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PARAMETERS OPTIMIZATION OF CONVOLUTIONAL NEURAL NETWORK USING PARTICLE SWARM OPTIMIZATION FOR MENTAL DISORDER DETECTION THROUGH FACIAL MICRO-EXPRESSIONS

Anum Saher[1], Shafqat Ali[2], Samer Parveen[3], Ghulam Gilanie[*4]

[1, *4]*Department of Artificial Intelligence, Faculty of Computing, The Islamia University of Bahawalpur, Pakistan.*
[3]*Department of Mathematics, Faculty of Physical and Mathematical Sciences, The Islamia University of Bahawalpur, Pakistan.*
[3]*Department of Mathematics, Ripha International University Sahiwal Campus, Sahiwal, Pakistan.*

[1]anum.sehar@iub.edu.pk, [2]shafqat.ali@iub.edu.pk, [3]samer.parveen@riphahsahiwal.edu.pk, [*4]ghulam.gilanie@iub.edu.pk

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Ghulam Gilanie

Abstract
Schizophrenia is a prevalent mental illness with a significant global impact. Millions of individuals suffer due to the lack of early diagnosis and treatment. Detecting schizophrenia through facial micro-expressions offers a novel and promising approach. However, traditional deep learning methods often demand extensive computational resources and require complex hyperparameter tuning. This study proposes the use of Particle Swarm Optimization (PSO) to optimize the hyperparameters of Convolutional Neural Networks (CNNs), effectively replacing conventional backpropagation. PSO iteratively adjusts the parameters to find an optimal solution. Due to their computational efficiency and adaptability, CNNs are well-suited for deployment across various platforms. In this research, key CNN hyperparameters, including the number of epochs, batch size, number of filters, filter size, pooling size, and input pixel dimensions, are optimized. Additionally, PSO hyperparameters, including population size, social and cognitive weights, inertia weight, and the maximum number of iterations, are fine-tuned. The results show that the optimized CNN significantly outperforms conventional models in terms of reconstruction error and classification accuracy. This study presents an efficient method for optimizing CNN architectures, with applications in image compression, feature extraction, and anomaly detection. It also contributes to the early prediction of schizophrenia while maintaining low memory usage. The experimental results proved that the proposed CNN model gave the best accuracy values in comparison with other studies in the field. The proposed method can be considered as a powerful technique for prediction of schizophrenia mental disorder.

1. INTRODUCTION

During the last twenty years of the previous century, swarm intelligence emerged as a significant subject in the field of artificial intelligence. Numerous algorithms were developed to facilitate self-organization within a population composed of only a small number of distinct units. However, the utilization of swarm intelligence in artificial intelligence did not occur until the later years of 2010 [1]. This research focuses on two primary subjects: deep neural networks, namely convolutional neural networks, and the PSO algorithm[2]. Convolutional Neural Networks (CNNs) have

emerged as a novel architectural advancement in the fields of artificial intelligence and machine learning. CNN, which was originally designed for image recognition, has since proven to be exceptionally effective in a wide range of fields, including computer vision and natural language processing [3-6]. Convolutional neural networks are fundamentally powered by their capacity to discover spatial hierarchies of features autonomously and dynamically within unprocessed data and are significant not solely because of their exceptional performance, but also because of their versatility across a vast array of domains [3-6]. Constantly improving their capabilities, CNNs continue to be a pillar in the landscape of deep learning, enabling machines to comprehend and interpret complex data with unprecedented precision and efficacy.

For solving more complex real-world issues, Deep neural networks have shown impressive performance in a variety of difficult tasks, but they also need many computational resources for training, and they may be prone to overfitting if they are not adequately regularized. Despite these drawbacks, deep neural networks continue to be an exciting and promising field. Despite this, they are important tools in the field of machine learning and artificial intelligence because of their capacity to learn hierarchical representations and extract complicated patterns from the data. CNN, auto-encoder, Deep Belief Network (DBN), and Restricted Boltzmann Machine (RBM) are widely used Deep learning (DL) architectures [7]. To deliberate upon these network parameters, human expertise is required [8-31]. With a vast array of applications in computer vision, CNN is incredibly ubiquitous among all deep networks. PSO algorithms have been the subject of significant research to optimize parameter selection in deep neural networks [32]. The objective of our research is to use PSO to automatically learn an efficient architecture and the optimal neural network designs for solving real-world problems that are more complex and are best solved by networks with more than three layers. For effective training, you need a great deal of data, quick computing resources, and a great deal of computing time, which presents numerous obstacles. Handcrafted traits are used in traditional machine learning methods. CNN is very well-known among deep networks because it has so many uses in computer vision. Using PSO algorithms, a lot of studies have been done in the past to find the best way to choose parameters in deep networks [33-59]. For the best parameter selection, researchers have come up with hybrid forms of CNNs [60].In this suggested article about deep learning, VGG16, GoogleNet, AlexNet, ResNet, and EfficientNet are used to find depressed faces in aligned images of faces [61].

Deep learning uses CNN models like VGG16, GoogleNet, AlexNet, ResNet, and EfficientNet to find sadness in aligned face images. VGG stands for Visual Geometry Group, and it has sixteen layers of convolution. At the start, the image size is 224 by 224 pixels. It takes more time to set up its settings. GoogLeNet has 22 layers and is a deep convolutional neural network. The input picture is 224 pixels wide and 224 pixels tall. AlexNet has 8 layers. Five of these layers are convolutional, and three are connected. The network has an input size of 256 by 256 by 3. It can only handle RGB pictures. The name "ResNet" stands for "Residual Network." It is a neural network on the cutting edge. Resnet50 is the version that can work with 50 levels of neural networks. EfficientNet is a structure and scaling method for convolutional neural networks that uses a compound coefficient to scale all variables of depth, width, and resolution in the same way [62].

The goal of a new deep learning model is to be able to accurately predict schizophrenia. A special optimization method has been added to the model to make it even more effective. This method has been tested with big datasets, including the locally developed schizophrenia dataset. It can handle the growth of the datasets while still making accurate predictions. Its effectiveness is judged by comparing it to other models and taking into account the different performance measures that different classifiers use.

Each iteration of PSO results in a more optimal solution than the previous one. CNN is essential in carrying out the fitness assessment of each swarm particle, even though it demands considerable calculation power [63]. Population size is the number of particles, representing how many individuals are in the search area. Max

iterations is the number of iterations or stages that the PSO algorithm can go through [64-93]. Cognitive weight is the factor that controls a particle's tendency to move toward its best position. Social weight is the factor that determines how much a particle wants to move toward the global best position. Inertia weight is the factor that influences how much a particle's current speed affects its next speed update.

The PSO algorithm [2],] is a heuristic approach used to optimize a fitness function without relying on gradient calculations. Inspired by the collective behaviour found in fish schools and bird flocks, PSO operates on the premise that individuals within a group can derive benefits from the collective knowledge and experiences of the entire assembly. For instance, when one fish in a school discovers a plentiful food source, all members can reap the advantages of this discovery. PSO is an evolutionary optimization method based on a random population and uses metaheuristics.

The Particle Velocity Update Equation in PSO is a key component that determines how the velocity of each particle is updated in each iteration of the algorithm. From one cycle to the next, a swarm of particles changes their relative positions, which helps the PSO algorithm do its job of searching. Assuming there is a minimization problem, one has

$$p_{best_i}^t = x_i^* | f(x_i^*) = \min_{k=1,2,\ldots,t} (\{f(x_i^k)\}) \quad (1)$$

where I ∈ {1, 2..., N}, and

$$g_{best}^t = x_*^t | f(x_i^*) = \min_{\substack{k=1,2,..,t \\ i=1,2,...,N}} (\{f(x_i^k)\}) \quad (2)$$

where i is the particle's index, t is the number of the current iteration, f is the goal function to be optimized (minimized), x is the position vector (or a possible solution), and N is the total number of particles in the swarm. The following equations change the speed v and location x of each particle I at each step t + 1.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \left(p_{best_i}^t + x_i^t\right) + c_2 r_2 (g_{best}^t - x_i^t) \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

Where v is the speed vector and w are the weight used to balance local exploitation and world exploration. r1 and r2 are random vectors that are evenly spread across the range [0, 1] while c1 and c2, which are called "acceleration coefficients," are constants that are always positive. Most of the time, a higher limit is set for the speed vector. The "velocity clamping" method was used to stop particles from cutting into the search area and force them to take the right number of steps to look over the whole search domain. Clerc and Kennedy also came up with the "constriction coefficient" technique, in which the speeds can be slowed down by observing and theorizing about how the swarm moves. By looking at Eq. (3), we can see that the first part, which is called the "inertia component," is the particle's previous speed. This gives the particles the right amount of momentum to move around the search space. The second part called the "cognitive component," refers to how good each particle is on its own. It gives the particles a reason to move towards their best places so far. This happens over and over again. The third part, called the "social component," shows how the particles work together to find the best answer for the whole world. Figure 1 shows the flow chart of PSO.

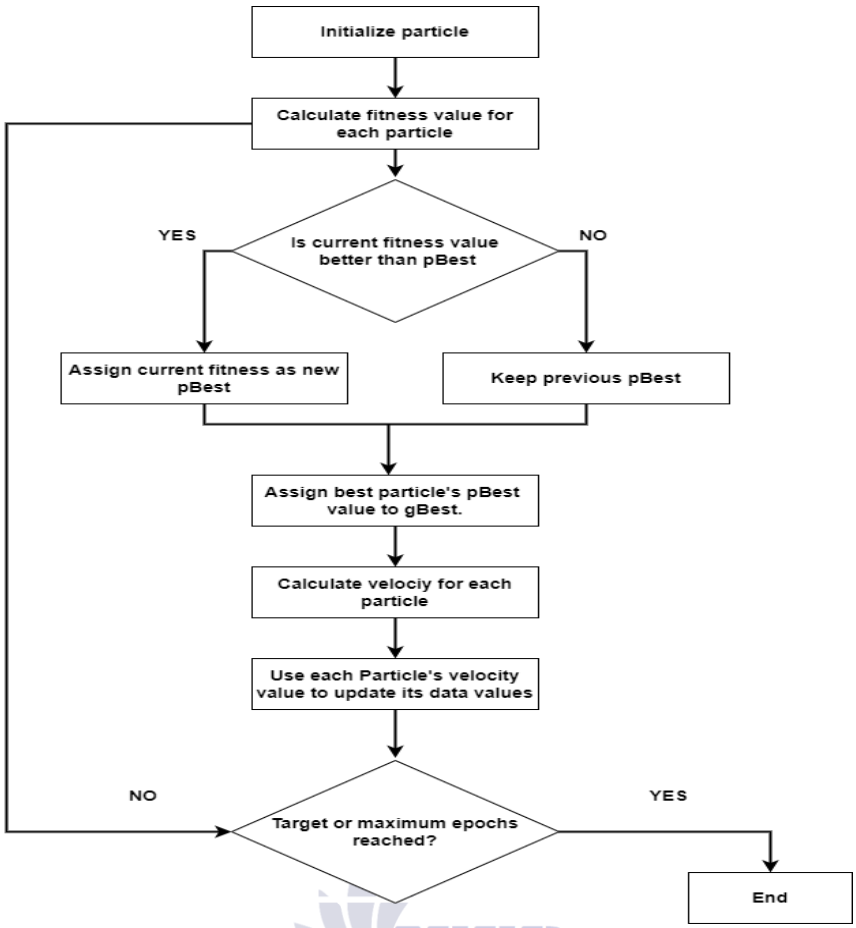


Figure 1. Flowchart of PSO model

The paper is organized as follows: Section 2 contains a literature review, while Section 3 is embodied in the proposed methodology, and Section 4 contain results. In Section 5, a conclusion on the proposed methodology.

2. LITERATURE REVIEW

The author of this study [94] works on static face emotion recognition using CNN with a PSO algorithm for tuning hyperparameters. The experiment was carried out using the dataset provided by FERC. The proposed model has been shown to have an accuracy of 92% when using PSO-CNN.

In [95], CNN features with PSO algorithms and SVM are used to identify micro expressions. Methods were the focus of the work documented in experiments carried out using standard datasets such as CASME-II, SMIC-HS, and SAMM. The accuracy achieved by the model that was proposed was 87%.

A Multi-level Particle Swarm Optimization (MPSO) approach is suggested in this work [96] to determine the parameters of the CNN architecture. The exploration and exploitation properties of particles were adjusted using the suggested method, which employed a sigmoid-like inertia weight. Five datasets, i.e., MNIST, CIFAR-10, CIFAR-100, Convex Sets, and MDRBI, were used in the experiments. The PSO-optimized CNN produced a 99.89% accuracy for the MNIST dataset.

In a related article [97] Convolutional neural networks are used to recognise static face expressions, with the hyperparameters being optimized by the PSO algorithm. ERUFER and JAFFE datasets were used for the experiment. With the ERUFER dataset, the proposed model's accuracy was 92.56%.

In work [98], video datasets, convolutional neural networks, and the PSO method are used to study how students learn. The model was tested using the NTU-RGB+D and NTU-RGB+D120 data sets. The NTU-RGB+D data set scored 88.8% on cross-subject and 94.7% on cross-view.

In [99], we looked at X-ray photos using PSO based on CNN. The project used 91 photos and

could also make CXR images with a higher resolution. The sample was made up of COVID-19 patients with lungs, opacity, pneumonia, viruses, and normal patients. With CXR SR, the model was at its most accurate (90.25%).

3. THE PROPOSED METHODOLOGY

Experiments were conducted using the schizophrenia dataset. At first, there was a set of default factors that were used to classify things. Then, a PSO was used to optimize these settings after each iteration. This was done until the settings were optimized in a way that helped improve speed.

1.1. Dataset

There are 2 to 3-minute videos of schizophrenia patients obtained from the Psychiatry Department of the BVH, Bahawalpur, Pakistan, and some private hospitals are also involved in taking datasets. Each patient has signed a consent form, providing their informed consent for permitting the taking of videos when conducting interviews according to the CGI-SCH [7]. The team of experts, i.e., psychiatrists and psychologists affiliated with BVH, Bahawalpur, and Pakistan, also validated the dataset. According to a clinical experiment done by a staff of specialists, there were 300 schizophrenic patients and 299 healthy volunteers (normal), particulars of them are organized in Table 1.

Table 1: Details of patients and healthy controls

No. of patients	Gender M/F	Age
30	Male	21-38
45	Male	31-42
30	Male	40-54
30	Male	50-65
34	Female	21-36
37	Female	31-46
50	Female	42-55
40	Female	49-64
30	Female	49-70
53	Male	22-40
42	Female	25-57
24	Male	32-46
43	Female	48-60
51	Male	41-65
60	Female	57-65

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1.2. CNN Hyperparameters

Optimizing CNNs for facial expression detection is a complex task due to the large number of parameters and high computational cost. This study uses Particle Swarm Optimization (PSO) to efficiently find the best-performing CNN model. Since CNN performance heavily depends on hyperparameters, fine-tuning them is essential but requires expertise. Metaheuristic algorithms like PSO are effective in enhancing CNN accuracy by optimizing these parameters.

Table 2: Hyperparameter of CNN model

Hyperparameter	Description
Kernel (Filter) Size	Size of the convolutional filter (e.g., 3×3, 5×5) that extracts features from input images.
Feature Map Number	Number of filters in a convolutional layer, determining the depth of the output feature map.
Stride	Step size by which the kernel moves across the input image (e.g., 1 or 2 pixels per step).
Padding	Technique to retain spatial dimensions by adding zeros around input borders ("same" or "valid").

Pooling Type	Downsampling operation applied to feature maps (MaxPooling or AveragePooling).
Number of Epochs	Total training iterations over the entire dataset.
Number of Layers	Depth of the neural network (convolutional + dense layers).
Number of Neurons	Units in fully connected (dense) layers.
Batch Size	Number of training samples processed in one forward/backward pass.
Weight Initialization	Method to set initial weights (e.g., Xavier, He initialization) for stable training.
Loss Function	Measures prediction error (e.g., Cross-Entropy for classification, MSE for regression).
Optimizer	Algorithm to update weights (e.g., SGD, Adam, RMSprop, Adadelta).
Dropout Rate	Fraction of neurons randomly deactivated (0.1–0.5) to prevent overfitting.
Activation Function	Non-linear function applied to neuron outputs (e.g., ReLU, Sigmoid, LeakyReLU).

1.3. Particle Swarm Optimization

The metaheuristic optimisation method called Particle Swarm Optimisation (PSO) can be used to tune the hyperparameters of convolutional neural networks (CNNs). In a CNN, the weights are the parameters that can be taught and that decide how strongly neurons in the network are linked to each other. They show how each input affects the output of a neuron or how important it is. During the training process, the weights are changed to make the gap between the predicted output and the ground truth labels as small as possible.

On the other hand, the biases are the learnable factors that supply an offset or bias to the weighted sum of the inputs. They make it possible for the network to change the activation function, which in turn makes the model more flexible in terms of its ability to capture various patterns and relationships in the data.

During the process of training, optimisation methods such as PSO are used to update the weights and biases of the CNN based on the calculated particle of the loss function with respect to these parameters. These weights and biases are determined by the computed particle of the loss function. The goal is to identify the ideal settings of the network's weights and biases, which will reduce the amount of data that is lost while simultaneously improving the performance of the network on the task at hand, which may be picture classification or object detection.

1st Iteration

$$Y^1 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (6)$$
$$Y^2 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (7)$$
$$Y^3 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (8)$$

⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯

$$Y^n = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (9)$$

After 1st Iteration we got n/2 optimized parameters

2nd Iteration

In this iteration n/2 parameters used from previous iteration and rest of the parameters are selected randomly.

$$Y^1 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (10)$$
$$Y^2 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (11)$$
$$Y^3 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (12)$$

⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯

$$Y^n = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (13)$$

nth Iteration

$$Y^1 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (14)$$
$$Y^2 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (15)$$
$$Y^3 = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n \quad (16)$$

⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯⋯

$Y^n = (w_1, w_2, w_3, \dots\dots\dots\dots, w_n$ (17)

After iteration obtained objective function as mentioned in equation no 13.

$\boldsymbol{Y^{min}}$ =f(x) = V (18)

Where 'V' is minimum for the loss function.

Such that

$Y \leq g \geq h$ (19)

Images are normalised before processing, thus g=1 and h=0.

Parameters to optimise are y, weights are w. The first iteration employed "n/2" parameters, and the second used random weights. nth iteration optimised parameters best. Model parameters are given after each iteration to see if outcomes improved. V is loss function. 'g' is 1 and 'h' is 0.

Steps of the PSO Algorithm

Initialize the swarm by assigning initial positions and velocities to all particles.

Evaluate the fitness of each particle in the population.

Store the best solution found by each particle and the overall best in the swarm.

Iterate through the following steps:

(a) **Update** the velocity and position of each particle using the relevant equations (e.g., Equations 1 and 2).

(b) **Recalculate** the fitness for each particle based on its new position.

(c) **Revise** the best personal and global solutions if improvements are found.

Repeat the iteration until a predefined stopping condition is fulfilled.

SO PSO is known for its faster convergence compared to Genetic Algorithms [26,27], making it well-suited for optimizing CNN architectures. Manual experimentation is highly time-consuming since training a single CNN can take days or even weeks, even on powerful GPUs. Given the large number of parameters in CNNs, there is a clear need for automated algorithms that can efficiently design and evaluate models.

1.4. CNN Architecture Design

In this section, we developed a custom Convolutional Neural Network (CNN) model from the ground up. The architecture includes three convolutional layers, each followed by a max-pooling layer. A dropout layer is incorporated to reduce overfitting, followed by a flattening layer and two fully connected (dense) layers. The ReLU activation function is applied to all layers except the output layer, which uses the Sigmoid function to produce a result within the [0, 1] range.

1.5. The PSOCNN Algorithm Overview

Using the Particle Swarm Optimization (PSO) algorithm , the proposed PSOCNN approach generates CNN architectures. The detailed steps of implementing the PSOCNN algorithm to optimize CNN structures are outlined in Algorithm 1 and summarized as follows:

Initially, the necessary input parameters for the algorithm are defined. These include the dataset required for training as well as configuration settings for the CNN architectures to be generated. Next, the population is initialized. During this phase, a specific number of particles (defined by Popsize) are created. Each particle represents a set of CNN hyperparameters, and their positions, personal best positions (pBest), and the global best position (gBest) are all initialiDuring each iteration, particles update their positions based on their individual best-known position (pBest) and the overall best-known position found by the swarm (gBest), using the update strategy described in Section 2.3. This process continues until a predefined stopping condition is met—such as reaching the maximum number of iterations. Each particle corresponds to a CNN architecture that is trained and evaluated on the dataset. The resulting classification accuracy is recorded as the particle's fitness score. Based on this, pBest and gBest values are updated accordingly. If the algorithm reaches the maximum number of iterations, the gBest particle is considered the optimal solution, representing the best-performing CNN architecture for the given dataset. If not, the algorithm returns to the iteration phase and continues the optimization process.

1.6. The PSOCNN Process

This section introduces an optimization strategy that applies the Particle Swarm Optimization

(PSO) algorithm to fine-tune the key hyperparameters involved in constructing an effective Convolutional Neural Network (CNN). The main objective is to identify and optimize the hyperparameters that have the greatest impact on the CNN's performance using the PSO method.

- In this research, the following hyperparameters were selected for optimization:
- Kernel Size (ks)
- Stride (s)
- Number of Filters in Convolutional Layers (nf)

The optimization process begins by initializing a set of particles, each representing a potential solution. The position of each particle corresponds to a unique set of hyperparameter values, effectively defining a specific CNN configuration for training.

Algorithm 1: The proposed PSOCNN model.

1. Set PSO parameters (e.g., swarm size, maximum iterations).
2. Initialize the positions of particles within the search space.
3. Assign initial velocities to all particles.
4. Record the initial personal best positions and their corresponding fitness values.
5. **While** the stopping criteria not met (e.g., convergence or max iterations):
6. 6. **For** each particle in the swarm:
7. 7. Update the particle's velocity based on PSO update equations.
8. 8. Adjust the particle's position accordingly.
9. 9. Evaluate the particle's fitness using CNN performance as the objective.
10. 10. **If** the new fitness is better than the particle's personal best:
11. 11. Update the personal best position and fitness value.
12. 12. **End if**
13. 13. **If** the new fitness is better than the global best:
14. 14. **Update** the global best position and fitness value.
15. 15. **End if**
16. 16. **End for**
17. **End while**

1. This study utilized the BAHAWALPUR VICTORIA HOSPITAL datasets for image classification and analysis.
2. The particle population was initialized for the Particle Swarm Optimization (PSO) algorithm. Details of the experimental setup are provided in Table 3. Key PSO components include particles, the total number of iterations, inertia weight (w), cognitive coefficient (c1), and social coefficient (c2).
3. The initial structure of the Convolutional Neural Network (CNN) was defined. Hyperparameters such as the number of filters, filter size in convolutional layers, and stride were initialized using PSO, along with additional parameters from Table 4. The CNN was then configured for training with the image data.
4. **:** The CNN was trained by dividing the dataset into training, validation, and testing subsets. The model's accuracy was measured during the testing phase, and this performance metric was passed to the PSO algorithm as part of the objective function.
5. The PSO algorithm assessed the objective function to identify the most optimal hyperparameter values.
6. During each iteration, the velocity and position of every particle were updated based on its personal best position (pBest) and the global best position (gBest) found across the swarm.
7. The optimization continued through multiple iterations, analyzing each particle, until the stopping condition—such as reaching the maximum number of iterations—was satisfied.
8. Finally, the particle corresponding to the global best position (gBest) was selected as the optimal solution. This particle defines the best CNN configuration obtained through the PSO process.

Table 3: Parameter values range [min to max] of the proposed CNN model

Parameter	Range

No. of filters in layer 1	[8 to 64]
No. of filters in layer 2	[16 to 128]
Filter size in layers 1 and 2	[3 to 5]
Pooling size in pool layers 1 and 2	[2 to 3]
No. of pixels in the fully connected layer	[64 to 512]

Table 4: Parameter values range [min to max] of the proposed PSO model

Parameter	Range
Size of Population	20
Max number of iterations	50
Cognitive_weight	0.5
Social_weight	0.5
Weight of inertia	0.9

1.7. Compile the CNN model by specifying the optimizer, loss function, and metrics

At first, classification is done with the default parameters. After each repetition, the PSO algorithm is used to improve these parameters until the best parameters are found that improve performance. Optimizer='adam' tells the computer to use the Adam optimizer, which is a well-known optimization algorithm that works well in many deep-learning projects. loss='categorical_crossentropy' tells the program to use the categorical cross-entropy loss function, which is often used for cases with multiple classes. Metrics= ["accuracy"] tells the training method that we want to keep track of the accuracy metric. A CNN model that uses the Adam optimizer and a loss function based on binary cross-entropy and the accuracy measure. The Adam optimizer is an adaptive optimization method that changes the learning rate during training to improve convergence speed and performance. Binary cross-entropy is a type of loss function that is often used for situations involving two classes. It measures the difference between the outputs that were expected and the ones that were given, where the outputs are either 0 or 1. During training, the model tries to reduce the loss in binary cross-entropy between the input and the output that was rebuilt. The Adam algorithm is used to change the model's weights so that the loss is as small as possible.

4. RESULTS

Schizophrenia dataset used for experiments, First of all, classification is done through default parameters, after PSO is used to optimize these parameters after each iteration and optimize until getting optimized parameters that help to improve performance. Table 5 demonstrates the results of schizophrenia classification by features using the PSO-CNN algorithm. Similarly, Table 6 compares with the PSO-CNN algorithm. Schizophrenia dataset used for experiments. First of all, classification is done through default parameters, after PSO is used to optimize these parameters after each iteration and optimize until getting optimized parameters are obtained that help to improve performance.

In this section, we compare the results of the proposed CNNPSO model with those of another model convolutional neural network. The experiments demonstrate that CNNPSO outperforms other ANN models. While the basic CNN achieves high accuracy with the schizophrenia dataset, our proposed model shows a 2-4% increase in accuracy, even with fewer than half the number of epochs used in the basic CNN model.

In our research, we trained the CNNPSO model for 3 epochs and achieved an accuracy of 99.7%, whereas the testing accuracy of the CNN model was only 99.6% after 20 epochs shown in Figure 2 The error calculated from our research work also indicates the superiority of the CNNPSO model over the CNN model.

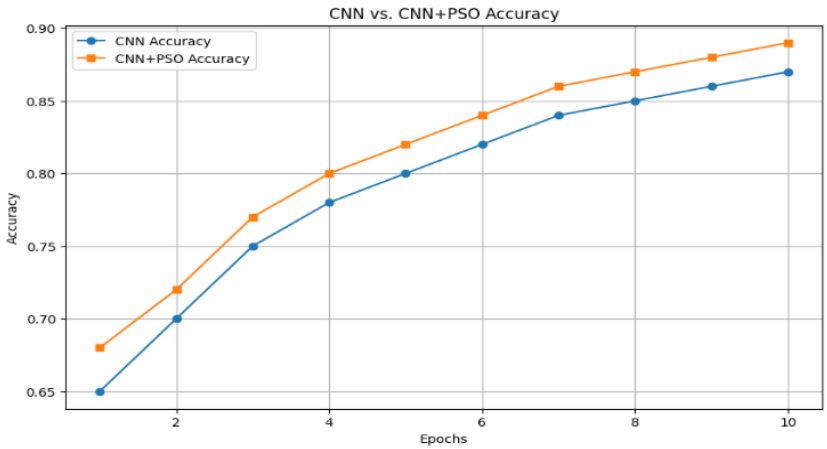


Figure 2. Accuracy graph for PSOCNN

In this experiment, PSO demonstrated a notable consistency in the quality of hyperparameters across ten independent runs. Regardless of swarm size, the hyperparameters optimized through PSO consistently yielded strong performance for Ψ. Interestingly, larger swarm sizes sometimes resulted in poorer-performing configurations (as indicated by the minimum values in Figure 3, likely because these swarms struggled to refine initially weak positions. In contrast, smaller swarms, benefiting from faster particle dynamics, were more effective in overcoming such poor initializations. However, larger swarms did show gradual improvement in discovering better-performing hyperparameters overall. Statistical analysis using two-tailed Wilcoxon tests revealed a significant difference ($p = .05$) only between swarm sizes 4 and 16. These findings suggest that even very small swarms are capable of identifying high-quality CNN hyperparameters.

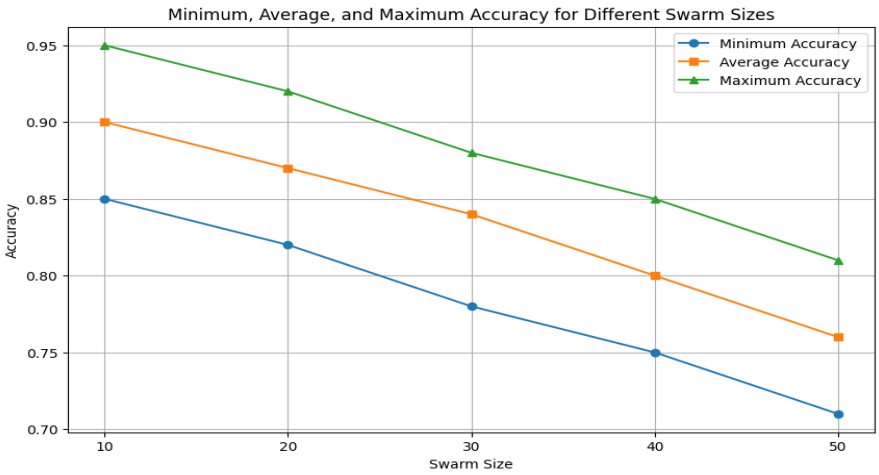


Figure 3. The minimum, average, and maximum accuracy of the best PSO particles across all folds obtained for Ψ using the optimized CNN for all swarm sizes

The best hyperparameters identified by PSO exhibit very similar quality and were obtained in a significantly shorter time shown in Figure 4 Specifically, for $s = 16$, PSO outperforms the results for schizophrenia shown in Figure 5, demonstrating similar properties to those obtained from different types like Cipher10 dataset despite the schizophrenia dataset being more challenging. Across all s values for the schizophrenia dataset, PSO consistently reduces optimization time by two orders of magnitude compared to grid search. Increasing s noticeably enhances PSO's search capabilities for complex datasets. This study also investigates PSO's ability ($s = 4$) to identify suitable hyperparameters in a vast search space. It

explores PSO's scalability as CNN architectures become more complex and the cost function becomes more computationally expensive to evaluate.

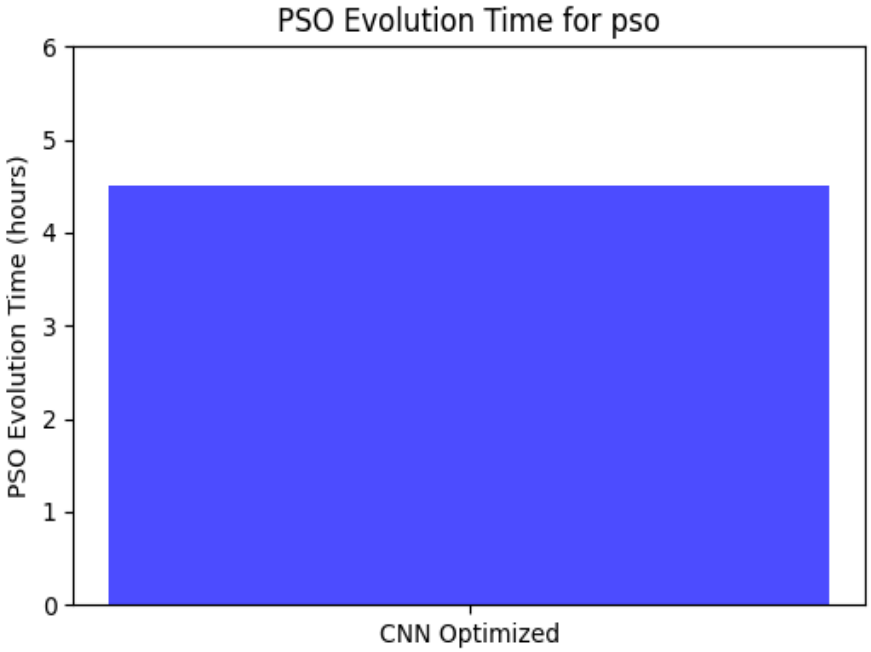


Figure 4. Evolution time of PSO (in hours)

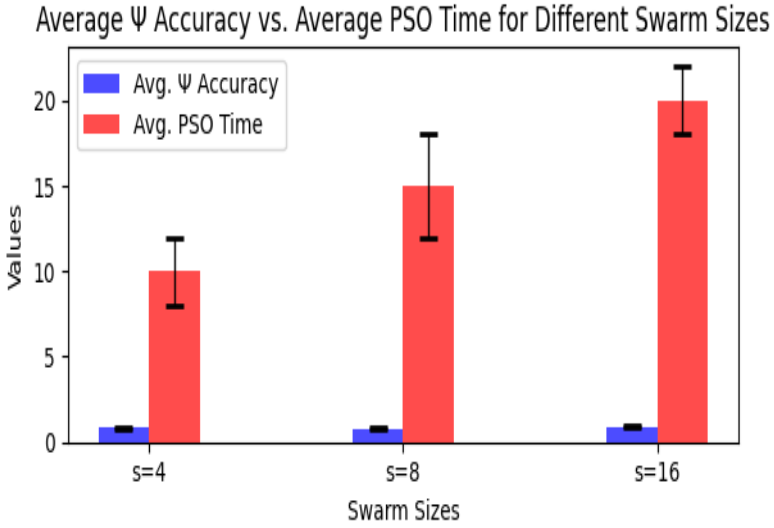


Figure 5. Average PSO Time for Different Swarm Sizes

This visualization illustrates the positions of particles in the first, second, and last generations of a Particle Swarm.

The optimization process for optimizing a Convolutional Neural Network is shown in Figure 6. Each line represents a particle, and the position of the particle is shown along different axes (e.g., Position 1, Position 2, etc.). This visualization helps analyze how the particle positions evolve across generations during the optimization process

Table 5: Accuracy results

Dataset	Algorithm	Accuracy
300 schizophrenic patients and 299 healthy volunteers	CNN	99.6%
	PSO-CNN	99.86%

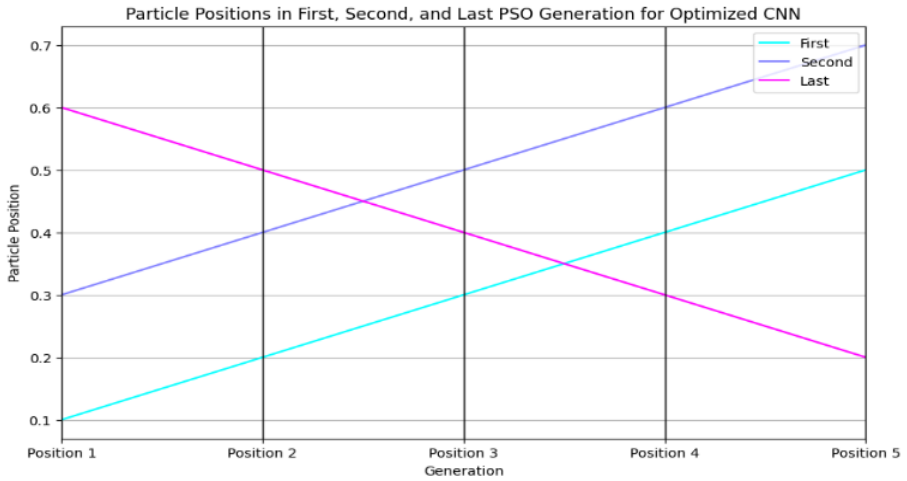


Figure 6. Particle Positions in First, Second, and Last PSO Generation for Optimized CNN

Table 6: Results of schizophrenia classification by features using the pso-cnn algorithm

Features	Trained Model	Average Accuracy	Best accuracy
Aligned faces	VGG16	84.52	95.67
	MobileNet	81.40	99.0
	EfficientNet	90.10	97.63
	GoogleNet	82.46	96.57
	ResNet50	86.9	97.43

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5. DISCUSSION

Table 7: Comparison with state-of-the-art using CNN parameters with PSO algorithm

References	Parameters and hyperparameters	Evaluation measure
[95]	CASME-II, SMIC-HS, SAMM	Population size=10 No. of iteration=100 In KNN, K=5 Cognitive factor=2 Social factor=2 Max epoch=32 Batch size=16 Learning rate value=0.001 No.of filters=64 Filter size=13 No.of neuron=1024
[96]	MNIST,CIFAR-10,CIFAR-100,Convex Sets, and MDRBI	Population size=15 Social coeffiecient=2 Cognitive coefficient=2 Inertia weight=0.9 Max iteration=5
[97]	ERUFER and JAFFE	Training data=70% Testing data=30% 10 and 5-fold cross-validation Particle size =10

		Iteration number=10, Cognitive coefficient 1.49, Social coefficient 1.49, Inertia weight 0.7
[100]	The Chinese Academy of Sciences Micro-Expression dataset (CASME-II), Spontaneous Micro-Expression Corpus - High Speed (SMIC-HS), Spontaneous Actions and Micro-Movements (SAMM)	CNN+PSO+SVM
[98]	NTU-RGB + D and NTU-RGB + D120 data set	Learning rate 0.00098 Batch_size 64

5. DISCUSSION

In article [95] the size of the maximum iteration was 100 and epochs were 16 so accuracy was not up to the mark, Similarly in another article [96] population size was 15 and the number of iterations was 5 so accuracy was 99.89 only on MNIST data but in another data this fitness model does not perform well. In a related study [97], the population size was 10 the number of iterations was also 10, and the crossfold was 5 or 10 so the accuracy was 92.56%. According to [98] accuracy was dependent upon. According to the proposed methodology, the iteration size is 50 and the population size is 20 so the accuracy is 99.6%.

6. CONCLUSION

The use of a PSO algorithm to do parameter optimization within a CNN can be an efficient method for increasing the performance of the algorithm. It is a form of optimization algorithm that is modeled after the process of natural selection. These algorithms can be utilized to search for the best possible combination of parameters to solve a particular problem. When utilizing a PSO to optimize the settings of a CNN, it is essential to choose proper selection criteria, such as reconstruction error or another type of performance statistic. In addition to this, the PSO algorithm needs to be adjusted so that it strikes a healthy balance between exploration and exploitation, while also maintaining adequate control over the variety of the population.

In general, the utilization of a PSO algorithm to optimize the parameters of CNN might result in superior performance when compared to more conventional optimization strategies. However, the efficacy of this strategy will be determined not only by the nature of the issue at hand but also by the calibre of the implementation.

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