AN OPTIMIZED DEEP LEARNING METHOD FOR CLASSIFICATION OF KB DATASET

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Abstract: Machine Learning is the fast emerging technology which is poised to dominate in almost every walks of today's life. There exist several machine learning methods for classification of 2D images. Using Convolutional Neural Networks (CNN) for deep learning is becoming more popular nowadays due to ability of CNNs to learn feature extraction directly. Different kinds of models have been proposed to achieve an improved learning rate for CNN. Training a CNN model is interesting yet challenging due to the large number of hyperparameters involved. Hyperparameter optimization can be done using metaheuristic algorithms like Genetic Algorithm, Particle Swarm Optimization, Antcolony Optimization, Simulated Annealing and Harmony Search. In this paper, CNN hyperparameter optimization is achieved by particle swarm optimization (PSO). In this work, the KB dataset that contains poses from karate and bharathanatyam is used for classification. By optimizing CNN hyperparameters with PSO higher accuracy is achieved when compared with a standard CNN. As a result, the baseline standard CNN achives an accuracy of 73.39%, compared to 82.51% for PSO CNN, which improves accuracy.

KEYWORDS: CNN, Deep learning, Particle Swarm optimization, KB dataset

1. INTRODUCTION

There exist several methods for classification of 2D images. Using Convolutional Neural Networks (CNN) for deep learning is becoming more popular nowadays due to ability of CNNs to learn feature extraction directly. In CNN an already trained network can be used as a base model and a new network can be built on top of it for new recognition tasks. This enables the network to produce easy, fast and effective results. The inputs are separated into classes for classification depending on the objective function. The layer's extract complex features by stacking and down sampling from different parts of the input. Convolutional Layer, Pooling Layer and Fully-Connected Layer are the three varieties of layers used. Convolutional layer uses kernels to detect features all over the image. The Kernels carries out a convolution operation in which element wise product is taken first and sum of the matrices are taken. Generally, large amount of computation is needed. This can be reduced by inserting Pooling layers between convolutional layers. This also prevents overfitting and reduce the parameters.

Recently, Metaheuristic algorithms have been used to optimize deep learning models like CNN. These methods greatly improve the accuracy of the model when compared with the standard models. Metaheuristic are used in almost all research applications in various fields like

Engineering, Science, and in different Industrial applications. They are powerful methods to solve difficult optimization problems as they are flexible, easy to design and easy to be applied for various types of applications. The prime objectives of metaheuristic is to solve larger and diverse problems in a faster and robust way. Most of the metaheuristics algorithms are inspired by nature and are based on principles in biology (Differential Evolution, Evolution Strategy, Genetic Algorithm), maths (Base Optimization, Sine Cosine algorithm), physics (Threshold Accepting method, Microcanonical Annealing, Simulated Annealing), ethology (Ant Colony Optimization, Dragonfly algorithm, Particle Swarm Optimization) and social(Teaching learning based optimization).

2. LITERATURE SURVEY

Fister et al. [3] proposed a classification of metaheuristics based on nature inspired and non-nature inspired. Swarm intelligence based, bioinspired and physics/chemistry-based are nature inspired metaheuristics. Other algorithms were inspired by diversified characteristics and are non-nature inspired from different sources, such as social, emotional, etc. Different such classifications was proposed by Akyol and Alatas [4], Binitha and Sathya [5] - introduced another bio-inspired classification of metaheuristics and Ruiz-Vanoye [6] introduced a new classification of metaheuristics algorithms based on animals groups: swarm, schools, flocks, and herds algorithms. Osman [7] classified metaheuristics into local search (repeatedly makes small changes to a solution), construction-based (builds solutions from their component parts by adding one part at a time to an incomplete solution), and population-based (combine solutions into new ones iteratively) metaheuristics.

Gendreau and Potvin [8] proposed a metaheuristic classification- trajectory-based metaheuristics and population-based metaheuristics. A trajectory-based algorithm initially starts with a single solution and during each iteration the current best solution is replaced by a new one. The population based algorithm begins with randomly generating a population of initial solutions. This population will be progressively enhanced through search iterations. Another metaheuristic phenomenon is inspired by music, such as Harmony Search algorithm[10]. Classifications of metaheuristic can also be based on single-solution based metaheuristic: S-metaheuristic and population-based metaheuristic: P-metaheuristic. Examples of S-metaheuristic are Simulated Annealing, Guided Local Search, and Tabu Search. P-metaheuristic can be broadly classified into Swarm Intelligent and Evolutionary Computation.

Various forms of PSO have been proposed for network optimization. PSO converges faster than GA and is attracting attention as an excellent method[16]. Da Silva[17],in their study optimized the hyperparameters of CNN used to classify pulmonary nodule candidate images into nodule and non-nodule by using simple PSO. Wei-Chang[18] the weight of the artificial neural networks model has been optimized using a new method called improved Parameter-Free Simplified Swarm Optimization obtaining a better performance. The weight parameter is an important one for optimization. The linear decreasing inertia weight proposed in [19] is an excellent method for converging PSO efficiently and is used in many researches.

2.1 particle swarm optimization (PSO)

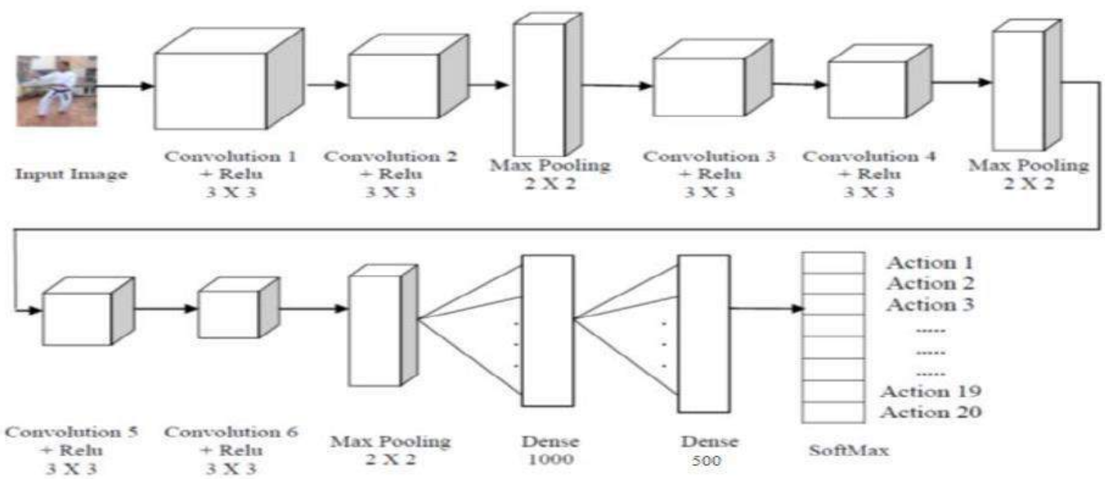
Reynolds formulated three distinct rules of flocking for a particle to follow: separation, alignment and cohesion. While the separation principle allows particles to move away from each other to avoid crowding, the alignment and cohesion principles necessitate directional updates to move towards the average heading and position of nearby flock members respectively. The inherent nonlinearity of the boids render chaotic behavior in the emergent group dynamics whereas the negative feedback introduced by the simple, low level rules effect in ordered behaviour. PSO is one of the heuristic algorithms proposed by James Kennedy and Russell Eberhart (1995). By incorporating local information exchange through nearest neighbor velocity matching, the flock or swarm prematurely converged in a unanimous fashion. Hence, a random perturbation or craziness was introduced in the velocities of the particles leading to sufficient variation and subsequent lifelike dynamics of the swarm. The PSO algorithm is given below:

```
iter = 0
Initialize v and x of all particles
Initialize pBest and gBest
while iter ≤ itermax do
   for i = 1 to N do
        for j = 1 to D do
                Update the velocity and position of the particles
        end for
      Calculate evaluation value of particle i
       if f(xiiter+1) < f(pBestiiter) then
         pBesti
         iter+1 = xi
         iter+1
       end if
    end for
k = arg min f(pBestiiter+1)
if f(pBestkiter+1) < f(gBestiter) then
         gBestiter+1 = pBestk
         iter+1
end if
t = t + 1
end while
```

3. PROPOSED WORK

The KB dataset that contains images from twenty different poses of karate and bharathanatyam are taken for classification(Fig 1). The poses are from different parts of action sequence while doing kata and different parts of dance sequence for bharathanatyam. There a total of 5441 images with approximately 250 images in each class. This is a twenty class classification problem. A standard CNN with six convolution layer and two fully connected layer is build. The network is an eight layer architecture and is shown in Fig 2. The baseline parameter and the optimized value using PSO are listed in Table 1.

Fig (1) Sample images from KB Dataset



Fig(2) Baseline CNN Network Architecture

Hyperparameter	Baseline	Optimization Value
Number of Filters-C1	32	50-100
Number of Filters-C2	64	50-100
Number of Filters-C3	64	50-100
Number of Filters-C4	128	100-200
Number of Filters-C5	128	100-200
Number of Filters-C6	256	100-200
Number of Neurons-FC1	1000	500-700
Number of Neurons-FC2	500	200-300

Table 1: Optimized Values of Hyperparameters

The parameters of PSO used for optimization are : the Swarm size is 50 and the maximum number of iterations is 10. The Cognitive parameter and Social parameter are both 2.0, and the weight decreases linearly from 0.9 to 0.4. It ends when the maximum iteration is reached as an end condition.

4. RESULTS AND DISCUSSIONS

The RGB images are resized to 300 x 300 and are taken for classification. The standard network uses a filter size of 3 x 3 for all the convolutional layers. The pooling size is 2 x 2. A batch size of 50 is used for training the data. Droput layers are added to prevent overfitting. The baseline CNN attains an accuracy of 73.39% after training it for nearly 50 epochs. In the proposed PSO-CNN model optimization is performed every 5 epochs. Based on the obtained parameters the learning is performed. An accuracy of 82.51% is obtained after 30 epochs. Table 2 shows the performance measures of networks. 80% of data was utilized as the training set and 10% for validating set. The remaining 10% was used as test sets. The learning rate can be varied between 0.2 and 0.9. By increasing the learning rate, both the performance ratio and training time will increase. Fig 3 shows the analysis of network performance.

METHOD	ACCURACY	PRECISION	RECALL	F1-SCORE
BaseLine CNN	73.39	76.71	73.65	74.81
Proposed PSO-CNN	82.51	81.32	79.41	80.35

Table 2 : Performance measures of Networks

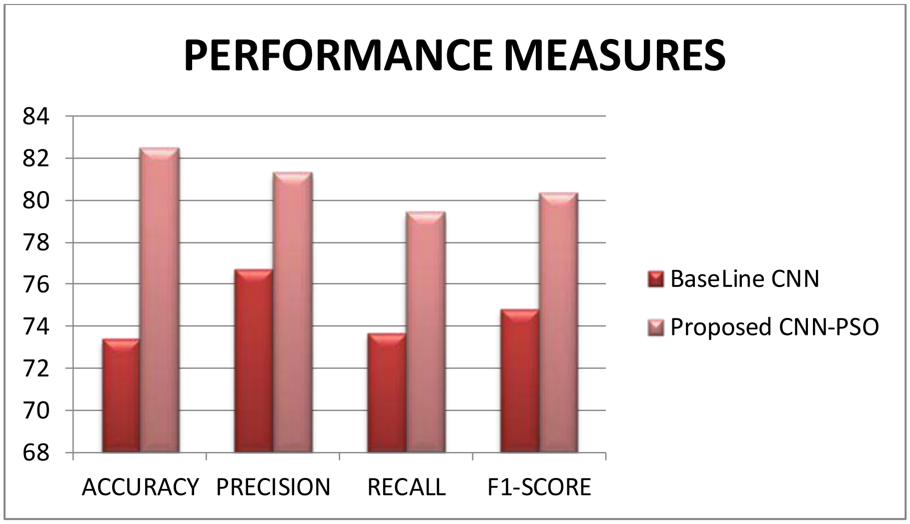


Fig (3) Analysis of Network Performance

5. CONCLUSION

In this paper, we propose a optimized CNN with PSO for hyperparameter optimization. The KB dataset containing 20 classes are trained using a standard CNN as well as the optimized CNN with PSO. Instead of taking standard datasets for classification, naïve dataset that contains karate and bharathantyam poses are taken in this work. The accuracy of baseline CNN is 73.39% compared with the optimized CNN which acquires an accuracy of 82.51 %. When looking at any epoch, it is found that the PSO-CNN achieves a higher accuracy than the baseline CNN. Also, the optimized CNN converges to higher accuracy at an early stage. The PSO-CNN that is proposed can find the optimal parameters and can obtain better results compared to the baseline CNN.

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