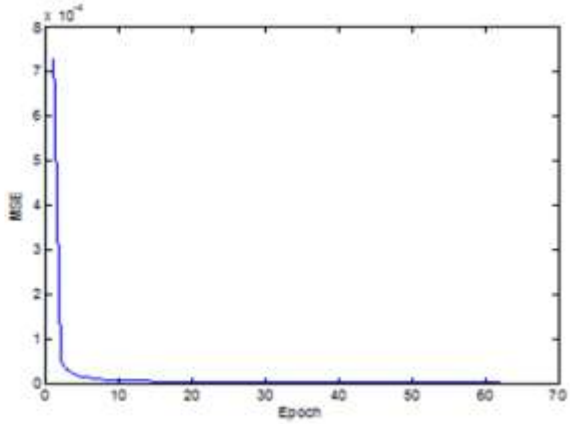
#### 4.3.3. Experiments DBBLM algorithm with Breast -Training set

We will run the DBBLM algorithm, the experience results are given in the Table 7.

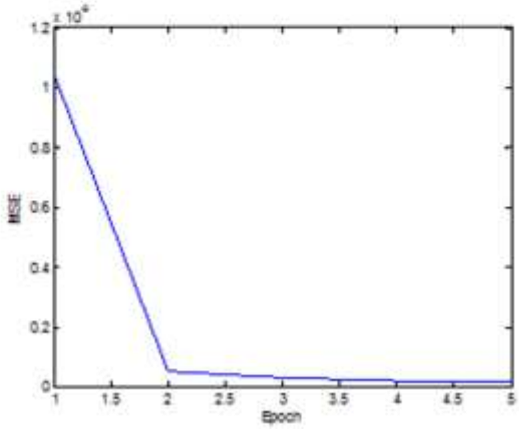
Table 7. Average the performance of DBBPLM algorithm with breast.- Training set

| | First structure | | | second structure | | |
|---|---|---|---|---|---|---|
| **Ex** | Time – sec | Epoch | Accuracy Training | Time-sec | Epoch | Accuracy Training |
| Av | 2.356 | 62 | 0.999 | 2.3034 | 59 | 0.9982 |
| S.D | 0.10709621 | 0 | 0 | 0.10685335 | 0 | 0 |

From Table 7, easily can see performance of DBBPLM algorithm. Both the structures the average of the training time is very short. The average S.D of time for both structures are nearst to zero.




(a)




(b)

Figure 4. Curve Training of the DBBLM algorithm for Breast-*T*raining set

Figure 4 from both structure, of the DBBPLM algorithm the training (a) and (b) have smooth curve training. Both Curves are attended fast with index time to the global minimum.

#### 4.3.4. Experiments result of the BBP algorithm with Breast -Training set

We used 374 patterns for training set. The results are shown in the Table 8. From Table 8 for first structure the average time training is 1547.8075 second with 12430 epochs whil second structure the average time is 1361.486667seconds with 15953.

Table 8. Performance of BBP algorithm with Breast-Training set

| Values of | | First structure | | Second structure | |
|---|---|---|---|---|---|
| $\gamma$ | $\mu$ | Time-sec | Epoch | Time-sec | Epoch |
| Av | | 1547.8075 | 12430 | 1361.486667 | 15953 |
| S.D | | 2094.247329 | 18617.69227 | 1829.096807 | 15385.18284 |

#### 4.3.5. Experiments DBBPLM algorithm with Breast-Testing set

From Table 9, the dynamic training rate and momentum factor helps the DBBPLM algorithm for reducing the time training. Both the structures, the average of the training time is very short. For first structure the average time is 0.844seconds with average 33 epochs, while the scond structure the average time is 1.6177with average 61 epochs.

Table 9. Average the performance of DBBPLM algorithm with Breast-Testing set

| | First structure | | | second structure | | |
|---|---|---|---|---|---|---|
| Ex | Time-sec | Epoch | Accuracy Training | Time-sec | Epoch | Accuracy Training |
| Av | 0.844 | 33 | 0.944206 | 1.6177 | 61 | 0.987 |
| S.D | 1.1102E-16 | 0 | 0 | 0.09217488 | 0 | 0 |

#### 4.3.6. Experiments results of BBP algorithm with Breast-Testing set

We used 251 patterns for testing the performance of BBP algorithm. The experments result is tabulated in the Table 10.

Table 10. Performance of BBP algorithm with Breast-Testing set

| Values of | | First structure | | Second structure | |
|---|---|---|---|---|---|
| $\gamma$ | $\mu$ | Time-sec | Epoch | Time-sec | Epoch |
| Av | | 1741.017714 | 17785.42857 | 1920.984143 | 10709 |
| S.D | | 2339.470119 | 15515.29408 | 2013.952547 | 9781.192989 |

Form the Table 10, the range of the training time for both structure is $100.3120 \leq t \leq 6300$ seconds and 60.1670 seconds $\leq t \leq 4560$seconds, this means the range of time training is widely time training

## 5. DISCUSSION TO VALIDATE THE PERFORMANCE OF IMPROVED ALGORITHM

To validate the efficiency of the improved algorithm, through compare the performance of the DBBPML algorithm with the performance of the batchBP algorithm based on certain criteria. We calculate the speed up training using the following formula [20]:

$$\text{Speed up} = \frac{\text{Execution time of } BP\ algorithm}{\text{Execution time of } BPDRM\ algorithm}$$

### 5.1. Proessing Time of DBBPLM Algorithm Versus the BBP Algorithm for with different Structure

To validate the improved algorithm or DBBPLM algorithm, we compare the performance between the DBBPLM algorithm and the BBP algorithm. The speed-up obtained in training is shown in Table 11.

Table 11. Speed up the DBBPLM algorithm versus BBP with different structure

| | First structure | | | Second structure | | |
|---|---|---|---|---|---|---|
| | DBBPLM algorithm | BBP algorithm | Speed up Rate (BBP/DBBPLM) | DBBPLM algorithm | BBP algorithm | Speed up Rate (BBP/DBBPLM) |
| | AV time -sc | AV time -sc | | | AV time -sc | |
| XOR | 1.9569 | 2351.985 | 1201.893 | 1.627 | 2172.495 | 1335.523 |
| Balance Training | 2.6034 | 1066.545 | 409.674 | 3.015 | 443.047 | 146.958 |
| Balance Testing | 4.6975 | 2301.596 | 489.9619 | 4.591 | 1756.005 | 382.522 |
| Breast Training | 2.356 | 1547.808 | 656.9641 | 2.303 | 1361.487 | 591.0771 |
| Breast Testing | 0.844 | 1741.018 | 2062.817 | 1.618 | 1900.984 | 1175.115 |

From Table 11, it is evident that the dynamic algorithm provides superior performance over the BBP algorithm for all datasets with both structure. However for first structure, the DBBPLM algorithm is $2062.817 \approx 2063$s times faster than the BBP algorithm at maximum training, and also the DBBPLM algorithm is $405.738 \approx$ 406s times faster than the BBP algorithm at minimum training. For second structure The DBBPLM algorithm is $1335.523 \approx 1336$ times faster than the BBP algorithm at maximum training, and also the DBBPLM algorithm is $146.958 \approx$ 147s times faster than the BBP algorithm at minimum training.

## 6. EVALUATION OF THE PERFORMANCE OF IMPROVED BATCH BP ALGORITHM

To evaluated the performances of the improved algorithm or DBBPML algorithm for speeding up training which presented in this study. The performances of the DBBPML algorithm are compared to previous research works [13][16]. The performance of the improve algorithm which proposed in this study gives superior performance than exists works.

## 7. CONCLUSION

This paper introduced the DBBPLM algorithm, which trains by a dynamic function for each the learning rate and momentum factor. This function influences on the weight for each hidden layer and output layer. From experiments resulting the DBBPLM algorithm gives superior training than BBP algorithm for all data set, with both structure. One of the main advantages of the dynamic training is that it reduces the training time and reduces the error training, number of epochs and enhancement the accuracy of the training. The performance of DBBPLM algorithm which presented in this study gave superior performance compare with exists work.

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