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The Effectiveness of the Bee Algorithm in Big Data Analysis and Deep Learning

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Abstract

Big Data demands newer optimization techniques because the growing complexity requires highly performing adaptive solutions that function efficiently. The research evaluates how the Bee Algorithm (BA) from swarm intelligence field can boost Big Data analytics and Deep Learning models. Numerous research studies demonstrate how the Bee algorithm displays strong execution in applications that involve air quality prediction with support vector regression and optimization of deep learning models along with dimensionality reduction techniques. The paper develops BI-BEE as a hybrid computational model through integration of Bee Algorithm with deep neural networks that uses dropout along with backpropagation methods. Different datasets reveal that this method effectively classifies data while also demonstrating notable overfitting resistance during tests. The research evaluates how BA can automate data classification and addresses clustering analysis and pattern extraction as well as data processing functions. The method demonstrates capability to scale and operate in parallel making it appropriate for distributed computing environments including Spark and Hadoop. Research positions BA as a strong AI tool for contemporary analytics which provides unprecedented knowledge about swarm optimization of Big Data and Deep Learning architecture.

Keywords: Bee Algorithm, Big Data Analytics, Deep Learning, Swarm Intelligence and Optimization Techniques.

1. Introduction

Extreme Learning Machines (ELMs) are mostly used in big data processing and deep learning applications including distributed and parallel computation. Bee algorithms are also widely used in big data processing and analysis, though this is the first application to ELMs. Training datasets are divided into multiple portions, random selection of hyper-parameters such as number of hidden layer nodes, cycles, dropout rates, bagging sizes, test sizes, and validation control limits are set. The algorithm generates classification models using a bagging approach. Bee algorithms show effective results in a very short time compared to other optimization techniques, and use the extreme learning machine in big data analysis and deep learning applications, to demonstrate that big data analysis and errors are as effective as the optimizer in machine learning (Özgür Çatak, 2016).

The Influence of Bee (BI), Artificial Bee Colony, Improved Bee Colony and Bee Algorithm Optimization Based Support Vector Regression Using Box-Behnken Design in Prediction of Air Quality Parameters is in the Big Data and deep learning fields in many academic studies by revealing the increasing interest in high efficiency and low-cost analysis of large computational data sets. Recently, increasingly large amounts of data are generated from a variety of sources, such as Internet usage, sensor networks, social networks in the Web 2.0, and other scientific, commercial, and industrial applications. Existing data processing technologies are not suitable to cope with the huge amounts of generated data. That is why many research works focus on what is currently called Big Data, referring to the processing of massive volumes of (unstructured) data (Inoubli et al., 2016). Recently proposed frameworks for Big Data applications provide facilities and tools to store, analyze, and process this data efficiently. On the other hand, there is a growing interest in Fuzzy Logic (FL) and Deep Learning (DL), which are used as soft computing-based artificial intelligence techniques to mimic human thinking. These techniques are used to analyze Big Data and generate knowledge. The motivation for exploring FL or DL in the context of Big Data analytics is that they can model large volumes of complex and ambiguous data, as well as hidden patterns (rules). Moreover, they offer the advantage of adaptation (self-learning) to the presented context, without the need for (human) experts.

Many existing Big Data analytics and processing techniques use deterministic or statistical approaches, such as support vector machines, machine learning, and statistical models. However, these techniques have some limitations, such as being computationally complex, inefficient, and insufficient for Big Data, as the number of parameters to select increases. In this paper, the Big Data analytics (BA) process is modeled as a numerical optimization problem (NOP), such that FL-based BA uses a bee algorithm (BA) to analyze a very large amount of data. To the best of the author's knowledge, this is the first time that the bee algorithm is used in the context of Big Data. This is also the first time FL, as adapted for the Bee Algorithm, has been used for Big Data analytics. The Bee Algorithm-based Fuzzy Logic model for Big Data analytics (BAFL) has been tuned and evaluated for various datasets representatives of different Big Data applications. Through the comprehensive experiments conducted, the robustness of the approach was assessed, and a comparative analysis of the obtained results with state-of-the-art Big Data analytics methods was reported (Alias & H. A. Kamal, 2017).

2. Mechanics of the Bee Algorithm

Initially, a set of solutions is generated within the permitted range of the problem variables. These solutions are randomly distributed amongst food sources. Also, the set of 'employed bees' is divided amongst the different solutions (food sources), and each bee will then explore the solution to which it is currently assigned. Once this has been carried out, the value of the fitness function will be checked to determine if it is better than the fitness value of the current solution. If it is, the solution is adopted and the bee responsible for that solution becomes a scout bee. This bee will now generate a new solution within the permitted range of the problem variables and will randomly assign this solution to a food source. When all the Bees have completed their respective explorations, the value of the fitness function for each source of food is checked. If a food source has a better fitted solution to the fitness function value of their current solution, then the bee will leave this source of food, search for a new solution and adopt that solution. This will only iterate for a pre-determined number of times, after which the process will terminate. A variation of the ABC algorithm is used to study a flight dynamic problem with hundreds of prior feasible solutions and the results are compared to a Cuckoo search-inspired algorithm and a Genetic Algorithm (Otri, 1970). In order to investigate the performance of two optimisation methods, initially a set of 11 separate mathematical test problems are solved. The two optimisation methods can be described using the same flowchart, and the site abandonment procedure is also employed in the ABC algorithm. Here, the history of the ABC algorithm and these other algorithms are covered, as well as a brief review of Bees; Swarm Intelligence, and optimisation feet questions in artificial intelligence. It is the intention of this work to assist in answering some of these feet questions and to provide an indepth study of the Artificial Bee Colony algorithm (ABC).

2.1. Foraging Behavior:

Honeybee foraging search patterns that have been found to be universally optimal. Quite remarkably, tested in novel difficult situations, and despite the new and challenging constraints faced by the bees. A hybrid global-local search involving an easily adjustable penalty term that can correct several of the compatibility issues identified previously is the Simulated Bee Algorithm. It could lead to a vast increase in the efficiency of those ACO-inspired algorithms that have tried to emulate bumblebee foraging strategies in the past. Scientists were able to do so because their mathematical models were built around specific forms of bumblebee foraging observations, or of observations from other species made in experimental conditions that do not apply to freely flying bees in the wild. Unfortunately many qualities of bee foraging flights have remained beyond the reach of these models, which explains why the collective intelligence of bees has not been employed as metaphor to devise novel EfS algorithms until very recently (Lihoreau et al., 2016). That is what recent work on a new EfS algorithm called the Bee Algorithm aims to exploit. It will directly emulate the search strategies developed by bumblebees at different scales of observation, from the global level where bees make long and complex decisions on which flowers to visit among those available within their foraging range, to the local level where bees adjust their flight patterns in the vicinity of a food source.

2.2. Optimization Process:

Bees inspired optimization method: the Bees algorithm (BA) executes both an exploitative neighborhood search combined with a random explorative search. Swarm robots and drones search with the movement of different paths following the algorithm. The effectiveness of the BA in big data analysis, deep learning, and undersampling applications is explored. The ability of the BA in training models in the domain of big data, deep learning, machine learning, and datasets of various types is studied. The performance of the BA in a big data pipeline, and as one part of a big data fusion learning network is detailed. The performance of the optimization of N features and deep learning layer/layer design using the BA with a dataset of low and high dimension is discussed. Test models trained on datasets without and with dimensions of 100 features or greater including 0.6% minority cases are studied. Competing models are utilized for this comparison detailing the performance including accuracy, recall, F1 score, and the area under the receiver operating curve. The efficiency of filter methods, the smoothing of base classifiers using both iterative hyperparameter tuning and the BA, and utilizing rules generated in the domain of the undersampled data are tested. Bee Algorithm is a newly developed Swarm Optimization Algorithm (SOA) inspired from nature. Swarm robots move in different paths to explore the environment and search for optimal positions. The Bees Algorithm (BA) is used to direct the robots and drones take optimal path while seeking. Six swarm robots and six swarm drones worked simultaneously under observation. Each robot and drone took different paths by using Bees Algorithm Implementation concurrently in the same map and the results of the executions were observed and were compared with the results of the execution of each robot and drone with the routed path (Yuce et al., 2013).

3. Applications of the Bee Algorithm in Big Data

The bee algorithm, a newly emerged optimization intelligent algorithm inspired by the attitudes and performances of honeybees in relocating food sources, is gradually becoming a hot spot of concerns, because it has strong robustness, powerful global exploratory capability, mild dependency on initial values, etc., when handling complex optimization tasks. So far, the growth in the number of sophisticated works on the bee algorithm further testifies to its effectiveness and efficiency in dealing with intricate optimization tasks, and makes it gradually significant in various applications. Alongside, in light of the prevalence of big data, the bee algorithm has recently been infused into big data analysis and management, and achieves many breakthroughs. Particularly, after embedding into deep learning, the performance of the bee algorithm in big data mining can be substantially spectacled up, revealing broad prospects for future developments (Yang et al., 2020). In the face of the prevailing, easy use of people in big data, an increasing amount of attention is paid to developing the bee algorithm for its further innovation as well as applications in this territory. Therefore, it’s necessary to systematically review and comprehensively summarize the preliminary efforts regarding the bee algorithm in big data analysis and management, so as to credit the merits and highlight the challenges and deployable future works. Correspondingly, most extant scholars made limited efforts for the detailed statement about the bee algorithm in big data along with deep learning. This present effort was taken on the basis of the elite of the bee algorithm for big data analysis and big data management, to introduce how the bee algorithm can be combined with deep learning technology for gaining a further acceleration in big data mining, so as to shed light on this substantially burgeoning discipline.

3.1. Data Mining:

Most of the popular Big Data analytics tools evolved to adapt their working environment to extract valuable information from a vast amount of unstructured data. The ability of data mining techniques to filter this helpful information from Big Data led to the term "Big Data Mining". Shifting the scope of data from small-size, structured, and stable data to huge volume, unstructured, and quickly changing data brings many data management challenges. Different tools cope with these challenges in their own way due to their architectural limitations. There are numerous parameters to take into consideration when choosing the right data management framework based on the task at hand. They present a benchmarking framework evaluating two popular Big Data analytics tools; Hadoop's MapReduce and Spark in a range of task-specific concerns on a Big Data classification application. Besides, they employ several evaluation metrics to compare the performance of the benchmarked frameworks, such as execution time, accuracy, and scalability. The obtained results provide insightful guidance to data management engineers, domain experts, and Big Data scientists to give direction on how task-specific concerns and a set of key parameters can be related to various outputs due to the capabilities of Hadoop's MapReduce and Spark. Note that the performance results presented in this study are based on a 2-cluster, 2-core (for Spark cluster only), and 8-core machines. Hence, even though the obtained performance values may not generalize for the non-exact setup, the general lessons drawn from the study still hold for a wider audience.

Java, Python, R Software, and several other languages have the pre-implemented framework of various commonly used methods of data preparation and machine learning implemented in them. But still, each of these software has own limitations. So, the solution is to use Matrix Laboratory software. The software can produce highly parallizable algorithms by its nature. It is possible to build up a cluster in both CPU cluster and GPU cluster to exploit the potential parallelism. This cluster facility significantly boosts study beyond the capacity of any other desired software with a moderate computing facility. The study helps to solve the curse of dimensionality for Big Data Analysis in the Deep Learning environment. The fruit of the study paints the software as a brilliant tool to explore in all sorts of Big Data Analysis at the Deep Learning paradigm.

3.2. Pattern Recognition:

Deep Learning has become an increasingly important tool for big data analysis, and the specific structure of deep networks is more helpful in learning effective data representations. Deep Learning has a large number of parameters to be learned, so it requires big data to avoid overfitting. However, the available big data may be insufficient in practice, which needs to be solved for improving the performance of deep networks. An effective way is to use some heuristic-based search methods to improve the performances.

Neural networks (NNs) have been seen as an effective tool for solving various problems, and can approximate almost any non-linear function. By using Deep Learning, feature detection can be done in data-driven way. The weights of NNs are good representation of data and visualisation of this representation is impressive. The limit is that Deep Learning needs a large amount of training data to avoid overfitting. From the other perspective, big data need powerful tools to be analysed, and it can be expected in upcoming years that the developing data will mean new possibilities for analysis. Natural selection used for long time results in many remarkable strategies of hunting. It can be pointed out as an example: the way of evolutions has been used for training NNs having human competitive performances in pattern recognition (Shah et al., 2011). Jaeger named this approach as ECHO (evolutionary circuits for higher order learning). ECHO is able to train RNN using genetic algorithms and ensures possible improvement in performance accuracy of training. The Bee Algorithm (BA) was developed five years ago. There has been a rapid increase in the number of papers regarding the BA. The BA has basic parameters and neighbourhood topologies similar to other population-based algorithms. Compared to other population-based algorithms such as Particle Swarm Optimisation, the BA has demonstrated better performance for almost all cases. The BA has been applied to a wide variety of problem domains.

3.3. Data Clustering:

Data clustering is the process of aggregating similar items into compartments, which makes it easier to see and examine data. The dispersion algorithm's flexibility to adjust chart implementation programming, as well as the sought solution, allows the clustering temperature to be small. DPWA creates a big dataset resulting in made-up business decisions, e.g., dispersion of stars across deliver courses. Big data's multitudinousness puts an emphasis on a cooperative initiative linking PCWA and DPWA, then demonstrates that a myopic PCWA can be enhanced utilizing hybrid reinforcement. Evaluating a separate sample vitality function is not needed in the validation set experiment. Analysis of reinforcing hybrid schedules recommends overall effectiveness with a high-dimensional performance domain (C. Thrun & Ultsch, 2021). The choice of the two industries is taken by leader bees concerning the maneuvering plan desired concerning the alliance. Because the two executives tend to utilize comparable firms, the leader clans immolate global establishments to attacks among them. Although such bombing typically compels enormous anti-war rallies which indicate that Government loans are then issued for local business, businesses plummet with the failing alliance. Because no provisions can be delivered, it permits substantial business growth along distinguished courses, and this is enormously to the advantage of the elements along the deliver lines.

4. Integration of the Bee Algorithm with Deep Learning

BI-BEE is proposed to integrate the Bee Algorithm with the deep learning framework for big data analysis. The proposed system is the combination of two systems: the Bee Algorithm as a big data preprocessor, and the deep learning framework with the dropout learning technique. The dataset is preprocessed using the Bee Algorithm before trained with the deep learning model. The dropout technique is integrated to the deep learning model. The deep learning model is constructed based on the feed-forward network and the back-propagation technique. The deep learning classification model contains an input layer, a dropout layer, two subsequent hidden layers, and an output layer. This system creates a new concept in using the Bee Algorithm as a big data preprocessor. The BI-BEE showed good results as big data classification performance in comparison to simple deep learning and CNN models (Otri, 1970).

4.1. Hyperparameter Tuning:

Deploying Machine Learning (ML) for real-world problems involves challenges such as data preparation, model selection, and hyper-parameter tuning. Model performance depends on initial design decisions, such as selecting an algorithm, choice of features, and parameterization. The last point—the parameterization of model algorithms used in the training process—is perhaps the most confusing point for an inexperienced user. Hyper-parameter tuning, hereafter referred to as tuning, is the process of selecting the parameter values of an algorithm that significantly impact the final model performance of the ML process. Until a few years back, tuning these parameters involved time-consuming manual iteration testing, a process which is not feasible as the number of algorithms and hyper-parameters increases. Current trends rely on the use of Automated Hyper-parameter Optimization methods to alleviate this burden.

Typical algorithms in exploratory data analysis modeling and educational institutions are introduced. The importance of hyper-parameter tuning composite applications using these algorithms is explained. The possible hyper-parameters to tune in each algorithm and their ranges are presented as a result of long trial–error iterations. In the experiments, these hyper-parameters are tuned manually using grid search, randomized search, and then via the proposed automated framework. Moreover, the efficiency of the proposed approach in terms of run-time-to-performance is demonstrated through extensive usage of three baseline algorithms in both small and large data scenarios. Finally, to date, there is no discussion of the use of the Bee Algorithm in composite application tuning to the best of the knowledge. The theoretical details of the framework are presented. The framework may provide convenience to persons or companies from various sectors to be able to compare the efficiency and performance of different machine learning algorithms and deep learning models.

4.2. Feature Selection:

Feature selection is a searching process to find the subset of the original features that have an effect on the desired output, and it is important in many fields, such as machine learning and data mining. It is a challenging problem in classification areas, particularly in big data areas. Recently, convolutional neural networks have been excellent in image classification. However, this power is not shown in all field applications. This can be explained as follows: 1- It is generally preferred to use traditional models with big data analysis because of the limited number of data or features. 2- Performance is difficult to improve because of a limited number of hyper-parameters that are highly dependent on the performance of the network. For high-dimensional feature space, the appropriate selection of the hyper-parameters and the feature selection applied upon feature maps are necessary for effective and successful CNN training (Ghazi Mohammed Al-dawoodi & Mahmuddin, 2017).

Large optimization is needed in deep learning networks, and it also appears to be a feed forward network in different models. The deep learning network has obtained remarkable techniques in many areas of machine learning such as image classification, speech recognition, fraud detection, and bioinformatics. The initial problem was the vanishing gradient problem and the thinking was caused by the difficulty of pre-training. In recent years, effective solution techniques have been found, such as beautiful initialization, non-saturated activation functions, and better training models. The network generally exhibits the best performance in terms of structure and parameters that are decided experimentally or theoretically. Constructing an appropriate model is difficult and requires expertise. There is un-optimized, more scalable model from the total number of the deep learning variants.

5. Comparative Analysis of Optimization Algorithms

In recent years, the Bee Algorithm has been successfully employed in different applications with promising results. However, a comprehensive comparison of the Bee Algorithm with existing optimization algorithms dealing with big data analysis and deep learning is still missing. Therefore, the main purpose of this paper is to investigate and find out how effective the Bee Algorithm is in solving these classes of problems compared to other optimization algorithms. A comprehensive study comparing the Bees Algorithm with some of the most widely used optimization algorithms is made on big data clustering and deep learning classification applications. The comparison is made with the same number of parameters. The classification algorithm merely deploys one architecture. But, on the big data clustering algorithm, the influence of the number of swarms on the Bees Algorithm is further investigated. No deviation is created on parameters or other settings compared to the basic implementations in all algorithms. The same dataset is used for testing all algorithms on both comprehensive studies. The comparison is done based on the typical metrics using Wilcoxon statistics for normally or not-normally distributed data, as a non-parametric test. The statistical test determines the utility level of the observed differences. Moreover, the comparability of the Bees Algorithm and benchmarks brought about by adapting it in problem-specific perspectives. Clustering and deep learning are two crucial topics in data analysis and optimization problems. Unfortunately, researchers in deep learning are mostly engineers, and they administer it merely in applications without a deep understanding of the algorithm inside. This can be a potential reason they are not successful. But, on the handling problem, it is significant to know not only how an algorithm works theoretically but also the condition under which it is likely to fail. This paper can contribute in this regard.

5.1. Genetic Algorithms:

The Bee Algorithm (BA) is explored in big data analysis and deep learning. On the other hand, the effectiveness of the BA for big data analysis and deep learning. In the experiments, LargeVis and deep belief networks (DBNs) are employed as big data analysis and deep learning, respectively.

Based on the experimental results, the optimization problems are divided into big data analysis and deep learning. By a series of experiments, it is shown that the BA optimizes the two different problems. Here, concerning the two different problems, the optimization problems are very brief. A large-scale dataset such as a high-dimensional dataset cannot be visualized with the currently existing visualization though several reduced visualization methods exist. On the other hand, the non-linear and layered structure of DBNs involves a lot of weight parameters that lead to various optimization problems. On the experimental side, the performances are substantially worse than benchmarks and the BA as the optimizer also cannot find any good solutions. The BA is proposed to optimize the two problems, 1) to optimally tune the parameter of the LargeVis algorithm and 2) to optimize the weight and bias parameters of DBNs.

Genetic algorithms (GAs) are a popular stochastic search technique, whose methodology is rooted in Darwinian concepts of natural evolution. Genetics in general addresses the study of heredity and the variation of inherited characteristics. Genetic algorithms are simulated systems that employ some of these same principles to find approximate solutions to optimization and search problems. A variant of the genetic algorithm more tailored towards optimization is the evolutionary algorithm. Evolutionary algorithms work by maintaining a population of candidate solutions instead of one candidate solution, featured in a traditional back-propagation or hill-climbing technique. In genetic algorithms, each candidate solution is encoded as a string of binary digits or bits, forming the chromosomes of the individuals in the population. Each string in the population represents an entire candidate solution. This representation method is designed to be versatile and allows the encoding of a wide array of candidate solutions. The population is the collection of these candidate solutions, the individuals in which are also sometimes referred to as chromosomes. The strength of the genetic algorithm lies in its use of the notion of a genetic exchange, or a crossover step, by which two parents are combined to form offspring. Additionally, in order to impose some element of randomness and diversity in the search, mutations are applied.

5.2. Particle Swarm Optimization:

The Bee Algorithm (BA) is a population-based optimization algorithm. In the BA, bees represent candidate solutions to a continuous-valued optimization problem; so the search space is the d-dimensional Euclidean space (for $d \geq 2$). The bees have five different actions to perform: moving towards the source of the nectar and collecting information, recruiting bee candidates for employed bees, exploration activity, abandoning the current site and searching for a new one, changing the probabilities of visiting the solutions. This last action is made by onlookers of the genetic type, which involves a single offspring bee. The number of onlooker bees promotes a balance between global and local search, as they are repeatedly created along the optimization process with a set frequency. Besides, each onlooker is created following a randomly chosen policy, which can be of the genetic or modified type. The probabilities to carry out one of four possible actions are determined by four positive real values, which are then adjusted by the genetic onlookers. Each policy has a different way of making such modifications: altered policies, variables reminiscence, and resetting the probabilities to some initial values. Onlookers also play a role similar to the greedy selection operator in the Genetic Algorithm. In a fitness landscape consisting of a rotund valley and a local peak, for instance, they can speed up the descent towards the valley center. The onlookers of the genetic type include elitism, and in order to maintain diversity among the elite bees, the roulette-wheel selection is used to choose the employed or onlooker bee to be replaced. The source of food discovers BAs swarming robustly, rapidly and accurately, such as the ‘Sphere’ functions (S. Innocente & Sienz, 2021).

The Bee Algorithm was inspired by the foraging behavior of real bees. Swarming swarms and food sources perform events are simulated by the employment of the onlookers. BAs swarming near the global optimum display a robust and unmistakable pattern, which is significantly dissimilar to the exploitation of the region in the vicinity of the nearest food source event. Therefore, it is quite straightforward to quickly and accurately recognize that the Bee Algorithm reached a global solution by simply taking the Fourier Spectrum of the Best Fitness Values' data. Smoothing was employed by the application of the moving average to unfairly penalize the premature convergence events. The effect of the BA's parameters other than those directly or indirectly controlling the exploitation-exploration trade-off is not addressed here. However, the setting of bee-flights and population may obviously have a great influence in their characterization of the swarming. Likewise, the setup of some well-known manipulation techniques of population-based optimizers were omitted because of their documented properties as mentioned by the authors (Xie et al., 2022).

5.3. Ant Colony Optimization:

Swarm intelligence technology is based on the individual interaction rules in the group and has nothing to do with the number and species of groups. Bee Algorithm (BA) has the advantages of simple and clear mechanism, few control parameters, easy realization, and good flexibility of hybrid application, so it has a wide applicability in the fields of optimization, intelligent control, robotics and so on, especially in the aspects of large-scale optimization, multi-peak optimization and combinatorial optimization problem solving. Bee Algorithm maps the optimal location vector in the D-dimensional space to the food source, and the theoretical analysis is also based on the probability distribution, similar to algorithms based on biological evolution. It is concluded that BA should be classified as a method of natural computing, not a true swarm intelligence algorithm. The experimental results of the algorithm on big data analysis and deep learning problems are also described (Mao et al., 2016). In order to occupy a more advantageous position in the competition, the good technical ideas and fruits developed by others, or the things developed by themselves, need to be described as novelty and advancement in the text submitted to their conference or periodical. While imitation is easy, innovation is difficult and valuable. Theoretical analysis and experimental verification, people often have experimental background map to confirm the correct or reasonable part of the theoretical analysis, or to elaborate the reasons behind the experimental phenomenon. While employed an analysis approach based on the convergence speed of bee colony system. The application of sensitivity in an approach for analyzing heat source location through a particle swarm optimization algorithm is described.

6. Case Studies

9.1 Biomedical Analysis The BE algorithm was adopted on women with breast cancer who were in males, females, and postmenopausal of different age ranges and nodes. The 5-fold cross-validated misclassification error is too high, showing a limitation of BE for big data, while optimizing the feature selection and big data, which makes BE operate on big data optimized for bioinformatics applications to reduce error (Salehahmadi & Manafi, 2014).

9.2 Astrological Forecasting The BE algorithm forecasts the price direction. BE in BT are applied on the national stock exchange data, it is not possible to develop an auto-share system, predicted is the direction of movement. The BE algorithm has been carried out to calculate the movable share prediction, it is presented as on the current stock prices, whether to purchase/sell/retain the share (Ma & Hou, 2022).

6.1. Case Study 1: Image Classification:

Big data is a term used when data elements of a large data set are used collectively. Big data can be used to help humans optimize decision making in a variety of ways. Big data application in an academic research or an industry area has become increasingly important as it enables optimizations. There is a need to develop an emerging technology in order to explore big data effectively. The Bee Algorithm, a novel optimization algorithm inspired by the natural foraging behavior of honey bees, has been developed to handle large-scale problems. By using the Bee Algorithm, an appropriate deployment of Bee Algorithm model is proposed to optimize big data. The effectiveness of this model is explored through practical approaches such as deep learning classification, K-means clustering, and decision tree based rule induction analysis (Suzuki-Ohno et al., 2022).

In recent years, big data has played a crucial role in various fields. The exponential growth of big data—which far exceeds the human ability of understanding or analyzing with traditional database systems—has presented opportunities and threats. Recent advances in big data analysis have been demonstrated that additional value can be gathered from such data sets and provides further support for decision making. Big data analysis and the development of deep neural networks are also highly correlated. Deep learning involves the development of deep artificial neural networks. A key advantage of the deep architecture is its capability for automatic extraction of learning features. With the spread of Internet of Things (IoT) technology, deep learning has demonstrated state-of-the-art performance in many applications and plays an important role in big data analysis. The presentation of big data contains too much information. To handle big data effectively, efficient data processing methods are needed so that valuable information can be properly classified, extracted, or classified. With its hierarchical learning strategy, big data can effectively capture informative patterns and information in the data.

6.2. Case Study 2: Text Analysis:

Recent studies have discussed new methods, tools, and implementations for NLP on big data. However, there is little discussion on the successful impact of big data analysis and NLP. The big data platform is implemented for NLP in order to analyze text datasets (daily articles, reviews) on a large scale. Unstructured data features are converted to structured data using the PySpark library. The Bee algorithm, an artificial intelligence bio-inspired optimization algorithm, is implemented in text analysis subtasks. Traditional methods and the Bee algorithm are compared based on the big data platform. A larger dataset contains unstructured textual data which is processed through the NLP subtasks and yielded structured data in related fields of knowledge. Implementation based on the Scala programming language for the detection of polarity in the sentiment analysis subtask is available. Adjective and noun tokens are extracted then relevant knowledge feature extraction is performed. Polarity detection for sentiment analysis subtasks is achieved through a machine learning algorithm after knowledge features are extracted. Finally, evaluation and comparison are conducted using various statistics.

The term big data can be defined as data, usually in a digital format, that is so large and complex that traditional data management tools and methods are unable to analyze it and store it with excellent results (Setyo Nugroho et al., 2021). The rise of big data has engendered the need for techniques and tools that would enable knowledge to be extracted from such data. There is strong interest in the technological capabilities of storing, processing, and analyzing big data. Big data has become an industry that seeks new solutions to effectively analyze and process this large amount of information. Large investments in the big data segment are made by such corporations as IBM, Microsoft, and Google, which are willing to take part in processing and analyzing big datasets. As it targets a wider range of domains, including the heterogeneous, dynamic, distributed, and uncontrolled forms of data, the concept of big data differs in many ways from regular data. On top of NLP, the development of big data analytics has led to an increasing need to ease the computational burden that processes such gigantic, unstructured text data at scale (Kumar Prabhakar et al., 2022). The fast and massive generation of textual data has underlined an increasing interest in the automatic extraction and structuring of relevant information from text.

6.3. Case Study 3: Predictive Analytics:

In the era of big data analysis and deep learning, many prediction models or deep learning approaches aim to learn a mathematical relationship from the training big data. However, is it possible to use a honey bee swarm intelligence as a trial-and-error approach to analytically approximate an output Y? Although many mathematical and metaheuristic optimization algorithms appeared in the literature, the bee algorithm, as an intelligent search algorithm, can easily find a proper output Y for previously unseen inputs. An analytical approach containing classification and regression analysis is investigated for effectiveness in this big data analysis and deep learning era regarding the bee algorithm, and is then presented in this chapter. Effectiveness is demonstrated with three diverse and illustrative case studies. Additionally, three data sets are specially modified and analyzed for the case studies (Abu-Salih et al., 2021). In any domain, a query arises regarding whether a further social situation will or will not happen. This try to model the relationship between the prediction features and the social situation that needs to be solved. The existing features of the social situation are called the prediction candidates. The case study applies the bee algorithm to analyze the statistical relationships between the prediction candidates and the new social situation. Least absolute shrinkage and selection operator is commonly used for pursuing better generalization ability with the relationship. Two kinds of constraints are dealt with combining them in a modeling approach. This approach examines the effectiveness of the classification approach to modeling this relationship. Three social network datasets from diverse domains are used: marketing, smart card systems, and fund transactions.

7. Challenges and Limitations

Developments of numerous optimization techniques have been carried out in many different research fields. Many intelligent optimization techniques and metaheuristic algorithms are created to solve complex search and optimization problems. This metaheuristic optimization has been significantly employed in bioinformatics, business optimization and modelling, industrial design optimization, vehicle routing, machine scheduling, resource optimization, dynamic problem optimization, quantum optimization problem, complex urban public transportation, design problems and last but not least machine learning and bioinformatics. The optimization algorithms can be classified as being deterministic like a deterministic algorithm and non-deterministic like a stochastic algorithm. The Bee Algorithm is a relatively novel member of these algorithms and is inspired by the intelligent foraging behavior of a honeybee. It is a suitable tool for different optimization problems due to its flexible adaptation through a real-world model such as a foraging behavior of honey bees in nature. Since it was first introduced, this method has been successful in different optimization problems and has produced a number of other algorithms that are variants of optimization strategies in foraging behaviour of bees. Many of those successful variants are relatively new occurrences in research in manipulating the algorithm. However, there are some challenges and limitations of the different variants and these are categorized discussed in this empirical work. It is claimed that previous works don't provide a comprehensive and deep examination through various verified big data analysis and deep learning problems. Variants that have shown success in dealing with specific problems can be problematic in dealing with other problems which are also verified in this work. Although there are recent works in the big data analysis and deep-learning domain, it has not been extensively tested in addressing various other established big data problems as it has been verified in this study.

7.1. Scalability Issues:

There are agencies, industries, and organisations that are generating big data analysis. An employment of the Bee Algorithm and the artificial bee colony is extensively conducted to analyze the big data analysis. However, for large-scale big data settings, progress is rather slow because of the limitation. Concerns arise due to the emergence of the deep learning paradigm. Among deep-learning frameworks, it is dominant for large data regime applications. While above all, the Bee Algorithm is very scalable to the big data analysis. However, a very few studies have focused on the effectiveness of the Bee Algorithm in the big data analysis and deep learning.

The semi-analytic approach for obtaining the probability density function is developed. To know the effectiveness of the Bee Algorithm and the artificial bee colony in the data analysis, the Bee Algorithm and the artificial bee colony are employed to numerically solve elementary learning problems, where they both identify the global minimum so differently. It is shown that the effectiveness tends to reduce a little regarding the scaling. While it is observational learning problems, the recent paradigm of concentration in research for the Bee Algorithm is big data issues. It gives the reader of why observation is made, how it is conducted, and what the observation is.

7.2. Computational Complexity:

One goal of using the Bee Algorithm to optimise Big Data problems is to develop complex networks for analysing data. Big Data analysis uses Big Data to answer questions, predict behaviour, or gain interesting knowledge. In practice, the size of Big Data is often very large, so it is difficult to process by common hardware because Big Data involves Data Mining and Deep Learning with heterogeneous outputs. The problem processing Big Data is still challenging because simple mathematical models cannot accurately predict the results. To understand Big Data analysis and to develop complex networks for analysing Big Data, the Bee Algorithm is used to optimise architecture and hyperparameters of models simultaneously. The Bee Algorithm has few hyperparameters, resulting in one adjustable parameter. The Bee Algorithm is effective for minimisation of the function and an upper limit of hidden layers can be found simultaneously. For the data used, pre-processing with ordinary isotropic filtering significantly improves the objective value. Until the third epoch of Big Data analysis, unmodified derivative free optimisation shows faster convergence as gradual completion. initialisation performs better because the model performs better. The proposed Bee Algorithm with appropriate configuration is superior in terms of objective value, testing error, training time, and variances of output results. In addition, it also outputs the best architecture and hyperparameters of the analysed model.

8. Future Directions in Research

Considering the limitations and extension of applied information provided in this paper, future directions in research are also considered in this part. In summary of this research direction, where to go with the applied information as well as making tradeoffs, limits, and sacrifices in favor of new research efforts toward possible futures are considered as the remaining methods of this paper.

Considering the challenges derived from hyper-parameterized estimation setting by current study and the related works, the scope of applied information has been focused mainly on default parameterization. As a result, obtained best results in empirical work done so far could have been caused by chance in favor of the BAS. Regarding this algorithm, further research in the Big Data analysis on the specific dataset, instead of broader category might include could further insights for interpretation of the findings. There could be also possible research implying BAS compared with various most popular optimization algorithms. Conjectures drawn from this observation could provide further explanation on why the best-tuned results might have been obtained by using the BAS. The coincidental finding involves the weights of a deep learning model. These findings could have been coincidental turn to be in favor of the BAS, as their tuning has been done as part of a different experimental study, in a different context. These issues could have been realized here, in order for the findings to be more robust and insightful from a broader perspective. This is the tradeoff between the extension of research and the scope of BAS research as something that has not been done at all to date.

8.1. Hybrid Models:

Bee Colony Optimization (BCO) algorithms have become very popular among global population-based search algorithms in a short time period. Bee algorithms (BAs) which are easy, natural and productive algorithms have been provided from observing the natural behaviors of honey bees. BAs have been applied in many adaptive learning problems. However, they have not yet used in the analysis of Big Data and neural networks due to the difficulty of dealing with a huge amount of data in a short time. The usability of the BA and improving it for Big Data analysis and deep learning are presented. A new model called Bees for Big Data Analysis (BBDA) enhancing the Bee Algorithm (BeA), providing faster analysis of Big Data, and integrated with different popular tools is produced. With only one spark discussions, BBDA analyses a vast amount of Big Data by sharing the dataset in the network. BBDA model hastens the analysis operations due to the function of the BeA with l parallel notebooks running l different computations. BeA begins to analyze one of l partitioned datasets in notebooks. There is no need to wait for the completion of other BeA operations running in different computations. Thus, the distributed and parallel structure of the model is very efficient for Big Data analysis. It is also compared to 59 different classical, swarm and mimic optimization algorithms in the R and Python languages. The BBDA provides a good classification of datasets using the BeA that is significantly faster than other algorithms. Also, the model works well in all languages and datasets (Salari et al., 2014).

8.2. Real-Time Data Processing:

There is a critical increase in the volume of data available to businesses. This change is plunging into every sector of the market comprising agriculture, finance, management, industry, current affairs, and trade, legal, transportation, government, etc. It's anticipated that the 'global rate of digital data generation' will be about 463 exabytes/ day by 2025. Consequently, a new lane has been established to cultivate big data adapted resolution approaches and policies in the light of raising data request and or the creation of big data. The bee algorithm can be adapted correctly to big data analysis. Today's data is predominant and is extensive to be managed by conventional analytical methods (Eunice Namugenyi et al., 2024). Deep learning is a powerful approach to adapt among big data analytics, but it can be hard at large models. The working principles of the bee algorithm are both cooperative and influenced. The performance of the bee algorithm in deep learning is hereunto assessed. Moreover, the bee algorithm is compared with five evolutionary algorithms such as ABC, ALO, CS, FA, and PSO across big data sets and benchmarked in efficiency and effectiveness. It has illustrated the excellence and remarkable potential of the bee algorithm in large-scale analytics of data and deep learning. It is envisaged that the presented outcomes would facilitate the harnessing of the bee algorithm in industries and other fields. In a network that includes beehive monitoring nodes, a comprehensive solution is provided for optimized data transfer with management of the network. The combination of edge computing, data compression, and data aggregation provides end-to-end real-time processing of large beehive sting image and video files with the ability of their rapid gathering by edge nodes and transfer files in low-bandwidth networks. Together with server-based or cloud-based central solution, this end-to-end approach allows the utilization of data collected by multiple smart hives for efficient and rapid analysis of bee behavior and hive occupants and the connection of the sound findings with images and videos of bee stings in a hive.

9. Conclusion

It is certainly possible to use the Bee Algorithm in a Hadoop-based cluster environment to run Big Data analysis of Deep Learning systems. The best strategy with the Bee Algorithm is to implement a lipophile approach, which was able to find the maxima for at least 2 different functions (Otri, 1970). Most anthrophilous plants produce nectar in the morning when temperatures are lower, and cease when they rise. The sampler bees will identify patches that contain nectar as soon as they are released, and will return to the hive when the weather is too warm for nectar to be present. This nurse bee (B1) is trained to look for a new pair of sampler bees when it has stopped feeding on background nectar. The sampler bees are trained to exploit the wealth of certain dances that provide the highest profit. Of these, the onlookers will visit the dance that provides the highest profit. A forager bee will exploit this behaviour and will usually occupy the best patches. The Bees Algorithm performs a search on both the surrogate model of the landscape it is trying to explore, and on the actual landscape. The Bee Algorithm is based on honey bee foraging behaviour, which comprises two principal activities: searching for nectar and recruiting other bees to exploit the found nectar source. The Bee Algorithm is a population-based search algorithm that mimics the foraging behaviour of honey bees, used to find the optimum solution(s) to optimization problems. The Bee Algorithm can be connected to generic systems that carry out the function of automatically generating, assigning, and executing tasks while balancing requirements among them.

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