# GA-NN and PSO-NN for medical images classification: a comparative analysis

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*Abstract*—**This work proposes a couple of hybridizations that are tested and compared; the first is based on genetic algorithms and neural networks (GA-NN), while the second stands for neural network hybridization with Particle Swarm Optimization (PSO).Where GA and PSO are used to enhance the neural network parameters, leading to better results than either algorithm alone. The advancement of neural network strategies and GA, PSO, is a key task to raise performance, avoid time waste, and effectively enhance the classification process. The optimization of the NN structure was observed to attain both convergence and efficiency. Based on the experiments, it was determined that the utilization of a combination of (GA+NN) yields superior results in terms of accuracy (99%) when compared to the employment of (PSO+NN), which achieved an accuracy of 96%. In addition, there are numerous types of outcomes in neural network design optimization. Overall, these approaches offer promising solutions for the medical images calssification (MIC) problem.**

***Keywords— COVID-19, Image Classification, Feature Extraction, Feature Selection, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Neural Network (NN)***

## I. INTRODUCTION

The medical images calssification is a difficult task that necessitates original methods of information exploration and performance enhancement. Neural network great success in various applications such as image analysis has enabled the collection of big data, providing significant opportunities for a wide range of areas, including e-commerce, industrial control, and healthcare. However, big data poses significant challenges in data mining and information processing due to its high volume, variety, velocity, and veracity. In recent years, Neural networks have played a crucial role in big data analytic solutions. This paper reviews emerging research on Neural network models for big data feature learning, highlighting the remaining challenges and future topics. Furthermore, artificial intelligence approaches, including machine learning, increasingly popular in healthcare for the diagnosis of various diseases, including the COVID-19 pandemic [1][2][3][4].

The Coronavirus disease (COVID-19) has become a global health crisis, and there is a need for accurate and efficient diagnostic tools to combat it. In this context, medical imaging techniques such as X-ray imaging have been explored for the detection of COVID-19. In 2020, Apostol Poulos and Mpesiana conducted a study to evaluate the performance of state-of-the-art convolutional neural network architectures for medical image classification in detecting Covid-19 disease. They utilized a dataset of X-ray images from patients with confirmed COVID-19 disease, common bacterial pneumonia, and normal conditions. The study employed Transfer Learning, which showed that Neural networks with X-ray imaging can extract significant biomarkers related to COVID-19 disease, achieving high accuracy, sensitivity, and specificity. The findings suggest that incorporating X-rays into the diagnosis of Covid-19 could be assessed by the medical [5][6][7][8][9].

However, while these models have shown promise, they may not be able to distinguish between COVID-19 and other viral infectious diseases. Therefore, there is a need for more specific and accurate diagnostic tools to combat the pandemic. Future research could focus on developing machine learning models that can differentiate between COVID-19 and other viral infections, using a combination of various data sources, including medical imaging and clinical data, to improve accuracy and specificity [10][11][12][13].

In contrast, methods for feature selection have been used to improve model performance. These methods entail choosing the most crucial factors that affect classification accuracy. The paper is organized as follows: Section I is the introduction, Section II the techniques and methods used for this investigation. Genetic algorithms (GAs), Particle swarm optimization (PSO), Proposed method GA+NN, and The PSO+NN algorithm. Section III describes the dataset, the experimental protocol, and the results. Comparative analysis using parametric and non-parametric statistical methods are detailed in Section IV, results comparision in Section V, conclusion and perspectives are in Section VI.

## II. TECHNIQUES AND METHODS

GA+NN and PSO+NN are two powerful optimization techniques for image classification that have been proposed. First is based on genetic algorithms and neural networks (GA-NN), and second is neural network hybridization with PSO. Where GA and PSO are used to improve the parameters of a neural network, resulting in superior results over either algorithm alone.

### *A. Neural Network (NN)*

Artificial intelligence, called neural networks, is based on the composition and operation of the human brain. They may be used for a variety of activities, including picture and audio recognition, natural language processing, and predictive analytics, and they have the ability to spot patterns in data. In order to reduce the discrepancy between the expected output and the actual output, training entails changing the weights

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and biases of the neurons that make up a neural network's layers, as shown in Fig. 1.

In order to enhance neural networks and broaden their potential applications in industries like engineering, finance, and health, researchers are constantly developing novel designs and methodologies [14][15]. The features fed into a neural network include the output of our Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). can be used to find the best parameters for the neural network, which is a type of machine-learning algorithm that can learn to classify images. The neural network will learn to associate features with different image classes and can then use that knowledge to classify new images. One of several categories, such as COVID-19, pneumonia, normal pneumonia, or viral pneumonia.

which can improve classification accuracy. The overall process of classifying X-ray images using a neural network is as follows:

Converting the image into features 148 ---> Extracting 148 features from images.

In our case the imput is a feature vector representing the Xray image, and the output is coded vector representing the decision.

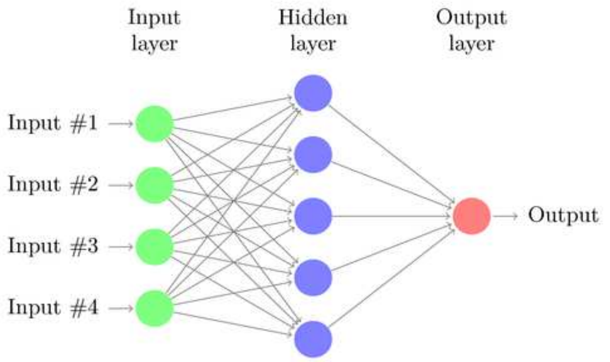


Fig. 1. Neural Network Structure

### B. Genetic Algorithm

Genetic algorithms (GAs) are a type of evolutionary algorithm that is inspired by natural selection. They are heuristic optimization methods that simulate genetic mechanisms such as mutation and crossover as well as population dynamics such as reproduction and selection. GAs can be used to build artificial intelligence algorithms or to teach machines. In GAs, solutions are encoded in arrays called chromosomes. The algorithm begins with an initial population of randomly generated chromosomes and then evolves the population in search of an optimal solution. At each generation, the fitness values of the chromosomes are evaluated, representing the degree of success of the encoded solution. The algorithm then selects the "parents," or mating pool, for the next generation based on the concept of survival of the fittest introduced by Darwin [16][17][18]. The combination of GA and NN can often lead to improved results compared to using either algorithm alone.

### C. Particle swarm optimization (PSO).

The population-based stochastic optimization method known as particle swarm optimization (PSO) draws its inspiration from the aggregative behavior of some animals, such as herds of birds or schools of fish. Kennedy and Eberhart first presented the PSO algorithm in 1995, and it has since gained widespread use in several industries thanks to its quick convergence time and simplicity of implementation. The PSO method, however, has low accuracy and is prone to early convergence. By fusing parallel models with PSO's built-in parallelism, the parallel mutation PSO approach was created to overcome these problems [19].

### D. Proposed method GA+NN

Finding the most informative subset of characteristics that can provide high performance while lowering computing costs is the goal of feature selection. A GA may be used to create an initial population of candidate feature subsets, which will help optimize the selection of features. To produce new generations, the population goes through processes like selection, crossover, and mutation. The chosen individuals go through crossover, in which parts of their feature subsets are switched to produce offspring with a fusion of characteristics. To add variety, arbitrary adjustments or alterations are made to the feature subsets of certain people.

The NN component evaluates the fitness of each individual in the GA by training and testing a neural network model using the selected features. The performance of the NN, such as accuracy or error rate, is used to determine the fitness of the associated individual in the GA. The GA explores the search space of potential feature subsets, guided by the fitness evaluations from the NN, to find an optimal or near-optimal subset of features for the given task, as shown in Fig. 2.

Overall, this GA+NN approach for feature selection combines the strengths of genetic algorithms in searching for good solutions and the representation power of neural networks to evaluate the quality of the solutions. It can be a valuable technique to address high-dimensional data problems and improve the efficiency and performance of machine learning tasks.

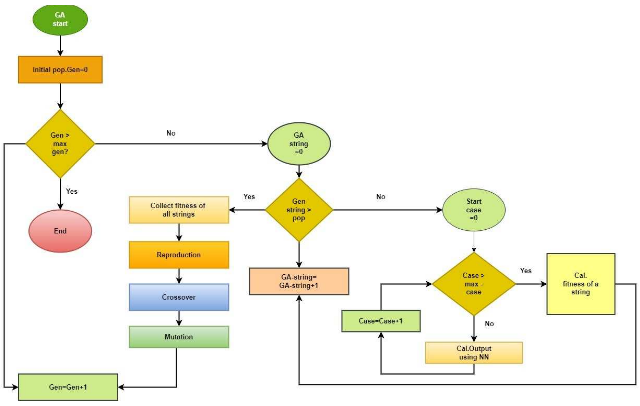


Fig. 2. GA+NN algorithm

The GA+NN algorithm involves the following steps:

- Initialization: A population of neural networks is initialized using random parameters. Each member of the population represents a set of parameters for the neural network.

- Fitness evaluation: The fitness of each member of the population is evaluated by training the neural network with the supplied parameters on a training dataset. The fitness is commonly computed as the accuracy or error rate of the neural network on a validation dataset.

- Selection: The fittest neural networks are selected for reproduction.
- Crossover: The fittest neural networks are crossed over to create new neural networks.
- Mutation: Some of the new neural networks undergo mutation, which randomly changes their parameters.
- Repeat: Steps 2-5 are repeated until the population converges, meaning that the fitness of the neural networks does not improve significantly over time.
- Best selection: The best neural network is selected from the final population based on its accuracy on the dataset.

### *E. The PSO+NN algorithm can be broken down into the following steps*

The PSO+NN algorithm is a powerful optimization technique that combines the Particle Swarm Optimization (PSO) algorithm with Neural Networks (NN) to find the optimal parameters for a given problem. PSO is used to search for the best set of weights and biases in a neural network that minimize a given objective function. In PSO+NN, a population of particles, each representing a set of weights and biases for the neural network, is initialized with random positions and velocities. The fitness of each particle is evaluated using the neural network, and particles are updated iteratively based on their own best position and the global best position found by the swarm. The PSO+NN algorithm can be used to solve a variety of problems, including image processing problems, and is particularly useful when combined with a neural network to improve performance. At the end of the algorithm, the weights and biases of the best particle are used as the optimal values for the neural network, as shown in Fig. 3.

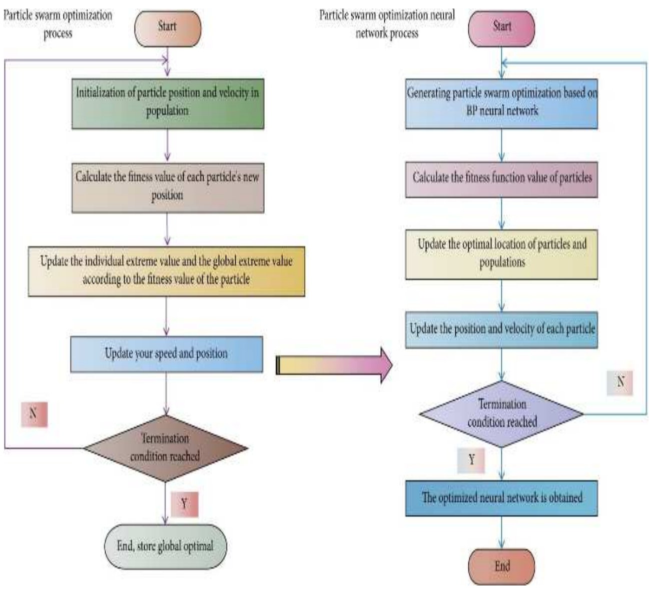


Fig. 3. PSO+NN algorithm

These performance results are calculated using Eqns. (1) - (2), as follows [20]:

$$vi(t+1) = w * vi(t) + c1 * r1(p\_besti(t) - xi(t)) + c2 * r2(g\_besti(t) - xi(t)) \quad (1)$$

$$xi(t+1) = xi(t) + vi(t+1) \quad (2)$$

*Where vi(t) is the velocity of particle i at time t, xi(t) is the position of particle i at time t, w is the inertia weight, c1 and c2 are the cognitive and social acceleration coefficients, r1 and r2 are two random numbers between 0 and 1, p_besti(t) is the best position found by particle i sofar, g_best(t) is the best position found by any particle in the population so far.*

## III. Results Discussion and Analysis

### *A. Dataset*

The dataset [21][22] that the study is are working on is of four types (COVID-19, lung-opacity, normal, viral pneumonia) according to the pictures of the diseases that have been worked on, which are 21165 images, as shown in Fig 4.

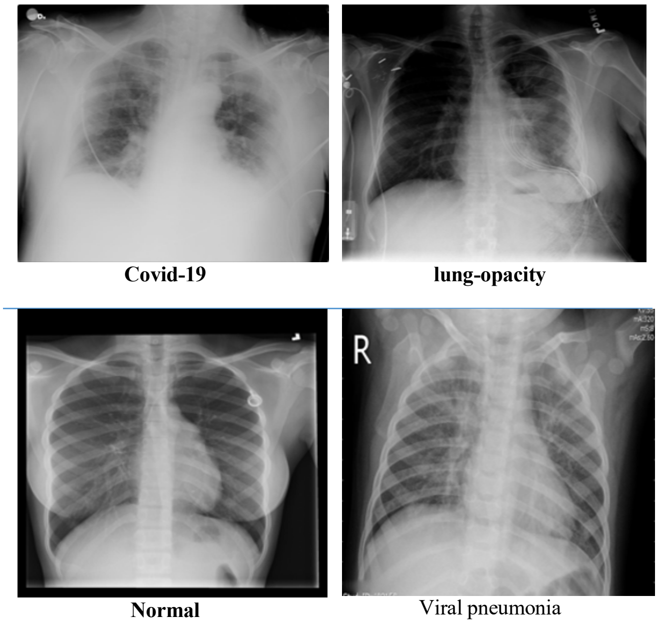


Fig. 4. The samples of the database

### *B. Results*

- *The GA+NN algorithm*

To split an X-ray imaging dataset into training and testing sets, such as 80% for training and 20% for testing. Next, the study can apply the GA+NN algorithm to train a neural network on the training set by defining a fitness function that takes in weights, creates a neural network, trains it on the training set, and evaluates its performance on the testing set. and then run the algorithm to determine the optimal set of weights for the neural network. Once the research has the optimal weights, it can create a neural network with those weights and evaluate its accuracy and loss on the testing set using the `classify function. Overall, using the GA+NN algorithm on X-ray imaging datasets can lead to improved accuracy and efficiency in medical diagnosis, potentially resulting in better patient outcomes, as shown in TABLE I.

TABLE I. GA+NN Result

| ID | GA+NN | | |
|---|---|---|---|
| | *Accuracy* | *Loss* | *Time* |
| 1 | 0.78 | 0.88 | 30.34 s |
| 2 | 0.79 | 0.85 | 27.23 s |
| 3 | 0.83 | 0.74 | 33.34 s |
| 4 | 0.85 | 0.65 | 31.98 s |
| 5 | 0.87 | 0.58 | 32.45 s |
| 6 | 0.89 | 0.49 | 37.68 s |
| 7 | 0.93 | 0.37 | 38.59 s |

| ID | GA+NN | | |
|---|---|---|---|
| | *Accuracy* | *Loss* | *Time* |
| 8 | 0.97 | 0.23 | 32.62 s |
| 9 | 0.98 | 0.18 | 38.45 s |
| 10 | 0.99 | 0.06 | 46.33 s |

The GA+NN algorithm achieved better time and lower loss, suggesting that it was able to find a better set of weights and biases for the neural network than the PSO+NN, resulting in better performance. Figures 5 and 6 illustrate these results.

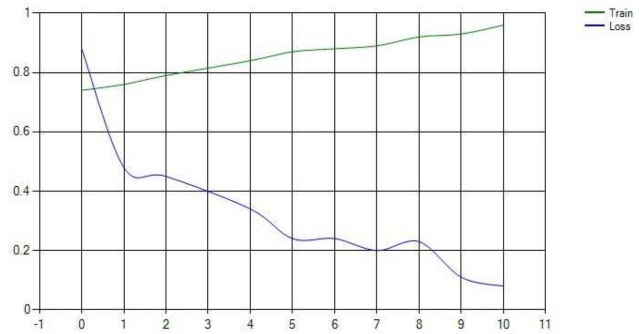


Fig. 5. GA+NN Result

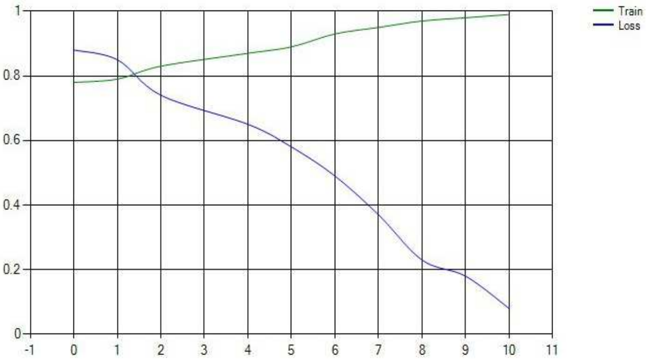


Fig. 6. PSO+NN Result

- *The POS+NN algorithm*

In the PSO+NN method, the study could divide the dataset into training and testing sets with a ratio of 80% for training and 20% for testing. Then, by constructing a fitness function that accepts weights, builds a neural network, trains it on the training set, assesses its performance on the testing set, and provides the fitness value, the study can use the PSO+NN method to train a neural network on the training set. The best set of weights for the neural network may be found by running the PSO algorithm after initializing it with the fitness function and other parameters. Once research has the ideal weights, it can build a neural network with those weights and, using the "classify ()" function, assess its performance on the training set in terms of accuracy and loss. In general, using the PSO+NN method on X-ray imaging datasets enhances diagnostic precision and effectiveness, thereby improving patient outcomes, as shown in TABLE II.

Based on the information provided, it appears that the GA+NN algorithm outperformed the PSO+NN algorithm in terms of accuracy and loss on the given datasets, as indicated in Figures 7 and 8. The GA+NN algorithm achieved higher accuracy and lower loss, suggesting that it was able to find a better set of weights and biases for the neural network than the PSO+NN algorithm.

TABLE II. PSO+NN RESULT

| ID | PSO+NN | | |
|---|---|---|---|
| | Accuracy | Loss | Time |
| 1 | 0.74 | 0.88 | 34.23 s |
| 2 | 0.76 | 0.85 | 32.23 s |
| 3 | 0.79 | 0.48 | 24.32 s |
| 4 | 0.84 | 0.45 | 31.45 s |
| 5 | 0.87 | 0.34 | 32.45 s |
| 6 | 0.88 | 0.24 | 33.56 s |
| 7 | 0.89 | 0.24 | 35.56 s |
| 8 | 0.92 | 0.2 | 32.65 s |
| 9 | 0.93 | 0.11 | 23.56 s |
| 10 | 0.96 | 0.08 | 24.54 s |

However, the performance of these algorithms is not solely determined by the combination used but also depends on various factors such as the specific problem being solved, dataset size, and hyperparameters used. Therefore, it is essential to consider these factors and conduct multiple experiments with different settings to determine which algorithm performs best for a particular problem.

Furthermore, in Figures 7 and 8, it is noted that the model training did not reach the optimal performance expected. The curves displayed in the figures did not exhibit the typical patterns seen in well-converged models. To address this issue and improve the results, it is recommended to increase the number of epochs during training. By doing so, the training process is allowed to continue for a longer time, and the model may converge better, leading to improved accuracy and reduced loss. Increasing the training duration can help the model learn better representations from the data and result in better overall performance.

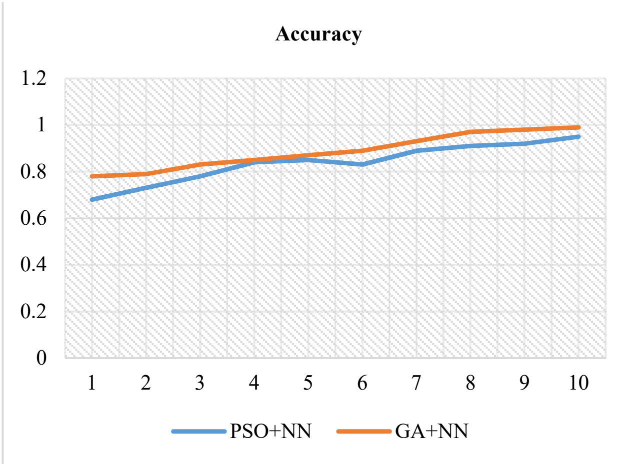


Fig. 7. Accuracy PSO+NN and GA+NN

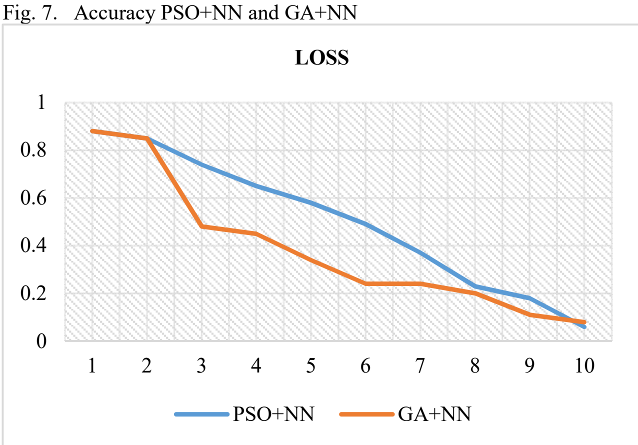


Fig. 8. Loss GA+NN and PSO+NN

## IV. WILCOXON SIGNED-RANK TEST.

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used either to test the location of a population based on a sample of data or to compare the locations of two populations using two matched samples.

### A. *Test for Evaluation Time (Descriptive Statistics)*

The results in TABLE III show that the median value for GA+NN is 31.47700, and for PSO+NN is 30.45500. This shows us that the central tendency of the GA+NN data is somewhat greater than that of the PSO+NN data, which gives an advantage to GA+NN.

Additionally, the results show the estimated upper and lower bounds show that the standard deviation of the GA+NN variable is 1.652325, which is smaller than the standard deviation of the PSO+NN variable, which is 4.509962. This suggests that the GA+NN data is less spread out around the mean than the PSO+NN data, which gives an advantage to GA+NN.

TABLE III. THE MEDIAN FOR THE VALUES AND DEVIATION OF THE VARIABLE

| | N | Mean | Std. Deviation | Minimum | Maximum | Percentiles | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | 25th | 50th (Median) | 75th |
| GA | 10 | 31.48 | 1.6523 | 27.23 | 33.34 | 31.57 | 31.98 | 31.98 |
| PSO | 10 | 30.46 | 4.51 | 23.56 | 35.56 | 24.485 | 32.34 | 33.7275 |

### B. *Wilcoxon Signed Ranks Test*

The results in TABLE IV illustrate that the Wilcoxon test values are calculated for three cases, namely a. PSO < GA, which showed four of the values are the least, that is, the time is less, and b. PSO > GA, which showed six of the values are greater, its time is greater, and c. PSO = GA. There are no equal values, which makes GA+NN superior in terms of results to PSO+NN, leading to improved accuracy and reduced loss, resulting in better overall performance.

TABLE IV. THE WILCOXON TEST VALUES ARE CALCULATED FOR THREE CASES

| | Ranks | | | |
|---|---|---|---|---|
| | | *N* | Mean Rank | Sum of Ranks |
| PSO - GA | Negative Ranks | 4[a] | 7.25 | 29 |
| | Positive Ranks | 6[b] | 4.33 | 26 |
| | Ties | 0[c] | | |
| | Total | 10 | | |
| a. PSO < GA | | | | |
| b. PSO > GA | | | | |
| c. PSO = GA | | | | |

## V. RESULTS COMPARISION

Modern medical systems depend on X-rays and CT scans for rapid diagnosis. The pneumonia infections in the patients' images help in this diagnosis. Where GA and PSO are used to enhance the neural network parameters, leading to better results than either algorithm alone. The advance of neural network strategies and GA and PSO effectively enhance the classification process in TABLE V.

TABLE V. COMPARATIVE DISCUSSION OF THE PROPOSED METHOD WITH THE COMPETENT METHODS

| Reference | Approach | Dataset used | Method /Algorithm | Accuracy |
|---|---|---|---|---|
| ALAM *et al.*(2021) [23] | CNN and HOG | CHEST X-RAY scans | Convolutional neural networks (CNN) Histogram -oriented Gradients(HOG) | 95.36% |
| MADAAN *et al.* (2020) [24] | XCOVN et (CNN) | 392 CHEST X-rays (50% positive ,50%negative | Pre-processing cnn, adam optimizer with learning rate o.oo1 | 94.44% |
| Umer *et al.*(2021) [25] | CNN with Keras Image Data Generator | COVID-19 datasets | *Convolutional Neural Networks (CNN)* | *94.56%* |
| Albahli and Yar (2021) [26] | Layered deep learning pipeline model | ImageNet dataset | Deep learning pipeline model | 95% |
| **Proposed method** | **PSO+NN** | **x-ray** | **Particle swarm optimization PSO + Neural Network (NN)** | **96%** |
| **Proposed method** | **GA+NN** | **x-ray** | **Genetic Algorithm (GA) + Neural Network (NN)** | **99%** |

## VI. CONCLUSION

The medical images calssification is a difficult task that necessitates original methods of information exploration and performance enhancement two potent optimization techniques for classifying images have been proposed: GA+NN and PSO+NN. The PSO+NN method is successful in locating the best NN parameters, but the GA+NN approach is more suited for feature selection and robustness in choosing the best feature for classification. The difficulty of the issue being solved, the amount of the dataset, and the hyperparameters employed by each approach can all affect how well any technique performs. To ascertain which algorithm works best on a certain problem, it may be necessary to do several trials with various settings. Future investigations will be focused on deep-evolutionary hybridations using deep echo state architecture combined with PSO and GA such in [27].

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