Backward-Forward Algorithm: An Improvement towards Extreme Learning Machine

Dibyasundar Das, Deepak Ranjan Nayak, Ratnaka Dash, and Banshidhar Majhi

Abstract—Extreme learning machine (ELM), a randomized learning paradigm for single hidden layer feed-forward network, has gained significant attention for solving problems in diverse domains due to its faster learning ability. The output weights in ELM are determined by an analytic procedure, while the input weights and biases are randomly generated and fixed during the training phase. The learning performance of ELM is highly sensitive to many factors such as the number of nodes in the hidden layer, the initialization of input weight and the type of activation functions in the hidden layer. Moreover, the performance of ELM is affected due to the presence of random input weight and the model suffers from ill posed problem. Hence, here we propose a backward-forward algorithm for single feed-forward neural network that improves the generalization capability of the network with fewer hidden nodes. Here, both input and output weights are determined mathematically which gives the network its performance advantages. The proposed model provides improvement over extreme learning machine with respect to number of nodes used for generalization.

Index Terms—Extreme Learning Machine, Single Layer Feed-forward Network, Image classification.

I. INTRODUCTION

Neural networks (NNs) have been extensively used in literature for solving various regression and classification tasks due to its generalization and universal approximation ability. Gradient-based methods are the most commonly used methods for training NNs, however, these iterative methods have several major pitfalls such as slow convergence, local minima issue and overfitting problem. Randomized algorithms for training single layer feedforward neural networks such as extreme learning machine (ELM) [1] and radial basis function network (RBFN) [2], have become a popular choice in recent years because of their generalization capability with faster learning speed [3], [4], [5]. These methods use least square method (Moore-Penrose (MP) generalized inverse) to approximate the weights from hidden to output layer and require no parameter tuning. The randomized algorithms involve two phases for learning: 1) random feature mapping and 2) output weights computing using an analytical method. These algorithms differ in feature mapping phase such as ELM uses random feature mapping (weights from input to hidden layer generated randomly), and RBFN uses distance-based random feature mapping (centers of RBFs are generated randomly). However, RBFN obtains unsatisfactory solution for some cases and results in poor generalization [6]. In contrary, ELM provides effective solution for SLFNs with good generalization and extreme fast learning, thereby, has been widely applied in various applications like regression [7], data classification [11], [7], image segmentation [8], dimension reduction [9], medical image classification [10], [11], [12], face classification [13], etc. In [7], Huang et al. discussed the universal approximation capability and scalability of ELM.

The accuracy of classification in ELM depends on choice of weight initialization scheme and activation function. To overcome this shortcoming many researchers have used optimization algorithms which choose best weight for input layer. However, this again introduced the iteration and choice of parameter problem for chosen optimization scheme. Hence, here we propose a backward forward algorithm for ELM (BF-ELM) that generalizes the SLFN in two pass. The main contribution of the paper is as follows:

- The paper propose a new backward forward algorithm for single layer feed-forward network that generalizes the model in two pass.
- The study also includes evaluation of the model on two image classification dataset namely MNIST and Brain-MRI.
- Further, the model is validated with various weight initialization schemes and several commonly used activation functions.

Rest of the paper is organized as follows. The Section II gives an over-view of motivation and objective behind development of ELM algorithm and its limitation. In next section, the proposed backward-forward ELM algorithm is described in brief. The Section IV summarizes the experiments conducted and finally, Section V concludes the study.

II. EXTREME LEARNING MACHINE

Feed forward Neural network are slow due to gradient based weight updation and requirement of parameter tuning. Extreme learning machine is one of the single hidden feed forward neural network (SLFN) where the input-weights are randomly chosen and the output-weights are determined analytically. This makes the network to converge to underlying regression layer in one pass which is faster algorithm than the traditional gradient based algorithms. The development of ELM algorithm is based on the fact that input weight and bias does not create much difference in accuracy and a minimum error is acceptable if many computational steps can be avoided. However, the accuracy and generalization capability highly depends on the learning of the output-weight and minimization.
of output-weight norm. The approximation problem can be expressed as follows:

For \( N \) distinct samples \((x_j, t_j)\), \( M \) hidden neurons and \( g(.) \) be the activation function, so the output of SLFN can be modeled as:

\[
o_j = \sum_{i=1}^{M} \beta_i g(w_i.x_j + b_i), \text{ for } j = 1, \ldots, N
\]  

(1)

Hence, the error \( E \) for the target output \( t \) is \( \sum_{j=1}^{N} ||o_j - t_j|| \) and it can be expressed as:

\[
|| \sum_{j=1}^{N} \sum_{i=1}^{M} \beta_i g(w_i.x_j + b_i) - t_j || \]

(2)

For an ideal approximation case error is zero. Hence,

\[
|| \sum_{j=1}^{N} \sum_{i=1}^{M} \beta_i g(w_i.x_j + b_i) - t_j || = 0
\]

\( \Rightarrow \sum_{i=1}^{M} \beta_i g(w_i.x_j + b_i) = t_j \) for all \( j = 1, \ldots, N \)

This equation can be expressed as

\[
H\hat{\beta} = T
\]

(4)

where,

\[
H = \begin{bmatrix}
g(w_1.x_1 + b_1) & \ldots & g(w_M.x_1 + b_M) \\
\vdots & \ddots & \vdots \\
g(w_1.x_N + b_1) & \ldots & g(w_M.x_N + b_M)
\end{bmatrix}
\]

\[
\beta = \begin{bmatrix}
\beta_1 \\
\vdots \\
\beta_M
\end{bmatrix}
\]

\[
T = \begin{bmatrix}
t_1 \\
\vdots \\
t_N
\end{bmatrix}
\]

If given \( N = M \) (i.e Number of hidden neuron is same as sample size); the matrix \( H \) is square and invertible if its determinant is nonzero. In such case the SLFN can approximate with zero error. But however, in reality \( M << N \) hence \( \beta \) is not invertible. Hence rather finding exact solution, we try to find a near optimal solution that minimizes the approximation error. Which can be expressed as:

\[
||\hat{H}\hat{\beta} - T|| \simeq ||H\beta - T||
\]

(6)

\( \hat{H} \) and \( \hat{\beta} \) can be defined as

\[
\hat{H} = \begin{bmatrix}
\hat{g}(\hat{w}_1.x_1 + \hat{b}_1) & \ldots & \hat{g}(\hat{w}_M.x_1 + \hat{b}_M) \\
\vdots & \ddots & \vdots \\
\hat{g}(\hat{w}_1.x_N + \hat{b}_1) & \ldots & \hat{g}(\hat{w}_M.x_N + \hat{b}_M)
\end{bmatrix}
\]

\[
\hat{\beta} = \begin{bmatrix}
\hat{\beta}_1 \\
\vdots \\
\hat{\beta}_M
\end{bmatrix}
\]

In any learning method for SLFN we try to find \( \hat{w}, \hat{b}, \hat{g}(.) \) and \( \hat{\beta} \) in order to minimize the error of prediction. Mostly \( \hat{g}(.) \) is chosen as a continuous function depending the model consideration of data (various activation function are Sigmoid, tan-hyperbolic, ReLU etc.). The \( \hat{w}, \hat{b} \) and \( \hat{\beta} \) are to be determined by the learning algorithm. Back-propagation is one of most famous learning algorithm that uses the gradient decent method. However the gradient based algorithms have following issues associated with them:

1) Choosing proper learning rate \( \eta \) value. Very small \( \eta \) converges very slowly and Very high value of \( \eta \) makes the algorithm unstable.
2) The gradient based learning sometimes may converge to local minima which is undesirable if the difference between global minima and local minima is significantly large.
3) Some times over training leads to worse generalization, hence proper stopping criteria is also needed.
4) Gradient based learning is very time consuming.

For the above reasons ELM, chooses \( \hat{w}, \hat{b} \) randomly and uses MP inverse to calculate \( \hat{\beta} \) analytically. Hence \( \hat{\beta} \) can be expressed as

\[
\hat{\beta} = \hat{H}^\dagger . T = (\hat{H}'\hat{H})^{-1} . \hat{H}' . T
\]

(8)

**Drawbacks of ELM:**

In our work \[14\] we have studied deeply on behavior of ELM with respect to various weight initialization schemes, activation functions and number of nodes. From this study we found ELM has limitations as follows.

- The accuracy of classification in ELM depends on choice of weight initialization scheme and activation function.
- It is observed that the ELM needs relatively higher hidden nodes to provide higher accuracy, which suggest the network is memorizing the samples as more number of nodes are being added.
- It is also observed that due to random weights in final network ELM suffers from ill posed problem.

To overcome this shortcoming many researchers have used optimization algorithms \[13, 16\] which choose best weight for input layer. However, this again introduced the iteration and choice of parameter problem for chosen optimization scheme. To avoid using the iterative method, this paper propose a backward forward method form ELM which has following advantages:

- The algorithm generalizes the network with few hidden layer nodes only in two steps. In, first step (backward pass) the input weights are evaluated and in second step (forward pass) the suitable output weight is determined.
- The final model of the network does not contain any random weights thus giving a consistent result even when choice of activation changes.
- Unlike optimization based ELM the proposed method evaluates input weight in two step, hence the model does not need iterative steps.
III. PROPOSED BACKWARD FORWARD ALGORITHM FOR ELM

The ELM algorithm is one of the simplest model for learning with SLFN. However, the choice of random weights for input layer does not take into account for the class label, which makes the choice of hidden node size very high to achieve performance. The large hidden layer size explores the possible outcomes and the weights of output layer (which is determined mathematically), chooses the required features to provide the result. However, the uncertainty in random input weight causes ill pose problem in neural network. To remove this randomness we propose backward-forward algorithm for ELM (BF-ELM), which learns in two phases namely backward phase (where, input weight is determined mathematically) and forward phase (where, new output weight is determined using the learned input weights).

A. Backward Pass

Let’s assume the size of hidden nodes for SLFN to be \( N \). The backward pass determines input weight for \( N/2 \) hidden node and the other half is obtained from orthogonal transformation of learned input weight. In our approach for backward pass we choose a random output weight (\( \hat{\beta} \)) of size \( (N/2, c) \), where \( c \) is the size of output layer. By using \( \hat{\beta} \) and the given target output (\( T \)) the hidden layer output (\( H' \)) is determined by equation (9) Setting activation function to be linear the input \( \hat{I} \) output (\( \hat{I}^* \)) is also introduced to the network. The obtained weight now concatenates with its orthogonal transformed weight to find the input weight of size \( (M, N) \), where \( M \) is the size of input layer nodes. The equation for the input weight (\( W^* \)) is given in equation (11)

\[
H' = T \times \hat{\beta}^\dagger + \text{Random Error} \tag{9}
\]

\[
W_1 = I^* \ast H' \tag{10}
\]

\[
W^* = [W_1, \text{Orth}(W_1)] \tag{11}
\]

B. Forward Pass

The obtained input weight (\( W^* \)) from backward pass phase is used in forward pass to determine new output weight(\( \hat{\beta} \)). The activation function (\( g(.) \)) is also introduced to the network in this stage. The final output weights (\( \hat{\beta} \)) is calculated using equation (12) and (13). The final network consists of input weight (\( W^* \), activation function(\( g(.) \)) and output weight (\( \hat{\beta} \)) which is used for testing the model.

\[
H = g(I \times W^*) \tag{12}
\]

\[
\hat{\beta} = H^\dagger \ast T \tag{13}
\]

The overall diagram of the proposed BF-ELM model is given in Fig. 1 which shows the determination of input weight (\( W^* \)) and output weight(\( \hat{\beta} \)). The next section various experiments have been carried out on multiple image classification dataset that shows the learning capability of the network. The proposed algorithm needs fewer number of nodes to achieve generalization accuracy.

Fig. 1. The proposed backward forward extreme Learning Machine (BF-ELM)

IV. DATASET DESCRIPTION

MNIST dataset: MNIST is a standard dataset for handwritten digit recognition. It was released in 1999 and has become a standard for testing various learning algorithms. The dataset consists of 60000 training and 10000 testing samples. The images have already been normalized and presented in vector format. The Fig. 2 shows some of the samples in MNIST dataset.

Fig. 2. MNIST sample images

Multiclass brain MRI dataset: The multiclass brain MR dataset comprises 200 images (40 normal and 160 pathological brain images) is used to evaluate the proposed model. The pathological brains contain diseases of four categories, namely brain stroke, degenerative, infectious and brain tumor; each category holds 40 images. The images are re-scaled to 80 before applying to network directly. The Fig. 3 shows some of the samples in brain-MRI dataset.

Fig. 3. Multiclass brain MRI dataset samples
V. RESULTS

The model is program is developed using MATLAB 2018b environment in a Linux system and are run on a machine with Intel i7-4710HQ 2.5 GHz processor and 16 GB RAM. In first experiment we studied the number of nodes needed for the network to converge. From Fig. 4 and 5 we can observe that the proposed BF-ELM converges faster and provides better accuracy than ELM with fewer nodes.

In the next experiment we evaluate model using various weight initialization scheme and activation function as described in TABLE I and II respectively. The experiment is conducted for each combination of weight initialization scheme and activation function. The obtained results for MNIST and multiclass Brain-MRI dataset are documented in TABLE III and IV respectively.

| TABLE I |
| Weight initialization scheme investigated in this work |
| Name | Description |
| Uniform random initialization | $W \sim U[l, u]$, where, $l$ represents lower range and $u$ represents upper range of the uniform distribution $U$ |
| Xavier initialization | $W \sim N\left(0, \frac{2}{n_{in} + n_{out}}\right)$ where $n_{in}, n_{out}$ represent the input layer size (dimension of features) and the output layer size (number of classes) respectively. |
| ReLU initialization | $W \sim N\left(0, \sqrt{\frac{2}{n_{c}}}\right)$ where, $n_{c}$ is hidden nodes size |
| Orthogonal initialization | Random orthogonal matrix each row with orthogonal vector |

| TABLE II |
| Activation functions investigated in this work |
| Activation function | Expression |
| Linear | $g(x) = x$ |
| Sigmoid | $g(x) = \frac{1}{1 + e^{-x}}$ |
| ReLU | $g(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$ |
| Tanh | $g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ |
| Softsign | $g(x) = \frac{x}{1 + |x|}$ |
| Sin | $g(x) = \sin(x)$ |
| Cos | $g(x) = \cos(x)$ |
| Sinc | $g(x) = \begin{cases} 1 & \text{if } x = 0 \\ \frac{\sin(x)}{x} & \text{if } x \neq 0 \end{cases}$ |
| LeakyReLU | $g(x) = \begin{cases} x & \text{if } x > 0 \\ 0.001x & \text{if } x \leq 0 \end{cases}$ |
| Gaussian | $g(x) = e^{-x^2}$ |
| Bent Identity | $g(x) = \frac{\sqrt{x^2 + 1}}{2} + x$ |

From TABLE III and IV we can observe that performance of BF-ELM is superior to ELM for every activation and weight initialization scheme combination. It can be observed that choosing the orthogonal weight gives better accuracy in every case of activation function.
### Table III

**Accuracy comparison on MNIST data set with ELM for 20 hidden nodes**

| Activation function | Weight initialization | ELM Accuracy | BF ELM Accuracy |
|---------------------|-----------------------|--------------|-----------------|
| **None**            |                       |              |                 |
| ortho               | 63.87                 | 85.98        |
| rand(0,1)           | 60.97                 | 86.06        |
| rand(-1,1)          | 65.6                  | 86.03        |
| xavier              | 61.19                 | 86.03        |
| relu                | 62.87                 | 86.02        |
| **Relu**            |                       |              |                 |
| ortho               | 51.72                 | 86.94        |
| rand(0,1)           | 62.25                 | 86.56        |
| rand(-1,1)          | 53.33                 | 85.13        |
| xavier              | 51.91                 | 86.11        |
| relu                | 55.75                 | 85.35        |
| **Sigmoid**         |                       |              |                 |
| ortho               | 63.66                 | 86.83        |
| rand(0,1)           | 11.35                 | 86.71        |
| rand(-1,1)          | 56.32                 | 86.63        |
| xavier              | 62.76                 | 86.59        |
| relu                | 63.15                 | 86.61        |
| **Tanh**            |                       |              |                 |
| ortho               | 63.43                 | 87.53        |
| rand(0,1)           | 59.03                 | 86.39        |
| rand(-1,1)          | 62.19                 | 87.17        |
| xavier              | 61.57                 | 86.43        |
| **Softsign**        |                       |              |                 |
| ortho               | 62.92                 | 86.68        |
| rand(0,1)           | 9.8                   | 86.96        |
| rand(-1,1)          | 14.04                 | 86.04        |
| xavier              | 65.7                  | 86.72        |
| relu                | 63.16                 | 86.64        |
| **Sin**             |                       |              |                 |
| ortho               | 55.88                 | 86.58        |
| rand(0,1)           | 10.4                  | 86.71        |
| rand(-1,1)          | 14.61                 | 86.17        |
| xavier              | 48.25                 | 87.11        |
| relu                | 47.72                 | 86.4        |
| **Cos**             |                       |              |                 |
| ortho               | 51.37                 | 86.62        |
| rand(0,1)           | 62.11                 | 86.08        |
| rand(-1,1)          | 49.01                 | 86.52        |
| xavier              | 52.34                 | 85.83        |
| relu                | 53.26                 | 86.03        |
| **LeakyRelu**       |                       |              |                 |
| ortho               | 66.36                 | 86.88        |
| rand(0,1)           | 66.31                 | 86.59        |
| rand(-1,1)          | 60.25                 | 86.74        |
| xavier              | 60.91                 | 86.98        |
| relu                | 64.85                 | 86.75        |
| **BentIde**         |                       |              |                 |
| ortho               | 46.44                 | 86.48        |
| rand(0,1)           | 15.16                 | 86.32        |
| rand(-1,1)          | 27.79                 | 86.4         |
| xavier              | 44.98                 | 86.16        |
| relu                | 52.21                 | 86.44        |
| **Gaussian**        |                       |              |                 |
| ortho               | 61.41                 | 87.01        |
| rand(0,1)           | 61.46                 | 86.65        |
| rand(-1,1)          | 55.42                 | 86.82        |
| xavier              | 64.9                  | 86.54        |
| relu                | 66.97                 | 86.54        |

### Table IV

**Accuracy comparison on Brain MRI data set with ELM for 10 hidden nodes**

| Activation function | Weight initialization | ELM Accuracy | BF ELM Accuracy |
|---------------------|-----------------------|--------------|-----------------|
| **None**            |                       |              |                 |
| ortho               | 35                    | 100          |
| rand(0,1)           | 50                    | 100          |
| rand(-1,1)          | 62.5                  | 100          |
| xavier              | 47.5                  | 100          |
| relu                | 60                    | 100          |
| **Relu**            |                       |              |                 |
| ortho               | 25                    | 100          |
| rand(0,1)           | 35                    | 100          |
| rand(-1,1)          | 30                    | 92.5         |
| xavier              | 42.5                  | 97.5         |
| relu                | 45                    | 97.5         |
| **Sigmoid**         |                       |              |                 |
| ortho               | 57.5                  | 100          |
| rand(0,1)           | 20                    | 100          |
| rand(-1,1)          | 52.5                  | 97.5         |
| xavier              | 52.5                  | 87.5         |
| relu                | 50                    | 92.5         |
| **Tanh**            |                       |              |                 |
| ortho               | 62.5                  | 100          |
| rand(0,1)           | 20                    | 85           |
| rand(-1,1)          | 42.5                  | 62.5         |
| xavier              | 47.5                  | 72.5         |
| relu                | 27.5                  | 97.5         |
| **Softsign**        |                       |              |                 |
| ortho               | 45                    | 97.5         |
| rand(0,1)           | 42.5                  | 95           |
| rand(-1,1)          | 35                    | 82.5         |
| xavier              | 47.5                  | 87.5         |
| relu                | 45                    | 97.5         |
| **Sin**             |                       |              |                 |
| ortho               | 60                    | 95           |
| rand(0,1)           | 22.5                  | 97.5         |
| rand(-1,1)          | 12.5                  | 97.5         |
| xavier              | 50                    | 100          |
| relu                | 47.5                  | 60           |
| **Cos**             |                       |              |                 |
| ortho               | 45                    | 100          |
| rand(0,1)           | 15                    | 97.5         |
| rand(-1,1)          | 27.5                  | 85           |
| xavier              | 70                    | 85           |
| relu                | 40                    | 92.5         |
| **LeakyRelu**       |                       |              |                 |
| ortho               | 42.5                  | 97.5         |
| rand(0,1)           | 50                    | 90           |
| rand(-1,1)          | 47.5                  | 85           |
| xavier              | 32.5                  | 92.5         |
| relu                | 57.5                  | 75           |
| **BentIde**         |                       |              |                 |
| ortho               | 55                    | 92.5         |
| rand(0,1)           | 50                    | 75           |
| rand(-1,1)          | 42.5                  | 75           |
| xavier              | 50                    | 92.5         |
| relu                | 32.5                  | 85           |
| **Gaussian**        |                       |              |                 |
| ortho               | 42.5                  | 100          |
| rand(0,1)           | 20                    | 82.5         |
| rand(-1,1)          | 42.5                  | 82.5         |
| xavier              | 55                    | 95           |
| relu                | 37.5                  | 82.5         |
| **ArcTan**          |                       |              |                 |
| ortho               | 42.5                  | 100          |
| rand(0,1)           | 42.5                  | 97.5         |
| rand(-1,1)          | 40                    | 97.5         |
| xavier              | 60                    | 87.5         |
| relu                | 35                    | 100          |
VI. Conclusion

Here we proposed a backward-forward algorithm for single hidden layer neural network which is a modified version of extreme learning machine. The proposed model performs better compared to ELM with fewer hidden nodes. Further, the evaluation of model with respect to weight various initialization scheme and activation functions proves the stability of the model as variance in the accuracy obtained for testing set is small compared to ELM. The proposed model can be directly used as classifier or can be used as a weight initialization model for fine tuning using gradient based model. In future, the model can be extended to multi layer neural network and convolutional neural network.

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[17] Banshidhar Majhi Banshidhar Majhi received his PhD degree from Sambalpur University, Odisha, India, in 2001. He is currently working as a Professor in the Department of Computer Science and Engineering at National Institute of Technology, Rourkela, India. His field of interests include image processing, data compression, cryptography and security, parallel computing, soft computing, and biometrics. He is a professional member of MIEEE, FIETE, LMCSI, IUPRAI, and FIE. He serves as reviewer of many international journals and conferences. He is the author and co-author of over 80 journal papers of international repute.

Deepak Ranjan Nayak Deepak Ranjan Nayak is currently with the Computer Science and Engineering at National Institute of Technology, Rourkela, India. His current research interests include medical image analysis, pattern recognition and cellular automata. He is currently serving as the reviewer of many reputed journals such as Multimedia Tools and Applications, IET Image Processing, Computer Vision and Image Understanding, Computer and Electrical Engineering, Fractals, Journal of Medical Imaging and Health Informatics, IEEE Access, etc.

He also serves as the reviewer of many conferences.

Ratnakar Dash Ratnakar Dash received his PhD degree from National Institute of Technology, Rourkela, India, in 2013. He is currently working as Assistant Professor in the Department of Computer Science and Engineering at National Institute of Technology, Rourkela, India. His field of interests include signal processing, image processing, intrusion detection system, steganography, etc. He is a professional member of IEEE, IE, and CSI. He has published forty research papers in journals and conferences of international repute.

Banshidhar Majhi Banshidhar Majhi received his PhD degree from Sambalpur University, Odisha, India, in 2001. He is currently working as a Professor in the Department of Computer Science and Engineering at National Institute of Technology, Rourkela, India. His field of interests include image processing, data compression, cryptography and security, parallel computing, soft computing, and biometrics. He is a professional member of MIEEE, FIETE, LMCSI, IUPRAI, and FIE. He serves as reviewer of many international journals and conferences. He is the author and co-author of over 80 journal papers of international repute. Besides, he has 100 conference papers and he holds 2 patents on his name. He has received Samanta Chandra Sekhar Award for the year 2016 by Odisha Bigyan Academy for his outstanding contributions to Engineering and Technology.