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Proposing a new method of image classification based on the AdaBoost deep belief network hybrid method

Hasan Asil*[1], Jamshid Bagherzadeh[2]
Department of Computer Engineering, Faculty of Electrical and Computer Engineering,
Urmia University, Urmia, Iran
*Corresponding author, e-mail: h.asil@iauazar.ac.ir[1], j.bagherzadeh@urmia.ac.ir[2]

Abstract

Image classification has different applications. Up to now, various algorithms have been presented for image classification. Each of these methods has its own weaknesses and strengths. Reducing error rate is an issue which many researches have been carried out about it. This research intends to optimize the problem with hybrid methods and deep learning. The hybrid methods were developed to improve the results of the single-component methods. On the other hand, a deep belief network (DBN) is a generative probabilistic modelwith multiple layers of latent variables and is used to solve the unlabeled problems. In fact, this method is anunsupervised method, in which all layers are one-way directed layers except for the last layer. So far, various methods have been proposed for image classification, and the goal of this research project was to use a combination of the AdaBoost method and the deep belief network method to classify images. The other objective was to obtain better results than the previous results. In this project, a combination of the deep belief network and AdaBoost method was used to boost learning and the network potential was enhanced by making the entire network recursive. This method was tested on the MINIST dataset and the results were indicative of a decrease in the error rate with the proposed method as compared to the AdaBoost and deep belief network methods.

Keywords: *boosting, deep belief network, deep learning, hybrid methods, image classification*

1. Introduction

In order to identify the content of an image, it is necessary to extract and process information from image. Various methods have been presented for processing this information that each of them has its special features. Different algorithms have been presented for image classification up to now. Most of these algorithms are based on artificial intelligence and machine learning. The available methods have different potentials based on the datasets and learning methods. Each classification problems has error based on the network type and structure. This error can have different reasons. This study has acted to reduce the image classification error. Deep learning based mixed methods are used to reduce error.

Artificial neural networks have been employed for classification purposes given thepotentialof the layers to learn the new hybrid-based features. The deep belief models are the extended versions of the artificial neural network models. These models have numerous applications in classifying texts and images and processing satellite and medical images and they have been widely used recently [1]. Deep learning has been based on the artificial neural networks and researchers aim to model the high-level abstraction of the data. These models extract multiple features from the data and analyze them. A data can be a word, pixel, frequency, etc. Although this data can convey an insignificant meaning, a combination of this data can lead to better results [2].

Deep learning is useful for certain scenarios and it involves the use of the machine learning models and other techniques for the creation of meaningful results [3]. Deep models have several latent layers and numerous parameters that need to be taught. This computational complexity and the larger parameter space have reduced the use of a large number of layers in the common neural network methods [4]. The large number of the layers in these networks not only reduces the speed but also results in the local minima and unsatisfactory results [5]. Deep belief networks have provided the solution to this problem and the opportunity to use multiple networks. In addition, Deep belief networks have applications to feature learning and classification [6]. A deep belief network is a generative probabilistic model composed of multiple

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layers of random hidden units, which are on top of a layer of visible variables or a data vector. Figure 1 shows an example of these networks.

Various algorithms have been proposed for training a deep belief network on the relevant weights [7]. One of the distinctive characteristics of a deep belief network is that all of the states of the hidden units of the network are identified on a forward path and regression is not allowed. Although this deduction is not completely accurate, it is relatively accurate. After training the deep belief network, all of the probabilistic models are ruled out and the resulting weights are used as a new starting set for the neural network weights. This process is called “pre-training”. Following the pre-training phase, one layer is added as the output of the network as aSoftmax function and the entire network is trained discriminatively. This network has been used in solving various problems [8]. The ensemble classifications belong to the family of the multi-component classification approaches, which were proposed to produce better results than a single-component classification approach [9]. In this classification, different ensemble classification approaches are used to obtain better results, and the hybrid approaches differ in their classification mechanisms and how they combine the base classifier in relation to the weights [10].

In fact, there are two possible frameworks for the ensembles: dependent (sequential) and independent (parallel) [11]. In a dependent framework, the output of one classifier is used to create the subsequent classifier. Hence, it is possible to use the knowledge generated through the previous cycles to direct the learning process in the subsequent cycles [12]. Boosting is an example of the application of this approach. In the second framework, i.e. the independent framework, each classifier is built individually and the outputs of the classifiers are combined with the polling methods [13]. The present research goal was to use the deep belief network hybrid methods to optimize the results of image classification.

Naturally, the main goal of this problem and the other learning problems is to provide better results. The hybrid methods were used in this research to improve the results. As humans use the previous results and research findings to make decisions and obtain better results, this method has been also employed in various studies on learning. One of the related techniques is the memory revival technique. Various studies have been conducted on this topic. The present research goal was to combine the AdaBoost, deep belief network, and neural networks methods. In fact, the goal was to combine AdaBoost with deep belief networks to create a memory-based network, use the previous learning results in the subsequent iterations, and produce better results. With the proposed hybrid method, the results from the large-scale studies are expected to be classified more specifically and the computational dimension is expected to decrease.

2. Literature Review

Recently the deep belief networks have been used to solve various types of problems such as image classification, object recognition, and feature extraction [14]. These networks employ different techniques to optimize these methods. The notion of the deep belief networks was proposed by Hinton. These networks offer plenty of advantages and have been used to solve different types of problems [15]. One of these problems was the classification of the social networks using a neural DBN network and the genetic algorithm (GA) [16]. In another study, a new method of neural network pre-training was introduced based on Boltzmann machines to accelerate the training process and enhance the phoneme recognition. Other researchers also used the deep belief networks to recognize the Farsi numbers [17]. In another study on deep learning, the context-based word recognition ability was analyzed [18]. Fritz et al. proposed a deep-learning model for image classification. Their model combines a deep network with the PixelRNN and DCGAN models and it is used for image recognition. These models were developed with regard to PixelRNN and DCGAN for handwritten data [19]. Other researchers conducted research on the ADGM project classification [20]. The Artificial Deep Generative Neural Networks Model (ADGM) was developed using a diverse set of encoders and decoders. This project was tested on the MINIST dataset [21]. The GAN project was also another project on image classification. The results from this project can be used for K-class classification. Moreover, one of the major deep-network approaches is based on the creation of different layers for feature learning [22].

3. The Proposed Method

The deep belief networks are RBM-based networks [23, 24]. There are also two other network types, namely the Deep Boltzman Machines (DBMs) and Deep Energy Models (DEMs), which are developed based on these networks [25]. Figure 2 presents the interconnections within these networks. As seen in Figure 2, the DBNs have undirected connections in the upper two layers, which form an RBM. In addition, the directed connections are in the lower layers [26]. The main characteristic of this network is that the training is unsupervised, which eliminates the need for the labeled data for training. A deep belief network is a generative probabilistic model, in which the joint probability distribution of the data is visible and provides the labels. A DBN first uses an optimum layered greedy strategy for the initialization (of the deep network parameters), and then sets all of the weights jointly in relation to the expected outputs. The greedy learning procedure has two advantages [27]: firstly, it provides for proper network initialization and therefore it reduces the difficulty of selecting the parameters (which may lead to the selection of local optima); secondly, the learning process is unsupervised, without a need for a class label. Hence, the training need for the labeled data is avoided [28]. However, the development of a DBN model icurs heavy computational costs because it is not known how to approximate the maximum training likelihood for the model optimization [29].

As stated in section 1, the ensemble classifications were proposed to improve the results. These multi-component classification approaches result in better results. The proposed algorithm was also designed to use the hybrid methods and the deep belief method to improve the image classification results. In this research, a boosting hybrid algorithm was used to combine the data, and the proposed design is illustrated in Figure 3.

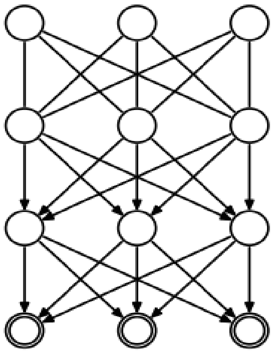


Figure 1. A deep belief network

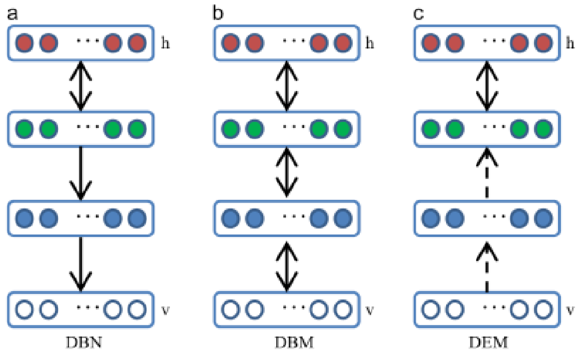


Figure 2. A comparison between the Deep Boltzman networks

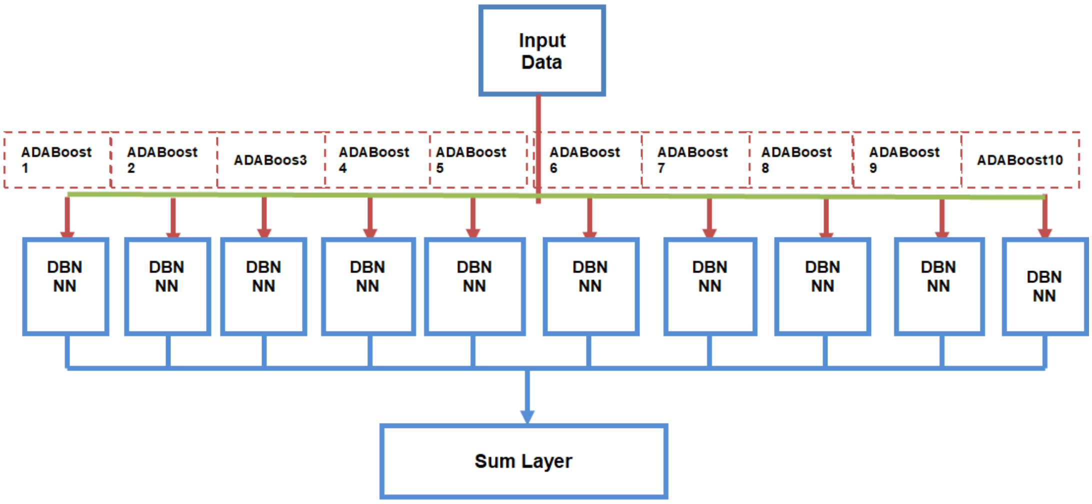


Figure 3. The proposed algorithm structure

4. Assessment of the Proposed Algorithm

In order to assess the proposed algorithm, it was implemented in MATLAB on the MINIST dataset. This dataset consists of approximately 60000 records of handwritten English numbers for learning and 10000 data records for testing. In order to compare the results, the deep belief network, AdaBoost, and the proposed DBN-based AdaBoosting methods were tested. On the other hand, for a more precise analysis, the results from each test were compared cycle-wiseas presented in the following.

4.1. AdaBoost

Figure 4 depicts the learning process in the AdaBoosting algorithm through different cycles. As seen, with an increase in the cycles the error rate decreases. To solve this problem, the problem space was divided into 10 segments and the learning process was completed for these classes. The AdaBoosting process also took place. Naturally, with an increase in the number of the cycles, the learning time escalated. For instance, 100, 500, and 2000 learning processes were completed for 10, 50, and 200 cycles, respectively.

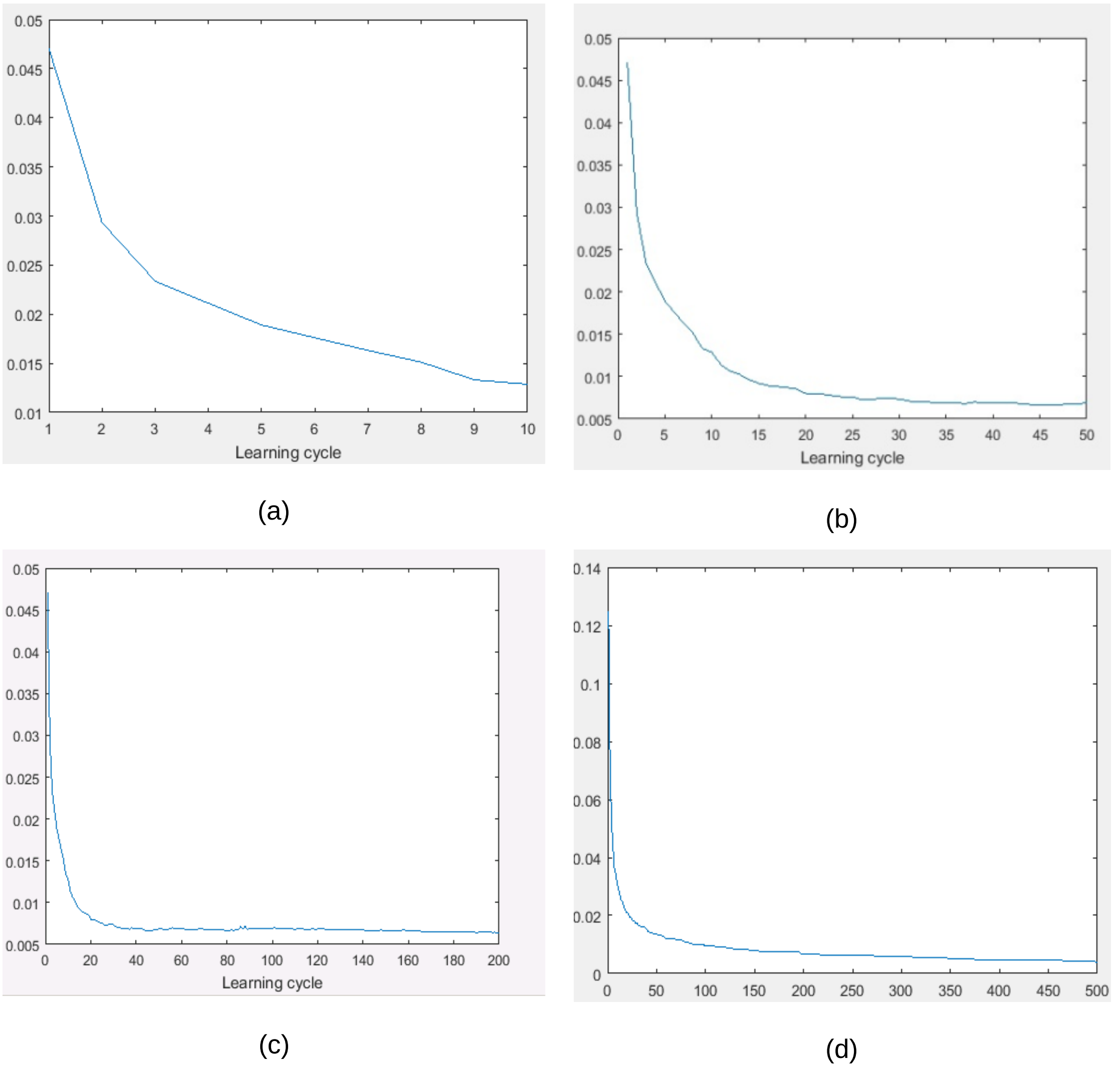
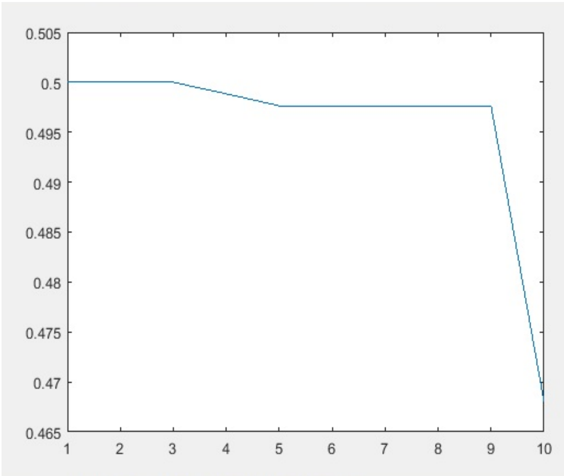
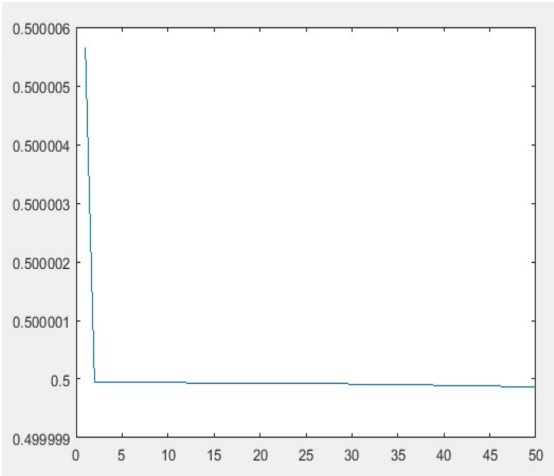


Figure 4. The process of learning based on the number of cycles using the AdaBoosting learning method: (a) 10 cycles, (b) 50 cycles, (c) 200 cycles, (d) 500 cycles

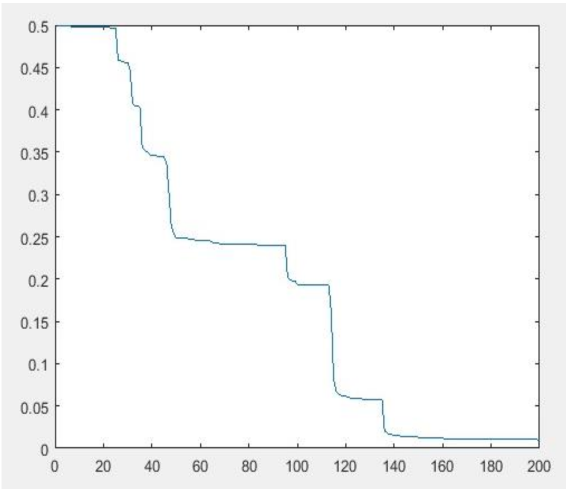
4.2. Convolution

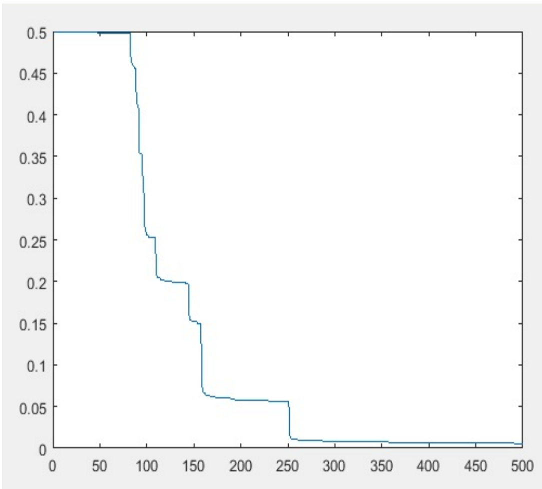
In the subsequent experiments, the convolutional network error rates at different iterations are examined and compared to the proposed algorithm. The convolutional algorithm is composed of three layers, namely the fully-connected, pooling, and convolutional layers. This method was tested on the MINIST dataset and the results are presented in Figure 5. This figure illustrates the completion of the convolutional learning algorithm process for 10, 50, and 200 cycles. As seen, the AdaBoosting method outpaced this method.





(a) (b)





(c) (d)

Figure 5. The process of learning based on the number of cycles using the convolutional learning method: (a) 10 cycles, (b) 50 cycles, (c) 200 cycles, (d) 500 cycles

4.3. Deep Belief Network

In order to compare the proposed method with the deep belief network, the MINIST dataset was converted and implemented using a typical neural network. The results are presented in the Figure 6.

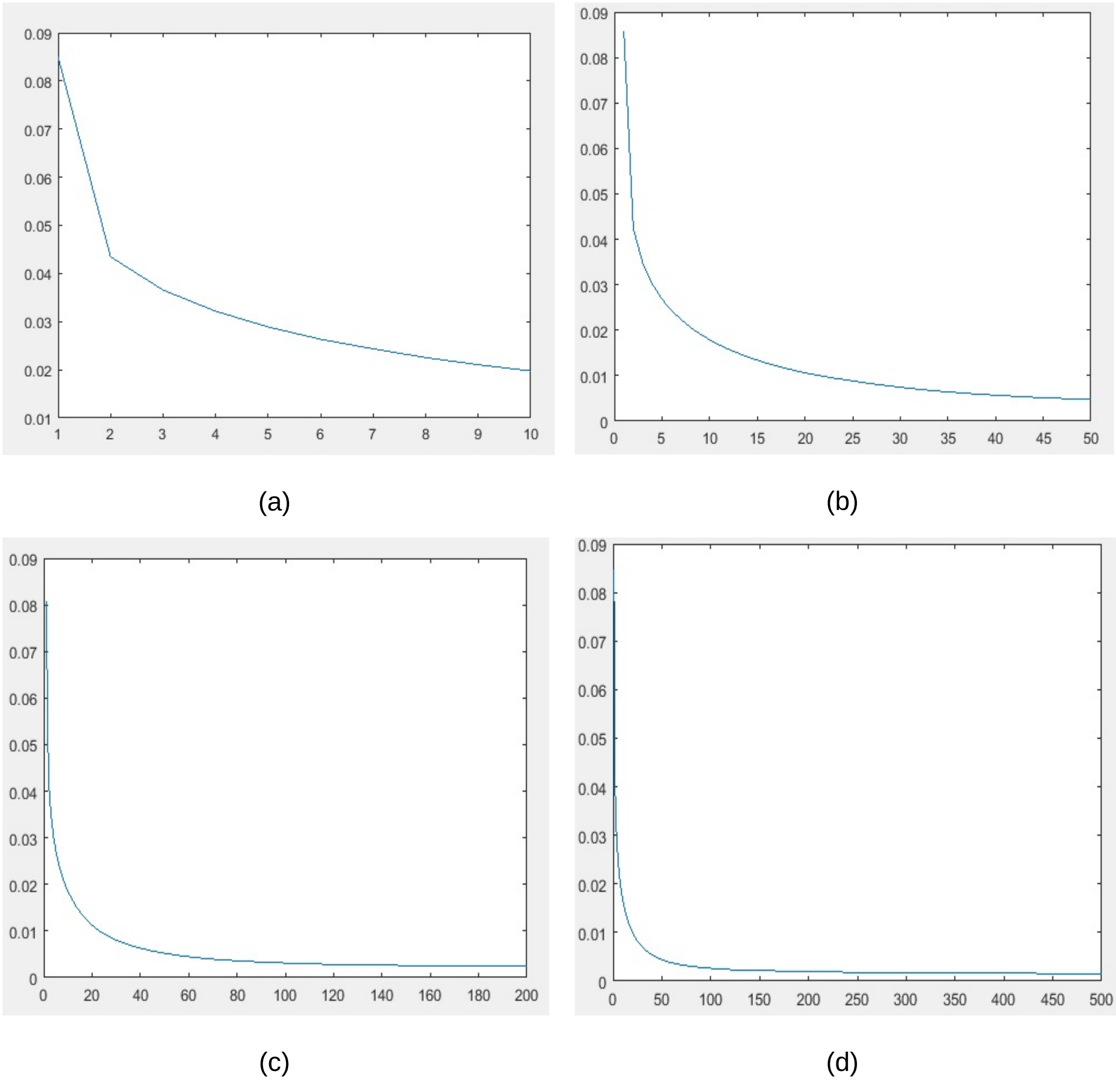


Figure 6. The process of learning based on the number of cycles using the deep belief network method: (a) 10 cycles, (b) 50 cycles, (c) 200 cycles, (d) 500 cycles

4.4. DBN-Based AdaBoosting

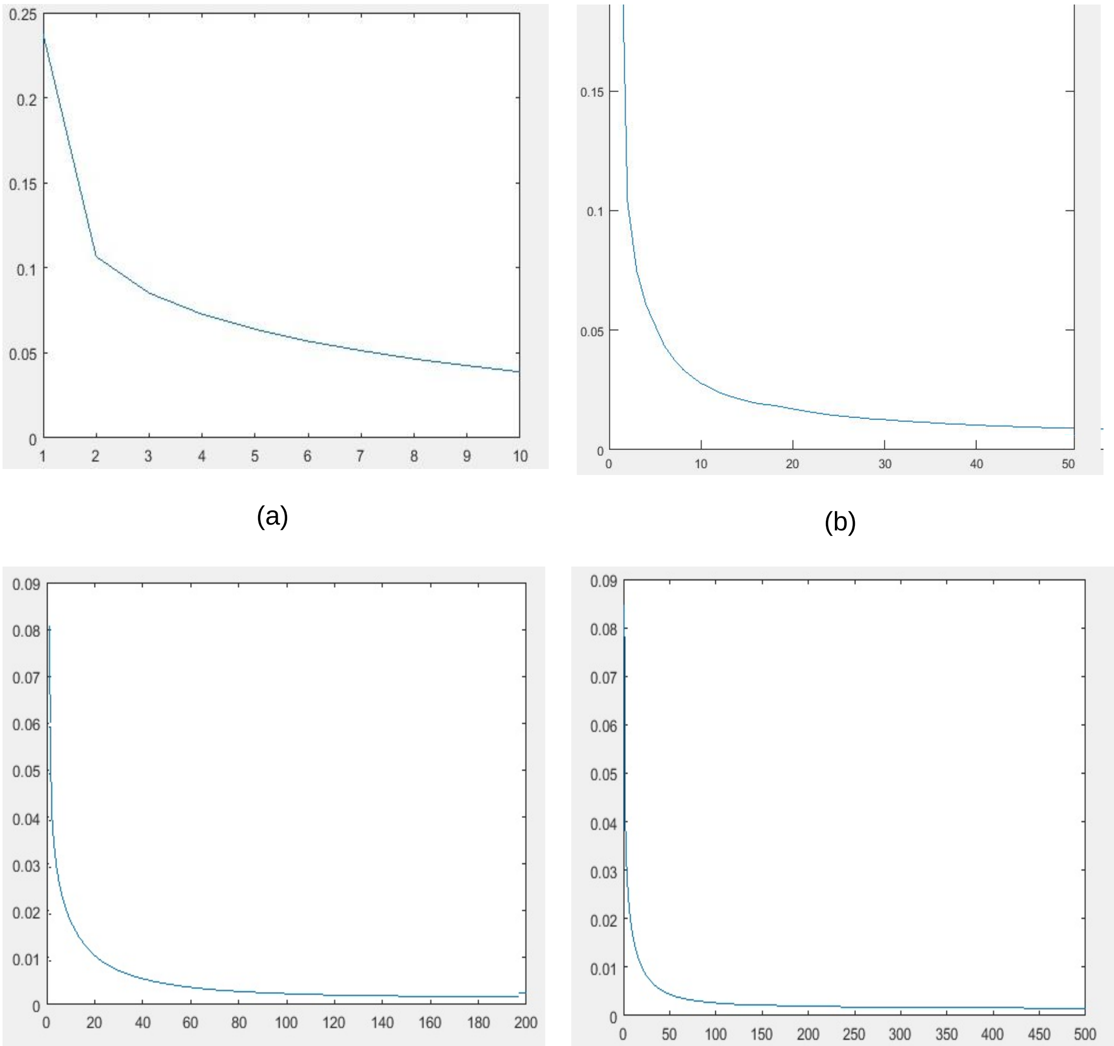
The proposed method is a combination of the AdaBoosting and deep belief network methods. In order to simulate this method, the sample space was combined in the space with the deep belief method. Figure 7 also presents the results of the learning process in different cycles.

5. Comparison of the Assessment Results

This project aimed to optimize image classification and as a result, reducing error rate in image classification. Four algorithms were evaluated in this research. According to the evaluation, learning time in the proposed method was higher than other methods. This is while the precision of system increased and as a result, error rate decreased.

According to the results of the comparison between this method and the proposed methods, the proposed method was slower than the aforesaid methods, but with an increase in the number of cycles, the convergence increased. On the other hand, the results of the cycle-wise assessment of all three methods are listed in Table 1. As seen, with an increase in the number of cycles the error rate declines and this method outperforms the mentioned methods in terms of the error rate.

The results for three error rates are presented in Table 1. Table 1 indicates error for three rates. The error rate in AdaBoosting for 500 iterations was 0.008, 0.197 for convolution, 0.0024 for deep belief, and 0.0008 for AdaBoostbased on deep belief that error rate has significant error rate. The diagram of the comparison of the proposed algorithm with the previous methods is depicted in Figure 8.



(a) (b)

(c) (d)

Figure 7. A cycle-wise comparison between the error rates using the deep-belief AdaBoosting method: (a) 10 cycles, (b) 50 cycles, (c) 200 cycles, (d) 500 cycles

Table 1. The Comparison of the Error Rates Based on Algorithm and the Number of Cycles

No.	Cycles	AdaBoosting	Convolution	Deep Belief	Deep-Belief AdaBoosting
1	10	0.0135	.04680	0.0198	0.0061
2	50	0.0094	0.5000	0.0048	0.0057
3	200	0.009	0.0197	0.0024	0.0028
4	500	0.008	0.0087	0.0015	0.0008

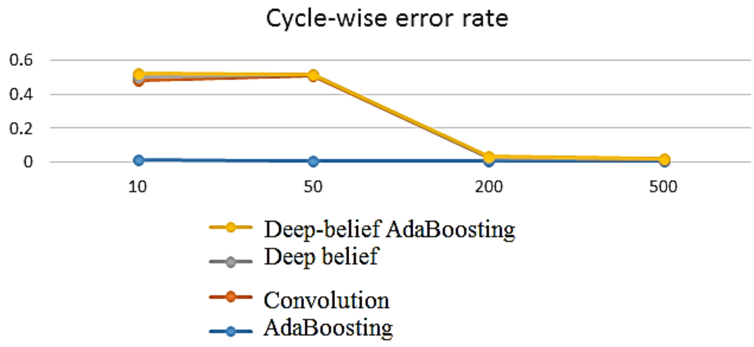


Figure 8. A cycle-wise analysis of the algorithm error rate

6. Discussion

The present research goal was to combine the AdaBoost, deep belief network, and neural network methods to obtain better results from image classification. One goal of machine learning is to develop patterns based on the previous data to implement the methods. Studies have also been conducted on memories and their effects on learning. Given the potentials of the AdaBoost method for the classification of the learning data and reinforcement of learning and given the capacity of the deep learning method for large-scale operations, a combination of these methods yields better results. Based on the investigation results, the error rate decreased approximately by 0.0007% and 0.008% as compared to the deep belief network and convolutional approach, respectively. The main advantage of this method is the reinforcement of learning through several iterations, which is inherited from AdaBoost, and its capacity for large-scale operations. The implementation of this method with many iterations yielded better results. However, the learning time was increased because of the classification and repeated learning processes. Evidently, the achievement of better results has a higher priority than learning.

7. Conclusion

Deep belief networks are techniques with applications to feature learning and classification. A deep belief network is a generative probabilistic model consisting of multiple layers of random hidden units that are placed on top of a layer of visible data or a data vector. These networks are used to increase the number of layers and conduct more precise investigations. The present research was also conducted using the hybrid methods and the deep belief networks to propose a new method for the classification of handwritten data. The hybrid methods classify learning and turn poor learning into strong learning. The deep belief networks are unlabeled, but they intend to select the proper learning parameters using the greedy approaches. The overarching goal of this paper was to combine the two methods to improve the results and reduce errors. This combination is based on regression and each class uses the previous class parameters for assessment. Hence, it can perform better with the semi-supervised methods. In fact, this method creates a memory-based hybrid network. The results also reflected the improved classifications and the decreased level of error rate. In this network, error rate has significant reduction relative to AdaBoost deep learning and convolution. It is, however, possible to use other hybrid algorithms or the memory-based methods to improve the results.

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