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Hybrid TLBO-PSO Algorithm Optimized Deep Learning Techniques for Analyzing Mammograms

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Abstract: Breast cancer which is the commonest malignant tumor in women, not only is a threat to life but also affects the mental and physical health of women. One of the most important tools in diagnosing breast cancer is Mammography. As mammogram images are complex, doctors find it difficult to identify the attributes of breast cancer clearly. The classification algorithm which is being used to study breast cancer at present is deep learning. So, this work proposes a Residual Network (ResNet) 34 and Convolution Neural Network (CNN) 18 model for benign as well as malignant mammographic images' proper as well as precise classification. Teaching-Learning Based Optimization algorithm (TLBO) with Particle Swarm Optimization (PSO) (TLBO-PSO), a fundamental deep learning approach, has been used in this study. This approach's key goal is for optimization of the outcome of the solution vectors on the CNN as well as the ResNet so as to enhance precision or recognition. The accuracy of this model not only helps in better performance and enhanced accuracy of malignant and benign classification of mammogram images but also proves the robustness and generalization of the model.

Keywords: *Breast Cancer, Mammography, Deep Learning, Convolutional Neural Networks (CNNs), Residual Network (ResNet), Teaching Learning Based Optimization Algorithm (TLBO), and Particle Swarm Optimization (PSO).*

1. Introduction

TLBO-PSO, which is a hybrid of the CNN's most fundamental deep learning-based approaches: the Teaching-Learning Based Optimization (TLBO) as well as the Particle Swarm Optimization (PSO). This algorithm can enhance the accuracy of recognition by optimizing the outcomes of solution vectors on CNN and ResNet. The proposed algorithm's better performance is able to enhance the classification accuracy of the mammogram images as malignant and benign.

Globally, breast cancer is a major reason behind female fatalities,and unfortunately, there is an increase of its incidence, especially in the developing nations. The WHO has given the prediction that, by 2025's year end, there will be about 19.3 million breast cancer cases. The most common technique to detect early breast tumors is a mammography-ultrasound combination. At times MRI is also used. The screening results can be interpreted only by skilled radiologists. However, there is a constant global shortage of radiologists, particularly in the under-developed nations [1].

The workload of doctors is reduced by Computer-Aided Diagnosis (CAD)-based medical screening. This is a better and more innovative technology in terms of medical diagnosis. Ultrasound, Mammography as well as MRI come under the category of CAD-based medical screenings. Mammography is accounted for as being the most reliable, less harmful, effective as well as cost-effective medical screening for the early-stage breast cancer detection. Mammography with CAD offers a better accuracy rate in detecting, operating, and speeding up the diagnostic procedure while also conserving the medical resources. Moreover, the breast mass has a distinctive role in the breast cancer diagnosis. Biological characteristics as well as growth pattern merely offers marginal information regarding the breast mass. Most of the time, irregular margins of breast mass can be correlated with breast cancer, and segmentation accuracy of the breast mass affects MBMC (Malignant Breast Masses Classification). Thus, in CAD, mass classification is a critical feature in the breast cancer classification as it aids in the early stages of diagnosis of breast cancer. Moreover, there are certain other features, including varying shapes and sizes and illness boundaries. Thus, the appropriate classification of segments is a challenging and popular problem in the CAD technique [2].

Machine learning has proved to be better than the traditional handcrafted technique as it can select significant features. When it comes to the arena of biomedical engineering, more specifically, Deep Convolutional Neural Networks (CNNs) prove to be more efficient. Its deep architecture will aid in the image processing by means of the following two distinct layers: the convolutional layer, and the pooling layer. The convolutional layer calculates the neurons' output that is connected by LAN at input by weight sharing and biases. The output of the convolutional layer is subsampled in

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pooling, where the size of the data is reduced. Large numbers of training images are included in CNN, along with the availability of its ground truth that prevents a number of deep CNNs from being applied in medical applications [3].

Though conventional CNN shows considerable precision, it still has a lot of scope for improvement. In recognition tasks, the CNN's efficiency improvement is done through utilization of the PSO for optimization of the CNN's output vector. PSO's utilization is because of its strong performance on optimization problems, which was developed by Eberhart and Kennedy. This technique finds its inspiration through the social behavior of animals which lack group leaders. Swarm particles are present in PSO, where the particles can be a representative of the potential solution [4]. It is easy to implement PSO, as the algorithm's global search is quite efficient. It is a fast algorithm, even though the dependency on the initial solution is smaller, and moreover, lesser parameters are involved in tuning the algorithm.

This work involves a hybrid TLBO-PSO algorithm with ResNet and CNN-18 in enhanced cancer detection through Mammography. The study's rest is thus arranged: Section two will detail the related literary works. Section three will elaborate on the study's diverse applied techniques. While Section four will discuss the simulated outcomes, Section five will offer the work's conclusions.

2. Related Works

CNNs such as Visual Geometry Group (VGG) VGG-16 and VGG-19 were pre-trained by Ahmed et al., [5] to identify and classify tumors of the breast on the breast dataset. In this model, pre-processing of breast images for enhancement of the image quality as well as for mitigation of the computational time. In the next step, the features that are learned through the networks are transferred so as to correlate with the breast parameters in order to enhance classification results. Thus, effective manipulation is done to make use of the information obtained from the huge data that is generated, so that exact classification might improve treatment options. Manipulation results showed that the ROC curve (AUC) for accuracy sensitivity, specificity, and area showed values of 97.1%, 96.3%, 97.9%, and 0.988%, respectively, in the proposed model

A new customized technique was proposed by Chakravarthy & Rajaguru [6], was an integration of the deep learning approach and the Extreme Learning Machine (ELM), that was optimized with the Improved Crow Search Algorithm (ICS-ELM), for better performance of the healthcare problems' resolution. This work helps in differentiating the abnormal mammogram from a normal mammogram; the next step is a classification of the abnormal types into benign or malignant. For this work, the digital mammograms were chosen from the following breast datasets: the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) as well as the Mammographic Image Analysis Society (MIAS). While this work had employed 570 digital mammograms from the CBIS-DDSM dataset, out of which, 250 were normal cases, 120 were malignant cases, and 200 were benign cases, 322 digital mammograms were picked from the MIAS database, out of which 207 were normal cases, 51 were malignant cases, and 64 were benign cases. From the breast dataset, 179 full-field digital mammograms were evaluated, out of which, 56 were benign, 57 were malignant, and 66 were normal. The proposed work had employed the ICS-ELM algorithm that used the ResNet-18 based on deep extracted features. This work was compared with the existing Support Vector Machines, the ELM, the PSO-optimized ELM as well as the crow-search optimized ELM, where the acquired maximum accuracy was 97.193% for the DDSM, 98.137% for the MIAS, and 98.266% for the breast datasets.

A new hybrid algorithm was proposed for breast mass classification and feature selection with multilayer perceptron by Rajendran et al., [7], which is a combination of the grasshopper optimization as well as the crow search algorithm, which was simulated using MATLAB 2019a. Later, this hybrid algorithm was compared against the butterfly optimization algorithm, the whale optimization algorithm, the grasshopper optimization algorithm and such multi-layer perceptron systems. Better classification accuracy with 97.1%, specificity of 95.4%, and sensitivity of 98% were found in the proposed grasshopper optimization-crow search algorithm with the multilayer perceptron method compared to other models for the dataset of the society of mammographic image analyses

The propagation technique of Ebola virus disease was used in a new metaheuristic algorithm - the Ebola Optimization Search Algorithm (EOSA) - proposed by Oyelade et al., [8]. The disease's improved SIR model was designed by the authors, that is, SEIR-HVQD: Susceptible (S), Exposed (E), Infected (I), RNext, a new model was used, which was a mathematical model with its basis on a system of first-order differential equations. Formulation of a new propagation as well as mathematical model was done to develop a novel metaheuristic algorithm. The performance and capability were evaluated by comparing with other techniques of optimization; two distinct sets of benchmark functions which were made up of 47 classical as well as 30 constrained IEEE-CEC benchmark functions, were examined in detail. It was evident from the simulated outcomes that the proposed algorithm's performance was competitive compared to other modern optimization techniques, which were based on the GA, the PSO as well as the ABC algorithms. This algorithm was also applied in addressing the complicated problem of choosing the best CNN hyper-parameter combination for classifying the digital Mammography's images. The study's outcomes had demonstrated the successful detection of breast cancer by the CNN architecture with a precision of 96.0%.

An Improved Crow Search Optimization algorithm was proposed by Sannasi Chakravarthy & Rajaguru [9] to classify the severity of the disease through digital Mammography as benign (B) or malignant (M). In general, according to the literature, CSOA is used to identify solutions for the problems of numerical optimization as well as feature selection. This technique's objective was to utilize this algorithm for resolution of the problems of biomedical image classification. In case of direct application of this algorithm, it might result in data classification which is quite poorly done. So, suitable enhancements are done to the original CSO algorithm with the help of control parameter tuning and operator and controlled randomness based on chaotic maps. The randomness is controlled through four specific chaotic maps in the OCSO algorithm. The image datasets were obtained from the Digital Database for Screening Mammography and Mammographic Image Analysis Society for evaluation. Statistical features based on discrete wavelet transform were used for classification, and the feature extraction took place at two distinct levels for decomposition: level L4 (L4), and Level L6 (L6). For both datasets, the ImCSOA with L4 and L6 decomposed bior4.4 wavelet features had offered about 85% to 86% of maximum accuracy, which was approximately 62% to 88% better than that of the OCSO algorithm with L4 and L6 decomposed bior4.4 wavelet features.

3. Methodology

Use This section discusses the hybrid TLBO-PSO with ResNet, and CNN approaches. In all these approaches, the input will be the mammogram, while the output is the classification of the mammogram as benign or malignant.

3.1 Teaching-Learning-Based Optimization (TLBO) Algorithm

Rao et al., (2011, 2012), Rao and Savsani (2012) as well as Rao and Patel (2012) had proposed the algorithm which had taken its inspiration from the TLBO's teaching-learning procedure on the basis of a teacher's influence on the learner's output within a class. Two basic modes of learning are explained by this algorithm: (i) the teacher phase (through the teacher phase), and (ii) the learner phase (via interaction with other learners). Here, the population will be a group of learners while the different subjects will be the problem of optimization's different design variables, and the learner's result will be the problem of optimization's analogous 'fitness' value. The entire population's best solution is considered as the teacher [10]. The objective function's design variables were composed of the attributes involved in the given problem of optimization as well as the best solution are the design variables. TLBO's working pattern was classified as the 'Teacher phase' as well as the 'Learner phase.

In actual terms, the design variables are the parameters involved in the given problem of optimization's objective function while the best solution is the objective function's best value. The the 'Teacher phase' as well as the 'Learner phase' are the two distinct parts of the TLBO's working.

Teacher phase: Here, the capability of the student decides the class's mean result in the subject which is taught by the teacher. At a given iteration, i, assuming that there are 'm' number of subjects (that is, design variables), 'n' number of learners (that is, size of the population size, k = 1,2,…,n) while Mj, i will be the learners' mean result in a particular subject, 'j' (j = 1,2,…,m). Xtotal-kbest, I, The best overall result which takes into account together all the subjects which have been acquired from the whole learner population, will be taken into consideration as the outcome of the best learner, kbest. Generally, since the teacher is accounted for as a highly learned person who has the ability to train the learners for accomplishing better results, the algorithm's teacher will be the best learner. Equation (1) will provide the difference between each subject's existing mean result of each subject as well as the teacher's corresponding result for each subject as follows:

$$Difference\_Mean_{j,k,i} = r_i (X_{j,kbest,i} - T_F M_{j,i}) \tag{1}$$

Here, $X_{j,kbest,i}$ will be the outcome of the best learner (that is, the teacher) in a subject, j, ri will be a random number in the range [0, 1] while TF will be the teaching factor which will decide the value of the mean to be changed. This TF value can be either 1 or 2, And its value is randomly determined with equivalent probability as Equation (2):

$$T_F = round[1 + rand(0,1)\{2-1\}] \tag{2}$$

TF is not a parameter of the TLBO algorithm. The TF value is not offered as the algorithm's input, and Equation (2) is employed by the algorithm for random determination of this TF value. After repeating the experiments 'n' number of times, the benchmark function will draw the conclusion that the algorithm is able to perform in a better manner if the TF value is between 1 and 2. Even so, the algorithm has been found to have even better performance if the TF value is either 1 or 2. Therefore, for the algorithm's simplification, the teaching factor is recommended to be as either 1 or 2 on the basis of the rounding up criteria that is offered by Equation (2).

With the $Difference\_Mean_{j,k,i}$ as its basis, an update of the current solution will be done in the teacher phase as follows:

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,I} \quad (3)$$

Where, $X'_{j,k,i}$ will be the updated value of $X_{j,k,i}$. Accept the $X'_{j,k,i}$ value if it will offer a better function value. At the teacher phase's end, all the accepted function values will get retained as well as will be accounted for as input to the learner phase. The learner phase has a dependence on the teacher phase.

Learner phase: The knowledge of learners is increased by interacting within themselves. There is random interaction between the learners in order to enhance /her knowledge. If others have more knowledge, then the learner learns a new thing. For a population size of 'n', this phase's learning phenomenon will be as follows:

Randomly pick two distinct learners, P, and Q, in such a way that $X'_{total-P,i} \neq X'_{total-Q,i}$ (in which, $X'_{total-P,i}$ and $X'_{total-Q,i}$ are the updated values of $X_{total-P,i}$ and $X_{total-Q,i}$, respectively, at the teacher phase's end).

$$X''_{j,P,i} = X'_{j,P,i} + r_i(X'_{j,P,i} - X'_{j,Q,i}), \text{ If } X'_{total-P,i} > X'_{total-Q,i} \quad (4)$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i(X'_{j,Q,i} - X'_{j,Q,i}), \text{ If } X'_{total-Q,i} > X'_{total-p,i} \quad (5)$$

Accept $X''_{j,P,i}$ if it will offer a better value of the function.

3.2 *Particle Swarm Optimization (PSO) Algorithm*

A nature-inspired metaheuristic technique was introduced by Kennedy and Eberhart in 1995, and was called the Particle Swarm Optimization (PSO), which took its inspiration from the behavior of flocking birds in search of feed. This behavior was the basis for particle search in a population for solutions that were globally optimal. The PSO will have random distribution of the particles all across the search space, and here, the assumption is that the particles are flying in the search space. Based on personal and social experiences, the position and velocity of each particle are updated iteratively. For every particle, local memory is created, and there will be storage of the best experience achieved so far. Also, the best solution's global memory is retained, and both memories' size will be restricted to '1'. While the particle's experience is accounted for as the local memory, the swarm is accounted for as the global memory. With the help of randomized correction coefficients, the balance between personal and social experiences is maintained. The velocity update procedure's underlying concept is for mitigation of the distance between the particle and the best personal as well as social locations. PSO implementation is quite easy and finds its application in diverse real-world problems [11].

With regards to basic PSO, every particle can be considered as a potential solution to the problem of numerical optimization within a dimensional space considered as D. This search space will assign every particle with a velocity as well as a space. Representation of the particle's position of the particle is given as $x_i = (x_{i1}, x_{i2}, ..., x_{iD})$ while the particle's velocity is given as $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$. Also, there is a local memory, pBest, for each particle that will retain the best position which has been experienced by the particle so far while a globally shared memory, gBest, will retain the best global position which has been found so far. With this information, the below Equation (6) as well as Equation (7) can be employed to find each particle's flying velocity:

$$v_i = v_i + \varphi_1 \times rand \times (pBest_i - x_i) + \varphi_2 \times rand \times (gBest_i - x_i) \quad (6)$$

$$x_i = x_i + v_i \quad (7)$$

Where, φ_1 and φ_2 are constants that will determine the relative influences of the personal as well as the social experiences. The PSO's performance will experience an increase when there is definition of the velocity component's upper bound. An update of the particle's position is given by Equation (7).

An inertia factor's introduction to Equation (6) will enhance the performance as it will adjust the velocity over time, and also will enhance the particles' search precision. It is possible to rewrite Equation (6) as:

$$v_i = \theta \times v_i + \varphi_1 \times rand \times (pBest_i - x_i) + \varphi_2 \times rand \times (gBest_i - x_i) \quad (8)$$

Where, θ will be the inertia factor while the rand will be a uniformly distributed random number that lies within the [0, 1] range. With introduction of a constriction factor, K, for more efficient control as well as constraints on the velocities, there will be modification of Equation (6) as the below Equation (9):

$$v_i = K \times (v_i + \varphi_1 \times rand \times (pBest_i - x_i) + \varphi_2 \times rand \times (gBest_i - x_i)) \quad (9)$$

Here, the K's expression will be in accordance with Equation (10):

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{10}$$

Where, $\varphi = \varphi_1 + \varphi_2$. The value $\varphi > 4$ will prevent the system's explosion, an event that may occur when there is absolutely no control over the increase in particle velocities. The successes of the inertia as well as the constriction factor equations are problem-dependent.

3.3 ***Proposed Hybrid Teaching Learning-Based Optimization - Particle Swarm Optimization Algorithm (TLBO-PSO) with ResNet 34 and CNN-18***

The classification of mammograms as either benign or malignant is boosted through the proposed TLBO-PSO Resnet 34 as well as the TLBO-PSO CNN 18, which can optimize deep learner's architecture. Also, batch size, activation, rate of learning, and a number of epochs of ResNet 34 and CNN-18 are optimized through this.

The TLBO algorithm's key goal is to replicate a class's teaching-learning procedure. The work of the teacher is to inculcate knowledge in the learners, while the duty of the learners is to imbibe the knowledge provided by the teacher in order to enhance their grades. According to the algorithm, the position of the individuals is updated based on the distance between the mean solution as well as the teacher in the teacher phase. The position of the individual is renewed based on the distance between the individual and the class. According to Equation (4), the teacher assesses the student's grade by means of the class's mean grade, and not by means of the distance between the teacher as well the student in the teacher phase. In the PSO, an individual's performance can be improved through the distance between the current individual as well as the manner in which the individual can help him enhance his performance. On the basis of this idea, the PSO's introduction was done on the TLBO for enhancement of the TLBO algorithm's learning efficiency [12]. The TLBO's main change is represented through modification of the Equation (4) as the below Equation (11):

$$X_{i,new} = X_{i,old} + r_1\left(X_{teacher} - T_F X_{gmean}\right) + r_2\left(X_{teacher} - X_{i,old}\right) \tag{11}$$

Here, $r1$ and $r2$ will indicate random numbers within the [0, 1] range. The TLBO algorithm may experience performance improvements due to this modification.

With regards to the original TLBO algorithm, duplicate individuals are identified and removed by comparing all genes with each individual. However, this is a high-cost procedure, and the essential evaluations are yet to be fully understood. At the beginning of the evolution, every generation does not require the duplicate testing. Assuming that both individual i as well as individual k will have similar genes in the t generation, when TF is a random number (either 1 or 2), these individuals' new position may end up being different. When evolution starts, better positions are generated by individuals easily. The diversity of class is maintained by a random operator for TF, but during the evolution's anaphase, the individuals' positions might be close to one another. When the mean solution is equivalent to the best solution, the individual does not change (TF = 1), or when the large change of genes may damage the individual to a great degree (TF = 2), it is hard to generate a better individual.

In order to reduce the effort of computation by comparing all the individuals, it is essential to remove the individual duplicate process with regards to TLBO, which is discarded in the improved TLBO algorithm, and the work will introduce a mutation operator on the basis of the successive generations' best fitness. If there is no change or a slight change in the best fitness of continuous n generations, the individual will be chosen randomly based on the possibility of mutation, which is p, to be mutated. The algorithm's global performance is maintained if there is no mutation of the individual. Algorithm 1 shows the subroutine for mutation.

$pop = sort(pop);$
$if\ abs(bestfit(gen) - bestfit(gen - 1)) < \varepsilon$
$then\ m = m + 1;\ else\ m = 0;$
$if\ (m == n)$
$m = 0;$
$for\ I = 2 : popsize$
$if\ rand(1) < p_c$
$k = ceil(rand(1) * \dim size);$
$pop(i, k) = pop(i, k) + \alpha * rands(1, 1);$
$if\ pop(i, k) > x_{\max}\ then\ pop(i, k) = x_{\max};$
$if\ pop(i, k) < x_{\min}\ then\ pop(i, k) = x_{\min};$
end
end
end
end

In the Algorithm 3, n will be the setting generation, pc will be the mutation possibility, will be a small number that is offered by the designer while α will be the mutation parameter between 0.01 and 0.1.

The TLBO-PSO's Steps

Step 1. Set the position's maximum Xmax as well as minimum Xmin, genmax, the maximal evolution generation, pc, the mutation possibility α, the mutation parameter, popsize, the size of the population size as well as the task's dimension size. The initial population, pop, can be initialized according to the below (12):

$$pop = X_{\min} + r * \left(X_{\max} - X_{\min} \right) \tag{12}$$

Where, r will be a random number within the [0, 1] range.

Step 2. Assess the individual. Then, pick the best individual Xteacher as the teacher, and also evaluate the population's mean solution, Xgmean.

Step 3. For every individual, use Equation (11) for its position update. If Xi, new is better than Xi, old, then Xi, old = Xi, new.

Step 4. For every individual, randomly pick another individual, and then, update its position as per Equation (4) as well as Equation (5), and also pick the better solution from Xi, old as well as Xi, new as the individual's new position.

Step 5. Use Algorithm 1 to execute the population's mutation operator.

Step 6. If there is no fulfilment of the TLBO-PSO's ended condition, the algorithm will either return to Step 2, or it will undergo termination.

While utilizing hybrid TLBO-PSO [13] for the deep CNN's training, there is encoding as solutions of the rate of learning, the size of the batch, the number of the epoch as well as the activation. The experimental outcomes prove that encoding will take place in the procedure's evolution with an increased rate of convergence, with a consequential higher precision threshold. Following are the steps followed:

1. Initialization of a population (TLBO and PSO) of individual particles. The batch size, activation, rate of learning as well as the number of epochs of the deep learner are indicated by each particle.

2. Assignation of fitness value of hybrid TLBO-PSO to each population member on the basis of its epresentative network's assessment.

3. Picking the individuals on the basis of their fitness values to reproduce a new generation of the individuals.

4. Creation of new velocity through execution of the local memory and global memory operations between the chosen particles.5. Repetition from Step 2 till fulfillment.

4. Results And Discussion

For mammogram classification, this section has evaluated methods such as the CNN-18 layer, the Resnet34, the CNN-18 layer - TLBO, the TLBO-GA Resnet 34, the TLBO-PSO Resnet 34, the CNN-18 layer - TLBO GA as well as the CNN-18 layer - TLBO PSO. Evaluation of diverse algorithms can be done with the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM). Being a database with 2,620 scanned film mammography studies, the DDSM is composed of normal, benign as well as malignant cases with verified pathology information. In this work, 550 Benign and 625 Malignant mammogram images are used for evaluation. Python, open CV, tensor flow, and keras are used for the implementation of the algorithms. Table 1 will illustrate the result summary. The classification accuracy, recall, precision as well as f measure will be as shown in figures 1 to 4.

Techniques	CNN-18 layer	Resnet34	CNN-18 layer - TLBO	TLBO-GA Resnet 34	TLBO-PSO Resnet 34	CNN-18 layer - TLBO GA	CNN-18 layer - TLBO PSO
Accuracy	0.9277	0.9021	0.9574	0.9557	0.9609	0.9719	0.9787
Recall for Benign	0.9327	0.9109	0.9564	0.9564	0.9618	0.9727	0.98
Recall for Malignant	0.9232	0.8944	0.9584	0.9552	0.96	0.9712	0.9776
Precision for Benign	0.9144	0.8836	0.9529	0.9495	0.9549	0.9675	0.9747
Precision for Malignant	0.9397	0.9194	0.9615	0.9614	0.9662	0.9759	0.9823
F Measure for Benign	0.9235	0.897	0.9546	0.9529	0.9583	0.9701	0.9773
F Measure for Malignant	0.9314	0.9067	0.9599	0.9583	0.963090022	0.9735	0.9799

Table 1 Summary of Results

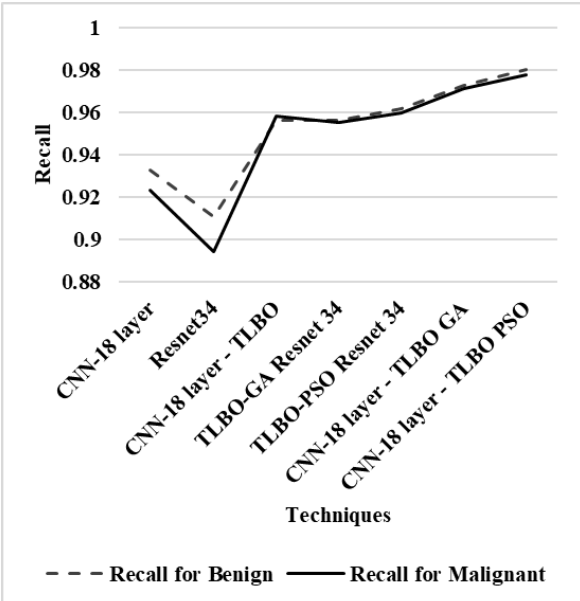

Figure 1 Accuracy for CNN-18 layer-TLBO PSO

From the figure 1, it can be observed that the CNN-18 layer - TLBO PSO has higher accuracy by 5.35% for the CNN-18 layer, by 8.14% for Resent 34, by 2.2% for CNN-18 layer - TLBO, by 2.38% for TLBO-GA Resnet 34, by 1.83% for TLBO-PSO Resnet 34 and by 0.69% for CNN-18 layer - TLBO GA respectively.

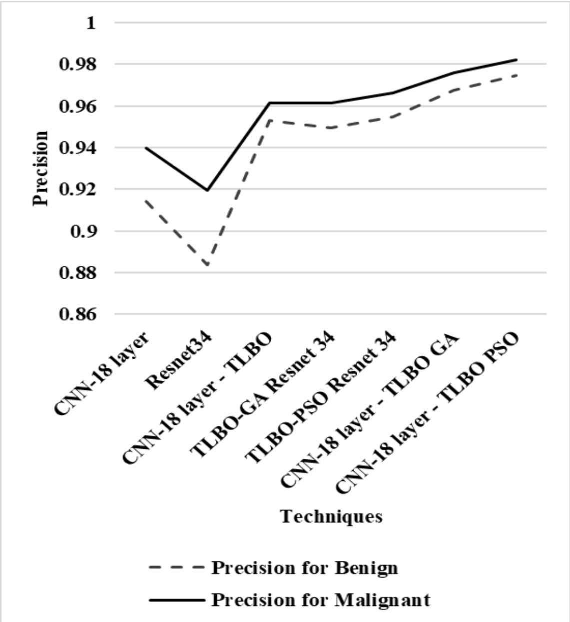

Figure 2 Recall for CNN-18 layer-TLBO PSO

From the figure 2, it can be observed that the CNN-18 layer - TLBO PSO has a higher recall for Benign by 4.94% for the CNN-18 layer, by 7.31% for Resent 34, by 2.44% for CNN-18 layer - TLBO, by 2.44% for TLBO-GA Resnet 34, by 1.87% for TLBO-PSO Resnet 34 and by 0.75% for CNN-18 layer - TLBO GA respectively. The CNN-18 layer - TLBO PSO has a higher recall for Malignant by 5.72% for CNN-18 layer, by 8.89% for Resent 34, by 1.98% for CNN-18 layer - TLBO, by 2.32% for TLBO-GA Resnet 34, by 1.82% for TLBO-PSO Resnet 34 and by 0.65% for CNN-18 layer - TLBO GA respectively.

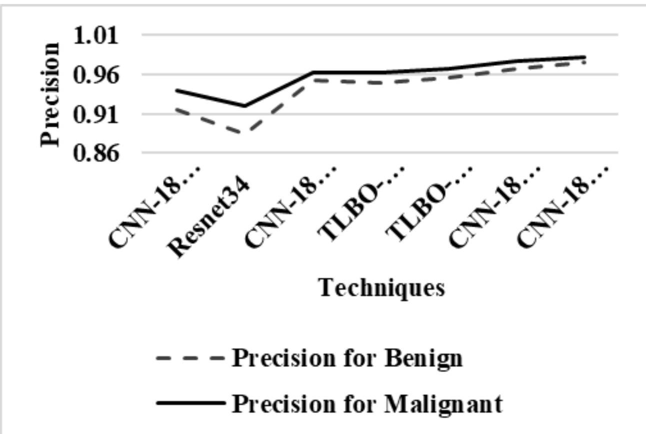

Figure 3 Precision for CNN-18 layer-TLBO PSO

From the figure 3, it can be observed that the CNN-18 layer - TLBO PSO has higher precision for Benign by 6.38% for the CNN-18 layer, by 9.8% for Resent 34, by 2.26% for CNN-18 layer - TLBO, by 2.62% for TLBO-GA Resnet 34, by 2.05% for TLBO-PSO Resnet 34 and by 0.74% for CNN-18 layer - TLBO GA respectively. The CNN-18 layer - TLBO PSO has higher precision for Malignant by 4.43% for CNN-18 layer, by 6.61% for Resent 34, by 2.14% for CNN-18 layer - TLBO, by 2.15% for TLBO-GA Resnet 34, by 1.65% for TLBO-PSO Resnet 34 and by 0.65% for CNN-18 layer - TLBO GA respectively.

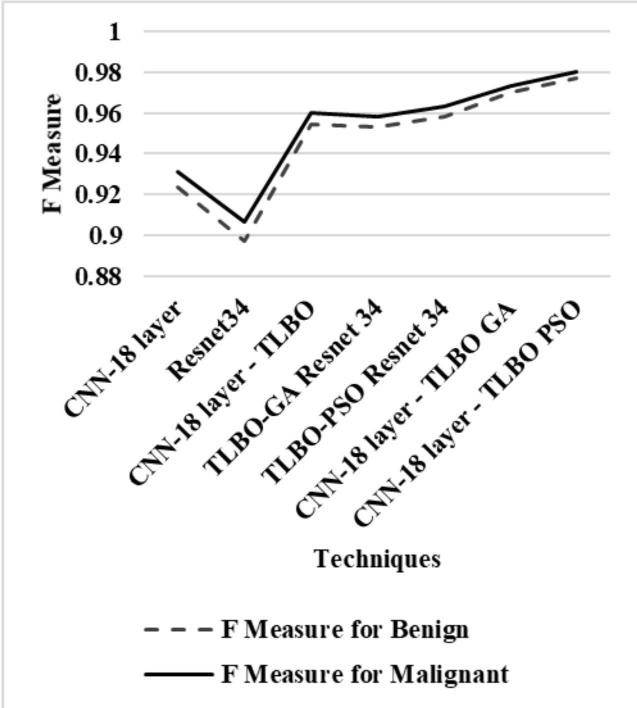

Figure 4 F Measure for CNN-18 layer-TLBO PSO

From the figure 4, it can be observed that the CNN-18 layer - TLBO PSO has a higher f measure for Benign by 5.66% for CNN-18 layer, by 8.56% for Resent 34, by 2.35% for CNN-18 layer - TLBO, by 2.52% for TLBO-GA Resnet 34, by 1.96% for TLBO-PSO Resnet 34 and by 0.74% for CNN-18 layer - TLBO GA respectively. The CNN-18 layer - TLBO PSO has a higher f measure for Malignant by 5.07% for CNN-18 layer, by 7.76% for Resent 34, by 2.06% for CNN-18 layer - TLBO, by 2.23% for TLBO-GA Resnet 34, by 1.73% for TLBO-PSO Resnet 34 and by 0.65% for CNN-18 layer - TLBO GA respectively.

5 Conclusion

The cost of radiology is decreased by the various techniques with deep learning involved in the processing of mammograms. The breast mass classification systems which are being used currently are implemented with the help of learning technologies such as CNN. Higher performance is achieved by CNN-based systems compared to that of machine learning-based systems while classifying mammographic images. The relationship between the teacher on the output of the learner in a class is the principle behind the TLBO algorithm. PSO is influenced by the swarm behaviour of birds and helps in optimizing continuous nonlinear functions. This work involves the TLBO-PSO algorithm, which helps in finding the solutions for the best individual and the individual who needs to be redesigned and renewed. A mutation operation helps in improving the global convergence performance of the algorithm. Results show that the CNN-18 layer - TLBO PSO has higher accuracy by 5.35% for the CNN-18 layer, by 8.14% for Resent 34, by 2.2% for CNN-18 layer - TLBO, by 2.38% for TLBO-GA Resnet 34, by 1.83% for TLBO-PSO Resnet 34 and by 0.69% for CNN-18 layer - TLBO GA respectively.

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