Research Article

BD-ELM: A Regularized Extreme Learning Machine Using Biased DropConnect and Biased Dropout

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1. Introduction

Extreme Learning Machine (ELM) [1], as the latest research achievement of Single-hidden Layer Feedforward Neural Networks (SLFNs), has attracted much attention due to its good generalization performance and fast training speed. Compared with traditional SLFNs, in ELM, the input weights and biases of the hidden layer are generated randomly without fine-tuning, and the hidden layer output weights are the global optimal solution solved by the least square method to avoid falling into the dilemma of local optimum [2, 3]. Although ELM has universal approximation [2, 4], it requires a considerable hidden nodes to ensure a good generalization performance, which is prone to overfitting. This makes the prevention of overfitting an urgent problem to ELM.

Regularization is one of the common methods to overcome the overfitting [5]. Various regularization methods are applied to the ELM algorithm to address the overfitting [6–9]. Wang et al. [6] introduced \( L_1 \)-norm into ELM to make network parameters sparse and improve the generalization performance of ELM. A Regularized ELM (R-ELM) based on \( L_2 \)-norm loss was proposed by Deng et al. [7], which avoids overfitting and improves the robustness of the algorithm. By incorporating \( L_1 \)-norm loss with OP-ELM (Optimal Pruned ELM), Miche et al. [8] proposed the TROP-ELM (Tikhonov-regularized OP-ELM). TROP-ELM adopted both \( L_1 \)-norm and \( L_2 \)-norm regularization methods, and its generalization performance was significantly improved compared with ELM and OP-ELM.

Dropout [10] and DropConnect [11] are new regularization methods for fully connected networks. In Dropout and DropConnect, the output and connection weights of the hidden layer are, respectively, set to 0 with probability \( p \), otherwise are kept with probability \( (1 - p) \). Dropout and DropConnect are both very efficient ways of performing model averaging with neural networks [11]. In Dropout and DropConnect, each iteration is a training of a smaller
network, and the final network is the average of a large
ensemble of networks which shared parameters. With
the success of Dropout and DropConnect, their improved
algorithms have been proposed by researchers [12–15]. Based
on the difference of the importance of hidden nodes,
Poernomo and Kang [12] proposed the Biased Dropout. In
Biased Dropout, hidden nodes were divided into different
groups according to their activation values, and different
groups were dropped with different probabilities, respect-
ively. Cao et al. [13], combining DropConnect with
Biased Dropout, hidden nodes were divided into different
groups according to their activation values, and different
Biased Dropout, in which the drop
probability of network can be calculated as
\[ p_D = \left( \frac{p_0 \times n_t + p_D'}{n} \right), \tag{6} \]
where \( p_0 \) is the drop probability of the nodes with the
high-activated value, \( p_D' \) is the drop probability of
the nodes with the low-activated value, and \( n \) is the
number of nodes in the hidden layer.

Training ELM is to find the least square solution of the
output weights of the hidden layer. Without considering
regularization, \( \beta \) can be calculated as follows:
\[ \beta = H^\dagger T, \tag{3} \]
where \( H^\dagger \) is the Moore–Penrose generalized inverse of \( H \).
When \( HH^T \) is nonsingular, \( H^\dagger = (H^T H)^{-1}H^T \); when \( H^T H \) is
nonsingular, \( H^\dagger = H^T (H^T H)^{-1} \).

2.2. Dropout and Biased Dropout. As a regularization
method for fully connected networks, Dropout can effec-
tively prevent overfitting [16]. During training, the output
of the hidden nodes is set to zero with probability \( p \), otherwise
being kept with probability \( (1 - p) \). The probability \( p \) is an
important constant and need to be set in advance. When
Dropout is applied to a fully connected hidden layer, the
output is given as follows:
\[ h = M \cdot g(Wv), \tag{4} \]
where \( \cdot \) denotes element-wise product, \( v_i = [v_1, v_2, \ldots, v_n]^T \)
is the input of the hidden layer, \( W \) (of size \( d \times n \)) is the input
weights (the bias is set to a fixed value of 1 and is included in
\( W \) for simplicity), \( g(\cdot) \) is the activation function, and \( M = [m_1, m_2, \ldots, m_N]^T \) is the binary mask matrix with each vector
\( m_i \sim \text{Bernoulli}(1 - p) \) (all elements in vector are set to 1, or
0).

Most commonly used activation functions, such as relu,
sigmoid, and tanh, have the property that \( g(0) = 0 \). Thus, (4)
can be rewritten as follows:
\[ h = g(M \cdot Wv). \tag{5} \]

In this case, Dropout is applied at the input of the ac-
tivation function.

Since each hidden node has different properties and
different contribution to the network performance, using a
universal probability for all nodes would render the effec-
tiveness of Dropout itself [15]. But the Biased Dropout takes
into account the difference of hidden nodes. Nodes with the
high-activated value are more important, whose deletion will
have a great impact on network performance. Therefore,
neural nodes with high-activated value should have a lower drop
probability. Viewed another way, limiting the drop proba-
bility for important nodes will make the network learn and
converge faster than the regular Dropout [15].

In the Biased Dropout, the hidden nodes are divided into
high and low group by the threshold of activation. The group
with high activation nodes is assigned with a low drop
probability to retain important information within, while
another group with low activation nodes is given a high drop
probability to keep the drop probability of the whole net-
work to a fixed constant. Suppose the drop probability of
the nodes with the high-activated value is \( p_{D_H} \), the drop
probability of the nodes with the low-activated value is \( p_{D_L} \).

The drop probability of network can be calculated as:
\[ p_D = \left( \frac{p_{D_H} \times n_t + p_{D_L} \times n_l}{n} \right), \tag{6} \]
where \( n_h \) and \( n_l \) are the number of hidden nodes with the high-activated value and low-activated value, respectively, and \( n \) is the total number of hidden nodes. When the median of the activation value is chosen as threshold, \( n_h = n_l, p_D = p^D_D + p^l_D/2 \). The output of the hidden layer is calculated in the same way as (4), except the generation way of the mask matrix.

### 2.3. DropConnect.

DropConnect, as a general regularization method of Dropout, sets the connection weights to 0 according to the drop probability \( p \) instead of the output of hidden nodes. Similar to Dropout, DropConnect also introduces dynamic sparsity in the network, but DropConnect is for connection weights, while Dropout is for the hidden output. When DropConnect is applied to a fully connected hidden layer, the output is given as

\[
h = g((M \cdot W)v),
\]

where \( M \) (of size \( d \times n \)) is the mask matrix and each element \( M_{ij} \sim \text{Bernoulli}(1 - p) \). Comparing (7) with (4), because of different objects, the way of generating the mask matrix in Dropout and DropConnect is also different.

### 3. BD-ELM

#### 3.1. Biased DropConnect.

Inspired by the Biased Dropout, the Biased DropConnect was proposed. The basis of Biased Dropout is the difference of hidden nodes, while the basis of Biased DropConnect is the difference of connection weights. Different connection weights have different contributions to the network. Connection weights with the high value have greater impact on the network than those with the low value. The difference of connection weights has also been applied in an amplitude-based pruning technology by Han et al. [17], which can obtain a more compact network structure by setting threshold to prune lower weights.

In the Biased DropConnect, the connection weights are divided into two groups by threshold. High weight group is assigned with a low drop probability to hold more important information, while low weight group is given a high drop probability to keep the initial drop connect of the whole network. Assume that the drop probability of the high weight group is \( p^h_{DC} \), and the drop probability of the low weight group is \( p^l_{DC} \). Then, the drop probability of the network can be calculated as

\[
p\_{DC} = \frac{(p^h_{DC} \times m_h + p^l_{DC} \times m_l)}{m},
\]

where \( m_h \) and \( m_l \) are the number of connection weights with high value and low value, respectively, and \( m \) is the total number of connection weights. When the median weight is used as the threshold, \( m_h = m_l \), the drop probability of network is \( p_{DC} = p^h_{DC} + p^l_{DC}/2 \). When using DropConnect, the calculation of the hidden output is same as (7), but the way of generating the mask matrix is different.

#### 3.2. Biased DropConnect- and Biased DropConnect-Based Extreme Learning Machine.

In order to prevent the overfitting of ELM and improve its generalization performance, we incorporate Biased DropConnect and Biased Dropout regularization into ELM and propose BD-ELM. On the basis of ELM, BD-ELM regularizes the input weights of the hidden layer by Biased DropConnect and the output of the hidden layer by Biased Dropout. Then, it solves the output weights of the hidden layer and completes the training of the network. Compared with ELM, the input weights and output of the hidden layer in BD-ELM is sparser, which reduces network complexity and is conducive to improving the overfitting.

It should be noted that the application of Biased DropConnect and Biased Dropout to ELM requires additional setting of four parameters, \( p^h_{DC}, p^l_{DC}, p^h_{D}, \) and \( p^l_{D} \). It is difficult to optimize those parameters. For reducing parameters, in BD-ELM, we set the drop probabilities of connection weights with the high value and hidden nodes with the high-activated value to 0, i.e., \( p^h_{DC} = p^h_{D} = 0 \). In other words, connection weights with a high value and hidden nodes with a high-activated value will be kept, and only the low will be dropped. Thus, the drop probabilities of Biased DropConnect \( p_{DC} \) and Biased Dropout \( p_{D} \) are only depended on the drop probabilities of connection weights with the low value \( p^l_{DC} \) and hidden nodes with the low-activated value \( p^l_{D} \), respectively. When the medians of input weights and activation value of hidden nodes are chosen as thresholds, the drop probabilities of Biased DropConnect and Biased Dropout are \( p_{DC} = p^l_{DC}/2 \) and \( p_{D} = p^l_{D}/2 \), respectively. For the simplicity of comparison with other words, we still use \( p_{DC} \) and \( p_{D} \) as the measurement scales and input parameters.

Thus, the training of BD-ELM is as follows:

Input: training samples \( \{X, T\} = \{(x, t)\}_{i=1}^N \), the number of hidden nodes \( L \), the activation function \( g(\cdot) \), the drop probability \( p_{DC} \), \( p_{D} \)

Output: the output weights of hidden layer \( \beta \)

Step 1: randomly generate input weights \( W \) and bias \( b \)
Step 2: generate the mask matrix \( M_{\text{weights}} \), according to \( W \) and the drop probability \( p_{DC} \)
Step 3: apply Biased DropConnect regularization to input weights, \( W = M_{\text{weights}} \cdot W \)
Step 4: calculate the output of hidden layer \( H \)
Step 5: generate the mask matrix \( M_{\text{output}} \), according to \( H \) and the drop probability \( p_{D} \)
Step 6: apply Biased Dropout regularization to output of hidden layer, \( H = M_{\text{output}} \cdot H \)
Step 7: calculate the output weights of hidden layer \( \beta \)

### 4. Performance Evaluation of BD-ELM

All evaluations were carried out in Matlab 2017(b), running on a desktop with 4.2 GHz CPU, 16 GB RAM, and 1 TB hard disk. The following experiments were designed to evaluate the performance of BD-ELM (it is noted that all the results in this paper are averages of 30 repeated independent experiments):
Experiment 1: the influence of the number of hidden nodes on the performance of BD-ELM
Experiment 2: the influence of the drop probability on the performance of BD-ELM
Experiment 3: performance comparison with other algorithms

4.1. Data Description. In evaluations, Ionosphere, Diabetes, Vehicle, Image Segmentation, Satellite Image, and Letter Recognition in UCI datasets [18], as well as MNIST and Rectangles datasets, are used to train and test the BD-ELM. Details of datasets are shown in Table 1.

| Datasets      | Attributes | Classes | Training data | Testing data |
|---------------|------------|---------|---------------|--------------|
| Ionosphere    | 34         | 2       | 180           | 171          |
| Diabetes      | 8          | 2       | 390           | 378          |
| Vehicle       | 18         | 4       | 446           | 400          |
| Image segmen-tation | 19   | 7       | 1210          | 1100         |
| Satellite image | 36        | 6       | 3217          | 3218         |
| Letter recogni-tion | 16         | 26      | 16000         | 4000         |
| MNIST         | 784        | 10      | 60000         | 10000        |
| Rectangles    | 784        | 2       | 1200          | 50000        |

4.2. The Influence of the Number of Hidden Nodes. The number of hidden layer nodes is an important parameter of the neural network. Insufficient hidden nodes will result in underfitting, while excessive hidden nodes will lead to overfitting. ELM needs a large number of hidden nodes to ensure its generalization performance, but this is easy to lead to overfitting. To verify that Biased DropConnect and Biased Dropout can effectively prevent overfitting of ELM, we change the number of hidden nodes and observe the performance of ELM and BD-ELM on typical datasets.

The experimental datasets are Ionosphere, Diabetes, Vehicle, and Image Segmentation, and the range of the number of hidden nodes is \( L = (20, 40, \ldots, 400) \). In BD-ELM, the drop probabilities are \( p_{DC} = p_D = p = (0.2, 0.4) \) and the thresholds are the medians of input weights and activation value of hidden nodes. And the activation function is sigmoid function. The variation of classification accuracy of ELM and BD-ELM with the number of hidden nodes is shown in Figures 1(a)–1(d).

As can be seen from Figure 1, BD-ELM is less prone to overfitting for the four datasets mentioned above. With the increase of the number of hidden nodes, serious overfitting appears in ELM. Compared with ELM, when overfitting appears, BD-ELM has more hidden nodes and less reduction in accuracy. This shows that Biased DropConnect and Biased Dropout can effectively improve the overfitting of ELM. The reason is that Biased DropConnect and Biased Dropout set the inputs weights and output of hidden nodes to 0, which is equivalent to removing these from the network. When the number of hidden is too large, setting part of input weights and output to 0 can remove the redundant information in the network, and the spare parameters reduce the network complexity so that BD-ELM can still keep a better accuracy than ELM.

And the generalization performance of BD-ELM with different drop probabilities show that a larger drop probability \( p \) is better for suppressing overfitting. But when \( p \) is too large, many input weights and output will be eliminated, and much important information will be lost, which will affect the generalization performance of BD-ELM. This is especially evident when hidden nodes are few. Therefore, it is very important to choose a suitable \( p \) for BD-ELM, according to the number of hidden nodes.

4.3. The Influence of the Drop Probability. The drop probability \( p \), as the important parameter of Biased DropConnect and Biased Dropout, will affect the effectiveness of regularization and the generalization performance of BD-ELM. In order to clearly the influence of the drop probability on BD-ELM, in this evaluation, a variable drop probability is adopted to observe the change of classification accuracy.

As shown in Figure 2, for Vehicle and Image Segmentation datasets, BD-ELM achieves optimal accuracy at the classification accuracy and training time of each algorithm are shown in Table 2 (the number in (0.1, 0.4)).

4.4. Performance Comparison. For testing the comprehensive performance of BD-ELM, this evaluation will use all the datasets mentioned above to compare BD-ELM with ELM, R-ELM, and Drop-ELM [19]. Suppose the number of hidden nodes is in the range of \( L = (10, 20, \ldots, 2000) \), the regularization parameter in R-ELM is \( 10^5 \), and the range of drop probability in Drop-ELM and BD-ELM is \( p = (0, 0.1, \ldots, 0.5) \). Multiple experiments have been performed by employing these parameters and the best performance is reported. The classification accuracy and training time of each algorithm are shown in Table 2 (the number in...
Figure 1: The variation of classification accuracy of ELM and BD-ELM. The plots show that BD-ELM is less prone to overfitting than ELM. (a) Ionosphere, (b) Diabetes, (c) Vehicle, and (d) Image Segmentation.

Figure 2: The influence of drop probability on accuracy of BD-ELM. The plots a suitable drop probability can improve the generalization performance of BD-ELM. (a) Vehicle and (b) Image Segmentation.
With ELM to prevent overfitting and improve generalization, the authors incorporate Biased DropConnect and Biased Dropout algorithms. The results show that it is necessary and effective to use Drop-ELM, thus its training time is more than other algorithms. However, BD-ELM requires more parameters and it is more difficult to find their best. These problems need further research and will be solved in the future. And inspired by other advanced machine learning methods [21, 22], the performance of ELM could be further improved.

**Data Availability**

The data used to support the finding of this study have been deposited in the GitHub repository (https://github.com/LynnW0W/BD-ELM).

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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### Table 2: The classification accuracy (%) of ELM, R-ELM, Drop-ELM, and BD-ELM.

| Datasets       | Hidden nodes | ELM     | R-ELM     | Drop-ELM    | BD-ELM     |
|---------------|--------------|---------|-----------|-------------|------------|
| Ionosphere    | 40           | 76.67 ± 1.29 | 77.51 ± 0.72 | 76.98 ± 1.58 | 77.38 ± 1.32 |
| Diabetes      | 60           | 84.21 ± 1.29 | 84.98 ± 1.35 | 85.04 ± 1.86 | 85.35 ± 1.32 |
| Vehicle       | 140          | 80.40 ± 1.60 | 81.40 ± 1.16 | 81.65 ± 1.42 | 81.80 ± 1.50 |
| Image segmentation | 200      | 94.85 ± 0.34 | 95.40 ± 0.41 | 95.31 ± 0.52 | 95.90 ± 0.50 |
| Satellite image | 300         | 85.42 ± 0.24 | 86.20 ± 0.16 | 86.01 ± 0.29 | 86.34 ± 0.16 |
| Letter recognition | 600        | 76.97 ± 0.51 | 72.68 ± 0.57 | 77.22 ± 0.67 | 77.54 ± 0.66 |
| MNIST         | 2000         | 94.78 ± 0.12 | 95.12 ± 0.15 | 94.89 ± 0.16 | 95.10 ± 0.19 |
| Rectangles    | 2000         | 73.99 ± 0.66 | 73.85 ± 0.83 | 74.26 ± 1.29 | 74.52 ± 0.84 |

### Table 3: The training time (10^{-2} s) of ELM, R-ELM, Drop-ELM, and BD-ELM.

| Datasets       | Hidden nodes | ELM | R-ELM | Drop-ELM | BD-ELM |
|---------------|--------------|-----|-------|----------|--------|
| Ionosphere    | 40           | 0.28 | 0.33  | 0.43     | 0.47   |
| Diabetes      | 60           | 0.25 | 0.29  | 0.41     | 0.52   |
| Vehicle       | 140          | 0.30 | 0.45  | 0.80     | 0.92   |
| Image segmentation | 200       | 0.49 | 0.65  | 1.26     | 1.71   |
| Satellite image | 300         | 0.83 | 1.12  | 2.43     | 2.75   |
| Letter recognition | 600        | 3.23 | 4.35  | 9.28     | 9.34   |
| MNIST         | 2000         | 20.65 | 26.24 | 50.55    | 51.45  |
| Rectangles    | 2000         | 0.84 | 1.24  | 1.87     | 2.00   |

Boldface indicates the highest accuracy and Table 3, respectively.

As can be seen from Table 3, in most datasets, BD-ELM can achieve higher classification accuracy, but requires more training time. (1) The performance of BD-ELM is better than that of ELM and R-ELM. Because, by dropping the unimportant weights and hidden nodes, BD-ELM has a sparser parameter and less redundant information, which is conducive to improving the generalization performance, while the L2-norm in R-ELM does not have such ability [20]. (2) The performance of BD-ELM is better than that of Drop-ELM because BD-ELM takes into account the differences of connection weights and hidden nodes and preserves more important information contained in the weights with high value and hidden nodes with high-activated. But Drop-ELM only gives the same drop probability to all input weights and output of hidden nodes.

At the same time, BD-ELM needs to generate masking matrixes and this process is more complicated than that in Drop-ELM, thus its training time is more than other algorithms. These results show that it is necessary and effective to incorporate Biased DropConnect and Biased Dropout with ELM to prevent overfitting and improve generalization performance.

### 5. Conclusions

For the aim to address the overfitting and improve the generalization performance of ELM, this paper proposes a Biased DropConnect regularization method and applies the Biased DropConnect and Biased Dropout to the ELM to construct BD-ELM. BD-ELM divides the input weights and output of hidden nodes into different groups by setting thresholds and gives different groups different drop probabilities, which enhance the sparsity and reduce complexity of the network. The empirical studies show that the Biased DropConnect and Biased Dropout can effectively prevent the overfitting, and BD-ELM can achieve better generalization performance on various benchmark datasets. However, BD-ELM requires more parameters and it is more difficult to find their best. These problems need further research and will be solved in the future. And inspired by other advanced machine learning methods [21, 22], the performance of ELM could be further improved.
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