Computing, Information Systems & Development Informatics Journal
Vol. 13 No. 3, September, 2022 - www.isteams.net/cisdijournal

A Review of Some Selected Swarm Intelligence Algorithms for Breast Cancer Diagnosis

[1]Lala, O.G., [1]Onamade, A.A., [1]Oduwole, O.A., [1]Nwamadi, C.E. & & [2]Olabiyisi, O.O.
[1]Department of Computer Science, Adeleke University Ede
[2]Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso
E-mails: [1]olusegun.lala@adelekeuniversity.edu.ng; [1]onamadeakintoye@ adelekeuniversity.edu.ng; oludayo.oduwole@adelekeuniversity.edu.ng; [2]soolabiyisi@lautech.edu.

ABSTRACT

In first-world nations, breast cancer is now one of the leading causes of death for women. There has been a lot of research done to find novel and efficient approaches to detect breast cancer. Although many different ways have been devised and put into practice employing intelligent strategies, some of them lack accuracy, precision, or specificity. The most widely used Swarm intelligence algorithms PSO, GA, ICA, ABC, IWO, FA, and AIRS were examined in this research to evaluate their benefits and highlight their drawbacks. Ten limitations identified by this review included; Lack of machine learning capabilities to train, and continuously build its dataset to maintain a correct classification of breast cancer diagnosis, Pattern recognition, and related problems, Interpretation problems of some classification models and classifiers, High Memory Consumption, Lack of Automation, Data Mining and Optimization problems, Complex/Evolving Dataset, Processing Time and Computational Cost optimization, Precision and Probabilistic Features and Iteration Cost. These gaps necessitate the need for further research and the development of Hybrid Swarm Intelligent algorithm models capable of solving combinatorial, real-time classification and optimization problems when attempting to improve breast cancer diagnosis.

Keywords: Swarm Intelligence, Diseases diagnosis, Breast Cancer, Hybrid, Dataset, Classification, Combinatorial

CISDI Journal Reference Format
Lala, O.G., Onamade, A.A., Oduwole, O.A., Nwamadi, C.E. & & Olabiyisi, O.O. (2022): A Review of Some Selected Swarm Intelligence Algorithms for Breast Cancer Diagnosis. Computing, Information Systems, Development Informatics & Allied Research Journal. Vol 13 No 3, Pp 11-24. Available online at www.isteams.net/cisdijournal

1. INTRODUCTION

According to Zamani and Nadimi-Shahraki (2016), breast cancer is described as the "malignant expansion of cancerous tissue in the breast. Breast cancer is caused by various factors, the principal of which are age, lifestyle, and dietary habits. Other risk factors identified by the National Health Scheme (2015) include family history, history of cancer cells, previous history of a benign breast lump(s), breast density, estrogen exposure, overweight, height, alcohol, radiation, hormonal replacement therapy, gene mutation, etc. Breast cancer shows little to no obvious signs at its early stages of development, hence, the most crucial aspect of diagnosis is patient evaluation. To assist specialists in their decision-making, a variety of machine learning techniques and pattern recognition methods have been developed. These algorithms aid in information extraction, reduction of time, and cost of diagnosis. Over the years, most researchers have employed the use of various Swarm Intelligence Algorithms in breast cancer diagnosis.

An artificial intelligence multi-agent system known as swarm intelligence (SI) is interested in leveraging data analysis patterns gathered from the collective actions of various insects, including ants, termites, bees, and wasps, as well as airborne or aquatic creatures (Blum and Li, 2008). In recent years, SI has been applied in medical diagnosis, Particle Swarm Optimization (PSO) (Chang, Lin, and Liu, 2012; Chen et al., 2012) and Ant Colony Optimization (ACO) (Ganji and Abadeh, 2011), are two famous implementations of SI. Invasive Weed Optimization (IWO), Artificial Bee Colony (ABC) (Beloufa and Chikh, 2013), Firefly algorithm (FA) (Yang, 2010), and Artificial Immune Recognition System (AIRSO) (Mechrabian and Lucas, 2006) are some further examples.

1.1 Swarm Intelligence Based Techniques

This section briefly discusses the swarm intelligence algorithms: PSO, GA, ICA, ABC, IWO, FA, AIRS, FWA, BA, and CSA. in relation to breast cancer diagnosis.

Particle Swarm Optimization (PSO): The way that fish schools and flocks of birds behave inspired the name of this phenomenon. According to Qasim and Algamal (2018), it is a swarm-compatible population-based search method with a minimal set of required parameters. For a search problem, each of these particles has a velocity and position, which are mathematically denoted by the position vectors Xi = xi1, xi2.......xin and velocity vectors Vi = xi1, xi2.......vin, respectively.

Genetic Algorithm (GA): According to Mazen, Gody, and Abul Seoud (2016), GA is an effective algorithm for resolving complex optimization problems. Unlike FA, GA is derivative-free and has rapid convergence characteristics, hence is capable of generating new solutions to breast cancer diagnosis challenges.

Imperialistic Competition Algorithm (ICA): A population-based method called ICA divides individuals into two categories: colonies and imperialists. The initial population of this classification is referred to as “countries,” and from this initial population, the imperialists with the highest fitness values are chosen, while the other set becomes the colonies. Quinlan, (1996) summarizes the basic steps of ICA as;

i. Initial Empire Generation
ii. Classification of empire between colonies and imperialists.
iii. Positioning imperialists and colony
iv. Cost computation of all empires
v. Imperialistic competition
vi. Elimination and division

Invasive weed optimization (IWO): This stochastic optimization approach was modeled after weed proliferation in nature. Mehrabian and Lucas (2006) initially introduced IWO, and they emphasize the following as the fundamental steps of this algorithm:

i. Generation of Initial weeds population
ii. Evaluation of population fitness
iii. Reproduction
iv. Distribution
v. Activation of the competitive mechanism
vi. Monitoring termination criteria

Artificial Bee Colony (ABC): The ABC It is a population-driven strategy that is inspired by the behavior of honey bees. It is applied to solve challenges involving real-time optimization. ABC is reported to be very flexible and with a fewer number of control parameters. In comparison to other methods, ABC has shown some competitive advantage (Basturk and Kaboga, 2007).

Firefly Algorithm (FA): According to Nadhini et al. (2017), Xin-She Yang initially postulated FA based on the fireflies' social behaviour. This algorithm has been widely used for optimization and classification problems (Nayak et al, 2020). Despite the numerous Firefly Algorithm such as its simplicity, robustness, and its preciseness, it is generally slow in convergence, and has low memory capability, hence a need for a hybrid approach, suggestively with a Genetic Algorithm (GA).

Artificial Immune Recognition System (AIRS): The design of the immune system served as inspiration for the AIRS. Based on how the biological immune system functions, it makes use of memory cells, resource competition, affinity maturation, and clonal selection. The four stages of this algorithm's typical operation are data standardization and activation, memory cell recognition and the creation of artificial identification balls, resource competition, and finally the conversion of candidate memory cells into memory cells. Although an automated process, requires some supervision to transition to the next stage, it also experienced some immunological resistance and data redundancy Wafa Nebili et al (2021).

Fireworks Algorithm: This innovative Swarm Intelligence (SI)-based optimization technique called the Fireworks Algorithm (FWA) was introduced by Tan and Zhu in 2010. Evening fireworks displays served as the inspiration for this approach, which excels at locating the best value globally. When a firecracker explodes, sparks scatter everywhere. Those sparks will reappear and produce new spark displays in a smaller region. To discover the best solution, the sparks will eventually conduct a fine-structured scan of the entire solution space and concentrate on a particular area.

Clonal Selection Algorithm: Some of the best optimization techniques were inspired by natural events. The clonal selection technique was influenced by how the immune system works. It is commonly used in research and engineering fields and helps to create more cells that are better able to recognize specific antibodies.

2. LITERATURE REVIEW

This paper provides extensive performance comparisons of a few chosen swarm algorithms for breast cancer detection. Weli (2020) examined several algorithms for cancer prediction utilizing data mining methods. It was found that the optimum methods for feature selection and classification are provided by swarm algorithms. However, it does not highlight or identify any particular algorithm for solving complex problems sometimes encountered during data mining and optimization. According to Zamani and Nadimi-Shahraki, (2016), the Swarm intelligence (SI) approach focuses on the exploration of a problem space and the extraction of optimal solutions employing agents with intelligence. SI is now used to solve optimization issues, especially in the medical sectors of screening, diagnosis, and treatment. The following are some significant applications of swarm intelligence optimization techniques in medical diagnosis include Particle Swarm Optimization (PSO) (Chang, Lin, and Liu, 2012), Ant Colony Optimization (ACO) (Ganji and Abadeh, 2011), Artificial Immune Recognition System (AIRS) (Chikh, Saidi and Settouti, 2012), Artificial Bee Colony (ABC) (Beloufa and Chikh, 2013), Firefly algorithm (FA) (Yang, 2010) and invasive weed optimization (IWO) (Zwitter and Soklie, 2015).

For early breast cancer diagnosis, Raufi et al. (2017) created a prediction model. The four main module sequences used in their investigation were data collection, data preprocessing, extraction of features, and categorization. They also employed the Discrete Wavelet Transform feature extraction method. Classifiers used in this model were the SVM and the NN algorithms. Lastly, they evaluated their model using the MIAS digital mammography database. Their result suggested that the Neural Network produces a higher accuracy of about 95.15%. This model is not best suited for complex problems due to its lack of machine learning capabilities to train, and continuously build its dataset to maintain a correct classification of a breast cancer diagnosis. Zorlougu and Agaoglu (2017) proposed a breast cancer diagnostic model using an ensemble approach. The classifiers tested out in this model include: Decision Tree (DT), Artificial Neural Network (ANN), Support Vector Machine (SVM) likewise with the combination of these methods. Using SPSS Clementine software, their results suggest that SVM had 98.97% while ANN had 97.54%.

This work does not cover parameter optimization for these classifiers and this poses a great limitation to pattern recognition and related application. The degree of a breast cancer diagnosis was the focus of a study conducted by Muslim et al. (2018). It made use of the UCI machine learning dataset for Wisconsin breast cancer. Suganya and Porkodi (2018) suggested a different prediction model employing five different machine learning algorithms: Naive Bayesian, KNN, SVM, RF, and NN. Based on the proposed models' accuracy, precision, and recall, they calculated how well they performed. The findings revealed that, when compared to the other classifiers, KNN and NN had the best accuracy. Given that the model's training set is constantly retained in memory, it suffers from excessive memory usage. Aro et al., (2019) proposed an ensemble-based approach using the K-Nearest Neighbor (KNN), Decision Tree, and Support Vector Machines (SVM) classifiers and Bagging and Boosting ensembles. Their experimental result suggested that an individual-based approach to SVM presents an accuracy of 97.14% and is thus more advantageous than conventional methods. However, this was a supervised model and does not cover the possibility of automation and probabilistic learning. Chaurasia, Pal, and Tiwari (2018) proposed a predictive model for the survivability of breast cancers. These researchers used a dataset of 683 malignant tumors and three machine learning algorithms—Naive Bayes, RBF Network, and J48 to create original models.

For a comparison of their three models' estimates for optimal performance, 10-fold cross-validation was used. The findings showed that the Naive Bayes algorithm had the greatest accuracy with a score of 97.36 percent, followed by the RBF Network with a score of 96.77 percent and J48 with a score of 93.41 percent. Using PSO as a feature selection method, Nurhayati, Agustian, and Lubis (2020) enhanced the performance of the classification algorithms SVM, Naive Bayes, Logistic Regression, Decision Tree, and KNN. They demonstrated using data from the UCI Breast Cancer Dataset that PSO may enhance a number of classifiers. Their PSO model was unable to perform better as a feature selection method than the Genetic Algorithm, nevertheless. Supervised learning was the type of algorithm they used. Not every PSO factor used for selection had better outcomes in situations when breast cancer was predicted. The performance of Genetic Algorithms (GA) is superior to PSO, according to their experimental findings. They advised that PSO might also be utilized as an attribute selection alternative because the performance is not noticeably different. Additionally, it does not address the necessity of probabilistic modeling and unsupervised learning. To help in the identification of the most relevant aspects that are pertinent to breast cancer predictions, Vijayalakshmi et al. (2020) suggested using particle swarm optimization and quasi sorting with a classification algorithm.

Their model was used on two breast cancer data sets from the UCI machine learning data repository: the Wisconsin Diagnostic Breast Cancer (WDBC) and the Breast Cancer Colimbra Dataset (BCCD). When their experimental findings were compared to those of other algorithms, such as the genetic algorithm kernel density estimation, it was shown that the PSO was superior.

This algorithm incorporated many approaches to accurately categorize the breast cancer data sets, including the NDS technique, multiple classifiers, and the Bayes' theorem, and it was 98.8% accurate. Sensitivity and specificity were attained at 98.8%, 97.12%, 99.8%, and 98.38% respectively. They suggested that future studies concentrate on leveraging the Internet of Things (IoT) devices to forecast and detect cancer cells. PSO is a model that just needs a few parameters and straightforward computations, hence it cannot allow unsupervised learning of complicated and dynamic data sets. An application of feature selection to a dataset of breast cancer recurrences was carried out by Sakri SB, Abdul Rashid NB, and Muhammad Zain (2018). The classifier employed a rapid decision tree learner, KNN, and Naive Bayes. Their model revealed that PSO improves the performance of the classification of breast cancer. This model does not cover feature selection or classifier optimization. Nazarian, Dezfouli, and Haronabadi (2018) proposed an Ant Colony Optimization (ACO) technique to classify breast cancer samples through the use of data mining techniques. The results revealed some level of accuracy and functionality.

This model proved to be simpler and more understandable in the application; however, its success percentage was comparably lower than other algorithms. Al-Behadili, Ku-Muhamud, and Sagban (2020) proposed a hybrid ACO and Genetic Algorithm (GA). The GA used the multi-neighborhood structure's ideas to improve the classification criteria that the ACO had originally developed. Their model was compared to two other hybrid ant-mining classification approaches, namely ACO/SA and ACO/PSO2, in terms of classification accuracy, the number of created rules, and complexity. Their findings indicated that the proposed hybridization was capable of producing significant results in swarm evaluations; nevertheless, it does not cover the possibility of unsupervised learning using its hybrid structure. Nabat et al. (2020), applied data mining techniques such as classification and the Improved Particle Swarm Optimization (IPSO) algorithm to detect cancer types in a short response time. Their model produced significant results with remarkable speed, however, their combination with the decision tree algorithm was not able to reach the projected extent.

They suggest that future work should focus on Improved PSO classification techniques such as decision trees. Dou and Meng (2021) developed an improved optimization method (GSP SVM) that combines genetic algorithms, particle swarm optimization, and simulated annealing using a support vector machine algorithm. The results showed a high degree of classification accuracy and other metrics. When compared to earlier optimization techniques, their model offered reliable guidance for the selection of breast cancer early screening strategies. Future research, they suggested, might concentrate on the integration of more sophisticated kernel functions for other classes, which their study was unable to cover. In order to automatically assess the breast border and nipple position to detect a concerning region on digital mammograms, Sivakumar and Karnan (2018) devised an ABC algorithm optimization that employs simultaneous subtraction of the left and right breast images.

There is some data duplication in this approach, and the cost of iterations is substantial. For the goal of classifying breast cancer data sets for training and testing, Habib Shah (2021) suggested a model employing the new ABC as a probabilistic neural network. Their results showed that, with the least amount of iteration, this model may be successfully applied to a broad net of breast cancer data sets for prediction purposes. However, this model does not fill the gap in resolving real-time optimization problems. By combining the attacking phase with the employee bees' exploitative phase, Punitha et al. (2021) presented a hybrid artificial bee colony using a whale optimization algorithm (HAW). They combine ABC and Whale Optimization to create a metaheuristic-based swarm search algorithm that can address combinatorial real-time optimization issues in an effort to enhance breast cancer diagnostics. Using different datasets, the accuracy, complexity, and computing time of their hybrid versions were assessed.

The model, however, was complex and took longer to compute than the existing technique since parallel feature selection and parameter tuning operations were involved. ABC and PSO-based two-hybrid algorithms were proposed by Djellali et al. (2018). The first algorithm showed how to create fresh velocity position updates by fusing a hybridized employee bee phase with PSO. Improvements were noted in the second algorithm employing genetic algorithm mutations (GA). With a WBCD-optimized selection of 13 characteristics, both of these algorithms had an accuracy of 99.14%. This model also lacked parameter optimization. In their unique model for diagnosing breast cancer, Punitha et al. (2022) combined ABC with a modified AIS. To enhance the local search for ABC, they were able to integrate a hybrid ABC into an employee bee phase. They used the ABB model for feature selection as well as parameter tuning. Later they tested their model for resilience through back propagation, Levenberg, Marquardt, and gradient descent. These researchers reported high accuracy of 99.14% and poor connections of 12.40 using WBCD alone. By fusing HFA with the Controlled Genetic Algorithm, Sharma et al. (2018) suggested an algorithm. According to the authors' study, their recommended method outperforms the other comparable strategies.

However, it lacked precision and stochastic criteria for the best classification of breast cancer. Al-Thanoon et al. (2019) suggested a technique for parameter tweaking in Penalized Support Vector Machines (PSVM) that combines FA and statistical PSO. When put to the test on various datasets, their approach was more effective than statistical PSO, FA, and cross-validation (CV). A greater classification accuracy rate was also observed. However, this approach had a significant iteration cost. An improved Hybrid FA (HFA) with a collective mutation function was proposed by Wang et al., 2019. Their approach was effective in enhancing the algorithm's ability to navigate the entire diagnosis search space using Chaotic Search (CS), which exhibits superior ergodicity. This model was not tested for compatibility with real-time optimization parameters. (Nayak et al. (2020) conducted a thorough analysis of the variations, importance, applications, and advancements of FA in health and biomedical care. Their main objective was to give future researchers a valuable performance analysis on how to improve and create novel approaches to challenging problems in healthcare, like breast cancer, using FA. Wafa Nebili et al., (2021) investigated some of the drawbacks of the AIRS in terms of its data exploration and calculation cost. To enhance quality, they suggested several changes to the current models concerning lifetime counters for each memory cell.

Furthermore, they made an effort to enhance some algorithmic capabilities in the process of introducing memory cells and the mutation function. They suggest that future research might concentrate on utilizing AIRS to address immunological issues that arise when anticipating whether or not T-cell receptors will bind. They also suggested the possible use of deep learning and a multi-view learning approach for AIRS, a gap their research failed to fill. An artificial immune system model for correlative classification with competitive performance for breast cancer diagnosis was proposed by Gonzalez-Patino et al. (2020). The biological immune system served as the model's basis, simulating the immune system's detection abilities to offer accurate antigen recognition. To find the statistically significant differences between the suggested model and other techniques with a comparable bio-inspired model, they used the Wilcoxon test. Their test's results showed that their suggested model performed better than other well-known classification models, particularly in terms of computing cost. Another significant advantage of their model was its establishment of the fact that swarm intelligence can also be applied in classification tasks and not just optimization in breast cancer detections. Another significant advantage of their model was its establishment of the fact that swarm intelligence can also be applied in classification tasks and not just optimization in breast cancer detections. Using an actual database from WBCD, (Wbcd, 2021) suggested a methodology to assess AIRS' effectiveness. Their model demonstrated a great degree of generality, dependability, and computing efficiency.

The technique was effective, with a 99.77 percent accuracy rate for the swarm diagnosis. It does not, however, address the use of unsupervised AIRS on datasets with complicated graphs. For the purpose of diagnosing breast cancer tests, Frutuoso, Chavarette, and Lima (2022) presented a resistant framework. The tests were divided into groups in order to classify them as either generous or detrimental using a negative selection algorithm. WBCD database was utilized in achieving this model. However, the processing time and computational costs were a significant limitation and a suggested area for future modifications. A comparison of various comparable studies is shown in Table 1.

Table 1: Comparative table of some related works

Author and date	Purpose	Method	Sample	Findings	Uniqueness	Limitations	Contribution to knowledge
Wang et al (2017)	To diagnose breast cancer	A weighted Area under the Receiver Operating Characteristic Curve Ensemble (WAUCE)-based ensemble learning algorithm using Support Vector Machines (SVM) has been proposed.	SEER dataset.	WAUCE model improves accuracy by 33.4 percent while reducing variance by 97.89%.	The suggested weighted Area under the Receiver Operating Characteristic Curve Ensemble (WAUCE) method was the foundation for twelve alternative SVMs.	Only accuracy was measured.	To improve diagnostic accuracy and decrease diagnosis variation
Nidhi, and Saveta (2018)	To diagnose cancer	A classification model was created using J48, REPTree, Random Forest, and Random Tree.	The dataset is taken from UCI	For Random Forest, accuracy was 95.0791 percent, and for 93.4974 percent.	Readily made diagnostic measurements integrated into the dataset.	Other learning algorithms were non-convincing	A breast cancer diagnosing model was built
Qi et al. (2018)	In order to categorize breast cancer	suggested the deep active learning architecture (DALF)	Histopathological image data collection	A precision of 90.54% was achieved	To lessen the load of extensive picture categorization annotation.	The training sets contained samples from the dataset that had not been labeled.	A classification model for unlabeled samples for the classification of breast cancer was developed

Author and date	Purpose	Method	Sample	Findings	Uniqueness	Limitations	Contribution to knowledge
(Al-antari et al 2018)	Full resolution convolutional network (FrCN) with a CAD framework for X-ray mammograms	to identify and categorize the tumour as either cancerous or harmless.	breast database	The breast data set provides a 99.24 percent F1 score, a 97.62 percent Matthews correlation coefficient, and a 98.96 percent mass detection accuracy.	X-ray mammography using a full resolution convolutional network (FrCN) and CAD framework	For the sole purpose of classification, identification, and segmentation accuracy	A computer-Aided design framework was achieved
Pratee, (2019)	Support vector machines (SVM), decision trees, k-nearest neighbors, logistic regression, neural networks, naive bayes, random forests, and other machine learning techniques	To choose characteristics from the breast cancer dataset and determine which ones are least crucial	UCI dataset	Three algorithms—Naive Bayes, Random Forest, and SVM—produce an accuracy score of 0.94 that is encouraging, whereas SVM with fifteen features displays a precision score of 0.95.	The only metric of evaluation considered was precision	The outcome was ambiguous since just roughly thirty characteristics were used, and naive Bayes, random forest, and SVM were used to analyze them.	A model was created to determine a dataset's least significant attributes.

Author and date	Purpose	Method	Sample	Findings	Uniqueness	Limitations	Contribution to knowledge
Agara, (2019)	To find accuracy, sensitivity, and specificity.	on WBCD dataset	SVM, Linear Regression, MLP, KNN, Softmax Regression, and SVM are six machine learning methods that have been compared,	MLP exceeds all other applied ML algorithms in accuracy, scoring 99.04 percent.	To assist medical professionals in correctly identifying breast cancer.	There was no application of feature selection, which played a vital role in the result derived	The development of a machine learning algorithm for the detection of breast cancer.
Shamy et al., 2019)	For the detection and classification of breast cancer	WBCD dataset	Initialized the K-means Gaussian Mixture Model and Convolutional Neural Network (GMM-CNN)	The result analysis demonstrated that the Suggested model greatly reduces processing time and enhances the quality of the results.	The model considerably reduces processing time and enhances the effectiveness of the solutions.	Higher computational processing time	A mode to detect and classify breast cancer was built.

3. SUMMARY, CONCLUSION, AND FUTURE WORK

Having revived the various selected Swarm Algorithms. There are ten (10) limitations enumerated by this researcher. On their own, each of these selected Swarm Algorithms may experience two or more of these challenges and this varies in proportion to their strength. The ten limitations are highlighted below;

1. Lack of machine learning capabilities to train, and continuously build its dataset to maintain a correct classification of a breast cancer diagnosis.
2. Pattern recognition and related problems
3. Interpretation problems of some classification models and classifiers
4. High Memory Consumption
5. Lack of Automation
6. Data Mining and Optimization problems
7. Complex/Evolving Dataset
8. Processing Time and Computational Cost optimization
9. Precision and Probabilistic Features
10. Iteration Cost

Currently, the researcher is working on a comparative analysis of these selected Swarm Algorithms to ascertain which is best suitable for Breast Cancer Diagnosis given a particular dataset and despite the above limitations. However, these gaps necessitate the need for developing a swarm intelligent algorithm model capable of solving combinatorial (hybrid), real-time classification, and optimization problems when attempting to improve breast cancer diagnosis. Future works may therefore direct focus and resources on developing hybrid algorithms capable of resolving these limitations to optimal breast cancer diagnosis using Artificial Intelligence.

REFERENCES

Agarap, A.F.M. 2019. "On Breast Cancer Detection: An Application of Machine Learning Algorithms on the Wisconsin Diagnostic Dataset", ICMLSC 2018, Phu Quoc Island, Vietnam.

Al-antari, M. A., Al-masni, M. A., Choi, M. T., Han, S. M., & Kim, T. S. (2018). A fully integrated computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification. International journal of medical informatics, 117, 44-54.

Al-Behadili H.N., Ku-Muhamud R., and Sagban R. (2020). Hybrid Ant Colony Optimization and Genetic Algorithm for Rule Induction. Journal of Computer Science. Vo. 16(7): 1019, 1028. DOI: 10.3844/jcssp.2020.1019.1028

Al-Thanoon NA, Omar SQ, Zakariya YA. (2019). A new hybrid firefly algorithm and particle swarm optimization for tuning parameter estimation in penalized support vector machine with application in chemometrics. Chemometrics Intell Lab Syst. Vol. 184:142–152

Aro U.S., Akande T.O., Jibrin H.B., Jauro B.M. (2019). Homogeneous Wnsembles on Data Mining Techniques for Breast Cancer Diagnosis. Daffodil Int. Univ. J. Sci. Technol. Vol. 14(1); 9-12.

Basturk B., Karaboga, D. (2017) A powerful and efficient algorithm for numerical function optimization: Artificial Bee Colony (ABC) algorithm, J. Global Optim. 39,171–459.

Beloufa, F. and Chikh, M. A. (2013). Design of fuzzy classifier for diabetes disease using Modified Artificial Bee Colony algorithm. Computer Methods and Programs in Biomedicine. vol. 112, pp. 92-103.

Blum, C., Li, X. (2008). Swarm intelligence in optimization: Introduction and Applications. Springer Verlag, Berlin, pp.43–86.

Beloufa, F. and Chikh, M. A. (2013). Design of fuzzy classifier for diabetes disease using Modified Artificial Bee Colony algorithm. Computer Methods and Programs in Biomedicine. vol. 112: 92-103.

Chang, P.-C., Lin, J.-J., and Liu, C.-H. (2012). 'An attribute weight assignment and particle swarm optimization algorithm for medical database classifications.' Computer Methods and Programs in Biomedicine. vol. 107, pp. 382-392

Chaurasia, V., Pal, S., and Tiwari, B. (2018). Prediction of benign and malignant breast cancer using data mining techniques. Journal of Algorithms & Computational Technology, 12 (2):119-126.

Chen, H.-L., Yang, B., Wang, G., Wang, S.-J., Liu, J. and Liu, D.-Y. (2012). Support Vector Machine Based Diagnostic System for Breast Cancer Using Swarm Intelligence. Journal of Medical Systems. vol. 36, pp. 2505-2519.

Chikh, M. A., Saidi, M. and Settouti, N. 2012. Diagnosis of Diabetes Diseases Using an Artificial Immune Recognition System2 (AIRS2) with Fuzzy K-nearest Neighbor. Journal of Medical Systems, vol. 36, pp. 2721-2729.

Djellali H., Djebbar A., Zine N. G., and Azizi N. 2018. Hybrid Artificial Bees Colony and Particle Swarm on Feature Selection. Computational Intelligence and Its Applications IFIP Advances in Information and Communication Technology, pp. 93–105.

Dou Y. and Meng W. 2021. An Optimization Algorithm for Computer-Aided Diagnosis of Breast cancer Based on Support Vector Machine. Frontiers in Bioengineering and Biotechnology. Vol.9 (698390). DOI: 10.3389/fbioe.2021.698390

Frutuoso de Souza S.S., Chavarette F.R. and Lima F.P. 2022. Artificial Immune Systems applied to Clinical Diagnosis of Breast Cancer Samples. Research, Society and Development. V. 11(5). DOI: http://dx.doi.org/10.33448/rsd-v11i5.21941

Ganji, M. F. and Abadeh, M. S. (2011). A fuzzy classification system based on Ant Colony Optimization for diabetes disease diagnosis. Expert Systems with Applications. vol. 38(12): pp.14650-14659.

Gonzalez-Patino D., Viluendas-Rey Y., Arguelles-Cruz A.J., Camacho-Nieto O., and Yanez-Marquez C. 2020. AISAC: AN Artificial Immune System for Associative Classification Applied to Breast Cancer Detection. Applied Sciences. Vol. 10(515). www.mdpi.com/journal/applsci. DOI:10.3390/app10020515

Habib Shah. (2021). Using a new artificial bee colony as a probabilistic neural network for breast cancer data classification. Frontiers in Engineering and Built Environment. Vol. 1(20): 133-145. DOI: 10.1108/FEBE-03-2021-0015

Mazen F, Gody A.M. and Abul Seoud R.A. (2016). 'Genetic Algorithm and Firefly Algorithm in a Hybrid Approach for Breast Cancer Diagnosis. *International Journal of Emerging Trends & Technology in Computer Science*. https://www.researchgate.net/publication/296695751. DOI:10.14445/22312803/ IJCTT-V32P111

Mehrabian, A. R. and Lucas, C. (2006). A novel numerical optimization algorithm inspired by weed colonization. Ecological Informatics, vol. 1, pp. 355-366.

Muslim M.A., Rukmana S.H., Sugiharti E., Prasetiyo B. and Alimah S. 2018. Journal of Physics: Conference Series. Vol. 983; 012063

Nabat Z.M., Shnain S.A., Al Khafaji B.J., and Salih M.A. 2020. Cancer Diagnosis with Improved particle Swarm Optimization Algorithm (Hilla Hospital – Iraq) Case Study. Journal of Southwest Jiaotong University. Vol. 55(2). DOI ：10.35741/issn.0258-2724.55.2.34

Nandhini M, Rajalakshmi M, Sivanandam SN. (2017). Experimental and statistical analysis on the performance of firefly-based predictive association rule classifier for health care data diagnosis. J Control Eng Appl Inf.; 19(2):101–10.

Nayak J. et al. (2020). Applications and advancements of firefly algorithm in classification: an analytical perspective. In: Computational intelligence in pattern recognition. Springer, Singapore; pp. 1011–1028.

Nayak J., Naik B., Dinesh P., vakula K. and Dash P.B. 2020. Firefly Algorithm in Biomedical and Health Care: Advances, Issues, and Challenges. Sn Computer Science. Vol. 1(311). DOI: https://doi.org/10.1007/s42979-020-00320-x

Nazarian M. Dezfouli M. Haronabadi A. 2018. Classification of Breast Cancer Samples through using the Artificial Bee Colony Algorithm. International Journal of Computer Applications Technology and Research. Vol. 5(5): 523. www.ijcat.com

Nidhi W., Mukesh K. And Shaveta M. (2018). Classification of Breast Cancer Tissues using Decision Tree Algorithms. International Journal of Research in Engineering Applications and Management. (IJREAM). ISSN: 2454-9150. Vol. Issue 05. 342-346.

Nurhayati, Agustian F., Lubis M.D. 2020. Particle Swarm Optimization Feature Selection for Breast Cancer Prediction. The 8th International Conference on Cyber and IT Service Management (CITSM 2020) on Virtual, October 23-24, 2020. Accessed from ResearchGate 2020. https://www.researchgate.net/publication/347374488. DOI: 10.1109/CITSM50537.2020.9268865

Parkin DM, Pisani P, Ferlay J. "Estimates of the worldwide Incidence of Major Cancer in 1990". International Journal of Cancer 1999; 80: 827- 841.

Prateek. 2019. Breast Cancer Prediction: Important of Feature Selection, Springer Proceeding Advances in Computer Communication and Computational Sciences, (IC4S), series Advances in Intelligent Systems and Computing 924, pp 733-742, Singapore

Punitha S., Stephan T. and Gandomu A.H. 2022. A Novel Breast Cancer Diagnosis Scheme with Intelligent Feature and Parameter Selections. Computer Methods and Programs in Biomedicine. Vol. 214: 106432. DOI: doi.org/10.1016/j.cmpb.2021.106432

Punitha S., Stephen T., Kannan R., Abraham A. 2021. A Hybrid Artificial Bee Colony with Whale Optimization Algorithm for Improved Breast Cancer Diagnosis. https://link.springer.com/article/10.1007/s00521-021-05997-6

Qasim O. S. and Algamal Z. Y. (2018) 'Feature selection using particle swarm optimization-based logistic regression model' Chemom. Intell. Lab. Syst., vol. 182, pp. 41–46, DOI: 10.1016/j.chemolab.2018.08.016.

Qi, Q., Li, Y., Wang, J., Zheng, H., Huang, Y., Ding, X., & Rohde, G. K. (2018). Label-efficient breast cancer histopathological image classification. IEEE Journal of biomedical and health informatics, 23(5), 2108-2116.

Quinlan, J.R. (1996). Improved use of continuous attributes in C4.5. Journal of Artificial Intelligence Research. Vol. 4, 77-90.

Raufi B., Ajdari J., Zenuni X., and Ismaili F. 2017. Enhancing breast cancer detection using data mining classification techniques. In 2nd World Conference on Technology, Innovation, and Entrepreneurship. No 605; 310-316

Sakri S. B., Abdul Rashid N. B., and Muhammad Zain Z., 2018. Particle Swarm Optimization Feature Selection for Breast Cancer Recurrence Prediction. IEEE Access, vol. 6(c):29637–29647. DOI: 10.1109/ACCESS.2018.2843443.

Sharma M, Singh G, Singh R. 2018. Clinical decision support system query optimizer using hybrid Firefly and controlled Genetic Algorithm. J King Saud Univ-Comput Inf Sci. DOI: https://doi.org/10.1016/j.jksuci.2018.06.007.

Shamy, S. Dheeba J. (2019) 'A Research on Detection and Classification of Breast Cancer using k- means GMM & CNN Algorithms' International Journal of Engineering and Advanced Technology (IJEAT).

Sivakumar R. and Karnan M. 2018. Diagnose Breast Cancer through Mammograms using EABCO Algorithm. International Journal of Engineering and Technology. Vol. 11(5).

Suganya R. and Porkodi G. 2018. A Comparative Study of Different Deployment Models in a Cloud. Int. J. Adv. Res. Comput. Vol. 3(10); 185-191

Tan Y. and Zhu Y. (2010). Firework Algorithm for Optimization, In Y. Tan et al. (Eds): ICSI 2010, Part I, LNCS 6145, 355–364, Springer-Verlag Berlin Heidelberg.

Telikani A., Gandomi A. H., Shahbahrami A., and Dehkordi M. N. 2020. Privacy-preserving in association rule mining using an improved discrete binary artificial bee colony. Expert Systems with Applications. Vol. 144, p. 113097.

Unspecified. http://www.nhs.uk/Conditions/Cancer-of-the-breast-female/Pages/Causes.aspx, Accessed 16th, June 2022.

Vijayalakshmi S. John A. Sunder R., Senthilkumar M., Sweta B., Rajesh K., Guang F., and Usman T. 2020. Multi-model prediction of breast cancer using particle swarm optimization with non-dominating sorting. International Journal of Distributed Sensor Networks. Vol. 16(110). journals.sagepub.com/home/dsn. DOI: 10.1177/1550147720971505

Wafa Nobili. Brahim Farou. Zinedine Kouahla & Hamid Seridi. 2021. Revised Artificial Immune Recognition System. IEEEAccess. Vol. 5. DOI: 10.1109/ACCESS.2021.3133731

Wang H., Zheng B. Yoon S. W. And Ko H. S. (2017). A Support Vector Machine-based ensemble algorithm for breast cancer diagnosis. European Journal of Operational Research. 687- 699. www.elsevier.com/locate/ejor. https://doi.org/10.1016/j.ejor

Wang J, et al. Improvement and application of hybrid firefly algorithm. 2019. IEEE Access. Vol. 7:165458–165477.

WBCD – Wisconsin Breast Cancer Data – UCI Machine Learning Repository. 2021. Accessed via www.arquives.ics.uci.edu/ml/ May 6, 2022.

Weli Z.N. 2020. Data Mining in Cancer Diagnosis and Prediction: Review about Latest Ten Years. Curr. J. Appl. Sci. Technol. Vol. 39(6); 11-32.

Yang, X.-S. (2010). Firefly Algorithm. in Engineering Optimization. ed: John Wiley & Sons, Inc., pp. 221-230.

Zamani H. and Nadimi-Shahraki M. (2016) 'Swarm Intelligence Approach for Breast Cancer Diagnosis'. *International Journal of Computer Applications*. 0975 – 8887). Vol. 151(1): 0975 – 8887. https://www.researchgate.net/publication/309219130. DOI: 10.5120/ijca2016911667

Zorlouglu G. and Agaoglu M. 2017. Diagnosis of Breast Cancer Using Ensemble of Data Mining Classification models of Clementine used. Int. J. Oncol. Cancer Ther. Vol. 2: 24-27.

Zwitter, M. and Soklic, M. (2015) University Medical Centre, Institute of Oncology, Ljubljana, Yugoslavia. Available: https://archive.ics.uci.edu/ml/datasets/Breast+Cancer.