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ANN-ABC META-HEURISTIC HYPER PARAMETER TUNING FOR MAMMOGRAM CLASSIFICATION

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ABSTRACT

In recent past, artificial neural networks (ANN) have reaped improvements in the domain of medical image processing by addressing many unmanageable problems. The initialized hyperparameters control ANN performance and selecting sensible hyperparameters by hand is time-consuming and tiresome. This study suggests a metaheuristic optimization of the fine-tuning hyperparameters approach to remedy this flaw. The method is then evaluated on mammography images to assess whether the mammogram contains cancer. In the proposed ANN model, a modified Artificial bee colony (ABC) optimization method is used to fine tune the hyperparameters, and it categorizes the tumors in the breast as benign or malignant in two-class case and normal, benign, and malignant in three-class case with an accuracy of 97.52% and 96.58% respectively. Hyperparameters to the neural network framework were assigned instantly with the help of ABC method with wrapped ANN as objective function. Manual search, Grid Search, Random Grid search, Bayes search are all cutting edge ANN hyperparameters methods. In addition to the mentioned, nature-inspired optimization methods such as PSO and GA have adopted for fine tuning parameters. Additionally, the suggested model's performance in classifying breast pictures was compared to that of the published hyperparameter technique using sizable datasets on breast cancer that were made accessible to the public.

Keywords: *Artificial Neural Networks, Hyperparameters, Artificial bee colony, Mammogram images, Grid Search.*

1. INTRODUCTION

Out of two women newly breast cancer diagnosed one woman dies in India. Breast cancer ratio is 14% of all women cancers in India and in it is the topmost cancer in case of new cases registered in 2020 with 178361(26.3%) cases in women in India [25]. Overall, out of twenty-nine women one woman likely to detect with Breast cancer in her lifetime. Furthermore, it the second most common cancer in the world next to lung cancer, irrespective of gender [1]. Studies are proved that early breast cancer detection could cut the rate of death drastically, reduces the radiologist effort to treatment and disease morbidity [2]. For the Radiologist, early state breast cancer detection is a tiresome job as they must deal with huge number of digital mammogram images, which inclined to develop an automated and simplified early-stage cancer detection method. Medical diagnosis system could have been inculcated with the intelligent based systems like neural networks models [24]. Traditional decision-making methods are outperformed by the artificial intelligence-based ANN models. In this regard, many swarm based nature-inspired optimization algorithms (NIOA) like ABC, PSO (particle swarm optimization) and GA (Genetics Algorithm), etc. are adopted in finding the optimized solutions to real-time medical diagnosis problems [3]. This research proposed an automated hyperparameter fine tuning ANN model by adopting ABC as its tuning method instead of traditional methods like Grid Search.

1.1 Artificial Neural Networks

Biological neurons in human brain and their relationships inspire the development of basic ANN model. ANN metrics like performance accuracy and efficiency builds upon its structural parameters like number of neurons in input and output layers, count of hidden layers, activation

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function and weighted values. Generally, multilayer ANN have one input, one output and at least one hidden layer [4]. Figure one depicts the basic structure of ANN.

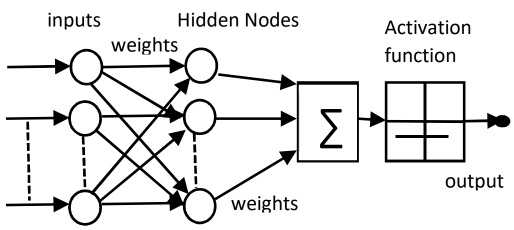

Figure 1: ANN Basic Structure [4].

1.1.1 ANN parameters vs hyperparameters

Decision making has huge involvement of Machine Learning (ML) models. In real time problems, the professionals working around with various algorithms depends upon the problem and the selected model. However, professional can increase the accuracy and performance of the ML model using hyperparameters. ML models are associated with both hyperparameters and parameters and both are intended for distinguished tasks. ML model estimates the parameters based on the input data history for result prediction. One cannot hardcode or set the parameters like independent variables coefficient, logistic regression, and linear regression to a ML model. Whereas professionals can specify some variables to the ML model manually those are called hyperparameters. Hyperparameters helps in evaluating the best optimal parameters to the model and these are decided by the one who builds model. Random forest algorithm max_depth, KNN classifiers k value, number of neurons in NN layers, etc. are some hyperparameter examples [26]. Table 1 shows the optimal range of ANN hyperparameters [5].

1.1.2 hyper parameter methods

Optimization of hyper parameter is achieved with various optimization methods. This section listed most popular four parameter optimization methods. 1. Manual search 2. Grid search [GS] 3. randomized search [RS] 4. Bayes Search [BS].

Table 1: ANN Model Hyperparameters and their ranges [5].

S.No	Hyperparameter	Description	Range
1	No. of Hidden Layers	between the input and output layers, the number of inner layers	1 to 3
2	Number of hidden nodes	in the hidden layer, the number of neurons	1 to 10
3	Number of training cycles	No. of the training iterations	10 to1000
4	Learning Rate	Weight variation updated during learning	0.0001 to 0.1
5	Learning algorithm	The learning process is carried out via an optimization algorithm in a neural network.	RMDprop, SDG, Adam,
6	Adam, SDG, RMDprop	activation function of Neurons	Linear, Tangent
7	Learning rate decay	The decay of learning rate across learning iterations' rate function	linear ,Exponential
8	Error function	the process through which a neural network's training function is reduced	mean square error, Log loss
9	Epoch limit	Maximum number of iterations for learning	Maximum number of learning iterations
10	Mini batch size	Group size submitted to model during training	10, 20, 30
11	Patience	a delay to the trigger in terms of how many epochs we'd prefer to go without improvement.	2, 5, 10

In Manual Search, the professional's expertise or intuition determines the required hyperparameters values for NN, but one who can set parameters has excellent grasp on learning data and NN structure. However, several trial-and-error experimentations leads to setting wise hyperparameters of the model. GS identifies the suitable and well performed hyperparameters by combining parameters and using many values for hyperparameters while calculation. GS needs minimal or less background knowledge, easy to apply and straightforward method. In GS, Lower and Upper limits of all hyperparameters are used to explore the potential and possible hyperparameter combinations and identify the best parameter set of models. As a result, GS creates a value space of hyperparameter in the predefined step. GS is recognized as a broad space as it executes all possible and potential combinations. Thus, GS is more time complex method and cost of computation is high. Moreover, GS gives different performances to the same set of parameters, when applied in ANN, Convolutional NN and Recurrent NN [5]. RS is same as GS method, whereas in RS comprehensive enumeration of parameters combinations are replaced by random selection of hyperparameters. RS with less cost, explores the more search space compared to GS. Major advantage of RS is independent evolutions are parallelized with ease and allocated resources effectively [6]. Furthermore, global optimization method BS is used erroneous black box functions. Bayesian optimization creates a mapping function's probabilistic model to map the validation set assessment objective to hyperparameter values. Figure 2a depicts that GS applying varying values of two hyperparameters. For the sum of hundred feasible combinations, every hyperparameter is compared and checked with 10 definite values. Blue and Red outlines denote the regions with robust outcomes and places with low results respectively. Figure 2b depicts that RS considered the hundred different options to do a random searching across the values of possible combinations for two hyperparameters. When compared to GS, RS examined a greater number of each hyperparameter values separately. Figure 2c illustrate that BS examine all hyperparameters alternate options by identifying next combination to be examined using past discoveries [7].

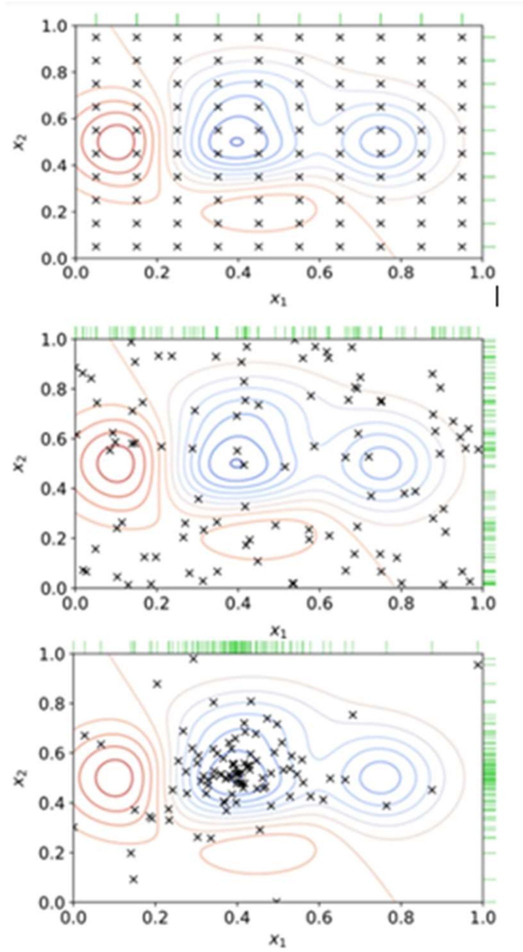

Figure 2: A. Grid Based Search B. Random Search C. Bayesian Search [7].

1.2 Nature Inspired Hyperparameter tuning

1.2.1 Genetics Algorithm

GA is evaluation theory-based metaheuristic algorithm. Every generation generates worse and superior individuals by inheriting traits from parents. In the long run, superior will persist and worse will gradually perish. After several generations, the best adaptable item will be the potential global optimum. Which means the entity with capable to adapt to surroundings and excellent survival capacity are likely to get over through the traits and live on. Figure 3 depicts the genetic algorithms template in four step methodology [11].

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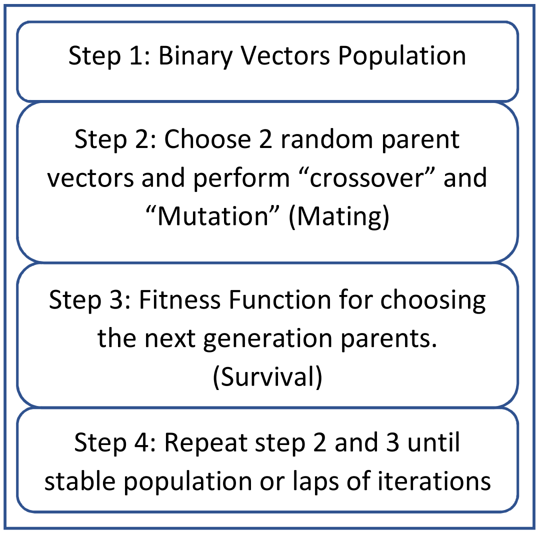

Figure 3: Genetics Algorithm Template [11].

1.2.2 Particle swarm optimization

PSO is initialized with a random solutions population, which is similar to GA. Whereas, PSO differs from GA algorithm in the system every possible solution is assigned with a randomly generated velocity and later these particles or potential solutions are flown in hyperspace. In PSO three best values called *best*, *pbest* and *gbest* are keep tracked. *best* solution is the coordinates in hyperspace achieved thus far are keep tracked by every particle. *pbest* is the fitness value of *best* solution. *gbest* is the location of best value obtained by any particle so far in the population [8]. The process of PSO is described as follows, in each iteration particle update its accelerating velocity towards its global version *gbest* and *pbest*. Acceleration is updated by a separately generated random number and a random term toward *gbest* and *pbest*.

This research main contributions could well be summarised as follows:

- *This research proposes integration of ANN with NIOA Hyperparameter Methods*
- *Proposed method is employed to Mammograms Classification using ABC based ANN.*
- *The mammogram classification results are compared and tested with other state-of-art methods in 2-class and 3-class ways.*

Artificial Bee Colony optimization

ABC is bio-inspired meta-heuristic optimization method, firstly materialized by Karaboga in 2005[13]. ABC mimic the foraging behavior of hive honeybees. Because of its low control parameter, simplest design model and good robustness takes over the other NIOA optimization algorithms among the young researchers. The process of basic ABC is described with foraging behavior, food sources, employee, onlooker, and scout bees [12]. ABC algorithm is divided into mainly four different phases. 1. Initialization Phase: scout bee specifies the population of food sources and control parameters. 2. Employee Bee: after finding a potential solution it searches for the nearby areas by comparing the fitness value of food source (Equation 1). 3. Onlooker Bee: employee and onlooker bees exchange the information about food sources in the dancing area of hive (Equation 2) 4. Scout bee: trial or limit exhausted food sources are abandoned by the scout bee using upper and lower bounds (Equation 3). Nectar amount and position of food source calculate the fitness value [3].

$$X_{new}^{j} = X^{j} + \emptyset(X^{j} - X_{P}^{j}) \tag{1}$$

Where ‘j’ is food source randomly selected, ∅ is a value between (-1, 1) generated randomly, and p partner food source selected randomly [12].

$$Prob_{i} = 0.9 * \frac{Fit_{i}}{\sum_{1}^{n} Fit} + 0.1 \tag{2}$$

Where ‘Fit_i‘ specific solution’s objective function value. X_k randomly generated new solution [12].

$$X_k = lb+(ub-lb)*r \tag{3}$$

2. RECENT RESEARCH

Roseline et all [2022], proposed a medical diagnostic system by employing the NIOA method called PSO to fine tune the hyperparameters of ANN and CNN. The WDBC (Wisconsin Diagnostic Breast Cancer) data set was tested with the proposed methodology and achieved the classification accuracy of 99.2% and 98.5% for ANN and CNN respectively [5]. Vishnu et al [2022], explores how can an ANN model predict the shear walls failure models using hyperparameter optimization and achieved comparatively good results. This study practiced the fine tuning of ANN hyperparameters using GS, RS, BS, HyperBandCV, PSO and GA methods [6]. Zhiqiang Guo et al[2022], aims at Multi-layer Perceptron (MLP) NN hyperparameter tuning to classify the samples of breast cancer. This proposed ensemble learning algorithm is intended to improve the NN performance by combining the traditional parameter optimization methods with the NIOA algorithms like GA, PSO and ODMA. In this study, comparison of different algorithms is made on three breast cancer datasets to achieve 98.79% of accuracy [14]. Warut Pannakkong et all [2022], used response surface methodology (RSM) as hyperparameter methos instead of most used GS method. This study applied RSM in fine tuning of three ML algorithms: ANN, deep belief network (DBN) and SVM. Proposed approach RSM for ANN, DBN and SVM outperform the GS for ANN, DBN and SVM in prediction accuracy, number or runs and settings of hyperparameter with large margin [15]. Punitha et al [2021], proposed a hybrid method for hyperparameter tuning by employing ABC and Whale Optimization (WHO). ABC phases are inculcated by inheriting the attacking behaviour of whale. WDBC, MIAS etc. are used to test the proposed method and got the 99.2% of accuracy using hybrid method [16]. Punitha S et al [2021], proposed IAIS-ABC-CDS (integrated Artificial immune system and-ABC-Cancer Diagnosis) method for ANN parameter optimization and feature selection. This method improves the local search process by taking the simulated annealing (SA) method advantages. WDBC data set was taken for testing the proposed methodology and it is reported that 99.11% and 99.34% mean classification in ANN [17]. siti Fairuz mat radzi et al [2021], developed a Automated ML (AutoML) method as an pipeline optimization technique for identifying ML models with excellent performance and simple pipelines for breast cancer diagnosis. Moreover, the presented method exceeded the GS performance in optimization process. The proposed classifier results the good outcome compared to other reported models with only couple of preprocessors and with 0.83 precision values [18]. Gamz Erdogan Erten et al [2020], developed a GS based ANN hyperparameter method. This method performance is compared with KNN (k-nearest nighbour), Naïve Bayes (NB), Support vector Machine (SVM) and decision tree (DT). It produced good accuracy values as 73.95%, 76.74%, 77.21%, 81.86%, 91.63% with the GS based KNN, NB, DT, SVM and ANN methods respectively [19]. Fernando Itano et all [2018], developed an optimization search method for MLP method using GA. It examines the classification performance with hyperparameter correlation by allowing the less search space. It added hyperparameter for the initialization and regularization of weights simultaneously with learning of Hyperparameter and MLP topology [20]. P. Shanmugapriya et al [2017], presented a novel Swarm Intelligence based hybrid method called ABC-AC (ant colony) for feature selection for the image classification. This study takes the advantages of both ABC and AC optimization algorithm to achieve the better results. Proposed method is applied on different decease datasets [21]. Fadzil Ahmad et al [2012], proposed an automated BC diagnosis method using GA for ANN feature selection and optimization of hyperparameters. This method is developed in three variations like GA_ANN_RP (resilient Back-propogation(BP), GAANN_LM (Levengerg Marquardt) and GAANN_GD (gradient descent) for ANN parameter and weight optimization. Interestingly, GAANN_RP is tops among the three proposed methods with the 99.24 % of average and 98.29% of classification correctness [22].

3. PROPOSED ANN-ABC METHODOLOGY

3.1 Problem statement

According to several researchers, adjusting the ANN parameters can increase model accuracy while lowering time complexity. The relevant investigation that was mentioned in the preceding section concluded that the best strategy for parameter tweaking was still needed. The primary goal of this study is to use NIOA's ABC method to fine-tune the ANN model's hyperparameters. The population space, search area, duration, and spatial complexity of traditional optimization methods each have their own pros and downsides. This paper addresses the some of the

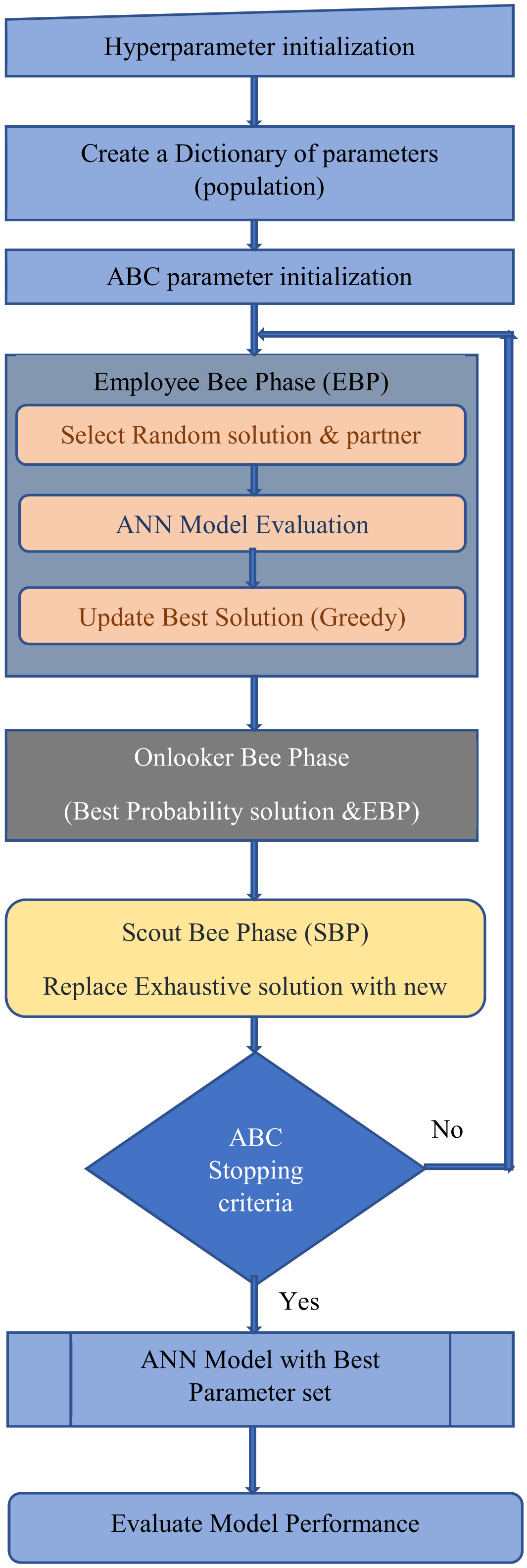

Figure 4: Proposed Methodology.

mentioned problems like time and search space complexity with reduced search space, exploration, and exploitation by adopting the NIOA ABC algorithm.

3.2 Overall design

Figure 4 illustrates the flow diagram of the proposed ANN-ABC model for hyperparameter tuning. The proposed method has primarily three steps: 1. Parameter initialization and population creation 2. Apply ABC parameterization to ANN model 3. Assess the accuracy and complexity of the best solution set obtained in the previous step. Firstly, ANN hyperparameters like the number of hidden layers, number of neurons in each layer, learning rate, activation functions, etc. are to be initialized with the most popular optimal set derived from the earlier research. After that dictionary of specified parameters is arranged as a dictionary, it is sent as a population space to the ABC phase. Second, in this step, a number of employee bees is assigned to the number of inputs, and they start exploring nearby locations randomly and comparing the fitness values. Once the greedy solution is discovered, it applies that solution set to the wrapped ANN model (passed as an objective function to ANN) and determines the model's accuracy. Later, by comparing the fitness values of solutions, the OBP determines the probability of the best solution being returned by the EBP and performs greedy selection. In SBP, if any solution is considered to have more than the limit of occurrences, then it is replaced with the newly randomly selected solution. The above process is iterated till it reaches the specified number of iterations or stopping condition. Furthermore, the ABC phase returns the best solution set of hyperparameters to the ANN model. Finally, tuned hyperparameters are again applied to determine the accuracy and complexity of the model.

4. RESULT AND DISCUSSIONS

4.1 Dataset: Experimental setup

Proposed classifier model performance is investigated by using an open source mini-MIAS (Mammogram Image Analysis Society) data set. The database involves a set of 322 mammogram digital images comprises 62 benign, 51 malignant and 209 normal mammograms [23]. Proposed classifier is implemented in two ways, three-class case (normal, benign, and malignant) and two-class case (normal and abnormal). In two class-case, proposed classifier is applied on dataset to categorize mammogram into normal and abnormal. Whereas, in three-class set, classifier categorize the images into normal, benign, and malignant. Out of 322 images, 70% mammogram are considered as training set and 30% as testing set and used k-fold cross-validation (CV). The input data is normalized by using scikit learn minimum-maximum scaler and the categorical variables are passed to ANN input layer after one hot encoding.

The proposed model performance is evaluated by using the metrics like specificity(recall), F-Score, sensitivity, precision, and accuracy. These metrics are calculated from:

Specificity = TN / (FP + TN)

Sensitivity (Recall) = TP / (FN+TP)

Accuracy=(TP+TN)/(FP+FN+TP+TN)

Precision =TP/(TP+FP)

FScore=(2*Precision*Recall)/(Precision+Recall)

4.2 ANN-ABC Hyperparameter setup

ANN model is wrapped as a single function and passed the set of hypermeters as parameter to the wrapped function. Further, the dictionary of hyperparameter is prepared with different parameters, such as the hidden layers count, every hidden layer's neuron count, activation functions, learning rate, dropout size, epochs (as ABC termination), and batch size. In this practice, ADAM algorithm, binary_crossentropy used as optimizer and loss functions while compiling ANN model. The created Dictionary grid space is considered as the ABC population and size of bees is depending on the count of hyperparameters used. Same parameter set is applied to all hyperparameters methods like GS, RS, BS, PSO, GA and proposed ANNABC models in two ways like two-class case and three class case. The performance of all mentioned models is compared and illustrated as confusion matrix and its metrics. Table 2 show the set of hyperparameters used for the experiments.

Table 2: Hyperparameter Dictionary

Parameter	Count	Range
Hidden Layers	1,2,3	[20], [40,20],[40,30,15]
Activation Function	2	Sigmoid, relu
Batch Size	2	64,128,256
Epochs	3	30,50,100
Dropout	2	0.3,0.1
Learning Rate	2	0.1,0.01

Proposed model trained with the possible combinations of listed hyperparameters. For example, the number of hidden layers to an ANN could be assigned in three ways like one layer with 20 neurons, two layers with 40 and 20 neurons respectively and three layers with 40, 30 and 15 layers respectively. The proposed model resulted best Hyperparameter set with least number of epochs compared to other methos. Best result is {activation:'relu', 'batch_size': 64, 'epochs' : 30 , 'dropout' : 0.3, 'learning_rate': 0.01, 'layers':[45,30,15]} with accuracy of 97.52% and 96.58% for two-class and three-class case respectively. Table 3 and Figure 7 shows the performance metrics of the two-case proposed model. Table 4 and Figure 8 demonstrate the comparison accuracy of all reported methods in two-class and three-class models. Figure 5 and Figure 6 illustrate the performance of two-class classifier and three-class classifier in confusion matrix respectively.

Table 3: Two-Case Performance Metrics

Method	Precision	Sensitivity	Specificity	F_Score
GS	94.74	96.12	90.52	95.42
RS	93.3	97.99	88.62	95.59
BS	95.69	98.04	92.37	96.85
PSO[6]	96.65	98.54	94.02	97.58
GA[22]	94.74	98.51	90.91	96.59
ANNABC	97.13	99.02	94.87	98.07

Table 4: Accuracy Comparison Of Two-Class And Three-Class Model.

Method	Two-Class	Three-Class
GS	94.1	92.55
RS	94.41	92.86
BS	95.96	93.48
PSO [6]	96.89	95.03
GA[22]	95.65	94.72
ANNABC	97.52	96.58

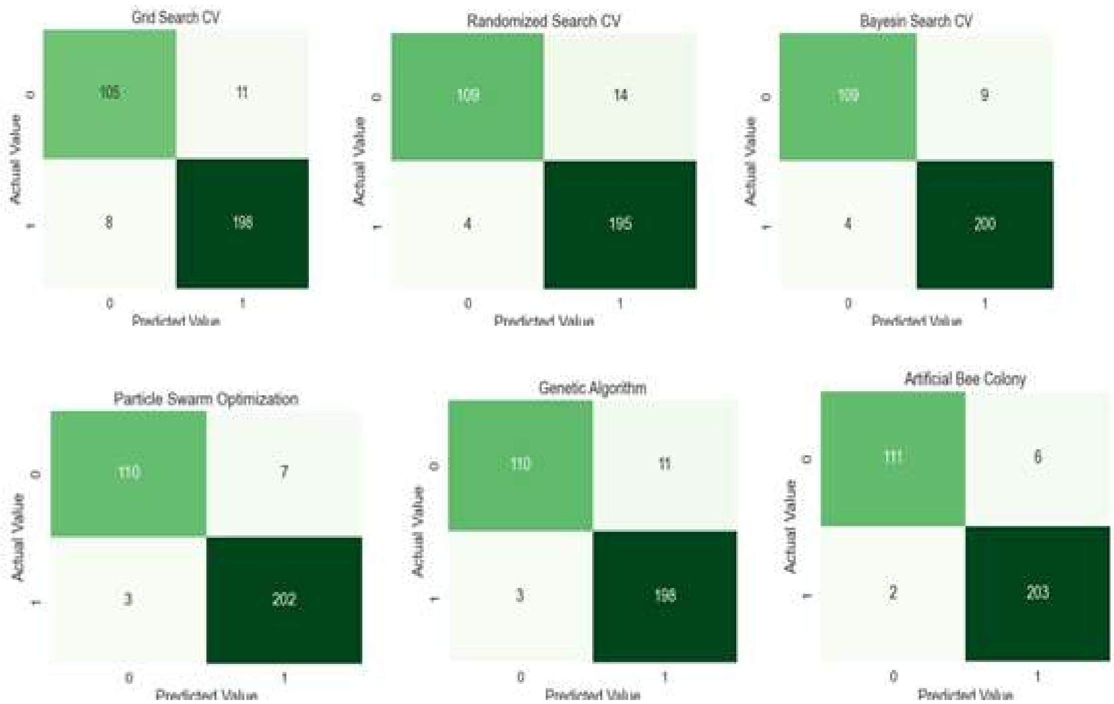

Figure 5: Two-Class Classification Confusion Matrixes A)Gridsearchcv B)Randomizesearchcv C) Bayesiansearchcv D)Paricleswarmoptimizationcv E)Genticalgorithmcv F)Artificialbeecolonycv

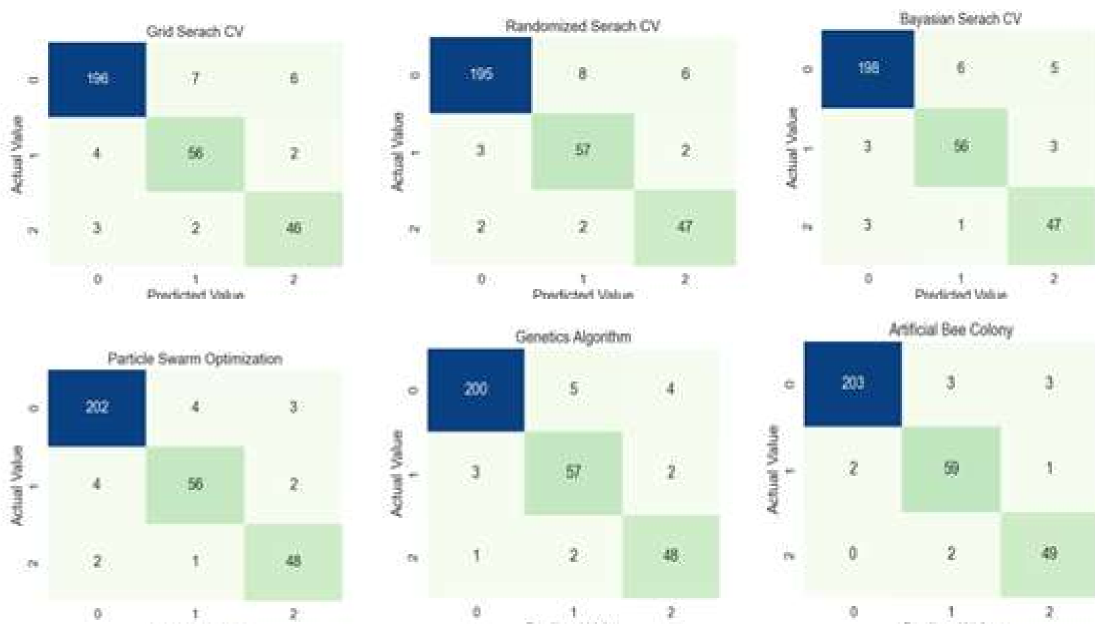

Figure 6: Three-Class Classification Confusion Matrixes A)Gridsearchcv B)Randomizesearchcv C) Bayesiansearchcv D)Paricleswarmoptimizationcv E)Genticalgorithmcv F)Artificialbeecolonycv

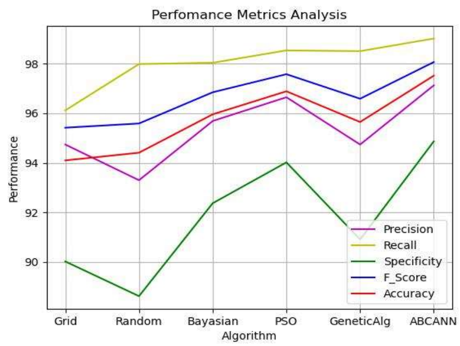

Figure 7: Performance Comparison All Methods

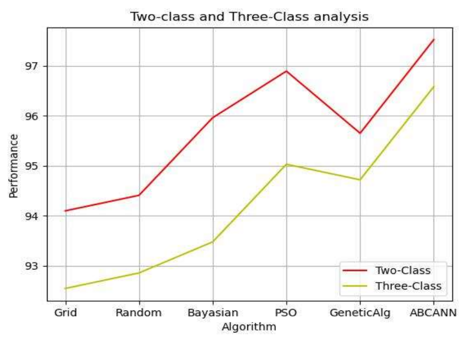

Figure 8: Two-Class Case And Three-Class Analysis

5. CONCLUSION AND FUTURE SCOPE

This study investigated at the performance of the ABC hyperparameter adjusted ANN in detecting malignancy in mammography images in the two-class and three-class models. The suggested technique produced good results: the accuracy of the two-class model was 97.52%, and the performance of the three-class model was 96.58%. Based on the findings, the categorization of the MIAS dataset provided in this work has the potential to assist radiologists in identifying breast tumours. The performance measures demonstrated that the ANN-ABC model outperformed other competing classifiers in prediction. The proposed ANN-ABC model results are displayed in a confusion matrix, which allows categorization of mammograms into "Normal" or "Abnormal" in the case of two-class and "Normal" or "Benign" or "Malignant" in the event of three-class.

In the future, we will reconnoiter ABC variants and hybrid models like ABC with other NIOA methods to fine tune the ANN hyperparameters. Finally, we will extend the ABC-based tuning process to other ML models like CNN and various breast cancer datasets.

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