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An Intelligent Deep Learning Framework for Early Breast Cancer Detection Using Medical Imaging

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Abstract
The early and correct diagnosis of breast cancer is important for better clinical results and prompt treatment planning. The analysis of medical images, however, is complex due to complex tissue structures, variations in image quality and subtle malignant patterns. In this paper, an intelligent deep learning framework is proposed for automated breast cancer detection from medical imaging, called ViT-GWO. The proposed framework is a combination of a Vision Transformer (ViT), which is used to learn global contextual and discriminative representations from medical images of the breast, and Grey Wolf Optimizer (GWO), which is used for selecting the most relevant subset of features from the high dimensional feature space. The methodology comprises of image preprocessing, image normalization, low-pass filtering, data augmentation, image patch generation, patch embedding, positional encoding, Transformer-based feature extraction, and GWO-based feature optimization. The optimized features are then given to a SoftMax classification layer which is used to separate benign and malignant breast tissue. It is tested on breast cancer data sets DDSM and MIAS, and the results are compared with the results of the CNN, MLP, and EML methods. The experimental results show that the proposed ViT-GWO framework model has an accuracy of 99.57%, a precision of 99.25%, a recall of 98.76%, MCC of 99.89%, and F1-score of 99.77%. Based on these results, it can be concluded that the use of Vision Transformer network for generating representations and GWO for optimizing those features can be a promising approach for automated breast cancer detection and classification. The proposed framework has the potential to enhance classification accuracy in computer-aided diagnosis, whilst minimizing the effect of redundant features.
Keyword: *Breast Cancer Detection, Deep Learning, Vision Transformer, GWO*

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I. Introduction

Breast cancer (BC) is leading women's health issue worldwide reported by world health- organization. the rate of death is very high, due to detection of breast cancer on last stage, the early detection of breast cancer survives millions of lives. [1,2]. The timely identification of malignant tissues is of great importance since it can make the difference in the prognosis of the patients and help them to follow less invasive treatment pathways [3]. The application of clinical requirement, process of screening like mammography and magnetic resonance imaging limitation of classification accuracy in terms of dense breast cancer tissue [4]. The diagnostic task of interpreting such large amounts of complex, yet important images is often subjective, subjective visual perception, artefacts and overlapping anatomical structures can reduce the diagnostic accuracy, which leads to the work being extremely labour intensive [5]. To overcome such systemic diagnosis limitations, the inclusion of intelligent deep learning frameworks has appeared as a strong option to automate complicated feature extraction and reduce human reliant variations [6,7]. Employed CNN algorithms increase the detection ratio of medical images, and reduces work-load of physical diagnosis process [8,9]. . Such computation models can be revolutionary in oncology, particularly by offering automatically generated, interpretable tools to support medical scientists in detecting tumors, categorizing them, and monitoring for their recurrence [10,11]. Moreover, when these methodologies were implemented, it was aimed at the immediate need to improve screening efficiency, thereby minimizing false-positive results which ultimately will optimize clinical workflow [12,13]. The model of deep learning handle high dimensions of data and overcome the limitation of different variation parameters. The screening load of mammography deflects the precision of detection [14]. The advancement of deep learning algorithms enhances, medical screening approach of breast cancer. The results of screening improve in manners of the sensitivity and specificity of patient data [15,16]. . Several research scholars focus on, machine learning (ML) algorithms have been widely used for the diagnosis of breast cancer based on clinical or medical-image data by extracting discriminative features from these data and then classifying samples as normal, benign, or malignant [16,17]. Other algorithms, like Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN) and some ensemble and optimization-based have shown to be promising for classification. however, the conventional ML methods rely on the careful design or manual extraction of features [18]. Thus, the performance of these systems may be affected by the features extraction process, feature-selection methods and dataset attributes. Machine learning algorithms has certain limitation as feature extraction and optimization of extracted features, this limitation overcomes, employ deep learning algorithms. deep learning algorithms has different variants to execute more accurate feature extraction and optimization for process of detection [19,20]. The reported studies have shown that the performance of several DL-based approaches, such as the transfer-learning and hybrid approaches are high. For instance, the investigated studies show the accuracy of about 84% to 99.1% on various datasets and imaging modalities. Although these advances have been made, there are still some obstacles to be overcome [21,22]. Performance of the ML and DL models may widely differ, depending on the dataset, the imaging modality, preprocessing technique, class distribution, feature representation or the validation approach. However, models trained on one data set might also suffer from poor generalization when used on images acquired by other institutions or imaging devices [23,24]. Moreover, there is a relative lack of existing research that focuses on computational complexity, robustness, interpretations and clinical applicability with the same emphasis given to classification accuracy. This paper addresses the limitation of existing algorithms of deep learning and proposed feature optimization-based breast cancer detection. The detection approach of breast cancer employed vision transformer (ViT), ViT overcomes the limitation of convolutional neural network (CNN) and enhance the detection ratio. We proposed an extensive framework for the classification of breast cancer at the patch and whole-slide levels as either benign or malignant. The proposed approach also separates ductal and lobular carcinoma in both the level of analysis and the proposed approach. For accurate and impartial assessment, a detailed five-fold cross validation method was adopted, where the dataset was systematically split into three sections: training, validation and testing subsets. Data augmentation was used to diversify the data and enhance the robustness and generalization ability of the model. In addition, advanced visualization techniques were added, especially Class Activation Mapping (CAM) to detect and emphasize diagnostically important areas in the tissue images. This visualization-based analysis helps model interpretability and allows a thorough evaluation of the regions that make a classification decision in the model. The rest of paper organized as in section II. Recently proposed algorithms for breast cancer detection, in section III. Methodology of breast cancer detection, in section IV explores experimental analysis, and finally conclude in section V

II. Related work

In current decade of medical science employed several approaches of artificial intelligence and deep learning algorithms for automatic and computer aided diagnosis of breast cancer. Convolutional neural network (CNN) is playing vital role for detection and classification of malignant cell of women breast. Transformers, and hybrid algorithms and high focused several aspects of the datasets, methodology, and clinical translation. CNN-based models often showed better diagnostic performance, and U-Net inspired models were commonly employed for tumor and tissue detection [1]. Machine learning defines several supervised algorithms for the classification of medical imagining system. these studies proposed an increasing trend in the use of hybrid models, transfer learning, ensemble learning, and explainable AI for enhancing robustness and clinical applicability [2]. Authors explores, high diagnostic performance is possible using advanced architectures such as CNNs, the Vision Transformers, and graph neural networks. But standardization, generalization, explainability and clinical integration of datasets are still significant challenges [3]. The study focus on emphasizes the need for diversity of data sets, the need to preprocess the data sets, the need for choosing an appropriate model, and the need for appropriate methods of validation of the model to achieve reliable diagnostic performance [4]. Their evaluation included applications in mammography, digital breast tomosynthesis, ultrasound, MRI, and nuclear medicine. Besides detecting and characterizing lesions, the review highlighted the novel application of risk stratification, molecular subtyping, prediction of gene-mutations and evaluation of treatment responses [5]. Automated breast ultrasound imaging (ABUS) has also been the focus of deep learning more recently. A recent review focused on computer-aided diagnosis (CAD) systems based on DL for ABUS, highlighting the potential of automated detection, as well as challenges in data quality, model generalization, annotation and clinical implementation [6]. The application of AI techniques in different imaging disciplines such as mammography, ultrasound, and thermography has been recently reviewed, while explainable AI has gained traction as a crucial component of enhancing the transparency and reliability of AI systems. Large language models (LLMs) and Multimodal large language models (MM-LLMs) are also pointed out as future technologies that can aid in breast cancer diagnosis [7]. Self-supervised learning (SSL) is a potential solution that is being explored for the scarcity of labelled medical images. Large amounts of un-labelled images can be used by SSL, and it can also lower the size of the annotations needed and enhance feature representation and generalization [8]. Breast imaging AI readiness is becoming a top priority. A recent review was carried out focusing on deep-learning applications in MRI, mammography, and ultrasound, and specifically taking the radiologist's point of view. The study highlighted that while these developments are significant, they must be further explored for explainability, integration into workflow, and clinical validation before they can be widely used [9]. The examples illustrate the growing application of deep neural networks to automatic breast-density assessment, a clinically relevant analysis that may affect the cancer risk assessment and mammographic interpretation, as breast density could affect the likelihood of developing breast cancer [10]. This hybrid transfer learning model resulted in an accuracy of 94.3% while the MVGG based model gave an accuracy of 88.8% [11]. One research used the combination of Fuzzy C-Means and a Genetic Algorithm (FCM-GA) to determine the surround pixels and to lessen human intervention in the clustering process. The highest accuracy of 94% was obtained using FCM-GA [12]. The application of transfer learning and convolutional neural network (CNN) technique is also a field of intensive research for classification and detection of ultrasound breast-image [13]. Another direction that has gained traction is Quantum machine learning, where a Quantum Support Vector Machine (QSVM) is being evaluated for the diagnosis of malignant breast cancer, and there exists a potential computational advantage over classical machine learning [14]. The potential of systematic neuron-selection strategies for the improvement of the classification performance was shown by the artificial neural network (ANN) optimized with the Taguchi method, which obtained a classification accuracy of 98.8% [15]. The hybrid learning methods have shown good performance on various datasets of breast cancer. The accuracy, sensitivity, F-measure, specificity, Matthew's correlation coefficient (MCC), and recall were used to evaluate a proposed hybrid model on six microarray datasets and it performed well [16]. For breast cancer detection, the two-stage method, which consists of the first stage using Faster R-CNN and the second stage combining with the majority voting of three classifiers, increased mean average precision (mAP) from 0.85 to 0.94, showing that it achieves better detection performance than the original Faster R-CNN model [17]. Likewise, an improved Breast Ultrasound Images (BUSI) database was employed to design a framework to achieve the maximum accuracy of 99.1% compared to the existing methods available [18]. The contribution of image processing and post-processing has also been great in the detection of breast tumors. Morphological operations have been used for localizing the tumor and estimating the tumor volume which could help in disease management and monitoring of patients [19]. A neural network-based optimization algorithm has been used in conjunction with feature-selection and classification techniques based on Support Vector Machines (SVMs) for both optimizing feature-selection and optimizing SVM classification [20]. In a similar way, SLGM is combined with a back-propagation based artificial neural network to study the classification of skin cancer [21]. Image enhancement techniques have been found to be useful in the diagnosis of breast cancer. The results of one study showed overall classification accuracy of 96.69% and an accuracy in the detection of malignant nodules of 95.11%, suggesting that the enhancement of images can aid in making earlier and more accurate diagnoses of malignancy [22]. Also, image-processing techniques have been suggested to automatically identify vibrational experimental observations with the goal of extracting features that could be used to predict tissue diseases [23]. Various deep-learning architectures have been found to perform differently across different tasks, with one study achieving an improvement over the state of the art of 8% to 20% [24] when compared with the same task. Another application of quantum neural networks (QNNs) is given to the early diagnosis of breast cancer, wherein the focus is on developing a baseline for the evaluation of the performance and outcomes of quantum neural networks [25]. The transfer learning with VGG16 architecture along with Adam and RMSProp optimizers has been integrated for the classification of normal, benign and malignant breast images. The accuracy of the reported classification varied from 85% to 94% and the Adam optimizer achieved the best accuracy [26]. The use of machine learning techniques has also been shown to be applicable for medical image analysis. In one of the studies, 98.6% of 905 images were correctly identified, showing the promise of machine learning to enhance the medical-image analysis and classification [27]. A study with one-dimensional CNN-based classification of numerical time-series data, however, showed poor results, and suggested that the architecture of the CNN and the representation of data can significantly affect the classification accuracy [28]. The broad review of the various methods found many of the most successful breast cancer detection methods are now focused on deep-learning methods [29]. With the advent of huge data and high computing power, artificial-intelligence systems have been developed to predict breast cancer using the mammographic image [30]. In addition, the DMR-IR public dataset has been explored for the diagnosis of breast cancer via thermography. Experimental results with various methods showed that the results obtained with Extreme Learning Machine (ELM) were better than the results obtained with Multi-Layer Perceptron (MLP) by over 19% [31]. Other research in breast imaging has been conducted for quantum noise and low-dose imaging. The first method used clinical data as input for training and real Digital Breast Tomosynthesis (DBT) projections as targets for testing a trained network that was constructed with quantum noise paired with standard dose projections [32]. The other approach was to fine-tune a pre-trained model for image prediction and to use attention-based pooling to boost the classification accuracy [33]. Classification of breast cancer into various classes has also been studied. A proposed approach was able to provide an average accuracy of 94.20% for classification of four breast cancer classes, with a classification training time of 226 s. The method performed an average accuracy of 90.10% and a training time of 147 s [34] for eight classes. Along with this, sensor-based methods have been suggested for the quick, cost-effective and effective identification of blood-related diseases like cancer [35]. Integrated feature-based and pipelined approaches have been investigated to predict the clinical outcomes of cancer treatment, and one study achieved 94.7% accuracy. The study also demonstrated the dilemma of balancing the prediction accuracy with the over and under fitting problem [36]. For automated analysis of cancer, metabolic profiling has been studied and it is reported that the novelty-detection time varies from 1.5 to 20 s depending on the number of training data and the type of the classifier used [37]. Clinical datasets have also been evaluated for the machine-learning methods. In an experiment with data from the University Hospital Centre of Coimbra, the combined procedures and machine learning methods were capable of achieving an accuracy of 86.97%, which indicates the potential of this approach for breast cancer analysis using the combined procedures and machine learning methods [38]. The use of nanotechnology in the treatment of breast cancer has also been explored for the delivery of therapeutic agents, coding of drugs, photodynamic therapy, photothermal therapy, combination therapy, gene therapy, immunotherapy and reversing multidrug-resistance [39]. Lastly, transferable texture-based CNN methods have been explored for mammographic screening on the DDSM, INbreast, and MIAS data sets. The proposed approach was found to be more accurate than the existing techniques considered in the study [40] with an average accuracy of 97.49%.

III. Proposed Methodology

This section describes the proposed methodology of early breast cancer detection approach based on feature optimization using GWO (grey wolf optimization) algorithm. for the detection apply vision transformer algorithm. the vision transformer (ViT) overcomes the limitation of CNN and improves the classification of breast cancer detection as early stage. The processing of classification model describes as (a) Deep learning, Vision Transformer (ViT), (b) GWO algorithms, and (C) proposed methodology.

III. (a) Deep Learning

As deep-learning methods have been developing, researchers have been increasingly interested in using hybrid models of CNN and recurrent networks like LSTM and RNN. Such architectures can improve the ability to analyze relationships and correlations between features of the image, in a way that better represents a more complex medical-imaging dataset, like DDSM. The hybrid models combine CNN with recurrent learning mechanisms, which allows them to learn spatial features and contextual relationships, enhancing the ability to classify complex patterns and variances in breast tissue images. The authors in [10] created a deep CNN structure with 50 layers for breast histopathology image classification into benign and malignant. The study showed that deep residual networks can be successfully applied to breast-tissue images, extracting discriminative features from complex images. CNN and RNN architectures were combined for the classification of histopathological images in another work [27]. This complement enhanced the ability of the model to acquire spatial relationships and contextual correlations between the image regions, which in turn helped to better visualize and discriminate the tissue characteristics. In[5] introduced an Efficient Net-based approach that utilizes discriminative patch-selection techniques for the classification of breast images from the DDSM database. The method emphasized boosting the classification accuracy without increasing the complexity of computation, showing the possibility of the light-weight and optimized deep-learning architectures for medical-image analysis. Han et al. [28] continued the trend of deeper architectures for extracting hierarchical representations from complex medical images by exploring a deep multi-layer CNN architecture for medical-image analysis. The authors in [29] suggested a novel Squeeze-and-Excitation ResNet (SE-ResNet) network for binary and multiclass classification with the DDSM dataset within the ResNet framework. The addition of Squeeze-and-Excitation mechanisms allows the network to adaptively learn channel responses such that the network focuses on more informative features and reduces the less informative ones. The enhancement of the model's learning of discriminative features from complex histopathological images is achieved by this architectural modification, which also aids in enhancing classification accuracy and computational efficiency. On the whole, these studies show that there are several shifts in the architecture of CNNs to hybrid CNN-RNN/LSTM, efficient CNNs, deeper CNNs and attention-based residual networks. Recurrent mechanisms, discriminative patch selection, and channel-attention strategies offer promising directions to enhance the robustness and accuracy of automated breast cancer detection.

III.(b) Vision Transformer

Adopting the concepts of Transformer architectures, Vision Transformers (ViTs) represent a strong deep-learning method for computer vision tasks. They excel in modeling complex visual patterns and in establishing relationships between different regions in a visual image, and hence are well suited to medical-image analysis. In ViT architectures, the input image is first segmented into a series of fixed-size patches, typically 16 X 16 pixels in size. Each image patch is then flattened into a one-dimensional vector and linearly projected into a lower dimensional feature space, resulting in patch embeddings. The image is thus encoded as a series of embeddings, similar to how words are encoded in Transformer-based language models. Positional embeddings are also included with the patch embeddings since the order of the image patches in the sequential representation doesn't necessarily represent the spatial locations. The embeddings offer information about where each patch was originally in the image, which helps the model maintain the relationships and general structure of the image. This sequence is then passed to a multi-layer multi-head self-attention and feed-forward neural network (Transformer) to produce the resulting sequence. In the self-attention mechanism, image patches are compared with each other while those patches that make more contribution to the target classification task are given a higher weight. This means that the model can learn the local and global contextual representation of an input image. There are multiple advantages to using ViTs for medical-image analysis. Especially, their capability of learning long-range dependencies and world context information is helpful for medical images where diagnostically important patterns can be found in spatially distant regions. For instance, in a histopathological image, one might find small characteristics of the cells and tissues in various areas of the image. The relationships between the distant image patches can be formed in ViTs, allowing complementary information to be fused and possibly enhancing the ability to recognise clinically relevant patterns. Another important advantage of ViTs is their flexibility in processing images with different spatial characteristics. The resolution, the image scale and the dimensions of the image vary from one medical image to another, depending on the imaging modality and the acquisition system used. The patch-based representation of ViTs offers a flexible approach for converting such images to sequences that can be used in the Transformer encoder. Additionally, ViTs are able to be pretrained on a large dataset comprising of a variety of sources, and then fine-tuned for specific medical-imaging related tasks. This transfer learning ability can prove useful in medical applications where large and well annotated datasets are hard to come by. Figure (1) present the encoding process of Vision transformer.

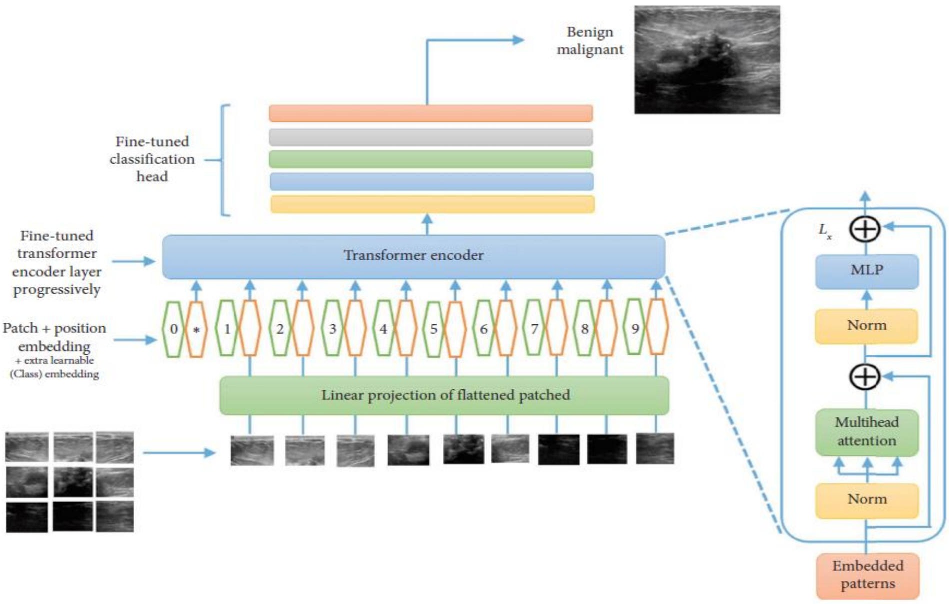

Figure (1) Vision Transformer feature encoder and patching

III.(c) Grey Wolf Optimization

Feature optimization is primary process of cyber-attack detection. The process of feature optimization adopts the GWO meta-heuristic function for the processing of features in manners of these parameters such as alpha, beta, delta and omega. The process of optimization follows the position of all wolves are updated based on the position of alpha, beta, and delta wolves. This combined planning enables the algorithm of search efficiently for the global optimum while avoiding premature convergence.

Process of GWO algorithm

1. Initialization of population $X_i = (xi1, xi2, xi3, \ldots \ldots \ldots \ldots xid), i = 1,2,3, \ldots \ldots \ldots \ldots .., N$
   Here N= number of wolves
   d= number of decision variable
   Xi= position vector of ith wolf
2. Estimate the value of fitness function as $Fitness(X_i) = f(X_i)$
3. The value of wolves identified as
   $$\alpha \ best\ solution, \beta\ second\ best\ solution, and\ \delta\ is\ another\ best\ solution$$
4. Estimate the prey location and surrounding it during hunting. The mathematical model expressed as
   $$D = \left|C.X_p(t) - X(t)\right| \ldots \ldots \ldots \ldots .(1)$$
   $$X(t+1) = X_p(t) - A.D \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

Here Xp(t)= position of prey
X(t)= position of wolf

A and C= vectors coefficient

5. Estimation of coefficient vectors as

$$A = 2ar1 - a \dots\dots\dots\dots\dots.(3)$$
$$C = 2r2 \dots\dots\dots\dots\dots(4)$$

Here r1, r2 ϵ random vector, a optimization during linearly decreases

6. Estimation of distance vectors

$$D_\alpha = |C1X_\alpha - X| \dots\dots\dots\dots.(5)$$
$$D_\beta = |C2X_\beta - X| \dots\dots\dots\dots..(6)$$

7. Update position of wolf

$$X1 = X_\alpha - A1D_\alpha \dots\dots\dots\dots\dots.(7)$$
$$X2 = X_\beta - A_2D_\beta \dots\dots\dots\dots\dots.(8)$$
$$X3 = X_\delta - A_3D_\delta \dots\dots\dots\dots\dots.(9)$$

Update position

$$X(t+1) = \frac{X1 + X2 + X3}{3} \dots\dots\dots\dots..(10)$$

8. Wolf represents as binary set $X_i = [1,0,1,0, \dots\dots\dots\dots\dots.,1]$
9. The continuity of feature employed sigmoid function

$$S(x) = \frac{1}{1+e^{-x}} \dots\dots\dots\dots.(11)$$

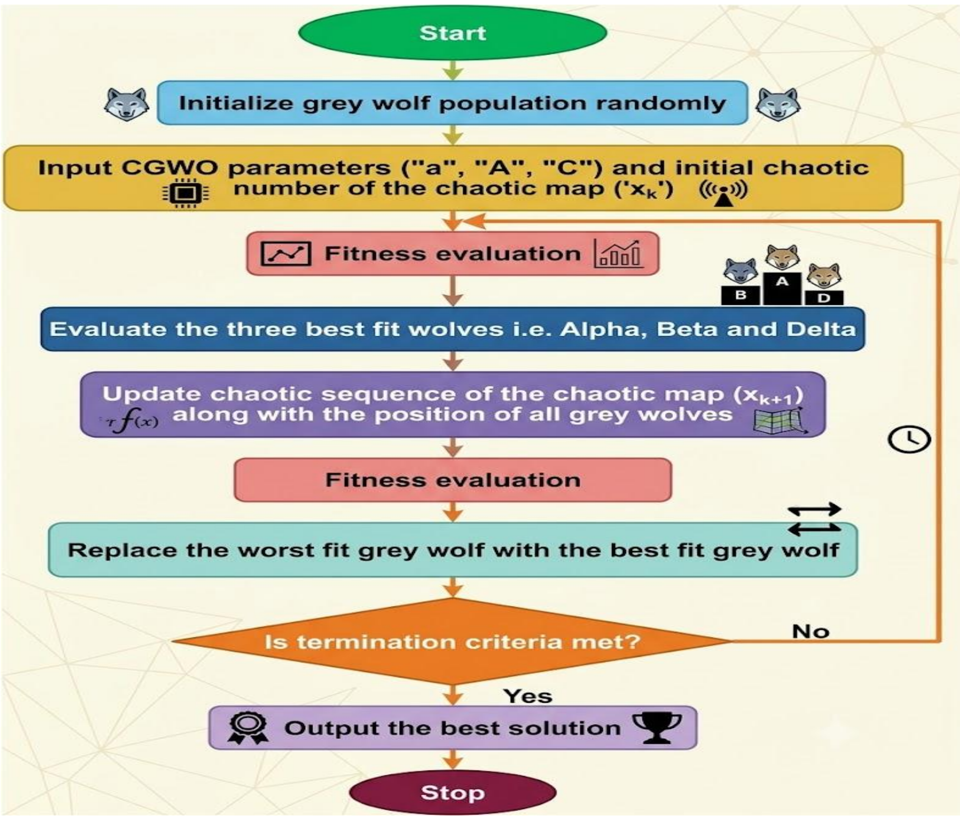

Figure (2) Processing Step of GWO algorithm

III.(d) Methodology

The proposed algorithm called ViT-GWO for automated breast cancer detection in medical images that combines a Vision Transformer (ViT) with the Grey Wolf Optimizer (GWO). The ViT is used to learn hierarchical and global contextual representations based on breast medical images, and GWO is used to select an optimal set of discriminative features in the high dimensional representation of the Transformer. The optimized features are then fed into a classification layer to differentiate between benign and malignant breast tissue. The processing of algorithm shown in figure (3).

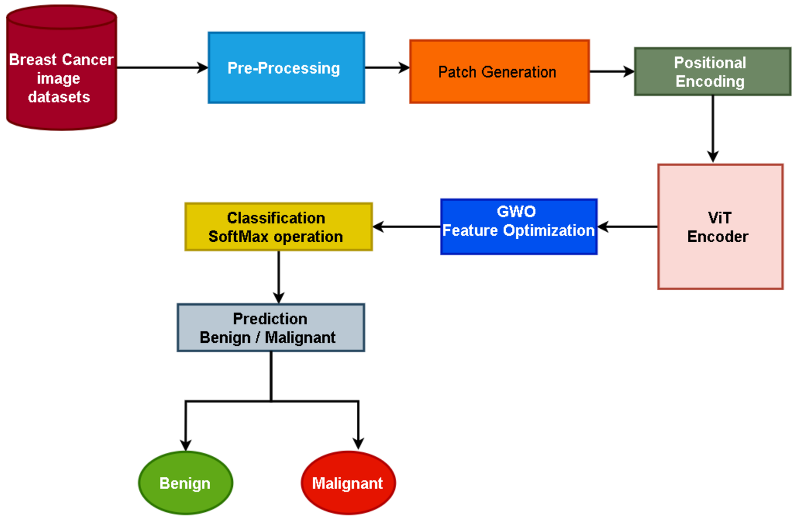

Figure (3) processing of proposed algorithm of breast cancer detection

Processing of proposed algorithm

1. Process breast cancer image dataset like DDMS AND MIAS.
2. The proceed dataset divide into training set, testing set.
3. Pre-processing of dataset in terms of image normalization.
4. Image dataset passes through low pass filter.
5. Preform data augmentation for training.
6. Proceed image dataset for patch generation.
7. Perform patch embedding.
8. Preform positional embedding.
9. Feed the embedded patch sequence into the Vision Transformer encoder.
10. Apply multi-head self-attention and feed-forward layers.
11. Extract the class-token representation as the ViT feature vector.
12. Initialize the GWO population with candidate feature subsets.
13. Evaluate the fitness of each candidate feature subset.
14. Identify the alpha, beta, and delta wolves.
15. Update the positions of the wolves according to the GWO search equations.
16. Convert updated positions into binary feature-selection vectors.
17. Recalculate the fitness of the updated feature subsets.
18. Repeat the optimization process until the maximum number of iterations is reached.
19. Select the feature subset represented by the final alpha wolf.
20. Pass the optimized features to the fully connected classification layer.
21. Calculate the class probabilities using SoftMax.
22. Assign the image to the benign or malignant class.

IV. Simulation and validation

To evaluate the performance of the proposed algorithm for breast cancer detection simulated in MATLAB software with version 2018R, the MATLAB software provides several functions for machine learning algorithms and image processing of breast cancer images. For the validation of algorithms, two standard datasets of breast cancer, such as DDSM, were employed. The DDSM dataset consists of 2620 mammography images; these images consist of normal, benign, and malignant images. Another dataset is the MIAS breast cancer dataset, with 330 total images. The total of 330 images in the MIAS dataset consist of all classes, such as malignant, normal, and benign. evaluation of results measured as accuracy, specificity, sensitivity, MCC, and F1. The process of evaluation also evaluates the existing methods of breast cancer detection, such as CNN, MLP, ELM, and ensemble. The estimation of results formula is mentioned here [25,26,27,30].

$$Accuracy = \frac{Total\ No.of\ Correctly\ Classified\ Instances}{Total\ No.of\ Instances} \times 100$$

$$pricision = \frac{TP}{TP + FN} \times 100$$

$$Recall = \frac{TN}{TN\ +\ FP} \times 100$$

$$F1 = \frac{2TP}{2TP + FN + FN}$$

$$MCC = \frac{TP\ XTN - FP\ X\ FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

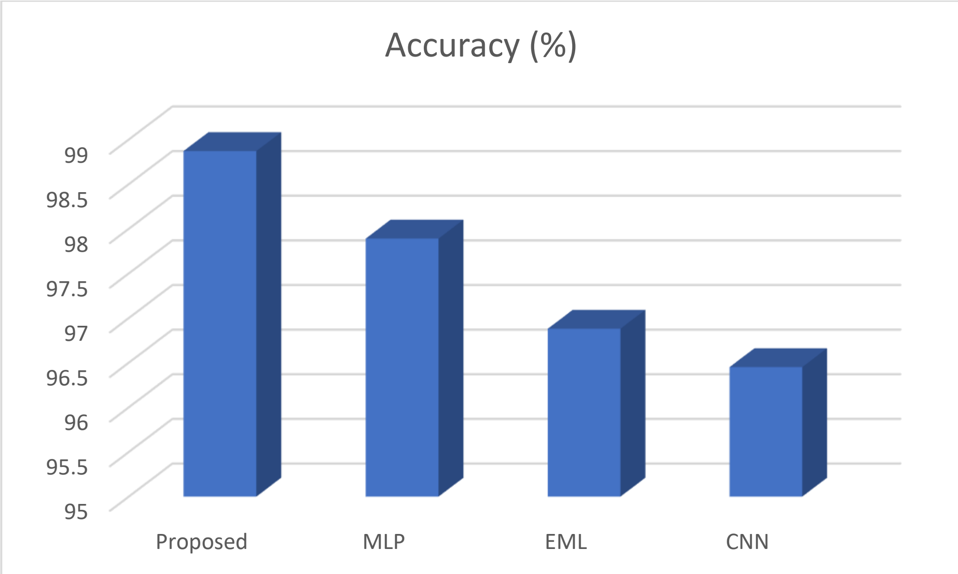

Figure: ((4) Performance analysis of Accuracy of proposed method along with EML, MLP and CNN

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 99.57 on the number of properties 6 and the value of CNN is also 98.61 on the number of properties 6 and we see that the value of hybrid is also 97.75 on the number of properties 6 which is less than other methods. The value of DCNN at the number of properties 20 is 98.72.

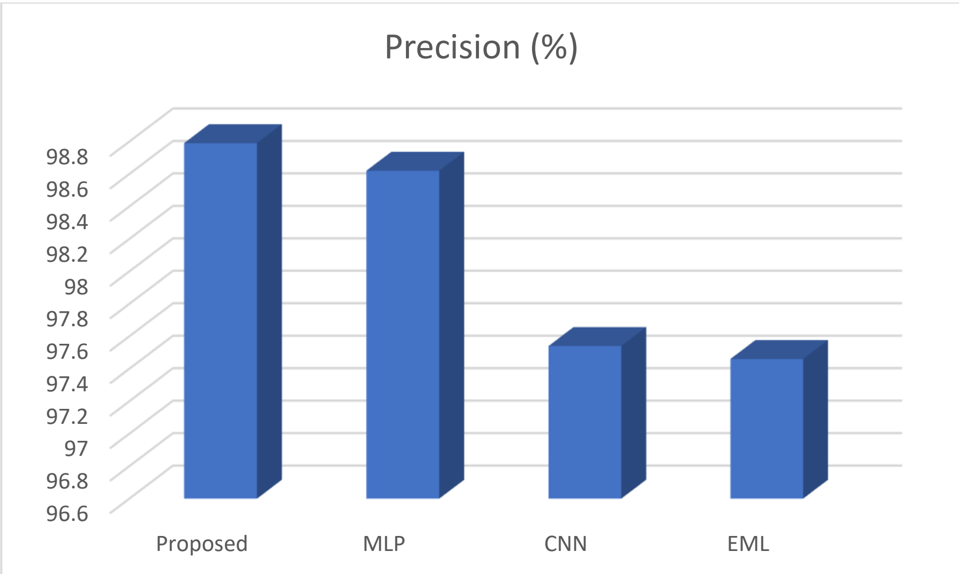

Figure: (5) Performance analysis of precision of proposed method along with EML, MLP and CNN

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 99.25 on the number of properties 3 and the value of CNN is also 98.87 on the number of properties 3 and we see that the value of DCNN is also 98.84 on the number of properties 6 which is less than other methods. The value of hybrid at the number of properties 20 is 98.89.

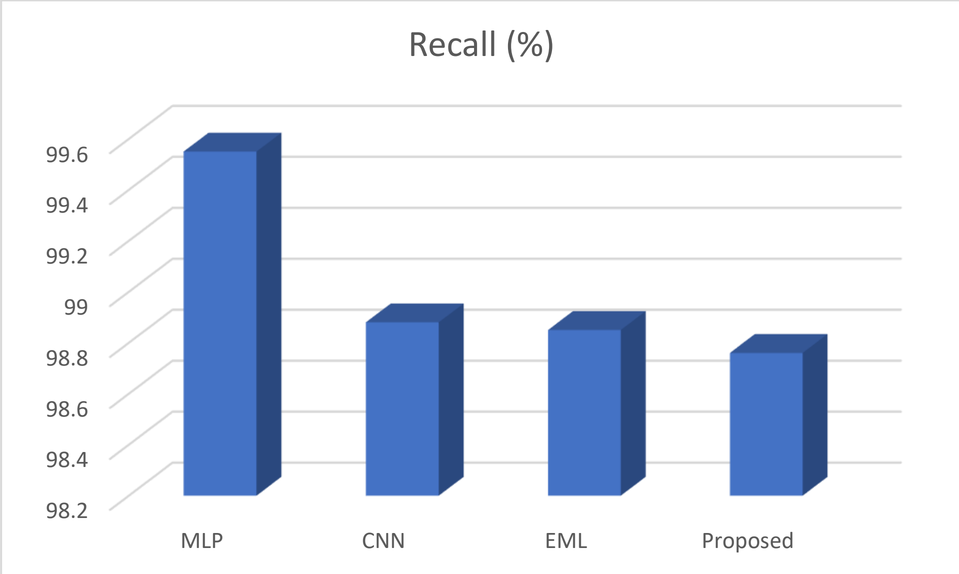

Figure: (6) Performance analysis of Recall of proposed method along with EML, MLP and CNN

We observe that the proposed one is better than the other three methods, which are as follows. We see, the value of the proposed is 98.76 on the number of properties 3 and the value of CNN is also 98.88 on the number of properties 3 and we see that the value of DCNN is also 98.85 on the number of properties 3 which is less than other methods. The value of hybrid at the number of properties 3 is 99.55.

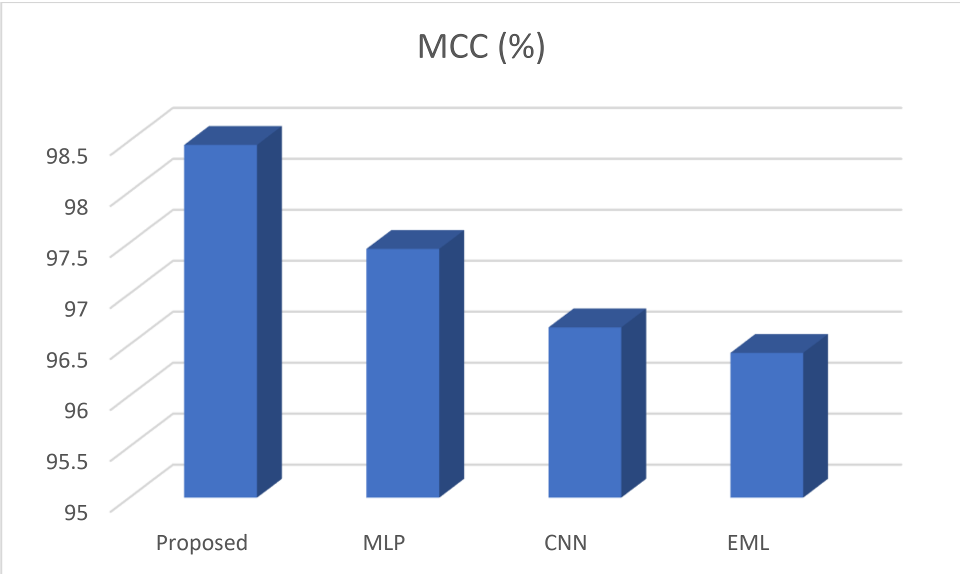

Figure:(7) Performance analysis of MCC of proposed method along with EML, MLP and CNN

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.89 at number of attributes 9 and the value of CNN is also 98.88 at number of attributes 9 and the value of Hybrid is 99.79 at number of attributes 9 and we see that the value of DCNN is also The number of attributes is 98.57 on 9 which is less than other methods.

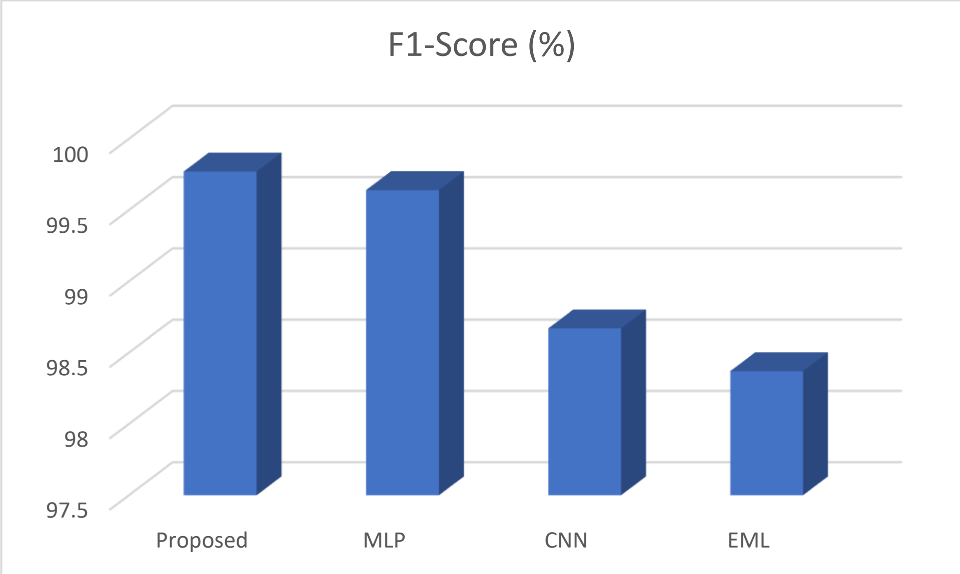

Figure: (8) Performance analysis of F1-Score of proposed method along with EML, MLP and CNN

We observed that Proposed is better than other three methods, which are as follows. We see, the value of proposed is 99.77 at number of attributes 15 and the value of CNN is also 98.67 at number of attributes 15 and the value of Hybrid is 99.64 at number of attributes 15 and we see that the value of DCNN is also the number of attributes is 98.37 on 15 which is less than other methods.

V. Conclusion & Future scope

In this paper, an intelligent ViT-GWO algorithm for automated breast cancer detection based on medical image processing was proposed. The proposed method is a hybrid of the two models, a Vision Transformer that has a global contextual feature-learning capability and Grey Wolf Optimizer for feature selection. The ViT takes breast medical images as the input and maps them to patch embeddings, and uses multi-head self-attention to model relation between various parts of the image. Then GWO has optimized the feature representation obtained from the extracted features by selecting those that are most informative for classification. The integrated approach offers a systematic approach for solving the high-dimensional representation of features that the deep-learning model generates. The proposed approach was tested on DDSM and MIAS breast cancer data sets and contrasted with the conventional techniques such as CNN, MLP and EML. The results of the experiments show that the accuracy of the proposed method was 99.57%, precision was 99.25%, recall rate was 98.76%, the MCC was 99.89%, and the F1 score was 99.77%. The reported results show that the proposed approach yields competitive performance in terms of the chosen metrics in comparison. The feature optimization step also shows the feasibility of GWO to remove irrelevant or redundant features while preserving discriminative information for breast cancer classification. The study suggests that the use of GWO for feature optimization and Vision Transformer for feature extraction is a viable approach in computer-aided breast cancer detection. The suggested framework could help in the discrimination of benign and malignant tissue, and can support automated medical-image analysis. The performance of deep-learning models, though, may be influenced by the characteristics of the datasets, imaging modality, and clinical preprocessing procedures, and discrepancies in acquisition institutions, and therefore, additional validation is needed before clinical use. Moving forward, larger and more diverse multi-institutional datasets along with other breast-imaging modalities, such as ultrasound, MRI and digital breast tomosynthesis, will be used to evaluate the ViT-GWO framework. More complex multiclass classification problems (normal/benign/malignant) and further subclassifications of carcinomas can also be applied to the framework. Moreover, explainable-AI methods like Class Activation Mapping can be incorporated into generate clinically relevant visual explanations of model predictions. Other potential future research directions include lightweight Transformer architectures, external validation, uncertainty estimation and real-time computer-aided diagnostic systems which will enhance the clinical applicability and robustness of the approach proposed here.

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