



Detection of Breast Cancer Based on Feature Extraction Using WPSO in Conjunction with CNN

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Abstract

According to cancer reports from the past few years in India, thirty percent of instances are breast cancer, and furthermore, it is possible that this percentage would increase in the near future. In addition, one woman is given a diagnosis every two minutes, and another woman passes away every nine minutes as a result of her condition. People who are diagnosed with cancer at an earlier stage have a better chance of survival. Micro calcifications are one of the most important symptoms to look out for when trying to diagnose breast cancer in its earlier stages. Several scientific investigations have been carried out in an effort to combat this illness, for which techniques related to machine learning can be utilized to a significant extent. Particle swarm optimization, often known as PSO, is acknowledged as one of several effective and promising methods for identifying breast cancer. This method helps medical professionals administer treatment that is both timely and appropriate. The weighted particle swarm optimization (WPSO) approach is utilized in this work for the purpose of extracting textural information from the segmented mammography picture for the purpose of classifying micro calcifications as normal, benign, or malignant, hence increasing the accuracy. A portion of the cancerous growth is removed from the breast region using optimizing techniques. In this article, Convolutional Neural Networks (CNNs) are presented for the purpose of identifying breast cancer in order to cut down on the amount of manual overhead. The CNN framework is built in order to extract features as effectively as possible. This algorithm was developed to identify areas in mammograms (MG) that are suspicious for cancer and to classify those areas as normal or abnormal as quickly as possible. This model makes use of MG pictures that were gathered from a variety of hospitals in the surrounding area.

Keywords: Breast cancer; microcalcifications; weighted particle swarm optimization (WPSO); Convolutional Neural Networks (CNNs) mammogram.

1. Introduction

Cancer of the breast is the type that affects women the most frequently and is the leading cause of mortality among women aged 20 to 59. In recent years, it has become the disease that affects the greatest number of people in Iran, as reported by the Ministry of Health and Medical Education [1]. Nowadays, the life expectancy of a woman who has been diagnosed with breast cancer is 10 years in

88% of cases. It has been observed that approximately 12% of women in the United States were diagnosed over their lifetime with cardiovascular disease, which is referred to as the second leading cause of mortality among women [2]. It is critical to make an early diagnosis of the condition due to the fact that, in its early phases, breast cancer masses are localized to that organ and there is a greater possibility of undergoing surgical treatment in a manner that is minimally invasive. Additionally, a lower death rate is observed throughout the early stage [3].

In addition, the usage of classifiers such as artificial neural networks is becoming increasingly prevalent in many subfields of engineering sciences in order to perform analyses of time series and a variety of classification problems. The recent development of methods for the early diagnosis of breast cancer has resulted in an increase in the percentage of patients who are expected to survive their disease. These days, X-ray mammography and MRI (Magnetic Resonance Imaging) procedures are frequently used despite having a small number of potential drawbacks and restrictions. Ionizing radiation is the cause of the harmful effects of X-rays; hence, patients can only be exposed to this type of radiation for extremely brief periods of time. On the other hand, the MRI approach is pricey, whereas mammography is less expensive but more difficult to offer consistent and accurate results when analyzing breast cancer [4].

In addition, mistakes can arise throughout the analysis. The development of supervised machine learning strategies such as KNN, SVM, and LSSVM is done with the goals of improving accuracy rates and cutting down on the number of errors that occur. These models are able to classify the features very effectively into the normal or abnormal categories. These procedures are not only difficult but also laborious, and they have a low success rate. Therefore, in order to give a solution for all of the downsides of breast cancer, an optimal classification model is required. For this, machine learning algorithms based on image processing are created to classify cancer and non-cancer images, including mammography images. This was done in order to classify cancer and non-cancer images. The procedure of feature extraction is considered to be of the utmost significance because the traits are necessary for classifying breast cancer as benign or malignant. With the help of the segmentation process, one may obtain qualities of the image such as its depth, coarseness, smoothness, and regularity once the features have been extracted [5].

Scientifically speaking, breast cancer is characterized by uncontrolled cell division within the tumor, and aberrant tumor cells have an increased demand for resources in order to maintain their rate of growth and procreate. In order to acquire more nutrients, the cancer cells spread over the surrounding tissue. Lesion morphology features and ambiguity with edges in diagnosing images are vital in indicators for evaluation since there is a diverse variation in the circulation of blood with various malignancies. This is why lesion morphology characteristics are important. Because the paramagnetic contrast agent travels through the blood, it enters the blood vessel, and it easily penetrates both the intercellular space and the cells of the body through the permeable capillary wall; as a result, the concentration of the sputum is highest in the area that contains the most tumors. When DCE-MRI is used for many imaging sessions of the same tissue at different phases, the TIC technique can be used to locate this anomaly. Because of this, the edge, shape, and other static properties of the lesion, as well as the initial increase and change in signal, which are dynamic aspects of the lesion, play a significant part in determining whether or not the tumor is benign or malignant. In most cases, MRI pictures are crystal clear and comprehensive, incorporating imaging from a variety of angles and perspectives. Regarding the breast, a surface coil has been implemented for clinical purposes, and MRI technology has advanced to the point where it is now much more transparent.

On the other hand, both the true positive rate and the true negative rate that are achieved during the process of diagnosing breast cancer are enhanced simultaneously [6]. This research contributes a weighted particle swarm optimization (WPSO) strategy for extracting textural information from a segmented mammography picture in order to improve the accuracy of classifying microcalcifications as normal, benign, or malignant. The breast region is the target for the extraction of the tumor component employing optimization approaches. In this article, Convolutional Neural Networks (CNNs) are presented for the purpose of identifying breast cancer in order to cut down on the amount of manual overhead. The CNN framework is built in order to extract features as effectively as possible. This algorithm was developed to identify areas in mammograms (MG) that are suspicious for cancer and to classify those areas as normal or abnormal as quickly as possible.

The latter portion of this work is summarized in the following sentence. An overview of related works is presented in Section 2, followed by a discussion of the technique that is provided in Section 3, and

then a description of the experiments and a discussion of the results achieved in Section 4. In the end, the effort is summarized in Section 5, which focuses on upcoming enhancements.

2. Related Work

In this section, a few relevant works that were carried out for the purpose of diagnosing breast cancer and that used various optimization strategies are discussed. It is common knowledge that breast cancer is one of the most serious and potentially fatal tumors that may affect women. As a result, detecting the disease at an earlier stage is preferable in order to maximize the chances of successfully treating patients and saving their lives. There have been many different methods developed for detecting breast cancer, each of which addresses a unique set of obstacles; a select handful of these methods are discussed in this article. In 2016, Asri et al. [7] used methods of machine learning for the prediction and classification of the WBC real dataset.

A number of different classifiers, including SVM, Naive Bayes, KNN, and decision tree C4, were utilized. Accuracy was achieved via SVM when using the Weka tool. Mammography images were used by Chowdhary et al. in their study [8] to detect breast cancer using an intuitive fuzzy histogram magnification approach. As a result, data was processed, and image quality was enhanced. After that, a method known as probabilistic fuzzy clustering was used to begin the process of segmenting and isolating the cancer tissues. Therefore, this model was appropriate for the processing of bigger cancer datasets with the aim of providing higher levels of accuracy.

The subsequent step was the extraction of textural attributes using techniques such as the grey area coefficient and the linear binary pattern. The accuracy of the results, which was 94%, was difficult to achieve when working with larger datasets and made the processing time longer. The classification of breast cancer was accomplished through the use of genetic meta-specificity reduction by Aalaei et al. [9]. We used the WBC dataset, the WDBC dataset, and the WPBC dataset in order to determine which Artificial Neural Network (ANN) cluster performed the best. The approach that was utilized with the WBC, WDBC, and WPBC datasets were estimated to have an accuracy of 96, 96.1, and 76.3 percent, respectively. Even though there was a reduction in the number of features, accuracy may be enhanced.

In 2017, Nilashi and colleagues [10] built a knowledge-based system that utilized fuzzy logic. The procedure consisted of the following three stages: initially, processing of the data on breast cancer in Wisconsin was performed. After that, the data was clustered by using the Expectation Maximization (EM) clustering technique. This technique is named after its namesake. In the end, after the characteristics had been narrowed down using principal component analysis (PCA), the fuzzy rule set was classified as data using a regression tree. The overall accuracy that was found was 93.2 percent. When learning rules are applied to datasets, the work of categorization might occasionally become more difficult. The Bat algorithm was utilized to pick the most useful characteristics for making a breast cancer diagnosis in [11].

From the WDBC dataset, a straightforward random sampling strategy was used to select 286 samples for feature analysis. This strategy involved the identification of features. After performing the step of picking the features, according to the classification similarity that involved Random Forest (RF), overall ranking was completed, and an accuracy was obtained. Due to the fact that samples are chosen at random, the selection of features proved at times challenging. Dore Swamy and colleagues improved the Bat algorithm in order to classify photos of breast cancer in [12]. 569 different samples of data from the UCI were used in the experimentation of this method. While the accuracy of the training set was 92.61, the accuracy of the testing set was just 89.95. PSO was used in a method that was described in reference number 13 to reduce the specificity of the breast cancer diagnosis. The purpose of this project was to determine the prevalence of breast cancer. Following a reduction in specificity, the PSO method was used to 699 pre-processed samples of UCI data. This was done in conjunction with the decision tree C4.5 in order to categorize the samples into one of two categories: malignant or benign. The overall accuracy that was attained was 95.61%. In their study [14], Sahu et al. used a combination of several methods to categorize and diagnose breast cancer. After using PCA to reduce the number of features and experimenting with several clusters, it was discovered that ANN classification generated 97% of the performance produced by other clusters. The investigation used 699 different samples, each of which had nine different characteristics, to classify them as either benign or cancerous. Despite the fact that the outcomes that can be attained are greater, every approach

has a few drawbacks and restrictions. SD-CNN was developed by Gao et al. in their paper [15], where they combined shallow CNN with deep CNN. While shallow CNN was employed with the goal of extracting "virtual" recombinations of images that have reduced energy, deep CNN was used to extract novel features that are connected to LE. In addition, information on nonlinear mapping was obtained from LE for the purpose of recombining images.

A shallow CNN and a deep-CNN were both developed with 49 CEDM each. The performance was improved in terms of the area under the curve (AUC), and it was more accurate than the approaches that were previously used. Ting et al. created CNNI-BCC, which assisted medical professionals in identifying breast cancer at an earlier stage, and they described their work in [16]. This model improved the classification using CNN, and the images of breast cancer were categorized as a variety of subtypes, including healthy, benign, and malignant. This model improves accuracy and sensitivity, as well as the area under the curve (AUC), based on the various trials that were carried out.

None of the methods involved in diagnosing and classifying breast cancer were put through the rigors of testing and evaluation using three distinct data sets pertaining to breast cancer. CNNs were used in the approach that Araujo et al. proposed in [17] for the classification of breast biopsy pictures that were stained with hematoxylin and eosin. This classification approach enables a high degree of sensitivity to be reached for cases of carcinoma. Image classification based on different classes was carried out with the help of LDA in the study that Belsare et al. This approach that has been proposed is useful for pathologists. Tan et al. developed a new method of breast cancer diagnosis by employing CNN, and they tested it on mammography pictures. This method can be found in [19]. This demonstrates the increased precision that was achieved. The effectiveness of CNN was evaluated with regard to the presence of breast abnormalities as seen on mammograms in the article [20] written by Henry et al. Using artificial neural networks (ANNs), Khan et al. devised a method for classifying tumors based on the relevant genes. Dhungel et al. present an original automated CAD system in their paper [22], which requires very little input from the user.

The use of deep learning and structured output models is investigated, and proposed CAD system results are provided for the INbreast data set. CAD method based on deep learning, deep convolutional network (CNN) is used to recognize the mass and classify it as either benign or malignant. This was proposed by Al-antari et al. in [23]. An integrated CAD system of deep learning detection and classification was proposed by Al-antari et al. in their paper [24]. Their goal was to design a Cad system for the practical diagnosis of breast cancer. CNN was developed by Fang et al. in the paper in order to make efficient use of the information provided by three-dimensional spatial correlations of breast cancers. A new automatic segmentation Method (SM) for detecting the ROI from breast thermograms is presented by Aya et al. This SM was developed by the researchers. Hu et al. present an overview of deep learning and hope on the survey for cancer detection and diagnosis in the article. The present investigation has a number of strengths, including a reduction in the costs of detecting, the use of a better classifier without the adverse effects of aggressive approaches, a higher accuracy of detection than the paper that was cited, selecting titles that are appropriate with the data that is available, and a comprehensive comparison with the research that has been done up to this point.

3. Proposed Methodology

Figure 1 presents an illustration of the work flow of the newly established approach. The next discussion will go over the processes, such as pre-processing, segmentation, and feature extraction. In order to achieve a high level of accuracy in classification, CNN's classifier is utilized.

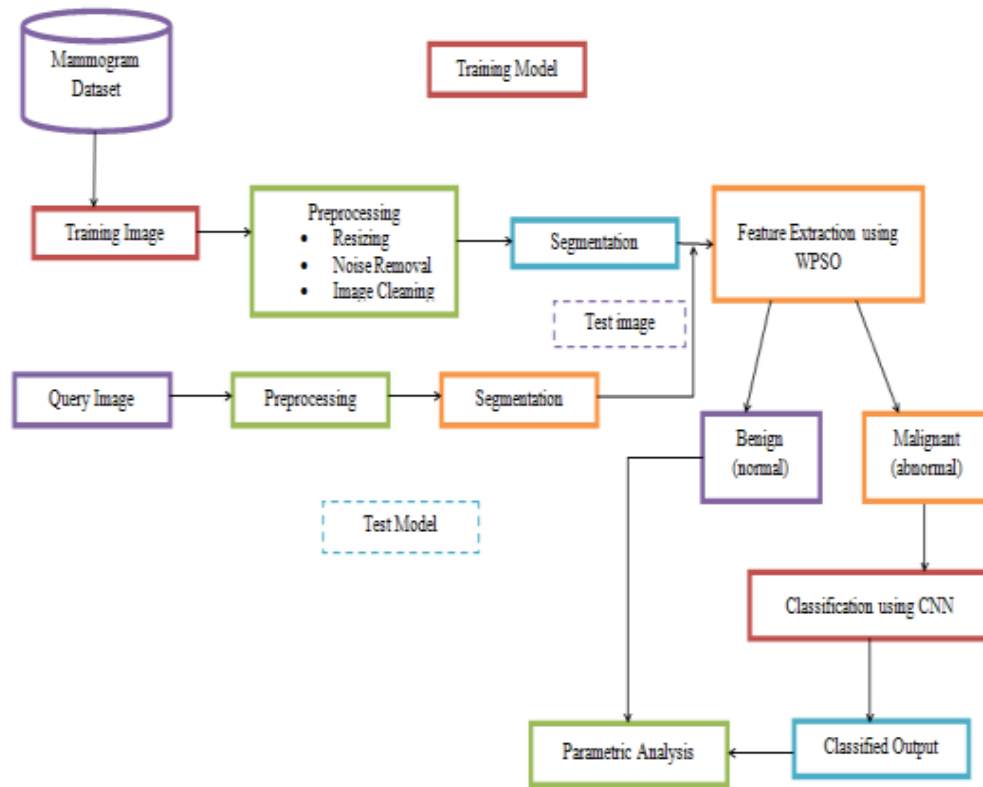


Figure 1: Architecture of the Proposed Method

A. Pre-Processing Steps

Step 1: Finding a Breast Image to Use as an Input.

Step 2: The raw image that was provided as the input raw is resized to 256 by 256 pixels.

Step 3: Converting 3-dimensional (3D) photos to 2-dimensional (2D) images is necessary when using them as input because most image processing can only be done with 2-dimensional images. This means that an RGB image must be turned into a grayscale image.

Step 4: Two different filtering strategies are utilized in order to remove noise, as will be shown below:

The Out₁ value indicates that a Laplacian filter has been applied to the grayscale image.

Out₂ indicates that a mean filter will now be applied to the grayscale image in Step 4.2.

Out₃ = Out₁ – Out₃.

The ultimate product of the pre-processing stage is the pre-processed image of the breast Out₃.

Step 5: Out₃.

B. The Steps in Segmentation

Input: A pre-processed version of the Out₃ image.

Step 1: The gradient is calculated along the X and Y axes, and the results are stored in the variables Out(X) and Out(Y).

Step2: the gradient values are added together to produce the gradient vector G_{val} , which can be written as.

$$G_{val} = \frac{1}{1+Out(x)+Out(y)} \quad (1)$$

Step 3: involves converting the value of G that was received in radians to degrees in order to obtain information regarding the orientation of image pixels.

Step 4: the image of Out_3 is partitioned into grids GR_i.

Step 5: the threshold values for the intensity T_i and orientation are defined. To.

Step 6: conduct a GR_{ido} for each and every grid.

- The histogram H_i is computed for each and every pixel P_j using the grid GR_i.
- The histogram of grid GR_i with the most frequent values was obtained, and this value is denoted as Freq H.
- Any arbitrary pixel P_j that is associated with Freq H is chosen; this pixel is then allocated to the pixel information seed point (SP), which is given the values for Intensity I_p and Orientation O_p.
- At this point, both the intensity and the orientation requirements for adjacent pixels have been checked.
- When both of the limits have been met, then it will be decided whether or not the region will grow.

The subsequent grid is evaluated for potential processing.

Step 7: The Finished Product, a Segmented Image

C. Extraction of Features Utilizing the Weighted PSO Algorithm

Weighted Particle Swarm Optimization (WPSO) is a heuristic global optimization technique that simulates the social behavior of flocks of birds as they move towards a point for the purpose of achieving an exact objective in a multidimensional space. The algorithm's name comes from the acronym for "weighted particle swarm." This strategy includes dispersing a group of particles, sometimes known as a "swarm," throughout the location being searched. The status of each particle is determined by its position, which is denoted by the notation $\vec{x}_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}$. Additionally, the velocity of each particle is denoted by the notation $\vec{v}_i = \{v_{i1}, v_{i2}, \dots, v_{id}\}$. In order to find the optimum answer, each particle will change the direction it is now looking in order to look in a new direction. This new direction will be based on two different concepts: the best position of the given particle (p_{best}), and the best location achieved by the swarm (g_{best}). After the velocity and position of each particle are updated in reference to the equations, WPSO determines which solution is the best one for solving the problem.

$$v_{id}^{(t+1)} = wv_{id}^t + c_1r_1(p_{id} - x_{id}^t) + c_2r_2(p_{gd} - x_{id}^t) \quad (2)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (3)$$

where t and d represent the iteration in the evolutionary space and dimension in search space respectively. w denotes the weight of inertia. c_1 and c_2 represent the personal and social learning factors. r_1 and r_2 are uniformly distributed random values ranging between 0 to 1. p_{id} and p_{gd} denotes p_{best} and g_{best} in the dimension d.

The following is a rundown of the fundamental operations that are carried out by the WPSO algorithm:

Initialization: In order to set the starting positions and velocities of the particles, we employ a random number generator.

Evaluation consists of approximating the value of the goal function for each individual particle.

Finding p_{best}: When the value acquired using the objective function is better than the p best for particle i, then the current value is assigned as the new p best. This happens when the objective function produces a value that is higher than the p best.

Finding g_{best} requires determining whether p best is superior to g_{best}. If this is the case, g_{best} will be set to the value that is currently in use. Adjusting the position and the velocity: For each particle, the equation 1 is used to make the necessary adjustments to the velocity, and Eqn.(3) is used to determine

where the particle should go next. Criteria for Termination: If the required number of iterations has been completed, the process is complete; otherwise, it is restarted from the second step.

In the search space, the control of exploration and exploitation is handled by weight, and velocity is modified in a dynamic fashion. In addition, weight determines the degree to which earlier velocities have an effect on the most recent one. Therefore, the capacities of exploration are reduced due to the competition between global and local swarms. A lighter weight makes it easier to search locally, while a heavier weight makes it easier to search globally for new locations. When the weight is selected correctly, both global and local exploration of the swarm are balanced, which results in a superior solution. As a result, the value of weight can theoretically be increased to a higher level for more effective global exploration of the search space, and then it can be gradually decreased to produce a more refined solution. When the weight is reduced in a linear fashion, the pattern of exploration shifts from being global to being local. It is necessary for search algorithms to have the ability to search in a non-linear fashion. After collecting only a few number of statistical features, the PSO search is easily comprehended, and the appropriate weight for the subsequent iteration is determined. In this scenario, the amount of weight w decreases in a linear fashion whenever there is a rise in the overall generation, whereas optimization in respect to

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}} \right) * iter \quad (4)$$

Where w_{max} and w_{min} denote the maximum and minimum inertia weight respectively, $iter$ and $iter_{max}$ are the current iteration and maximum number of iterations respectively. For particle i , the best position is position that the particle visited (past value of X_i), which provides highest fitness value. For minimization, a position with small function value is considered to have fitness. $f(X)$ denotes the minimized objective function for which the updated equation is

$$P_{bestid}^{t+1} = \begin{cases} x_{id}^t & \text{if } f(x_{id}(t+1)) \geq P_{bestid}^t \\ x_{id}(t+1) & \text{if } f(x_{id}(t+1)) < P_{bestid}^t \end{cases} \quad (5)$$

The g best algorithm provides a faster rate of convergence, but at the sacrifice of resilience; also, it only maintains a single optimal solution, which is referred to as the global best particle. This particle's job is to serve as an attractor, and as such, it draws the attention of every other particle in the vicinity. In the end, every particle will converge at this place, and as a result, it is imperative that this information is continuously updated lest the swarm converge too soon. The fitness value of each individual particle in the swarm is determined with the help of the objective function. After that, the values of P_{id} and P_{gd} are analyzed and then updated with the best global position or the best particle position, whichever was acquired first.

The first step in the WPSO process is to initialize the function.

Establish a function that is objective.

The brightness of the pixel serves as the basis for the objective function.

Iteration count should be set to 1000.

Determine the intensity of each pixel in photos.

Improve the quality of the cancer image by adjusting the pixel intensity.

Calculate best value for input picture pixel.

Determine the portion of the tumor that has the highest pixel intensity.

D. Classification using Convolution Neural Networks

The breast cancer picture collection is used as an input for the classification process by CNN. Next, deep convolutional kernels are trained by utilizing the CNN architecture that was presented earlier. The following formula is used to define the RELU nonlinearity that is employed in the convolution layers: $f(x)=x$, if

$$f(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

The formula for the convolution layer is typically written as:

$$y^j = f b^j + \sum_i k^{ij} + x^i \quad (7)$$

In this instance, x^i stands for the i^{th} input map, and y^j is the notation for the j^{th} output map. The bias parameter of the j^{th} map is denoted by the symbol b^j , the convolution process that occurs between two functions is denoted by the symbol $*$, and the convolutional kernel that occurs between the i and j maps is denoted by the symbol b_{ij} . After the convolutional layer came the max-pooling layer, which was the next layer in the series. Every neuron in the max-pooling layer contributes y^j pools to the output map, which compares those y^j pools to $s * s$ sections of x_i that are not overlapping. The max-pooling layer is defined as follows, in general:

$$y_j^i = \max_{0 \leq m \leq s} \{x_i^j \cdot s + m\} \quad (8)$$

Fully connected convolutional and max-pooling layers are followed by a Softmax classifier that has output classes that are equal to the number of outputs. This completes the neural network. In the architecture that has been presented, the non-linear protocol known as tan h is utilized in order to connect one layer with another. Squashing is the function that the Softmax function is responsible for, and it re-normalizes the dataset so that it produces real values in the range of 1 to 2. The mathematical expression for this is as follows:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^k e^{z_k}}, \text{ for } j = 1, \dots, k \quad (9)$$

Training and generalization mistakes are types of error that might occur when creating machine learning systems. The first is something that is seen during the training of the neural network, and the second is something that is produced during the testing of the proposed classifier. When engaging in deep learning, one's training is frequently subject to the processes of overfitting and underfitting. In the design that has been proposed for BCC, batch normalization is applied after each layer in order to get around these problems. Following the completion of the first fully connected layer, a dropout layer was added. Figure 2 provides a visual representation of the full architecture that was designed for breast cancer categorization.

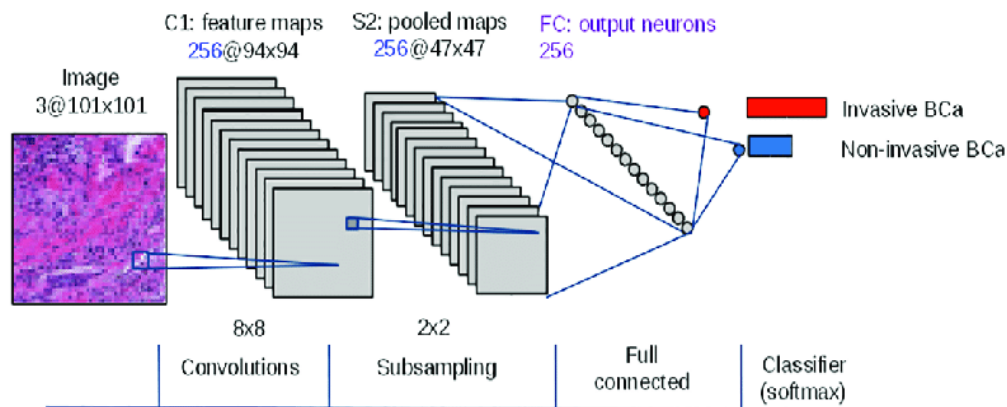


Figure 2: Proposed CNN Architecture for Breast Cancer Classification

E. Training of CNN

The suggested design for CNN is divided into two classes, which are referred to as benign and malignant. During the training process for the proposed CNN classifier, a weighted loss function was utilized.

$$\zeta(w, x_n, y_n) = -\frac{1}{N} \sum_{n=1}^N \alpha_n \sum_{k=1}^K t_{kn} \ln(y_{kn}) \quad (10)$$

In this case, x_n is the input vector, y_n is the prediction that was derived by the classifier for the n th clinical input, and t_n is the response that really occurred. K and N represent the total number of clinical samples that were taken from each class. The patch results from the full image are pooled in order to do recognition. Due to the fact that the model is taught using picture patches, a method is required for partitioning the real testing images into patches, which must be carried out, and the results acquired

must be combined in order to reach an ideal result; however, this strategy is computationally too difficult to be implemented. Instead, grid patches are created from the images, which offer the set of non-overlapping patches; this was a reasonable approach that balanced both the performance of classification and the computational cost; furthermore, it was a sensible approach. The use of this model resulted in each patch producing the probability of each class that could possibly apply to that particular patch of the image. It was determined that the Sum rule gave superior outcomes when compared to the other two different fusion rules that were used in the process of integrating the results produced by the patches for the test image.

4. Analysis and Discussion

The early detection of breast cancer is absolutely necessary for successfully treating and maintaining the status of the disease. This study gave a comprehensive derivation of methodologies and procedures, as well as the manner in which it is utilized in the process of tumor detection. The analysis of the impacts of the obtained number of glandular tissues is carried out in accordance with a procedure known as tissue segmenting. It has been noticed that the presence of a large number of glandular tissues makes the imaging effect later on worse. Concurrently, an incremental method for detecting numerous tumors is also being implemented at the same time. Imaging is performed in three stages: the preliminary examination, the focusing, and the image optimization. These stages allow for the successful detection of every tumor. In this scenario, WPSO-CNN is utilized for the extraction of features and classification of tumors; as a result, improved accuracy has been achieved. Histopathology was determined based on the features that were gathered and categorized the image. Figure 3 displays the retrieved features of the histopathological picture that was processed with WPSO-CNN. Figure 4 depicts a categorized picture with malignant characteristics.

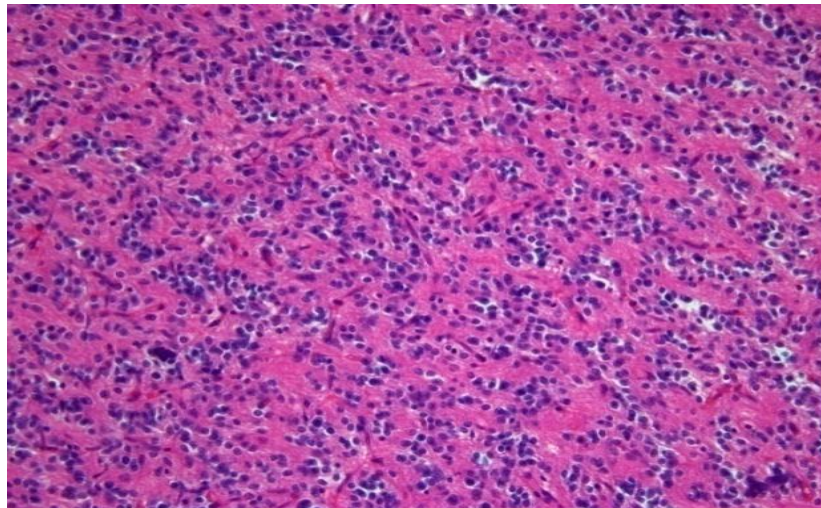


Figure 3: Feature Extracted Tumor Image of Histopathological Image

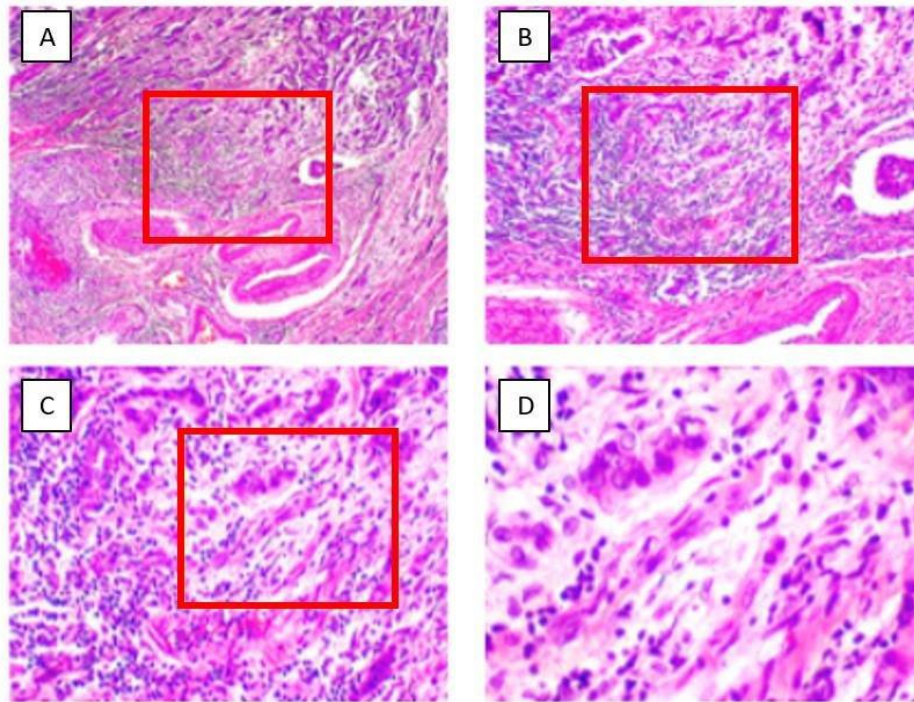


Figure 4: Classified Image of Histopathology Detecting Malignancy

Figures 5, 6, 7, and 8 provide a visual representation of the accuracy, precision, recall, and F-1 score graphs, respectively. The graphs that follow present a comparison of many parameters that apply to both the existing strategies and the proposed ones.

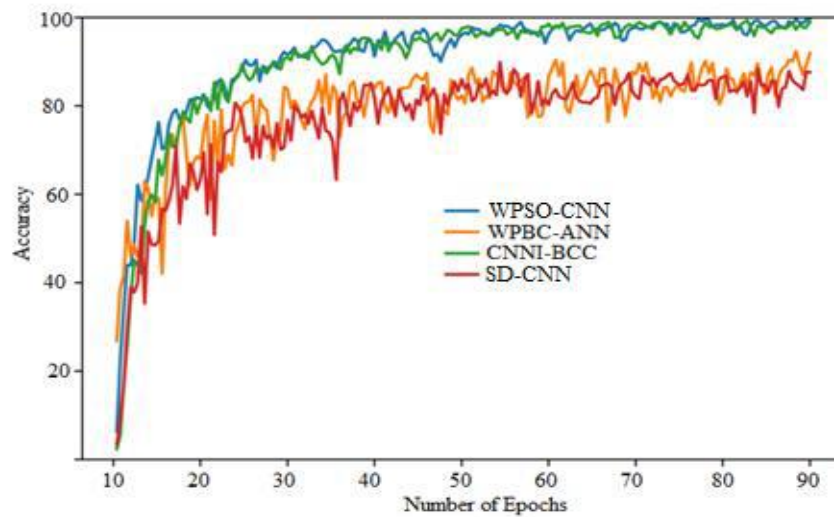


Figure 5: Comparison of Accuracy

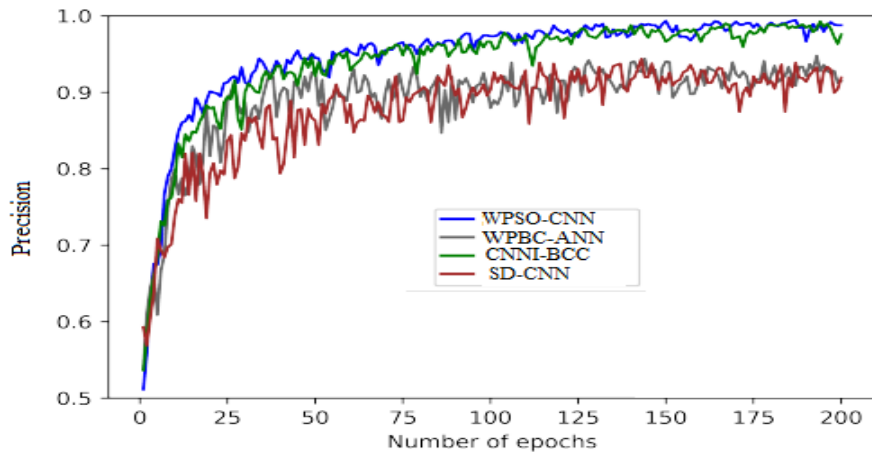


Figure 6: Comparison of Precision

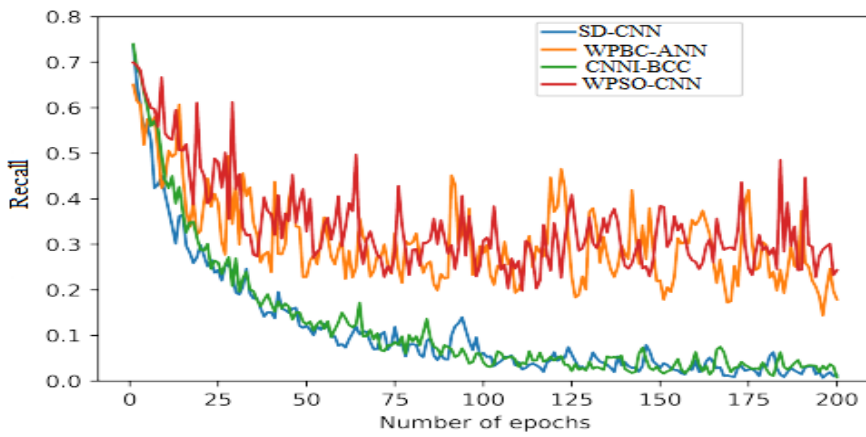


Figure 7: Comparison of Recall

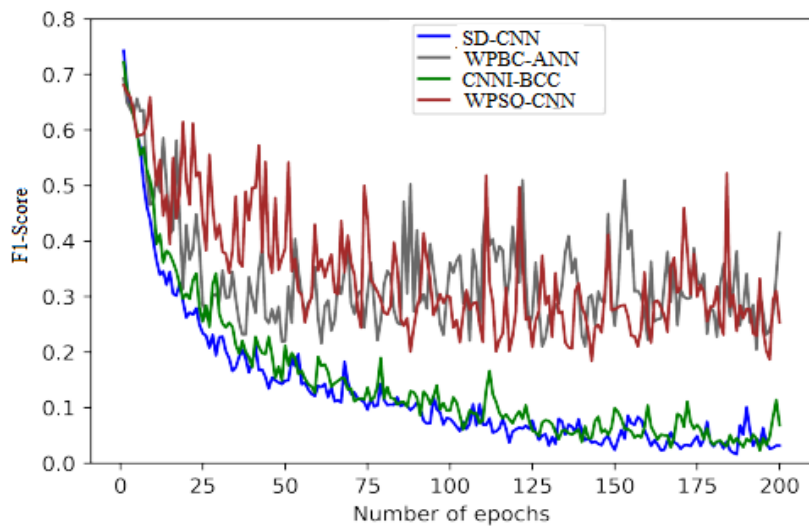


Figure 8: Comparison of F-1 Score

As a consequence of doing analysis on the findings that were acquired using the proposed method, it has been discovered that performance has greatly improved. Based on the examination of the results, it has been established that the suggested method has significant performance in Classification. The classification of the accuracy analysis for the suggested technique can be seen in Figure 5. When compared to the procedures that are now in use, the accuracy of the suggested technique is measured to be much higher.

The classification of the precision analysis for the suggested technique can be seen in Figure 6. The overall comparison of the proposed method with the various classifiers now in use is shown here. The analysis that the measurement of precision gives expresses shows that the proposed method delivers superior performance in comparison to other methods that are already in use. The classification of the Recall analysis for the suggested technique is displayed in Figure 7. The analysis is provided by the Recall measurement, and the comparative analysis demonstrated that the suggested method delivers better performance than the existing classification algorithms. The categorization of the F1-Score analysis for the suggested technique is displayed in Figure 8. The F1-Score is assessed, and the resulting analysis is provided. After conducting the study, it was determined that the proposed technique demonstrates enhanced performance in comparison to the classification technique that is currently in use. The proposed WPSO-CNN has the following restrictions: When dealing with high-dimensional data (pictures), image classification using WPSO-CNN is the most appropriate application for it. The WPSO-CNN algorithm is not optimal for use with more compact data sets. If there are a greater number of layers, the WPSO-CNN algorithm will run more slowly.

5. Conclusion

The purpose of conducting this research is to achieve the goal of improving the accuracy of detection utilizing the CAD technique for the purpose of diagnosing breast cancer. In order to accomplish this goal, a framework was contributed, together with its flow and the parameters that were used for simulation. The effectiveness of the method for categorizing normal and abnormal breast photos of many individuals is evaluated with the help of a dataset that is accessible to the general public. WPSO-CNN is an acronym that stands for weighted particle swarm optimization with CNN (Convolutional Neural Networks). Its purpose is to extract features and estimate the error between the estimated and true density using a kernel density estimation-based classifier for the purpose of diagnosing breast cancer. Based on the findings, it can be seen that the performance of WPSO-CNN is remarkable in comparison to other methods currently in use. In light of the fact that the detection systems that are currently in use are offline, the work that will be done in the future may involve developing an online breast cancer detection system.

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