Nature Inspired Meta-heuristic Algorithms for Deep Learning: Recent Progress and Novel Perspective

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Abstract. Deep learning is presently attracting extra ordinary attention from both the industry and the academia. The optimization of deep learning models through nature inspired algorithms is a subject of debate in computer science. In this paper, we present recent progress on the application of nature inspired algorithms in deep learning. The survey pointed out recent development issues, strengths, weaknesses and prospects for future research. A new taxonomy is created based on natured inspired algorithms for deep learning. The trend of the publications in this domain is depicted; it shows the research area is growing but slowly. The deep learning architectures not exploit by the nature inspired algorithms for optimization are unveiled. We believed that the survey can facilitate synergy between the nature inspired algorithms and deep learning research communities. As such, massive attention can be expected in a near future.

Keywords: Deep Learning; Deep Belief Network; Cuckoo Search Algorithm; Convolutional Neural Network; Firefly Algorithm; Nature Inspired Algorithms.

1 Introduction

Nature inspired algorithms are metaheuristic algorithms inspired from the nature. The inspiration of the algorithms can be from natural biological system, evolution, human activities, group behaviour of animals, etc. for example, biological human brain inspired the proposing of artificial neural network (ANN) [1], genetic algorithm (GA) inspired from the theory of evolution [2], cuckoo search algorithms (CSA) inspired from behaviour of cuckoo births [3], artificial bee colony (ABC) got inspiration from the behaviour of bee [4], among many other algorithms. These nature inspired algorithms are found to be very effective and efficient in solving real world optimization problems better than the conventional algorithms because of their ability to effectively handle highly nonlinear and complex problems especially in science and engineering [5].

The ANN is the early and major breakthrough in the field of artificial intelligence. The ANN model has been very active in solving real world complex problems in different domain of machine learning application such as the health [6, 7], agriculture [8], automobile industry [9], finance [10], etc. Currently, ANN in its single, hybrid or ensemble form remained an active research area [11] and expected to witness more attention in the future, for example it is role in self-driving vehicles [9]. However, the ANN is trained with back propagation algorithm with limitations such as the problem of being fall in local minima and over fitting of training data. As a result of that, many researchers propose the use of nature inspired algorithm for the training of the ANN to avoid the challenges. For example, GA [12, 13], ABC [14], CSA [15], particle swarm optimization (PSO) [16] were applied to train ANN and it was found to be better than the back propagation algorithm and avoid the local minima problem.

Presently, deep learning [17] is a hot research topic in machine learning. The deep learning is the deep architecture of ANN with logistic on node weights update and activation function. When supply with a large scale data, the deep learning models and extract high level abstraction from the large scale data set [18]. However, the deep learning is face with many limitations but not limited to: lack of systematic procedure to realized optimum parameter values, manual configuration of the deep learning architecture and lack of standard training algorithm. As such, many approaches including nature inspired algorithms were proposed by researchers to mitigate the challenges.

The application of nature inspired algorithms in deep learning is limited because of the lack of synergy between the deep learning and nature inspired metaheuristic algorithm [19]. [18] present the role of natured inspired algorithms in deep learning in the context of big data analytics. However, the study argued that limited study can be found to apply nature-inspired algorithm in deep learning. Only one study that incorporated nature inspired algorithm in deep learning is reviewed in the study.

In this paper, we propose to extend the work of [18] by surveying more number of literature that hybridized nature inspired algorithm and deep learning architecture. This is to show the strength of the application of nature inspired algorithms in deep learning and new perspective for future research to encourage synergy between the natured inspired algorithms and deep learning research communities.

2 Nature Inspired Meta-Heuristic Algorithms

As already discussed in section I, these category of algorithms are inspired from nature. The number of nature inspired algorithms are many, likely more than 200 as argued by [20]. In this section, only the nature inspired algorithms that are found to be incorporated into deep leaning are outlined. However, the discussion of each of the algorithm is beyond the scope of this study. In the literature, little attention is given to the combination of the strengths of nature inspired algorithms and deep learning to create more powerful algorithm for solving real world problems. The nature inspired algorithm that are found to be hybridized with deep learning includes GA, CSA, harmony search algorithm (HSA), simulated annealing (SA), gravitational search algorithm (GSA), ant colony optimization (ACO), firefly algorithm (FFA), evolutionary algorithm (EA) and PSO. Interested readers can refer to [21] for the description of these algorithms and how their computational procedure operates to achieve a target goal.

3 Deep Learning

In machine learning, deep learning is considered as one of the most vibrant research area. The deep learning started gaining prominence from 2006, the time it was presented in the literature [22, 23]. In the real sense of it, the deep learning has been in existence since the 1940's. However, it is prominence came to lamplight starting from 2006 to current times because of the technological advancement in computing such as high performance computing systems, GPU, etc and the advent of large scale data [24]. Machine learning algorithm success highly depends on data representation, as such, the deep learning plays a vital role in processing the large scale data because it can uncover valuable hidden knowledge [23]. The Design of the deep learning architecture resulted from the extension of the feed forward ANN with multiples number of hidden layers [18]. The ANN forms the core of the deep learning. The major architecture of the deep learning involves convolutional neural network (ConvNet), deep belief network (DBN), deep recurrent neural network (DRNN), stacked auto-encoder (SAE) and generative adversarial network (GAN). The deep learning has performed excellently in different domain of applications including image and video analysis [25-27], natural language processing [28], text analysis [29], object detection [30], speech processing [31] and dimension reduction [32].

4 The Application of Nature Inspired Algorithms in Deep Learning

The application of nature inspired algorithms to train ANN is a subject of debate in computer science community. Those kicking against the application of nature inspired algorithms to ANN argued that the local minima that is being targeted to solve using nature inspired algorithms is not a serious problem. It is also echoed by [22] that the local minima problem is not a grave issue. Therefore, the application of nature inspired algorithm to train ANN to deviate from the local minima does not worth the effort. The local minima problem is believed to be caused by permutation at the hidden layers of the ANN which can be resolved amicably by minimizing errors. However, the school of thought on the other hand argued that the application of the nature inspired algorithms to train the ANN have its own strengths: Optimum weights can be realised. It can find the best optimum solution that is very hard to realise at a minimal computational cost. Therefore, the application of the nature inspired algorithms in deep learning architectures warrant extensive investigation to unravel the benefits [18].

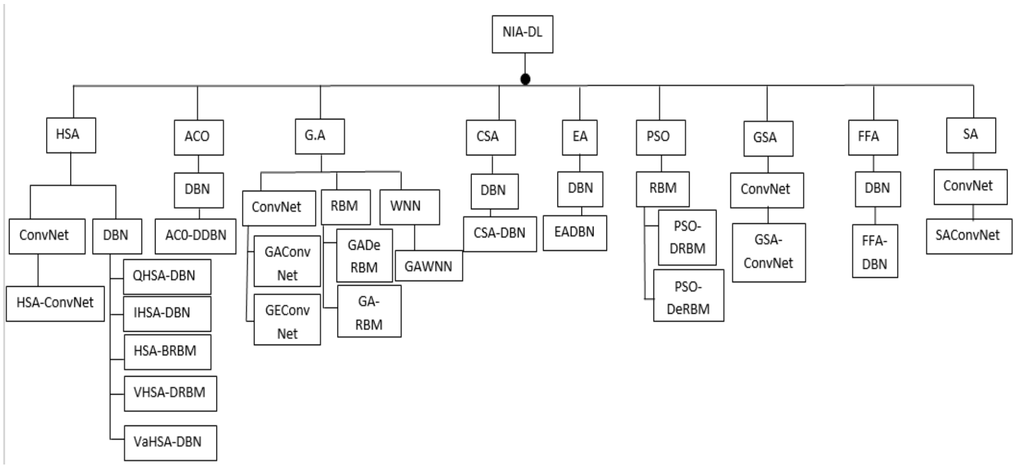

Fig. 1. Taxonomy of the natured inspired algorithms for deep learning architecture

There are efforts been made by researchers in the optimization of the deep learning architecture parameters through nature inspired algorithms. Fig. 1 is the taxonomy created based on the combination of the nature inspired algorithms and deep learning architecture as found in the literature. The efforts made by researchers are discussed as follows:

4.1 Harmony Search Algorithm for Deep Belief Network

The HSA and it is variants are found to be applied by researchers to optimise the parameters of DBN. For example, [19] propose quaternion HSA (QHSA) and improve quaternion HSA (IQHSA) to optimise the parameters of the DBN. The QHSA and the IQHSA are used to optimise the learning rate, hidden layer neurons, momentum and weight decay of the DBN (QHSA-DBN and IHSA-DBN). Both the QHSA-DBN and IHSA-DBN are evaluated on image reconstruction problem. It was found that the QHSA-DBN and IHSA-DBN perform better than the standard algorithms based on the HSA. [33] optimise Bernoulli restricted Boltzmann machine through HSA to select suitable parameters that minimizes reconstruction error. The HSA selected the suitable learning rate, weight decay, penalty parameter, and hidden units of the Bernoulli restricted Boltzmann machine (RBM) (HSA-BRBM). The HSA-BRBM is evaluated on benchmark dataset to solve image reconstruction. The HSA-BRBM is found to improve the performance of the state-of-the-art algorithms. [34] applied the optimization of discriminative RBM (DRBM) based on meta-heuristic algorithms to deviate from commonly use random search technique of parameter selection. The variants of the HSA (VHSA) and the PSO were used to select the optimum parameters (learning rate, weight decay, penalty parameter, and hidden units) of the DRBM (VHSA-DRBM and PSO-DRBM). The VHSA-DRBM and PSO-DRBM effectiveness were tested on benchmark dataset and found to perform better than the commonly use random search technique of selecting parameters. The HSA provide trade-off between the accuracy and computational load. [33] propose vanilla HSA (VaHSA) for optimizing the parameters of DBN. The parameters of the DBN were optimised by the VaHSA (VaHSA-DBN). The VaHSA-DBN is tested on multiple dataset and it was found to performs better than the classical algorithms. However, the convergence time is expensive.

4.2 Firefly Algorithm for Deep Belief Network

The FFA is one of the nature inspired algorithms that is used to optimise the parameters of deep learning architecture e.g DNN. For example, [35] introduce FFA in DBN (FFA-DBN) to calibrate its parameters for image reconstruction. The DBN calibration is done automatically by the FFA to eliminate the manual method of calibrating the DBN. The FFA-DBN is applied for binary image reconstruction. The results show that the FFA-DBN outperform the classical algorithms.

4.3 Cuckoo Search Algorithm Deep Belief Network

The CSA is among the active algorithm that gain prominence in the literature. It finds it is way into deep learning for parameter optimization. For example, [36] fine tune the parameters of DBN through CSA to optimise the parameters. The CSA optimises the DBN parameters to realise the CSA-DBN. The performance of the CSA-DBN is evaluated on multiple datasets. The CSA-DBN performance is compared with that of the PSO, HS and HIS for optimising the DBN with different layers. The results suggested that the CSA-DBN perform better than the compared algorithms.

4.4 Evolutionary algorithm for Deep Belief Network

The EA is used to optimise the parameters of DBN. This is the only study to the best of the author's knowledge that applied EA for DBN parameter optimization. [24] applied adaptive EA in DBN to automatically tuned the parameters without the need for pre-requisite knowledge on DBN domain knowledge. The EA DBN (EADBN) is evaluated on both benchmark and real world data set. The result of the evaluation shows that the EADBN enhance the performance of the standard variants of the DBN.

4.5 Ant Colony Optimization for Deep Belief Network

The ACO is an established algorithm for solving optimization problem. It is found to be used for the optimization of DBN parameters. To deviate from the challenges of getting optimum parameters of discriminate deep belief network (DDBN), ACO is applied to automatically determine the best architecture of the DBN without heavy human effort. The number of neurons on 2-hidden layers and the learning rate of the DBN were automatically determined by the ACO (ACO-DDBN). The ACO-DDBN is applied in prognosis to assess the state of health of components and systems. The performance shows that the ACO-DDBN performs better than the classical grid based DDBN and support vector machine in both accuracy and computational time [37].

4.6 Particle Swarm Optimization for Deep restricted Boltzmann Machine

The PSO has been applied to solve many optimization problems. The DRBM parameters is optimise by the PSO as found in the literature. [38] applied PSO for automatic determining of the structure of deep RBM (DeRBM). The PSO determine the optimal number of units and parameters of the DeRBM, code name PSO-DeRBM. The PSO-DeRBM is used to predict time series. The performance of the PSO-DeRBM is evaluated by comparing it with multi-layer perceptron neural network (MLP). Results shows that the PSO-DeRBM is superior to the MLP.

4.7 Harmony Search algorithm for Convolutional Neural Network

The HSA has been applied to DBN as discussed in the precedent section. However, [35] proposes variants of HSA to fine-tune the large number of parameters in ConvNet (HSA-ConvNet) to avoid the manual process because it is prompt to error. The HSA-ConvNet is applied on handwritten, fingerprint recognition and classification of images. It has shown to perform better than the standard algorithms.

4.8 Genetic Algorithm for Convolutional neural network

The GA is one of the earliest nature inspired algorithm that motivated researchers to propose different variants of nature inspired algorithms. It has been used extensively in solving optimization problems. The GA is used to optimise the parameters of deep learning model. For example, [39] applied GA and grammatical evolution to reduce the manual trial and error procedure of determining the parameters of ConvNet (GAConvNet and GEConvNet). The evolutionary algorithms are used to determine the ConvNet architecture and hyperparametrs. The GAConvNet and GEConvNet are evaluated on benchmark dataset. The results suggested that the GAConvNet and GEConvNet enhance the performance of the classical ConvNet.

4.9 Genetic Algorithm for Restricted Boltzmann Machine

The GA is also applied for the optimization of RBM parameters, two studies were found to use GA for the optimization of RBM. First, [40] propose the use of GA for the automatic design of RBM (GA-RBM). The GA initializes the RBM weights for determining the number of both visible and hidden neurons. The GA is able to realized optimum structure of the Deep RBM. The GA-RBM was tested on handwritten classification problems. The results show that the GA-RBM performs better than the conventional RBM and the shallow structure of the RBM. [41] incorporated GA into DeRBM. The weighted nearest neighbour (WNN) weight is evolved using the GA. The effectiveness of the propose GA based WNN (GAWNN) and DeRMB (GADeRMB) is evaluated on classification problems. It is found to perform better than the SVM and statistical nearest neighbour.

4.10 Simulated Annealing for Convolutional neural network

[42] used SA to improve the performance of ConvNet. The SA is applied to ConvNet (SAConvNet) to optimize the parameters of the ConvNet. The performance of the SAConvNet is compared with the classical ConvNet. The SAConvNet enhance the performance of the ConvNet but convergence time increases.

4.11 Gravitational Search Algorithmfor convolutional neural network

[43] incorporated GSA into ConvNet to improve its performance and avoid been stuck in local minima. The GSA is used for the training of the ConvNet in conjunction with back propagation algorithm (GSA-ConvNet). The GSA-ConvNet is evaluated on OCR application. The GSA-ConvNet is found to improve the performance of the conventional ConvNet.

5. The general overview of the synergy between nature inspired algorithms and deep learning

An overview of the research area is presented in this section to show the strength of incorporating nature inspired algorithms in deep neural network architecture. It is clearly indicated that the penetration of nature inspired algorithms in deep learning has received little attention from the research community. This is highly surprising in view of the fact that both the deep learning and nature inspired algorithms research received unprecedented attention from the research communities (e.g see [44] for deep learning and [21] for nature inspired algorithms). Moreover, the two research areas are well established in solving real world challenging and complex problems. As already stated earlier, lack of synergy between the two research communities exist. However, evidence from the literature clearly indicated that combining nature inspired algorithms and deep learning has advantage of improving the performance of the deep learning architecture. This is because the empirical evidence shows that the synergy between the nature inspired algorithms and deep learning architecture always improve the accuracy of the conventional deep learning architecture. In addition, the laborious trial and error technique of determining the high number of parameters for the deep learning architecture is eliminated because the optimum parameters are being realized automatically by the nature inspired algorithms. As such, human effort in determining the optimum parameters is eliminated.

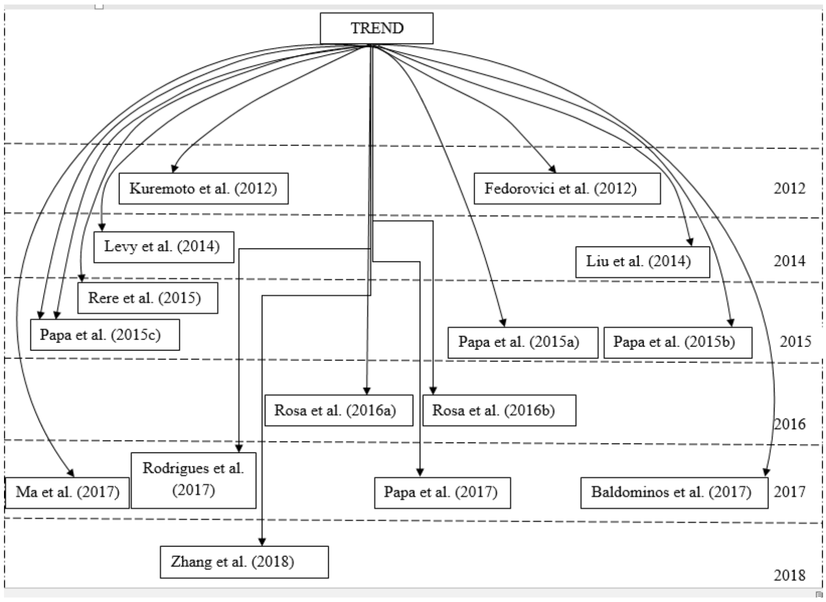

Fig. 2. The trend of the integration of natured inspired algorithms and deep learning architecture

Fig. 2 depicted the trend of the synergy between the nature inspired algorithms and deep learning. As shown in Fig. 2, despite the fact that the two research areas pre-date 2012, evidence from the literature indicated that the combination of nature inspired algorithms and deep learning started appearing in 2012 with two literature. In 2013, a break occurred without a single research in this direction. It is found that 2015 and 2017 witness the highest number of works. Though, 2018 is still active, a literature has appeared as at the time of writing this manuscript. We realised that papa et al. are at the forefront of promoting the synergy between the nature inspired algorithms and deep learning research communities. The research area does not get the magnitude of the attention it deserved. In general, it can be deduced that the research area is slowly gaining acceptability within the research community because the number of research in the last four years has increased. The trend is expected to grow in the near future at a faster rate.

5 Challenges and Future Research Directions

The nature inspired algorithms require setting of parameters themselves, the best systematic way to realize the optimum parameter settings of the nature inspired algorithms remain an open research problem. Therefore, adding nature inspired algorithm to deep learning constitute additional parameter settings. Though, the parameter settings of the deep learning architecture can be reduced in view of the fact that some of the parameters can be determine automatically by the nature inspired algorithms. In a situation whereby the parameter settings of the nature inspired algorithm is not good enough to provide good performance, it would have a multiplier effect on the deep learning architecture. Hence, reduce it is performance and possibly caused the model to stuck in local minima. This is correct because the performance of the nature inspired algorithms heavily depends on parameter settings. Future work should be on parameterless nature inspired algorithm to eliminate the need for human intervention in setting parameters. We expect future deep learning models to be autonomous.

Weights of the deep learning architecture plays a critical role because the performance of the deep learning architecture heavily depends on the optimal initial weights of the architecture. [32] argued that fine-tuning weights can be accomplished by gradient decent in auto encoder and it works well especially if the initial weights are near optimum. The critical nature of the weights in influencing the performance of the deep learning prompted many researchers to propose various ways of getting optimum weights (e.g [45-47]). Despite the critical role been played by the initial weights of the deep learning architecture, very few concern is shown on the deep learning architecture initial weights optimization through the application of nature inspired algorithms. Intensive study on the application of nature inspired algorithms for optimising deep learning initial weights should a major concern in future research.

Despite the fact that the nature-inspired algorithm improve accuracy, it sometimes increases convergence time for the deep learning architecture. As such, real life application that time is critical will not be suitable for implementing deep learning models incorporated with nature inspired algorithms. Typical example is medical facilities because one second can cause a serious tragedy or dead. Though, there is evidence that the nature inspired algorithms can improve the convergence speed of deep learning models. It can be concluded the performance of the nature inspired algorithm as regard to convergence speed is not consistent. In the future, researchers should work on the convergence speed of the nature inspired algorithm for deep learning to ensure it is consistency.

One of the major challenge of meta-heuristic algorithm is that it requires meta-optimization in some cases to enhance it is performance. The meta-optimization procedure is excessive in a deep learning applications. However, the deep learning application already has significant effort in computation [34]. As such, it can add to the complexity and challenges of the deep learning. In the future, researchers should work towards reducing the meta-optimization efforts in nature inspired algorithms.

[18] pointed out that the excessive optimization of ANN through nature inspired algorithm mitigates the flexibility of the ANN which can caused over fitting of the training data. Excessive training of deep learning models with nature inspired algorithms should be discouraged and control to the tolerant level.

The survey revealed that some major deep learning architectures such as the GAN, SAE, DRNN and deep echo state network were not exploit by nature inspired algorithms. The GAN [48] is a newly propose architecture of deep learning.

6 Conclusions

This paper proposes to present the recent development regarding the incorporation of nature inspired algorithms into deep learning architectures. The concise view of the recent developments, strengths, challenges and opportunities for future research regarding the synergy between the natured inspired algorithms and deep learning are presented. It was found that the synergy between the nature inspired algorithms and the deep learning research communities is limited considering the little attention it attracted in the literature. We belief this paper has the potential to bridge the communication gap between the nature inspired algorithms and deep learning research communities. Experts researchers can use this paper as a benchmark for developing the research area while novice researchers can use it as an initial reading material for starting a research in this domain.

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