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Deep Learning based on Classification of Breast Cancer Diagnosis using Binary Grey Wolf Optimization Algorithm

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ABSTRACT

For breast cancer treatment to be effective, early detection is key. Though current methods encounter obstacles in attaining ideal accuracy, Computer-Aided Diagnosis systems remain indispensable in the automated processing, interpretation, grading, as well as early identification of breast cancer through mammography images. This research overcomes these shortcomings by combining a Support Vector Machines radiation basis function Kernel with the upgraded binary Grey Wolf Optimizer, which is inspired by quantum mechanics. Finding the best Support Vector Machine features is the goal of this hybrid strategy, which tries to improve breast cancer classification accuracy. The requirement for better categorization performance in comparison to current optimizers like Genetic Algorithm and Particle Swarm Optimisation is what drives this hybridization. Analyse the MIAS dataset to determine how well the suggested BGW method performs in terms of accuracy, sensitivity, and specificity, among other metrics. In addition, we will compare the outcomes after investigating the use of BGWO in feature selection. Utilising a tenfold cross-validation datasets split, the experimental results show that the proposed BGWO method achieves better results than state-of-the-art classification methods using the MIAS dataset. Specifically, the mean accuracy is 99.65%, sensitivity is 98.99%, and specificity is 100%.

Keywords: Breast cancer, Binary Grey wolf optimization, Tenfold Cross-Validation Dataset, State-of-The-Art Classification Methods, Medical image analysis, Particle Swarm Optimization and Genetic Algorithm.

I.INTRODUCTION

Cancer is a disease that develops when aberrant cells grow in an unregulated manner in a manner that disregards the usual principles of cell division. This can lead to the abnormal cells growing and multiplying in an uncontrolled manner, which can lead to the development of cancer. In the event that the proliferation is permitted to persist and expand in a manner those results in the production of metastases, this can be a lethal phenomenon. In the event that the tumor invades the tissues that are

around it or spreads to other areas of the body, it is referred to as malignant or cancerous [1]. Breast cancer is a disease that develops in the same manner as other cancers and typically begins in the glands that produce breast milk or in the ducts that transport milk to the nipple. In breast cancer, cells begin to develop in an uncontrolled manner, resulting in the formation of a lump that can be felt or spotted by the use of mammograms [2].

Around the world, breast cancer is the second leading cause of death among women who have cancer [3]. It is also the most common form of cancer that appears in females. According to projections made by the American Cancer Society for the year 2019, there will be approximately 268,600 new instances of invasive breast cancer identified in women in the United States, approximately 62,930 new cases of noninvasive breast cancer, and approximately 41,760 total deaths that can be attributed to breast cancer [4]. Between the years 1989 and 2016, the death rates among women decreased by forty percent. Since 2007, the death rates in younger women have been stable, while the death rates in older women have been progressively dropping due to early detection through screening, increasing awareness, and improved treatment [5]. The screening for breast cancer can typically be accomplished by the use of mammography, which is carried out at modest X-ray photon energies [6]. In the event that the screening mammography revealed an anomaly in the breast tissues, it is customarily indicated to undergo a diagnostic mammogram in order to further analyse the areas that are deemed to be problematic. In most cases, the initial indication of breast cancer is a lump that is located in the breast or underarm that does not disappear after the period [7]. In most cases, screening mammography is able to detect these abnormalities well before the patient is able to become aware of them. This is true even if the lumps are so small that they do not cause any noticeable changes to the patient [8].

The use of screening mammography as an early detection method for breast cancer led to a reduction in the death rate associated with breast cancer, according to a number of studies [9]. Unfortunately, mammography has a low detection rate and can produce false-negative results ranging from 10% to 50% of the time, depending on the kind of lesion, the age of the patient, and the density of the breasts [10]. This is because there is less contrast between the malignant lesions and the backdrop in breasts that are denser, which makes it more difficult to diagnose [11]. When compared to breasts that are not dense, patients with dense breasts have a miss of classification in mammography that is approximately four to six times greater [12]. A dense breast decreases the test's sensitivity, which leads to an increase in the false-positive value, which necessitates a needless biopsy. Additionally, a dense breast decreases the test's specificity, which leads to an increase in the false-negative value, which results in the absence of malignancies.

II.LITERATURE SURVEY

Among the leading causes of death among women, breast cancer is expected to add 61,000 new cases in 2016, according to an estimate [1]. The likelihood of survival increases to about 90% if mammographic screening catches breast cancer [2] at an earlier stage. Radiologists heavily rely on digital screening mammography [3] for breast cancer diagnosis since it is the most dependable and economical method. Finding or interpreting breast masses using digital mammography [4] is a laborious process for radiologists. In addition, detection accuracy can drop to 60%-70% when using mammography on very thick breasts [5]. Thus, radiologists are able to distinguish between benign and malignant masses with the use of sophisticated computer-aided diagnostic (CAD) systems. Multiple studies have recommended using computer-aided design (CAD) software [6] to analyse breast imaging

for diagnostic purposes. By reducing inter-observer variation and providing quantitative support for clinical decisions, this step can improve the performance of routine diagnosis [7]. This study details an initiative to build a computer-aided design (CAD) system to aid radiologists in the early diagnosis of breast masses utilising new characteristics and machine learning approaches [8]. Radiologists perform a number of crucial tasks, including the interpretation of digital mammograms [13] using a CAD system to distinguish between benign and malignant tumours in the breast. Medical professionals are able to distinguish between benign and malignant tumours with the help of an appropriate classification [14]. Dense breast tissue and uneven mass shape overlap, making the categorization step difficult. In addition, the current classification approaches mostly dealt with feature extraction through pre- or post-processing. Consequently, creating a better CAD system for accurate breast mass diagnosis is the main objective of our work [15]. The next section provides a detailed discussion of the study's history and review.

III.IMPLEMENTATION

In addition, a computer-aided design (CAD) method is presented for the purpose of splice site prediction. This method achieves remarkable accuracy levels of 96.27% and 98.56% for donor and acceptor sites60. In surveillance video anomaly detection, a system that is built on a hybrid convolutional neural network (CNN) and vision transformer functions exceptionally well, exhibiting excellent area under the curve (AUC) values across benchmark datasets61. Through its ability to recognise and understand anomalies in a proficient manner, the Vision Transformer Anomaly Recognition (ViT-ARN) framework makes important advancements in intelligent city surveillance. It outperforms alternative systems with substantial gains in accuracy62. The combined development that has been made demonstrates the versatility and usefulness of individualised machine learning solutions in providing solutions to a wide variety of problems. In light of this, the purpose of this study is to evaluate whether or not it is possible to use the BGWO framework to classify mammographic images that are contained within the MIAS dataset's original image.

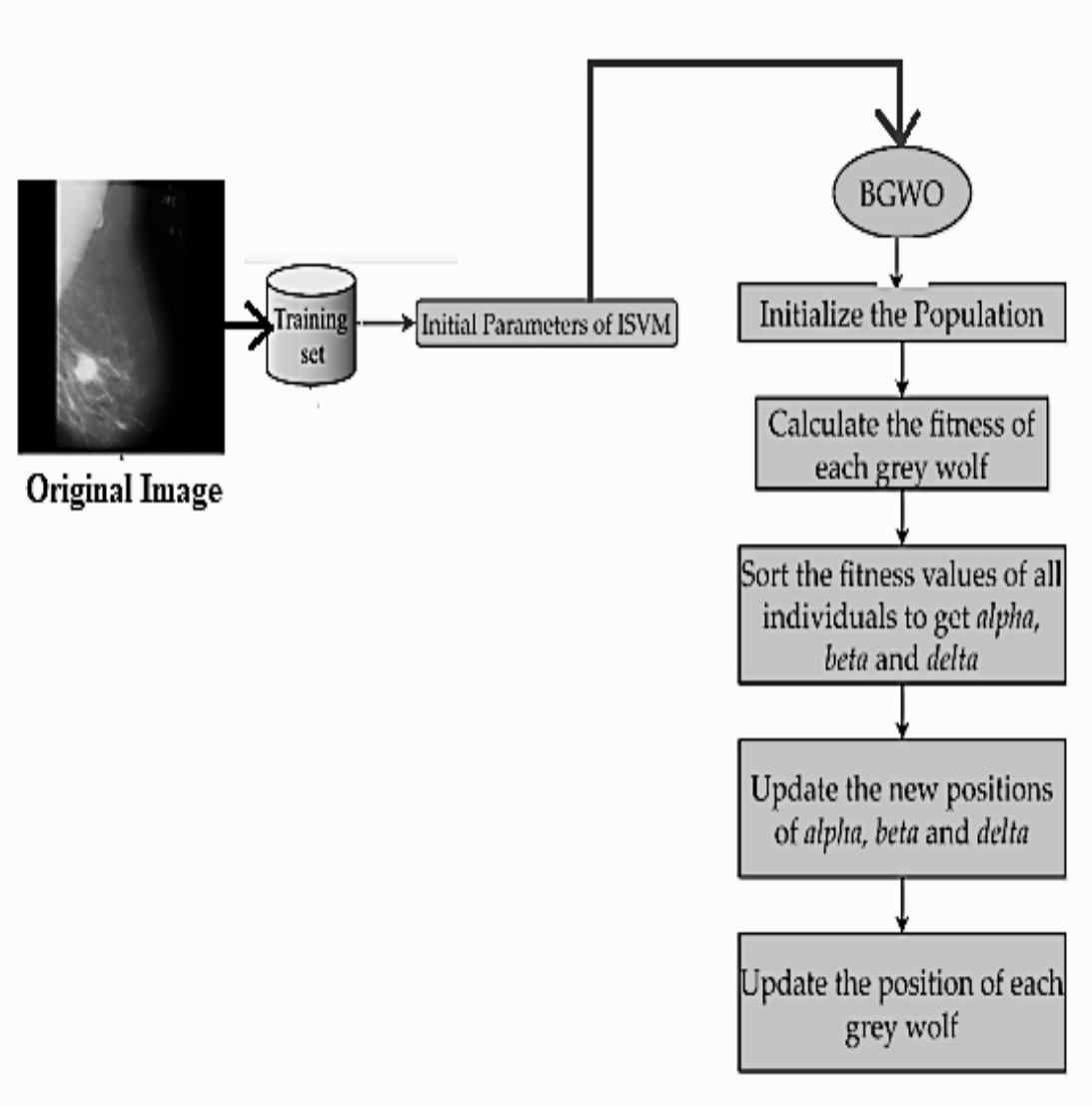

Figure 1: The Architecture of proposed methodology

The MIAS procedure starts with fundamental image processing in order to get rid of background noise and increase imaging quality. There are ten regions of interest (ROI) that are collected from both the benign and malignant groups, and then randomly selected ROIs are removed from the Normal collection. There is a single square area that is centred on this place that can be extracted as the region of interest (ROI). This is made possible since each anomalous region within the original image collection is tagged with its centre coordinates. The region of interest (ROI) is generated at random from the entire image and has the size that was specified above63. This is because the Normal class does not supply any location information. Additionally, there is a degree of differentiation that may be made between the Normal and Abnormal (sometimes known as aberrant) groups. Nevertheless, benign and malignant regions of interest (ROIs) exhibit similar patterns but are not distinguishable from one another. Following that, the purpose of this research is to propose the development of BGWO models in order to identify patterns that can be differentiated between the normal and abnormal categories. In this work, BGWO is used as a support vector machine (SVM) to construct an accurate classifier for the categorization of breast cancer as either malignant or benign. Through this work, an attempt is made to

automatically and accurately categorize breast cancer as either malignant or benign. The BGWO methods and the SVM classifier are combined into a single algorithm. An illustration of the overall framework of this study can be found in Figure 1.

3.1 Material and methods Datasets description

One of the most important parts of the UK NBSP, or National Breast Screening Program, is the MIAS database. This extensive collection includes 322 mammographic photos, which capture the breasts from 161 individuals64 in both the left and right views. Images in the dataset are high-resolution greyscale ones, saved in Portable Grey Map (PGM) format and measuring 1024 by 1024 pixels apiece. Two hundred and seventy-one normal images, sixty-three benign images, and fifty-two malignant images make up the MIAS database's main classification system. In addition, the dataset offers a thorough categorization of the photos based on the background tissue type, which encompasses dense-glandular, fatty glandular, and fatty. A number of etiological characteristics are also used to demarcate the pictures. Included in this category are calcifications (CALC), spiculated masses (SPIC), masses that are either poorly defined or miscellaneous (MISC), architectural distortions (ARCH), and asymmetries (ASYM).

The first picture shows a benign tumor on top of some fatty tissue; the tumor has regular shape and smooth margins, which point to a CIRC origin. On the other hand, the second picture displays a cancerous tumor with an ASYM origin, which is characterized by its squished borders and uneven shape; it is also set against a fatty background. Understanding the distinctions between benign and malignant tumor appearance in mammographic pictures requires these comparative visual representations.

1.2.Binary Grey Wolf Optimization Algorithm

We integrated a population-based Binary Grey Wolf Optimisation method, which partitions the population into easily exchangeable sections, allows them to evolve independently, and subsequently merges them. In this study, we apply the binary grey method by splitting the population into multiple sets on separate cores. A total of Nc cores were found. There were n randomly initialised particles in the starting population.

Here is how the group size was determined:

$$X(i+1) = \left[\frac{X_{rand}(i)}{X_m}\right]$$

1. Initialize the random population X_i (i = 1, 2, … , N)
2. Apply one of the scaling techniques after loading the data.
3. **for** (each fold j) do
   Divide the data into train and test subsets randomly
4. **while** (t < T) do
   for (each hawk (X_i)) do
   Pass X_i to particular functions
   Set function's output to parameter of SVM (C, γ)
   Train and test the SVM model
   Evaluate the fitness X_i with EQ (2)
   Update X_{rabbit} as the position of the rabbit (best position based on the fitness value)
   end (for)
   for (every hawk (X_i)) do
   Update E_0 and J (initial energy and jump strength)
   Update the E by EQ (3)
   if ($|E| \geq 1$) then ▷ **Exploration phase**
   Update the position vector by EQ (4)
   if ($|E| < 1$) then ▷ **Exploration phase**
   if ($r \geq 0.5$ and $|E| \geq 0.5$) then ▷ **Soft siege**
   Update the position vector by EQ (1)
   else if ($r \geq 0.5$ and $|E| < 0.5$) then ▷ **Hard siege**
   Update the position vector by EQ (1)
   else if ($r < 0.5$ and $|E| \geq 0.5$) then
   ▷ **Soft siege with PRD**
   Update the position vector by EQ (1)
   ▷$F(Y)$, $F(Z)$ *and* $F(X_i)$ **calculated by using RMSE**
   else if ($r < 0.5$ and $|E| < 0.5$) then ▷ **Hard siege with PRD**
   Update the position vector by EQ (1)
   end (for)

The steps that are proposed for the model are displayed in Algorithm.

Algorithm: Binary Grey Approach

1: Begin

2: Identify X_m (no. of cores);

3: Randomly initialize the population;

4: Compute X(i + 1) particles with Equation (1);

5: Make X_m sets;

6: Distribute the particles on cores.

7: Run the BGWO-SVM model on each core

8: Choose the optimal particles from all cores;

9: Update the model's parameters and particle positions;

10: For all folds, return the average accuracy.

11: End

To get an integer number of particles to spread on the cores, the ceil function was utilised. Each set has its own independent thread that ran the fundamental algorithmic procedures. After these steps were finished, the optimal particles were selected to solve the optimisation problem. In addition, these particles were mixed to get the optimal particles across all cores and then the position was updated accordingly.

IV.EXPERIMENTAL RESULT

Exploration Phase

This phase is mostly modelled mathematically for the purposes of waiting, searching, and having the ability to recognise prey. At each and every stage, Harris's hawks are the alternative or the best option. In accordance with Equation (1), the position $X(i+1)$ of Harris's hawks can therefore be stated.

$$X(i+1)=\begin{cases}\left(X_{rand}(i)\right)-r_1|X_{rand}(i)-2r_2X(i)| & \text{if } q\geq 0.5\\ \left(X_{rand}(i)-X_m(i)\right)-badrr_3\left(LB+r_4(UB-LB)\right) & \text{if } q<0.5\end{cases} \quad (1)$$

This is where we may find the average hawk position (X_m), where ithe iteration at the present time is, X_{badrr} is the position of the badrr, X_{rand} is a selected hawk at the current population, $r_j = 1,2,3,4,$ and q are random numbers between 0 and 1with Equation (2).

$$X_m(i)=\frac{1}{N}\sum_{j=1}^{N}X_j(i) \quad (2)$$

A vector X_j represents the position of each individual hawk j, and N represents the total number of hawks in the area. The hawks will besiege the prey from all directions in order to hunt it during this phase. The intensity of this besieging will vary depending on the amount of energy that the prey still possesses. During this siege, the prey's ability to escape is contingent upon the chance r, therefore if r is less than 0.5, it is successful in escaping. If the value of E is more than or equal to 0.5, the HHO is besieging softly; otherwise, it is besieging hard. A gentle siege, a hard siege, a soft siege with progressive rapid dives, and a hard siege with progressive rapid dives are the four attack techniques that the HHO employs. These strategies are implemented in accordance with the phenomenon of prey escape and the strategies that hawks employ when they are pursuing their prey. In specifically, the rabbit possesses sufficient energy to escape if the value of E is greater than or equal to 0.5. However, the capacity of the prey to escape or not is contingent upon both the values of E and r. Soft Siege ($r \geq 0.5$ and $|E| \geq 0.5$). One way to express this process is as follows Equation (3) and (4):

$$X(i+1)=\Delta X(i)-E|JX_{badrr}(i)-X(i)| \quad (3)$$

$$\Delta X(i) = X_{badrr}(i) - X(i) \qquad (4)$$

in where $\Delta X(i)$ denotes the disparity between the rabbit's present position and its location vector at the i-th iteration, $J = 2(1 - r_5)$ denotes the strength of the rabbit's haphazard leaping while evading capture, and $r_5 \in (0, 1)$ is a random integer. To reduce the problem to a linear one, kernel functions could be employed to increase the dimensionality of the data. Figure 2 shows the linear and nonlinear support vector machines. As an added bonus, kernel functions could help with high-dimensional calculation speedups. The dot product of two features, for instance, can be computed in the expanded feature space using the linear kernel. Most support vector machines use RBF and polynomial kernels. They have the following form:

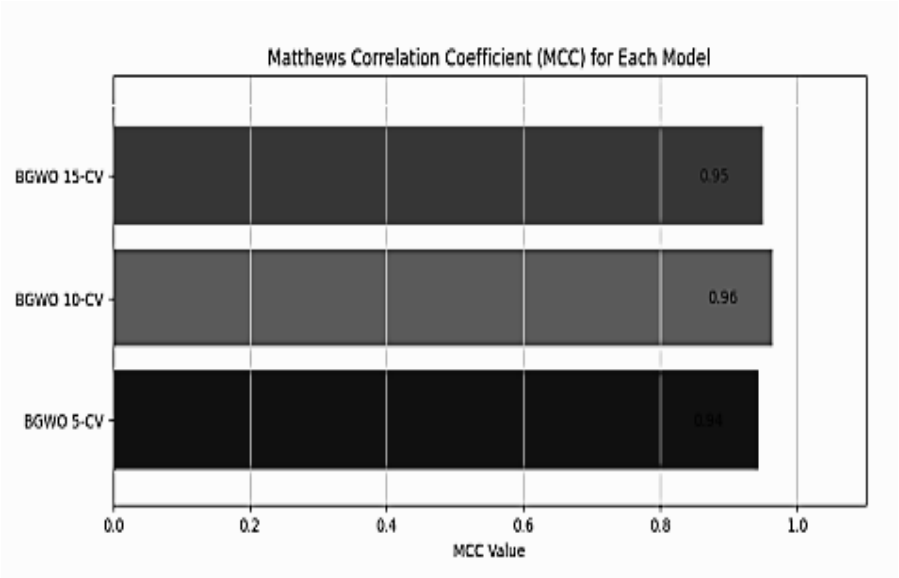

Figure 2. Analysis into the MCC values using BGWO-SVM methods in various cross-validation environments.

The parameters γ with p represent the width for the Gaussian kernel along with the polynomial order, according to that. It has been shown that SVM classification accuracy can be improved by setting the model parameters correctly. Tuning support vector machine (SVM) settings requires a fine hand. The SVM kernel function, which discovers the mapping from nonlinear to linear by increasing the dimension, and the parameters C and gamma are used for this.

V.CONCLUSION

The purpose of this innovative and improved quantum-inspired binary Grey Wolf Optimizer with Support Vector Machines Radial Basis Function Kernel is to improve the accuracy of breast cancer categorization. Research presents a two-phase strategy, which is significant from a theoretical point of view. The initial phase places an emphasis on the careful extraction of specified regions from mammographic images. This helps to ensure that a better understanding of potential breast cancer signs, particularly calcifications or masses, is achieved. In the subsequent step, the hybrid classification technique is utilised, and the primary classifications of breast cancer, which are benign and malignant tumors, are selected for further investigation. Through the utilisation of BGWO in conjunction with SVM, the achievement is based on the discovery of optimal parameters for increased BC classification accuracy.

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