International Journal of Multidisciplinary Engineering in Current Research
ISSN: 2456-4265, Volume 7, Issue 2, February 2022, http://ijmec.com/

OPTIMIZING DEEP NEURAL NETWORKS USING HEURISTIC AND META-HEURISTIC ALGORITHMS

Nuthalapati Koteswararao[1], B. Govardhan2[1], Dr. Pedapudi Sambasiva Rao[3]
[1] Assistant Professor, Department of CSE, Rise Krishna Sai Gandhi Group of Institutions,Ongole,[2] Associate Professor, Department of CSE, Rise Krishna Sai Prakasam Group of Institutions, Ongole,[3] Professor, Department of CSE, Rise Krishna Sai Gandhi Group of Institutions,Ongole.

Abstract— The main objective is to use heuristic and meta-heuristic methods to optimize deep neural networks.The increasing popularity of deep learning and artificial intelligence, which calls for quicker optimization techniques to produce more accurate results, is the driving force behind this effort. Particle Swarm Optimization (PSO), Backpropagation (BP), Resistant Propagation (Rprop), and Genetic Algorithm (GA) are the algorithms used. Several datasets are subjected to numerical analysis using the techniques.In order to reduce training loss, the performance of PSO, BP, Rprop, and GA are compared in this analysis. Finding out which algorithms find optimal solutions more effectively is the aim. It is underlined that meta-heuristic algorithms such as GA and PSO are higher-level, problem-independent methods that can be used to a wide variety of problems. It is well known that heuristic algorithms have extremely specialized characteristics that change according to the task at hand. All of the standard algorithms are extensively presented, including BP, GA, PSO, and Rprop.How these processes are used to optimize artificial deep neural networks is explained in the abstract. Numeral simulations applied to several datasets are run. Based on error convergence and training epochs, the results are assessed. The algorithms are evaluated, and it is noted that over the datasets, meta-heuristic algorithms (PSO and GA) fared better than traditional heuristic algorithms (BP and Rprop). The analysis is predicated on error convergence and training epochs, suggesting a thorough appraisal of algorithm performance.

Keywords— **Artificial Neural Networks, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Backpropagation (BP), Meta-Heuristic Algorithm, Heuristic Algorithm .**

I.INTRODUCTION

For more effective computational benefits, the exponential expansion of AI, ML, and DNNs demands quicker learning and optimization methods. For research purposes, Particle Swarm Optimization (PSO) is used. characterizes the neural network as a system with dense layers, neurons, synapses, and biases that is bioinspired. demonstrates how changing weights allows neural networks to learn by reducing the cost of predictions. In order to improve and increase the accuracy of the predictions made by the neural network, meta-heuristic and heuristic techniques are suggested for changing the weights. contrasts application-specific algorithms (BP, Rprop) and generic bio-inspired algorithms (PSO).explains the idea of resilient propagation as a heuristic algorithm and highlights the conventional application of backpropagation (BP). explains how neural networks work, including how they process patterns of input, update synaptic weights, and produce precise outputs. suggests comparing the performance of bio-inspired algorithms to those of heuristic Resilient Propagation and application-specific Backpropagation. raises questions regarding the possibility

ISSN: 2456-4265, Volume 7, Issue 2, February 2022, http://ijmec.com/

of long training times due to meta-heuristic algorithms becoming stuck in local minima. Recognizes ramifications, such as the possibility that local minima may trap meta-heuristic algorithms, lengthening the training time.

II .DEEP NEURAL NETWORK OPTIMIZATION

An ANN with numerous dense layers is referred to as a deep neural network. Each layer is made up of biases, synapses, and neurons. Multiple degrees of abstraction can be learned for data representation using DNNs. Algorithms that can optimize a simple neural network's weights are mentioned. acknowledgement of a notable advancement in the neural network optimization discipline. Numerous fields, including as object identification, pattern recognition, modeling, and prediction, have benefited substantially from the use of neural networks. An explanation of how a neural network works: it takes inputs, propagates them forward, produces outputs, then compares those outputs to target values to determine the loss. explanation of how a model's accuracy is affected by loss. a focus on reducing the loss in order to forecast results that are as near to the actual data as feasible. Introduction of the loss optimization approach for neural network weight training. The objective is to identify weights that, when applied to the dataset, reduce loss, showing that the model fits the problem well.

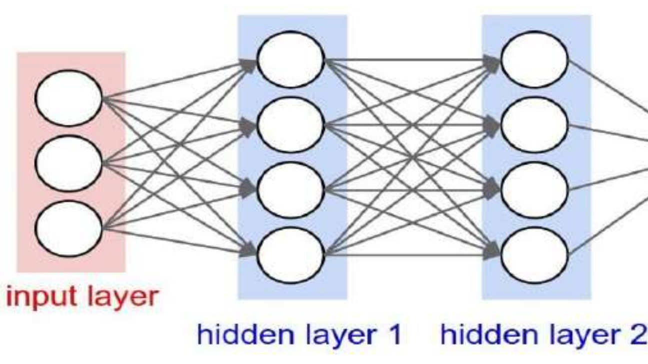


Fig. 1. Deep Neural Network

III. PARTICLE SWARM OPTIMIZATION

PSO begins with a population of particles, which are hypothetical solutions. In the solution space, every particle is a potential solution. The objective function that must be minimized or maximized is defined by the optimization issue. This objective function is used to evaluate the placements of the particles in the solution space. Based on its own and its neighbors' experiences, every particle modifies its position and velocity. A particle moves according to two parameters: the best-known position inside its own population (local best) and the best-known position across the entire population (global best). The following formulas are utilized to update the position and velocity of every particle: Velocity Update: Until a termination condition is satisfied, the algorithm iteratively modifies the particle locations and velocities.Indeed, in the context of neural network optimization, you have given a thorough explanation of Particle Swarm Optimization (PSO). The relationship between the algorithm and the optimization of synaptic weights in neural networks is highlighted by the manner you have presented it.

With this method, a neural network's synaptic weight values are represented by each particle in the population. The next step is to iteratively update the position and velocity of these particles in order to explore the solution space and converge on the neural network's global optimum. The importance of the particle's personal best-known position (pbesti), the global best-known position (gbest), and the inertia weight (w) in deciding how the particles travel across the search space is evident from the formulae you stated for position (xi) and velocity (vi) updates.

$$Vidn+1=wVidn+c1r1\ (pidn-xidn)+c2r2(pgdn-xidn)$$

$$Xidn+1=Xidn+Vidn+1$$

International Journal of Multidisciplinary Engineering in Current Research
ISSN: 2456-4265, Volume 7, Issue 2, February 2022, http://ijmec.com/

The relationship between PSO and neural network optimization is particularly intriguing since it makes effective use of the algorithm's social behavior inspiration to find optimal configurations quickly in a high-dimensional space.

IV .RESEARCH METHODOLOGY

1. **Data Acquisition**:

This entails gathering the information required for your research. It might contain datasets pertinent to your problem or research question. The effectiveness and generalizability of your machine learning models can be strongly impacted by the type and quality of the data you collect.

A.XOR Gate Dataset

• The XOR logical gate is represented by this dataset. It comprises four observations, two input variables, and one outcome variable. Artificial neural networks frequently utilize it as a basic example during training to demonstrate the network's capacity to understand and express non-linear decision boundaries.

B. Iris Dataset

There are 150 observations of iris blooms in the Iris blooms Dataset. The width and length of the petals and sepals are two of its four characteristics. There are three classes in the dataset: Iris Versicolor, Iris Virginica, and Iris Setosa. frequently used to practice classification algorithms, especially for determining the differences between various kinds of iris flowers based on their dimensions.

C.Sonar Dataset

Using sonar echoes from various angles, the Sonar Dataset is used to classify an object as a Rock (R) or a Mine (M). It comprises 60 input variables, 1 output variable, and 208 observations. A famous case of binary classification, especially with regard to underwater object recognition.

D.Ionosphere Dataset

Radar systems that measure free electrons in the ionosphere are associated with the Ionosphere Dataset. It is a binary classification problem with two classes that is utilized for weather forecasting. With 34 input variables and 1 outcome variable, it has 351 observations total. used in binary classification problems with an uneven distribution of observations per class to determine whether the atmosphere is "Good" (G) or "Bad" (B).

2. **Applying Algorithms**

Using the Encog machine learning library, you have implemented a number of machine learning algorithms. These algorithms consist of a modified Genetic Algorithm, Particle Swarm Optimization, Backpropagation, and Resilient Propagation. These algorithms are all used to optimize the weights of neural networks.

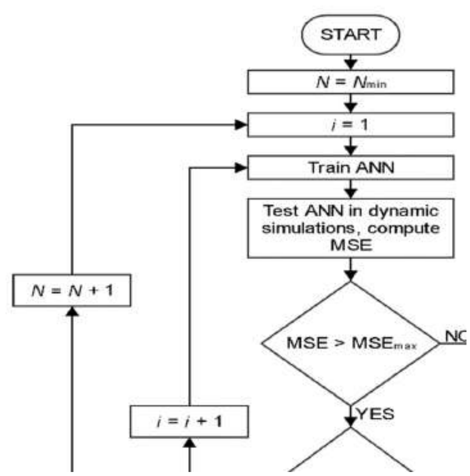


Fig 2 :Training Neural Network with Algorithms

3. **Evaluation Metrics**

International Journal of Multidisciplinary Engineering in Current Research
ISSN: 2456-4265, Volume 7, Issue 2, February 2022, http://ijmec.com/

The epoch has been mentioned as an outcome measure. This is typical in machine learning, particularly in the training of neural networks, where an epoch denotes a whole run through the training set. Analyzing resource usage and training loss outcomes can reveal information about the algorithms' efficacy and efficiency.

4. **Tools**

Utilizing Matplotlib and NumPy, you have employed the Graph Tool to visually represent and examine the impacts of the classification procedure. A well-liked plotting library is Matplotlib, and NumPy is a commonly used Python module for numerical computations. Understanding the behavior of various algorithms and interpreting the results can both be aided by visualizations.

5. **Training Time**

You have chosen to use the epoch as a result, despite having indicated that training time can be calculated by averaging each iteration. The fact that epochs offer a standardized way to quantify training progress and are a natural metric in iterative training processes may have an impact on this decision.

V. RESULTS AND ANALYSIS

The main goal is to evaluate how well different heuristic and meta-heuristic techniques perform in lowering artificial neural network training losses or mistakes over a range of datasets. This research compares heuristic and meta-heuristic algorithms with the use of XOR gates, Iris, Sonar, and Ionosphere datasets. The results indicate that when compared to other algorithms, the Particle Swarm Optimization algorithm outperformed the others in every scenario. Seeing the decreases in training mistakes when the neural network is trained is the main focus of the investigation. A lower training loss value corresponds to increased accuracy. The goal of the research is to optimize artificial neural networks using a variety of algorithms, including heuristic and meta-heuristic techniques. The objective is to minimize the neural network's loss function and adjust the weights. It is reported that the Particle Swarm Optimization method fared better than other algorithms in terms of optimizing Neural Networks across the datasets, according to the study.

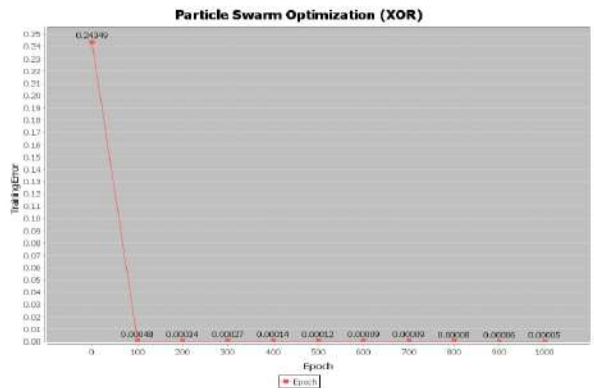


Fig 3: Applied Particle Swarm Optimization on xor gate

Epoch		Training Loss		
BP	Rprop	GA	PSO	
0	0.32482	0.81928	0.24622	0.24349
100	0.00902	0.00054	0.11366	0.00048
200	0.00226	0.00021	5.0E-41	0.00034
300	0.00133	0.00013	5.0E-41	0.00027
400	0.00089	0.00011	5.0E-41	0.00014
500	0.00065	0.00001	5.0E-41	0.00012
600	0.00051	0.00008	5.0E-41	0.00009
700	0.00041	0.00007	5.0E-41	0.00009
800	0.00034	0.00006	5.0E-41	0.00009
900	0.00029	0.00006	5.0E-41	0.00006
1000	0.00026	0.00005	5.0E-41	0.00005

TABLE 1 :CONTAINS ALL THE TRAINING LOSSES FOUND WHILE WE ARE TRAINING THE NEURAL NETWORK FOR THE XOR GATE

The findings in Table 1 show that Particle Swarm Optimization performed better than the other algorithms. They were able to reduce neural network loss and obtain improved convergence. The graphs show that GA and PSO had the lowest error rates in fewer epochs, especially Fig. 4 The graphs probably serve as a visual representation of each algorithm's performance and rate of convergence. The lowest loss values—which are associated with greater accuracy—are highlighted. The analysis and evaluation of each algorithm's convergence speed is extended to the Iris dataset in this study. The objective is to watch and contrast the outcomes in terms of loss values, where more precision is shown by lower values. The goal is to compare the convergence rates of several algorithms by closely examining the graphs for the Iris dataset. The precision attained by reducing the loss serves as the basis for evaluation. In addition, we have employed the Particle Swarm Optimization approach to facilitate faster neural network convergence when learning the Iris dataset. The findings presented in Figure 3 demonstrate that the algorithm outperformed other algorithms in finding the best solution for this dataset. We can observe that this bio-inspired algorithm, Particle Swarm Optimization (PSO), discovered the ideal solution in the first to last epoch while the other algorithm was still learning.

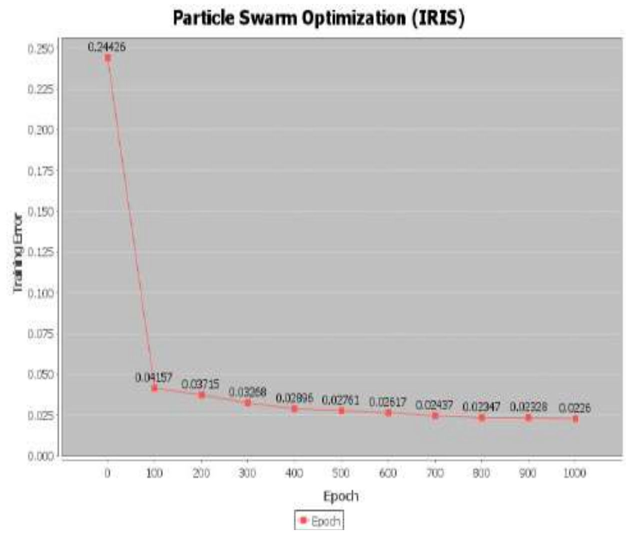
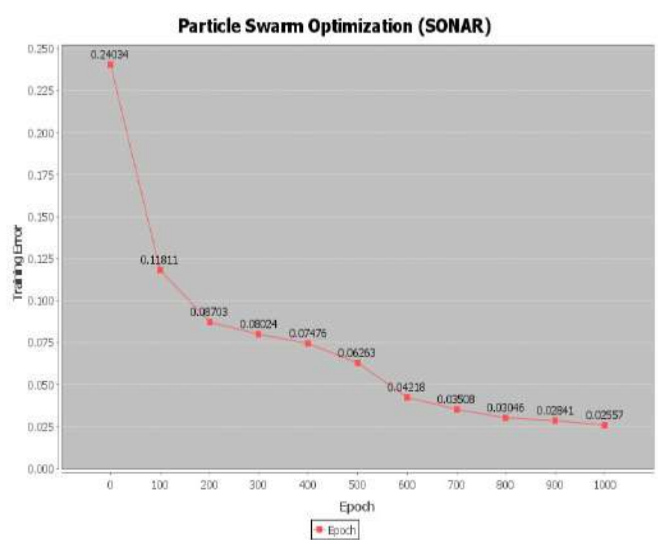


Fig 4 :Applied Particle Swarm Optimization on iris dataset

In addition, using Particle Swarm Optimization on the Sonar dataset is yielding effective results. In comparison to the Rprop algorithm we previously utilized, the Meta-Heuristic algorithm Particle Swarm Optimization (PSO) produced quite notable results in this case. The training loss that occurred during the training period is shown in Fig. 5. Furthermore, compared to the other method, this one offered a training error significantly more quickly.



International Journal of Multidisciplinary Engineering in Current Research
ISSN: 2456-4265, Volume 7, Issue 2, February 2022, http://ijmec.com/

Fig:5 Applied Particle Swarm Optimization on ionosphere dataset

The XOR gate, Iris, Sonar, and Ionosphere datasets are the four datasets that we have used in this instance. Particle Swarm Optimization performed better in the Iris, Sonar, and Ionosphere datasets.

In the study, we discovered that the evolutionary bio-inspired algorithm Particle Swarm Optimization—which is also a meta-heuristic algorithm—performed better after receiving training loss results.

VI CONCLUSION

Highlighting the effectiveness of bio-inspired and application-specific algorithms is the main driving force. These techniques are thought to be effective for optimizing loss functions and are modeled after natural behavior. Particle Swarm Optimization (PSO) is one of the meta-heuristic algorithms that is selected based on its computing efficiency. They draw inspiration from the evolutionary processes seen in nature and are efficient at optimizing loss functions. Neural networks are bio-inspired algorithms that are widely employed in many different industries. They are drawn from the behavior of living things. The goal is to improve the performance of neural networks by utilizing optimization methods that are inspired by nature, like PSO. The study emphasizes how crucial it is to use algorithms that are inspired by nature in order to achieve reliable and effective optimization. The goal is to improve algorithm performance by reverse engineering algorithms found in nature. Based on the case studies, it can be concluded that Particle Swarm Optimization (PSO), a bio-inspired algorithm, performed better than other algorithms in every circumstance. Even with the use of application-specific and bio-inspired algorithms, PSO consistently produced superior outcomes in all case studies, according to the study. According to the research, a more reliable and effectively organized algorithm can be created by employing nature-inspired algorithms, particularly PSO. According to the research, a more reliable and effectively organized algorithm can be created by employing nature-inspired algorithms, particularly PSO.

VII.REFERENCES

[1] *M. Carvalho and T.B. Ludermir, "Hybrid Training of Feed-Forward Neural Networks with Particle Swarm Optimization", Springer-Verlag Berlin Heidalberg, 2006.*

[2] *Venu G. Gudise and Ganesh K. Venayagamoorthy, "Comparison of Particle Swarm Optimization and Backpropagation as Training", 2003.*

[3] *Martin Riedmiller, Heinrich Braun, "A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm", 06 August 2002,*

[4] *Hong Cai, Yanda Li, "Fuzzy neural network optimization method based on Hopfield networks", January 1998.*

[5] *Seba Susan, Rohit Ranjan, Udyant Taluja, Shivang Rai, Pranav Agarwal "Global-best optimization of ANN trained by PSO using the non-extensive cross-entropy with Gaussian gain", Soft Computing 2020*

[6] *Abhijit Suresha, K.V Harisha, N. Radhikaa, "Particle swarm optimization over back propagation neural network for length of stay prediction", 2015*

[7] *Jiri Stastny, Vladislav Skorpil, "Designing Neural Networks using Genetic Algorithms." August 2007.*

[8] *Santosha Rathod, Amit Saha, Kanchan Sinha, "Particle Swarm Optimization and its applications in agricultural research" April 2020.*

[9] *W. D, "Stacked generalization," Neural Networks, vol. 5, pp. 241–259, 1992.*

[10] *J. Heaton, "Encog java and dotnet neural network framework", Heaton Re-search, Inc., Retrieved on July 20 (2010) 2010.*

[11] Agnes Lydia, Sagayaraj Francis, "A Survey of Optimization Techniques for Deep Learning Networks", May 2019

[12] Thomas Ragg, Heinrich Braun, Heiko L, "A Comparative Study of Neural Network Optimization Techniques", February 1997

[13] Cao Li; Xiaoyu Liu , "An improved PSO-BP neural network and its application to earthquake prediction" 28-30 May 2016