INTELLIGENT CLASSIFICATION MODEL FOR BREAST CANCER DIAGNOSIS USING OPTIMIZED FEATURE SELECTION ALGORITHMS

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ABSTRACT

Breast cancer is one of the most common fatal diseases affecting women whose incidence rate is increasing worldwide. Early detection is the only approach to increase the survival rate because the stage of cancer at the time of detection determines how successfully it may be treated. Recent technological improvements in early screening techniques have decreased the death rate. Breast cancer is the second most frequent malignant tumor in the world. Early findings of breast cancer can significantly improve treatment effectiveness. Manual methods of breast cancer diagnosis are prone to human fault and inaccuracy, and they take time. A computer-aided diagnosis can assist radiologists in making better choices by overcoming the disadvantages of manual methods. One of the significant steps in the breast cancer diagnosis process is feature selection. In recent decades, many studies have proposed numerous hybrid optimization methods to select the optimal features in the breast cancer detection system. However, many hybrid optimization algorithms are trapped in local optima and have slow convergence speed. Thus, it reduces the classification accuracy. For resolving these issues, this work proposes a hybrid optimization algorithm that combines the grasshopper optimization algorithm and the crow search algorithm for feature selection and classification of the breast mass with multilayer perceptron. The simulation is experimented with using MATLAB 2019a. The efficacy of the proposed hybrid grasshopper optimization-crow search algorithm with multilayer perceptron system is compared to multilayer perceptron-based algorithms of enhanced and adaptive genetic algorithm, teaching learning-based whale optimization algorithm, butterfly optimization algorithm, whale optimization algorithm, and grasshopper optimization algorithm. From the results obtained, the proposed grasshopper optimization-crow search algorithm with the multilayer perceptron method outperforms the comparative models in terms of classification accuracy (97.1%), sensitivity (98%), and specificity (95.4%) for the mammographic image analysis society dataset.

KEYWORDS: breast cancer, classification, computer-aided diagnosis, crow search, feature selection, grasshopper optimization, mammogram, multilayer perceptron

I INTRODUCTION

Medical imaging is helpful for the early detection and diagnosis of diseases and is an integral part of the entire healthcare process. Image processing is an emerging field in medical applications. The fundamental processes in image processing are acquisition of image, storage, processing, communication, and output. Medical imaging techniques have produced a massive amount of data in recent years. However, the information is hidden in the images. As a result, developing an effective medical image processing system is crucial for extracting meaningful insights and assisting clinicians in making medical decisions. Machine Learning (ML) techniques have been widely applied in healthcare systems, specifically for breast cancer diagnosis and prediction. Over the last few decades, cancer-related research has been performed. Scientists and researchers have developed and applied various methods to predict disease before symptoms emerge. As a result, accurate diagnosis and predictions of breast cancer disease are seen as important and challenging tasks for clinicians in the healthcare field.

Cancer is a disease in which some of the body cells grow uncontrollably and spread to other body parts. These cells can combine to form tumors, which are lumps of tissue. Tumors can be cancerous (malignant) or non-cancerous (benign). A malignant tumor can grow and spread to other parts of the body. A benign tumor can grow but does not spread. Breast cancer is a form of cancer that grows in the cells of the breast. It is the second most diagnosed cancer in women after skin, lung, and cervical cancer. In 2020, there were 2.3 million new cases of breast cancer and 6,85,000 deaths worldwide, which will be doubled by 2025. While the number of women diagnosed with breast cancer continues to rise exponentially, death rates have recently decreased because of advances in medical research, image analysis, and ML approaches. If breast cancer is identified early and treatment is available, the survival rate may also be improved.

Breast cancer develops when cells build abnormally along the duct or lobules. The abnormal cells originate in the duct that forms the carcinoma. Lobular carcinoma is less common and is caused by cells in the lobules. Breast abnormalities are classified as lump masses, microcalcifications, or architectural changes in some cases. The deposition of the calcified milk gives the small deposits called calcification. Architectural distortion with no presence of mass refers to changes in breast architecture. The breast comprises two types of tissues: supporting or stromal tissues and glandular tissues. Glandular tissues include the milk producing glands called lobules and ducts (milk passages), whereas stromal tissues contain the breast's fatty and fibrous connective tissues. The breast also has lymphatic tissue, immunological tissue that removes waste and cellular fluids. Various types of tumors that can develop in different areas of the breast. Benign changes in the breast cause most tumors.

Breast cancer is classified into several subtypes based on the specific cells in the breast that develop into cancer and microanatomy. These cancer regions can be widely categorized as 'invasive' or 'non-invasive.' These two types of cancer may coexist in a single patient at some point. Noninvasive cancer is a type of cancer in which abnormal cells are formed in the milk ducts of the breast and cannot spread to nearby tissue or elsewhere in the body. As a result, this form of cancer region can be identified using scanning techniques and removed surgically in the medical system. In the case of invasive type cancer, the cancer cell grows across its original location into circumscribing normal breast tissue and can spread to other parts of the body.

The most significant aspect of the treatment of breast cancer is its early detection. Among numerous diagnosis platforms, imaging techniques are essential diagnosis methods that can give significant information on patients with breast cancer. Because the initial tumor rarely causes noticeable symptoms, early cancer identification should rely on screening a huge non-symptomatic population. These tests are known as cancer screening tests. These are normally reserved for a limited group of people who have a higher cancer risk. Cancer screening is performed using imaging modalities like mammography, ultrasound, Magnetic Resonance Imaging (MRI), thermography, Positron Emission Tomography (PET), electrical impedance based imaging, Computed Tomography (CT), and optical imaging. In addition to imaging approaches, biochemical biomarkers, including proteins, Deoxyribonucleic acids, Ribonucleic acids, and micro- Ribonucleic acids, will be used as additional diagnostic and treatment tools for breast cancer patients.

Factors like difficulty in identifying suspicious regions, the position of cancer tissue and the large volume of mammograms have been given to each radiologist and the repetitive nature of work adversely affects the accurate interpretation of mammograms. In some cases, superimposed tissues cause cancerous lesions that are difficult to detect. To overcome these issues, CAD systems are developed for interpreting improvement in breast cancer detection by reducing the number of false-negative interpretations that are caused by complex architecture, radiologist distraction, and subtle findings in an efficient way. CAD is a multidisciplinary technology that integrates digital image processing, artificial intelligence, and radiological image processing. Over the decades, several CAD systems that use ML approaches have been implemented on mammogram images to provide clinical evidence to radiologists. Furthermore, CAD may aid in avoiding human-based investigative errors caused by visualization problems related to imaging quality and examination efforts. A CAD method is made up of various modules, including digitizing mammogram images, image preprocessing, image segmentation, feature extraction, feature selection, and classification.

II LITERATURE REVIEW

Developed a computerized model for mammogram image preprocessing. To eliminate the pectoral muscles, they used the seed-based area growth approach. After the pectoral muscle has been eliminated, morphological methods are used to evenly disperse the contrast. The bottom and top hat procedures are employed to achieve consistent contrast in the images. The segmentation of mammogram images also employs K-means with spatial, mean shift with spatial and normalized cuts. They tested using both real-time data and the mini-MIAS dataset. They achieved a contrast enhancement of 3 dB with 92% accuracy for the real-time dataset and 97% accuracy for the mini-MIAS dataset. However, the performance is highly dependent on the number of seed points selected.

An implemented an image enhancement approach for the detection of breast cancer on mammogram images. They enhanced mammogram images with a Fuzzy Anisotropic Diffusion Histogram Equalization Contrast Adaptive Limited approach to lessen noise while maintaining contrast and brightness. The Fuzzy Clipped Inference System is used in the approach and automatically chooses the clip limit during the enhancement process. They tested both the MIAS and DDSM datasets and achieved improved image enhancing results.

A designed image pre-processing techniques for the removal of background, pectoral muscle removal and enhancement of the images. They have applied Huang‘s Fuzzy Thresholding techniques, Rolling Ball Algorithm to remove the background, Hough‘s Line Transform techniques and Canny Edge Detection to remove pectoral muscles. The Region Of Interest (ROI) and regions inside the ROIs on mammogram images are highlighted using the Invert, CTI RAS, and ISOCONTOUR lookup tables for image enhancements. The preprocessed images are used as input for deep convolutional neural networks. These techniques achieved a 99.06% accuracy rate for removing pectoral muscles from images and 100% accuracy for removing backgrounds. However, it does not perform well in images with a limited color spectrum. However, it does not perform well on low-contrast images.

An implemented a noise removal technique to improve the quality of mammogram images for breast cancer detection. The Non-Subsampled Shearlet transformation is used to filter out noise from the mammogram images. It combines shearing filters and nonsubsampled Laplacian pyramid filters. In this work, the low and high frequency components of mammogram images are derived using Non-Subsampled Laplacian Pyramid decomposition. Using the directed filters, the shearlet coefficients and sub bands are determined. Pre-processing algorithm is applied to increase the extracted pixel quality, which is ensured by visual evaluation parameters Peak Signal to Noise Ratio (PSNR) within the range of 43–53 and Mean Square Error (MSE) in the range of 0.017–0.025. However, there is a very subtle difference between abnormal and normal tissue.

A designed a method for image enhancement on mammogram images. The image is primarily improved using the spatial domain technique of Contrast Limited Adaptive Histogram Equalization (CLAHE), which is then given into the frequency domain approach bilateral filtering. The CLAHE method is compared to various existing spatial and frequency domain techniques and its performance is measured using standard performance metrics on the MIAS dataset. Compared to existing methods, CLAHE image enhancement technique gives better results for entropy,
Michelson contrast, and PSNR.

Designed a repeated median filtering technique for removing noises from mammogram Images. Repeated median filtering is a nonlinear median based processing technique which applies median filtering to an image N time to remove noises at various levels to obtain an enhanced image depending on the appropriate level. The standard image quality evaluation measures such as PSNR and MSE are used on the mini-MIAS dataset and achieved improved results.

Developed an image enhancement method for mammogram images. Initially, Techniques for pre-processing data such as the wiener, mean, median, wavelet denoising, non-local mean, and power law transformation have been applied for noise reduction. After that, a histogram is used to enhance the contrast. Then, the morphological operation for image smoothing is performed. Following that, the entropy maximization approach is used to improve images. The pre-processing methods performance is evaluated using statistical measures such as PSNR, MSE and entropy.

Suggested a noise removal algorithm for mammogram images, which uses tristate nonlinear values and a tree-based decision to remove high density outlier noise from mammogram images. The decision tree values in the algorithm are determined by the count of non-noisy pixels in the current processing area. Based on the decision tree in the current processing kernel, tristate values like an unsymmetrical truncated median, midpoint, or modified winsorized mean replaces the erroneous pixel. For reducing high density noise, this noise reduction method offers a strong structural preservation property.

III EXISTING SYSTEM

The most significant aspect of the treatment of breast cancer is its early detection. Among numerous diagnosis platforms, imaging techniques are essential diagnosis methods that can give significant information on patients with breast cancer. Because the initial tumor rarely causes noticeable symptoms, early cancer identification should rely on screening a huge non-symptomatic population. These tests are known as cancer screening tests. These are normally reserved for a limited group of people who have a higher cancer risk. Cancer screening is performed using imaging modalities like mammography, ultrasound, Magnetic Resonance Imaging (MRI), thermography, Positron Emission Tomography (PET), electrical impedance based imaging, Computed Tomography (CT), and optical imaging. In addition to imaging approaches, biochemical biomarkers, including proteins, Deoxyribonucleic acids, Ribonucleic acids, and micro Ribonucleic acids, will be used as additional diagnostic and treatment tools for breast cancer patients.

The most common and important imaging tool for diagnosing any type of tumor is MRI (Morrow et al. 2011). MRI is a strong magnetic field, radio frequency pulses, and a computer is utilized in breast MRI to obtain detailed images of the inner parts of the breasts. In addition, MRI provides images from various angles, which may aid clinicians in constructing a three dimensional perspective of the tumor. Abnormalities that are not obvious on mammography or ultrasound can be detected with MRI and it is also less expensive. MRI excels by providing good image quality and helping evaluate dense breasts. It also helps to evaluate inverted nipples, allows simultaneous examination of both breasts, signifies by establishing whether mastectomy or lumpectomy is the best treatment, and has no side effects because there is no radiation.

IV DISADVANTAGES

During the preprocessing stage, image preprocessing operations such as noise removal, artefact and pectoral muscle removal, contrast enhancement, edge detection, and histogram equalization are performed. Contrast enhancement aids in the detection of masses in specific regions during mass identification and segmentation. The resulting segmented mass should be subjected to feature extraction and followed by classification. Realizing the advantages of achieving a higher level of precision can be possible if all such approaches ensure a higher level of accuracy. The gap at each level is well understood, which forms the motivation and framework for this system. The framework of this thesis is consistent with the computational requirements for digital mammogram processing for early breast cancer CAD systems. The hybrid optimization mechanism is the foundation for the proposed feature selection approaches. The developed classification algorithms categorize the input mammogram as normal or abnormal based on the most effectively identified features. Any mammogram images taken for the system towards early identification of breast cancer can be classified using the combination of the algorithms created for this system.

V BLOCK DIAGRAM

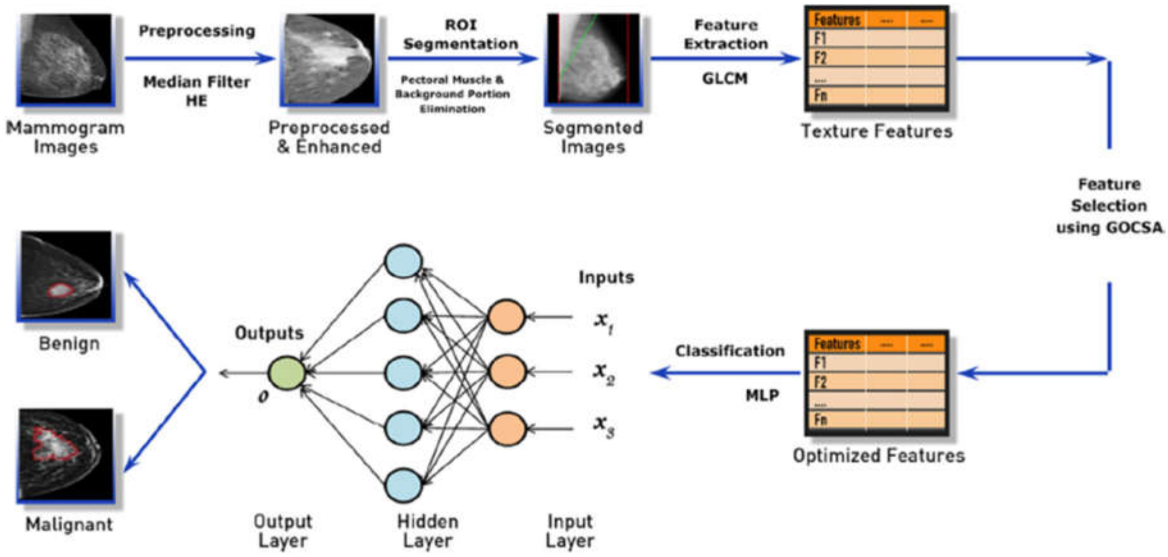


Figure: Block diagram of proposed GOCSA–MLP based CAD system

VI PROPOSED METHODOLOGY

This diagram explains the proposed feature selection based CAD system for breast cancer detection on mammogram images. In the last few decades, several optimization techniques and classification algorithms have been proposed and used to classify benign and malignant tumors. Each method has its own advantages and disadvantages. Early detection requires precise and reliable diagnosis. This work proposes an integrated algorithm called GOCSA-MLP by combining GOA and CSA with an MLP classifier. The hybrid based GOCSA algorithm eliminates inadequate or redundant attributes for effective classification. Subsequently, the MLP classifier was used as a precise classifier model for the breast cancer CAD system.

The methodological framework of the proposed CAD method comprises the following stages (i) Preprocessing (ii) Segmentation (iii) Feature extraction (iv) Feature Selection (v) Classification, and described in Figure In this proposed CAD framework, input mammogram images are initially preprocessed with adaptive median filtering and histogram equalization technique.

The processed images are subsequently segmented using background portion elimination and pectoral muscle elimination algorithms. Following that, textural, intensity, and shape features can be retrieved from segmented images using the GLCM technique. The retrieved features are higher and necessary to choose the optimal subset of features. By achieving this, the proposed hybridization based feature selection technique called GOCSA is applied for selecting the optimized features. Finally, the weight of the MLP network is updated and fine-tuned with the GOCSA algorithm. The GOCSA-MLP algorithm is used to classify the mammogram images into cancerous or non-cancerous with necessary training data.

Preprocessing is an important step in medical image processing that produces better image quality for segmentation and feature extraction. Mammogram images are difficult to interpret. Image preprocessing techniques are necessary to examine mammogram orientation, reduce noise, and strengthen image quality. Hence, the preprocessing technique enhances image quality so that the residual and unconnected portions in the mammogram background are removed for further processing. This can be done in two phases using an adaptive median filter and the histogram equalization algorithm.

Noise in an image is the presence of artefacts that do not originate from the original visual content. It is a statistical variation of a measurement produced by a random process. In general, two types of noises that corrupt digital images: additive Gaussian noise and impulse noise. The latter is the most common source of error. This noise can cause images to become corrupted by replacing some of the pixels in the original image and severely degrade the quality of the image. An adaptive median filter is used in this work to reduce impulsive noise from mammograms. It is a non-linear filter that eliminates non-repulsive noise from two-dimensional inputs while maintaining image quality and makes it appropriate for improving mammogram images.

In this procedure, the median value of each pixel is calculated with the window size. Then, the achieved ratio of every pixel is compared with the threshold value. If the obtained ratio is higher than a threshold, then the pixel value is restored by the median representation of the pixel. Otherwise, original pixel values are retained. The threshold value is determined automatically so that, only 8 - 10% of the pixels are restored in the original image.

VII ADVANTAGES

To develop the hybrid optimization algorithm based CAD system for breast cancer detection.

To diagnose the disease accurately based on the optimal feature subset selection which eliminates the redundant and irrelevant features

To minimize the search time, an effective hybrid Grasshopper Optimization Algorithm with Crow Search Algorithm is

integrated with the CAD system.

To eliminate false positives and improve the classification accuracy of the breast cancer datasets, an optimized GOCSA based MLP is implemented to update the weights and biases of MLPs.

To reduce the time complexity, an integrated optimized nature-based bat algorithm with chaotic maps and FCM will be used.

To assist radiologists for quickly identifying the target area which may also helps in early diagnosis of breast cancer, and optimize the workflow of radiologists.

To help the radiologists to carry out more value-added tasks such as more extensive patient interaction and integrated care.

The proposed method reduces the number of false positives and false negatives significantly, which reduces detection errors and improve the survival rate of patients.

VIII APPLICATION

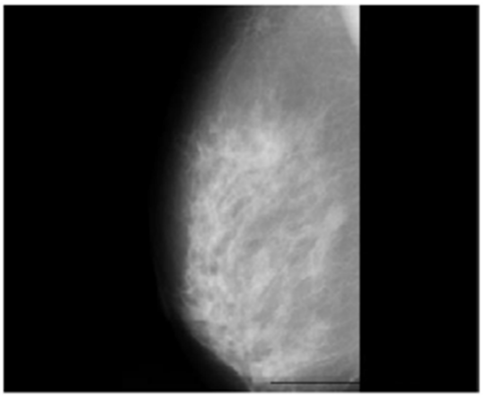
1.Image sharpening and restoration
2.Medical field
3.Remote sensing
4.Transmission and encoding
5.Machine/Robot vision
6.Color processing
7.Pattern recognition
8.Video processing
9.Microscopic Imaging

IX RESULTS AND CONCLUSION

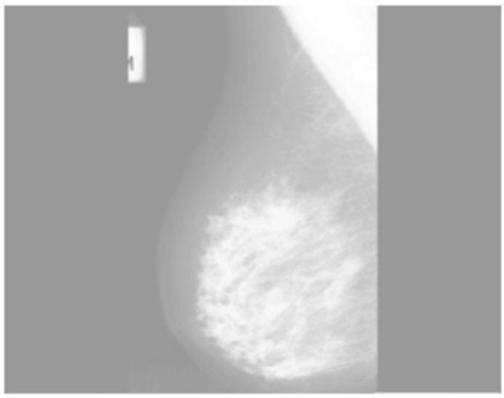
This section describes the experimental setup and parameter settings used to evaluate the performance of the proposed GOCSA-MLP algorithm for the classification of digital mammogram images. Also, this explains the benchmark datasets used for the validation of the proposed algorithm. Finally, simulation results, discussions, and a comparison of GOCSA-MLP results with those found in the literature presented.

Database samples of the mini-MIAS dataset are taken for analysis of this work. The MIAS database contains 322 left and right breast images of 161 patients with MLO views.52 Each image is accessible with a size of 1024×1024 pixels and it also includes types of abnormalities present in an image. The mammogram images are captured from an imaging process of a film screen used by a nationwide breast screening program in the United Kingdom. Patient details are categorized and verified with expert radiologists. Figure 8 shows the sample mini-MIAS dataset. There are four types of anomalies presented in the categories: mass, micro calcification, asymmetry, and architectural distortion. All 322 images are split into three classes depending on the magnitude of an abnormality: normal, benign, and malignant.

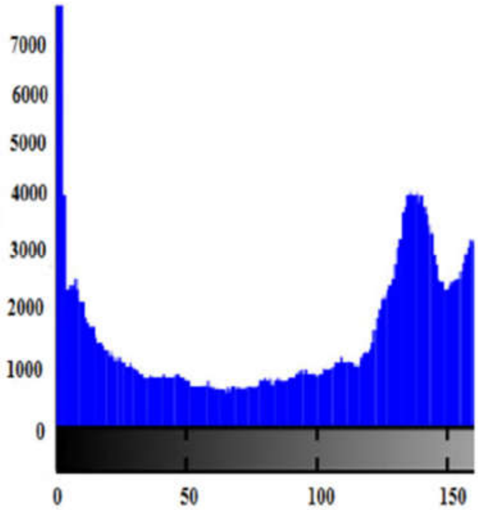
The experimental environment is as described: Ubuntu operating systems, MATLAB R2019a using 32GBRAM, HP Elite 7100 Business PC. The proposed system is validated with amini-MIAS dataset of 322 mammogram images which is divided into 70% of the images for training and 30% of the images for testing. Table 3 summarizes the datasets in terms of several training and test ing samples. Furthermore, stratified sampling is used in this partitioning to preserve the original class distribution of the data during the training and testing processes. In this article, the mammogram images are initially preprocessed to improve the quality of the images by removing noise, and then segmentation operation is performed using background portion elimination and pectoral muscle elimination algorithms to obtain the ROI. Subsequently, all 13 texture characteristics, 5 intensity characteristics, and 7 shape characteristics described in Table 2 are retrieved from segmented images using the GLCM technique for effective feature selection. Finally, the proposed GOCSA-MLP algorithm is applied to obtain the optimal features for classification. All experiments are performed for 30 individual runs to obtain effective statistical results, and each run consists of 250 iterations. Following that, the average measures are determined to assess the attainment of the proposed GOCSA-MLP. The proposed algorithm is compared with MLP-based optimization algorithms such as EAGA, TSWOA, BOA, WOA, and GOA.



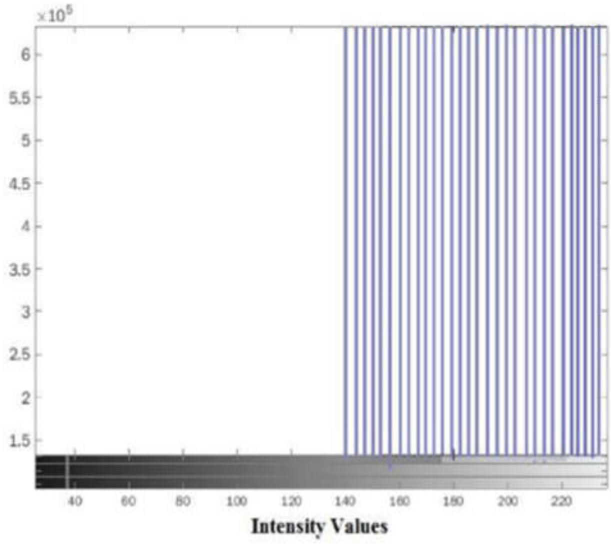
(A) Original input image



(B) Enhanced image using HE method



(c) Original input's Histogram



(d) Enhanced image resultant histogram

This system introduced a new GOCSA-MLP based CAD system designed for detecting breast cancer using digital mammograms. The key objective of this research is to determine the features selected from the breast cancer dataset and the importance of reducing the number of features with the feature subset selection approach to enhance the classifier efficiency. In medical image processing, the dimensionality reduction method serves a significant role. The proposed system addresses the main concern is to help pathologists improve the accuracy, efficiency, and consistency in breast cancer identification. The proposed approach is implemented as a novel hybrid approach of GOCSA for optimizing the extracted features and MLP used for classifying breast images into malignant and benign. The performance of the proposed method is validated and verified by experimental results. Further, this research extended by incorporating the proposed GOCSA-MLP method to detect other types of diseases, solve real-world problems, such as engineering optimization problems, scheduling problems and criminal behavior modeling. In future, GOCSA will be integrating with advanced network models to enhance the overall performance of the breast cancer CAD system.

X FUTURE SCOPE

The system could be advanced by conducting a clinical trial of the proposed CAD system and assessing the efficiency of the proposed work in a practical environment. This is done to assist the clinical process and to create knowledge-based clinical decision support systems. Furthermore, it will assist the healthcare practitioners and radiologists in treatment to predict the illness accurately and effectively with less time. To enhance the overall performance of the breast cancer CAD system, it can be integrated with advanced neural network models like Convolutional Neural network, Recurrent Neural Network and Deep Belief Network. The methods can be extended to detect other forms of cancer such as cervical, lung, skin, and brain.

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