

Optimizing Convolutional Neural Network Using Particle Swarm Optimization For Face Recognition

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Abstract: Deep Convolutional neural networks are the emanating deep learning models outperforming various classic machine learning algorithms in resolving many disputes. Any deep convolutional neural networks (CNN) has hyper-parameters such as number of convolutional layer, number of filters, filter size, activation function, learning rate and number of fully connected layer. Generally, these hyper-parameters are selected manually and it varies for different models and datasets. The time consumption and computational resources are large when the structure of the neural network is complex. To avoid this, in this paper the CNN is optimized using particle swarm optimization (PSO) algorithm which converges faster than any other evolutionary algorithm and finds a better architecture for face recognition. The performance of PSO optimized CNN surpasses other algorithms. As well as the time consumption gets reduced.

Keywords: Convolutional neural network, hyper parameter optimization, particle swarm optimization, face recognition

I. Introduction

Nowadays, the convolutional neural network is applied for wide variety of applications such as object detection [2], digit recognition [5], image classification [1,8,10,14], face recognition[17, 24], speech recognition [16], tumor recognition [6], crack detection [7], leaf classification [20] and so on. Almost for all these applications, supervised learning is preferred for training the network. In supervised learning, Backpropagation algorithm is used for training the CNN and parameter set up.

There are few disadvantages in using Backpropagation (BP) [12] algorithm. This BP algorithm stuck with local minima, since it is hard for finding the global minima and involves complex computations for weight updating. As the algorithm propagates in both backward and forward, the computational equations become more complex with the parameters.

To overcome the disadvantages of BP algorithm, PSO algorithm is used for optimizing the CNN. Along with PSO, RMS Prop algorithm is used for training the network and achieves better results. This RMS Prop algorithm makes the network learn faster and reach the global minima.

II. Background

Convolutional neural network: Convolutional neural network is a type of deep neural network which is mostly preferable for imaging tasks. This convolutional neural network generally consists of 3 layers: Input layer, hidden layer and output layer as shown in figure 1. The hidden layer involves convolutional layer, pooling layer and fully connected layer [23]. This hidden layer shares weights between the layers. The values from the input layers are convolved with the weights and then passed on to the next layer. The convolution process is given by:

$$(x, y) = (I * F)(x, y) = \sum_r \sum_c I(r, c)F(x - r, y - c) \quad (1)$$

where I is an input image, F is the filter used for convolution process, r and c are the row and column of image. This convolution process is carried out till the last convolution layer. The pooling layer reduces the size of the feature maps. The last fully connected layer classifies the image according to the trained dataset.

Particle Swarm optimization: Particle Swarm Optimization (PSO) is a stochastic optimization technique inspired by social behavior of animals like birds, fishes, herds and insects. These swarms adhere to a collective way for finding food. Each swarm in the group changes their search pattern with respect to the learning experience of its own and other swarms in the group. In PSO each individual swarm called particle has its local best and global best value. With these values the particles determine the new solution in search space and also the velocity. For each

generation, a new dimension and velocity are computed and a new position is achieved [15]. This process is repeated until an optimal solution is achieved.

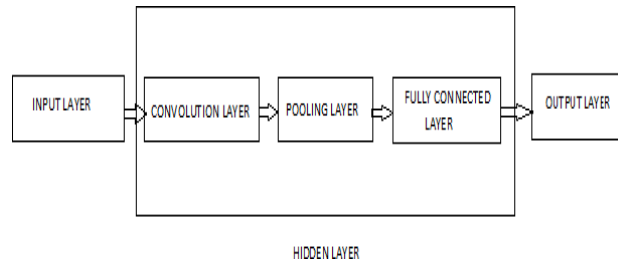


Figure 1. Block diagram of general CNN

Related Work

Many research works have been proposed for image recognition using various methods and novel approaches were also proposed. In early days, image classification was carried out using SVM [13, 19], decision tree [18], HMM [9], KNN [26] etc. Later CNN was developed and used for segmentation, object detection, image classification and for more such tasks. For CNN to perform the above mentioned tasks, stochastic gradient descent [2] was used. In this work, we propose an efficient PSO combined RMS Prop algorithms to construct an optimized structure and determine the hyperparameters of the CNN.

III. Literature Survey

A Deep Convolutional - Optimized Kernel Extreme Learning Machine (DC-KELM) algorithm proposed in [22] was found to provide better results at the earliest by fast learning speed and stable network for classification. To calculate the output of hidden layer, polynomial kernel was used. In this work the parameters of classifier KELM was optimized using Particle Swarm Optimization (PSO). With this proposed approach the error rate was very much reduced and found to be 0.5, 8.89, 0 and 21 for AT&T, Yale, CMU PIE and UMIST datasets respectively. Also the time consumption for training was less. In [4], a novel encoding strategy and the velocity operator was optimized using the PSOCNN. This proposed method was able to converge faster than other evolutionary systems and also automatically design DCNNs for image classification. On experimenting the proposed method using MNIST datasets, the error rate was 5.90 which is lesser than the state-of-the-art models. In [25], an automatic network structure selection method was proposed using PSO and steepest gradient descent algorithm. With the automatically generated network, MNIST and Kaggle datasets were trained and tested. The obtained results are observed to be excellent in both training and testing. In [21], an auto encoder was optimized using PSO algorithm. This PSO algorithm searches for an optimal architecture with less computational resources and does not require any manual assistance. The optimized CNN structure was evaluated for MNIST, CIFAR-10 and STL-10 datasets and it seems to outperform the state-of-the-art algorithms in terms of accuracy.

IV. Methodology

In this section, the framework of proposed algorithm is presented. Fig 2 shows the diagrammatic representation of steps involved in PSO algorithm. PSO is an evolutionary algorithm proposed by [3, 11] in 1995. It involves several steps starting from particle initialization, fitness evaluation, global best and local best value updating and at last velocity and weight updating. First step in PSO is randomly initializing the particles and velocity for searching. In the second step, the randomly generated particles are inserted into the cost function for finding the global best (*gbest*) and local best (*lbest*). Local best is the smallest cost of all particles and global best is the smallest of local best. Finally, the velocity and position are updated with the best as given in equations (2) & (3).

$$V_n(i + 1) = W \times V_{nd}(i) + C_a \times R_a \times (lbest_{nd} - X_{nd}(i)) + C_b \times R_b \times (gbest_{nd} - X_{nd}(i)) \quad (2)$$

where V_{nd} is the velocity of n-th particle in dimension d, W is the weight, C_a and C_b are constants, R_a and R_b are random numbers between 0 and 1, *lbest* and *gbest* are local best and global best and i is the iteration

$$(i + 1) = (i) + V(i + 1) \quad (3)$$

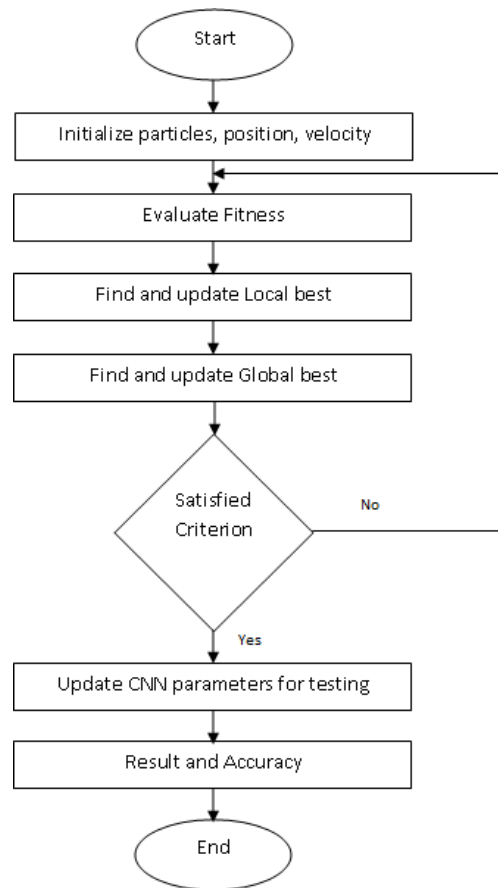


Fig 2. PSO Flowchart

To overcome the disadvantages, the CNN architecture is optimized using PSO algorithm in such a way that, the hyperparameters of the CNN are optimized using the PSO algorithm. While doing so, a best architecture is designed which has a less cost function and high accuracy with less computation time. Along with PSO, a different learning algorithm RMS Prop is used in CNN architecture for learning. The performance of the proposed approach is reasonably better than that of CNN with backpropagation and CNN optimized by genetic algorithm. The framework of PSO is given in algorithm 1.

Algorithm 1: Particle Swarm Optimization

INPUT: Number of individuals, velocity, position, Number of iterations

OUTPUT: Global best, Local best Calculate Old Fitness

for i= 1 to maximum iteration do,
for i=1 to maximum individual do,

%Update velocity

$$(i + 1) = W \times V_{nd}(i) + C_a \times R_a \times (lbest_{nd} - X_{nd}(i)) + C_b \times R_b \times (gbest_{nd} - X_{nd}(i))$$

%Update position

$$(i + 1) = (i) + V_{nd}(i + 1)$$

%Evaluate cost function

```
New fitness = f( $X_{nd}(i + 1)$ )
  if(New fitness < Old fitness)
    Old fitness = New fitness
     $X_{nd} = (i + 1)$ 
  else
    New fitness = old fitness
     $(i + 1) = X_{nd}$ 
  end if
end for
 $I = \min(\text{New fitness})$ 
 $lbest = X_{nd}(I)$ 
end for
```

The main use of using this PSO is to hunt for a neural network and its hyperparameters by varying the swarm's location. Each particle or individual are encoded as a network design for training process with a mini batch learning. Instead of SGD, RMS prop was used for learning. After training the network, the cost function and accuracy are calculated. Accordingly, the fitness value of the individual are updated until the best cost function and accuracy are obtained. The optimization processes involved in PSO are as follows:

1. Initialization: Firstly, the PSO algorithm needs initialization of the number of particles, maximum number of iterations, Coefficients, inertia weight. Likewise the network parameters such as number of layers, number of filters, learning rate, momentum and weight decay are also initialized. Along with these parameters, the numbers of epochs are also set for training and validation.
2. Population Initialization: In proposed approach, the population of the PSO indicates the parameters of the network. These parameters are a number which are generated randomly. Once the population is initialized, network architecture and its hyperparameters are obtained. The obtained architecture is now evaluated by training and validation process.
3. Evaluation: After the network was initialized, it was trained using the RMS prop algorithm with the mini batch from the whole dataset. After training the network, it is evaluated with the validation dataset which is not included in the training dataset. During the evaluation, the scores (fitness) of the individuals are calculated. Once the scores are calculated, the current score is compared with the previous score of past generation. In case, the current score is higher than the previous score, then the local best is updated with the current score. Similarly, the global best is decided by comparing the current individual score and the best individual score from past generations. In case the current best is larger than the previous best score then the current score is updates as a global best. With these local best and global best, the velocity and location of the individuals are updated.
4. Termination: The above three steps are repeated until the optimized network structure is obtained or till reaching the maximum number of iterations. Once the criterion satisfied, the algorithm is terminated.

V. Results and discussions

Dataset: In this work, Faces94 and ORL datasets are used for face recognition. Faces94 dataset contains 3000 images (20 images for 150 classes) of size 180 X 200 in RGB. For training and testing, the dataset is split into 60:40 respectively. ORL dataset contains 400 images of 40 classes of size 112 X 92.

Experiment Results: The PSO optimized CNN is evaluated using the ORL database and Faces94 dataset and found to be providing better accuracy and computational time with less error rate. The performance of the proposed approach is compared with the two other networks such as CNN with backpropagation and CNN with GA both trained using SGD and RMS prop. The performance comparison is shown in Table 1, 2, 3 and 4. As shown in Table 1, the performance of the CNN-PSO is comparatively higher than the other two models. Although the performance of CNN-GA and CNN-PSO do not differ so much, the accuracy of CNN-PSO for RMS prop surpasses with 97.3%. The accuracy, error and time comparison for three models are shown in the figures 3, 4, 5 and 6. Table 5 shows the performance of the proposed model with existing methods. In the previous works, the dataset with less number of images are used for evaluating the models. Apart from the ORL dataset, Faces94 dataset which has 3000 images are used for evaluating the proposed method.

Network	Optimizer	Accuracy (%)	Error	Time (sec)
CNN-BP	SGD	90.6	0.734	1532
	RMS prop	92.3	0.481	738
CNN-GA	SGD	94.2	0.362	438
	RMS prop	96.6	0.234	326
CNN- PSO	SGD	94.7	0.328	411
	RMS prop	97.3	0.121	307

Table 1. Performance comparison of different deep learning method

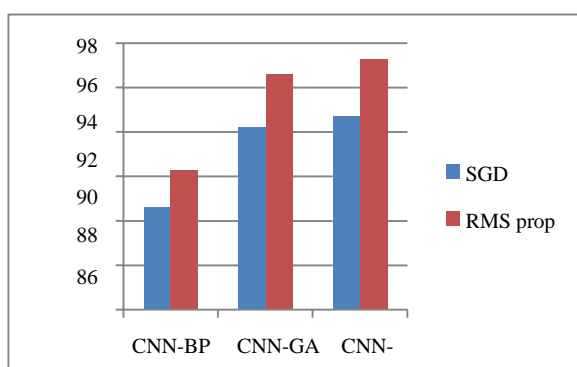


Figure 3. Classification accuracy of different algorithms

Network	Epochs				
	1	2	3	4	5
CNN-BP	84.7	86.8	90.2	92.9	94.3
CNN-GA	87.3	91.2	92.9	94.5	96.6
CNN-PSO	89.9	92.1	93.8	95.2	97.3

Table 2. Accuracy comparison for different epochs

Network	Epochs				
	1	2	3	4	5
CNN-BP	1.26	0.97	0.73	0.59	0.48
CNN-GA	0.89	0.60	0.55	0.37	0.23
CNN-PSO	0.85	0.58	0.43	0.19	0.12

Table 3. Error rate comparison for different epochs

Network	Epochs				
	1	2	3	4	5
CNN-BP	435	594	661	702	738
CNN-GA	227	279	293	311	326
CNN-PSO	219	223	265	291	307

Table 4. Time comparison for different epochs

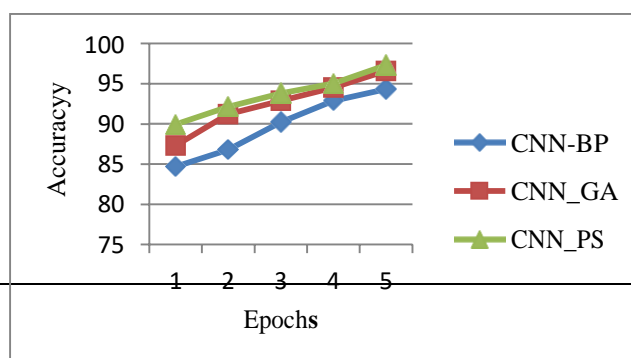


Figure 4. Accuracy Comparison

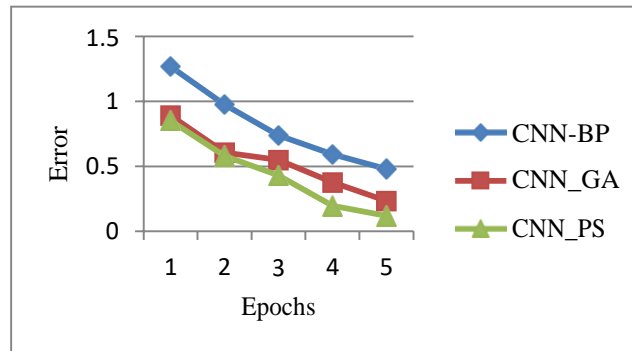


Figure 5. Error Comparison

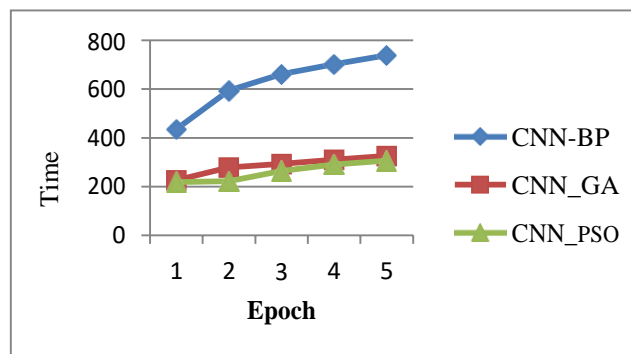


Figure 6. Time comparison

Methods	Accuracy (%)	
	ORL Dataset	ORL Dataset
Neural Network [26]	85.8	---
LBP-SVM [27]	89.5	---
LBP-ABC [27]	90.5	---
CNN [27]	92.5	---
CNN-ABC [27]	93.75	---
KNN [26]	95.7	---
ANFIS [26]	96.6	---
Kernel ELM [26]	97.3	---
Proposed method	99.1	97.3

Table 5 Performance of proposed method with existing methods

VI. Conclusions

In this work, a new approach for CNN was experimented by optimizing with PSO and training with RMS prop. From the experiment conducted, it is observed that the CNN-PSO method has a good accuracy, error rate and time consumption for faces94 dataset. The performance of the proposed method is compared with two other models such as CNN-BP and CNN-GA. In future, different datasets with more number of images can be used for evaluation and a hybrid PSO-GA method can be used for optimizing the CNN for better performance.

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