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Research Article

Quasi-Cross Bilateral Dual Domain Fourier Transforms Capsule Network with Sea Horse Optimization for Breast Cancer Identification

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ABSTRACT

Mammography images are necessary for early diagnosis and prompt treatment and better patient outcomes. Despite the development of the deep learning algorithms, there still are barriers to accurately and consistently identify breast cancer. This paper thus presents a new framework which is the Quasi-Cross Bilateral Dual Domain Fourier Transforms Capsule Network with Sea Horse Optimization (QCB-DDFT-CNet-SHO) to address these problems. The proposed approach is tested on the DDSM (Digital Database of Screening Mammography) data set and is based on some pre-processing done using Quasi-Cross Bilateral Filtering (QCBF) to reduce noise and artefacts in the image. Precise segmentation is performed on malignant patches using Dual Domain Attention with GAN (DDA-GAN). Short Period Fourier Transform along with Continuous Wavelet Transform (SPFT-CWT) is used to extract reliable feature and the parameters of the searched polygonal waterfall are represented through Pixel and Window mechanisms. The Elastic Decision Gate Graph Capsule Network (EDGGCNet) classifies by performing classification. Finally, robustness and efficiency in model performance is improved using the Sea Horse Optimization (SHO) technique. The proposed QCB-DDFT-CNet-SHO framework performs extremely well on the DDSM dataset with a 99.8% recall rate and a 99.9% accuracy rate. These findings demonstrate how well it works to improve the diagnosis of breast cancer from mammography pictures, outperforming current techniques and having a great deal of clinical application potential.

Keywords: Bilateral filtering, Breast cancer, Capsule Network, Fourier Transform, Sea Horse Optimization, Mammography images.

1. INTRODUCTION

The most prevalent disease that affects both men and women is breast cancer, which is brought on by aberrant cell formation in the breast. These cells create masses because they multiply more quickly than healthy cells. Two particular genes, BRCA1 and BRCA2, sometimes known as the breast cancer genes, are mutated in 5–10% of breast cancers [1-2]. With a 50% possibility of transferring the mutation from an affected parent to the following generation, inheriting dangerous mutations in these genes raises the

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risk of getting breast cancer. These genes can be harmed over time by environmental variables like chemicals, radiation, and poisons, which raise the chance of cancer [3-4].

The kind of cells that contribute to the disease determines the classification of breast cancer. The inner layer of milk ducts is where ductal carcinoma in situ (DCIS), a non-invasive malignancy, first appears. With 70–80% of all occurrences, it is the most prevalent kind of breast cancer [5-6]. One to five present of instances of breast cancer are inflammatory, which happens when cancer cells obstruct lymphatic veins, giving the breast an inflammatory appearance. About 15% of individuals have triple-negative breast cancer, an especially dangerous kind that lacks HER2, progesterone, and estrogenic receptors. About 1% of cases of breast cancer are of other uncommon forms [7-8].

The most popular screening method for early breast cancer detection is mammography. The American Cancer Society estimates that every year, across all age categories, breast cancer claims the lives of about 41,760 women and 500 men. According to the Global Cancer Project, there are 162,468 new instances of breast cancer in India annually, and 87,090 people die from the disease. Planning follow-up exams, therapies, or interventions requires early discovery. Accurate diagnosis depends on identifying all regions of interest (ROIs) in mammograms, including masses, calcifications, and distortions [9-10].

A biopsy is the only sure-fire way to establish the existence of breast cancer, even though imaging or physical examinations can raise the possibility. At the moment, the most widely utilized imaging methods to facilitate early breast cancer diagnosis are MRI, ultrasound, and mammography. These techniques do have several drawbacks, though, including the possibility of false-positive or false-negative results, high expenses, radiation exposure, and difficulty screening for dense breast tissue in younger people. When you have a mammogram, it typically leads to false positive results of unneeded anxiety, additional tests, and in a worst case scenario, even open heart surgery (biopsy) [11-12].

Machine learning algorithms in multi view radiological image evaluation seem have been shown a promise on graph based clustering. Deep learning has shifted diagnostic picture interpretation, and multilayer neural networks provide faster, more dependable and more durable replacements for conventional screening [13-14]. Convolutional neural networks (CNNs) have flourished as a method in image analysis because they offer better accuracy and efficiency in pattern identification in breast cancer imaging.

Novelty and contribution

The Novelty and contribution of this paper is given below:

- The Quasi Cross Bilateral Filtering (QCBF) helps the detection of breast cancer by improving clarity of mammography pictures with structurally preserving the features in a very efficient manner by sharpening edges and reducing noise.
- In picture segmentation tasks, the Dual Domain Attention with GAN architecture performs exceptionally well, attaining high accuracy while preserving computing economy.
- The Continuous Wavelet Transform and Short Period Fourier Transformation extract characteristics that pervade any scaling, and rotation. Both techniques push the limits of pattern recognition, and increase the drought on successful breast cancer detection systems.
- By effectively evaluating complicated information in medical images, the Elastic Decision Gate Graph Capsule Network increases classification accuracy, improves diagnostic precision, and lowers false positive rates.
- The efficacy of QCB-DDFT-CNet-SHO in mammography image processing for breast cancer detection is increased by the Sea Horse Optimization, which also improves the learning process and flexibility of the system.

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2. LITERATURE SURVEY

In 2023, Ahmad et al. have presented, Breast Cancer Detection Using Deep Learning: Using a Customized Alex Net and Support Vector Machine [15] for an Investigation Using the DDSM Dataset. A novel method of Breast Net SVM was presented for detecting and classifying breast cancer in mammograms. To extract the data features, a nine layer model with two fully connected layers is used. For classification, support vector machines (SVM) are employed. The popular Digital Database for Screening Mammography (DDSM) dataset was used in the trial. The accuracy, sensitivity, and specificity of the suggested model were 99.16%, 97.13%, and 99.30%, respectively. Breast Net-SVM achieved better in accuracy on the DDSM dataset than other state-of-the-art methods.

In 2023, Jafari et al. have presented Breast cancer detection in mammography images: However, it uses a CNN based approach along with feature selection [16]. In this study propose a novel breast cancer detection feature extraction and reduction method from mammography pictures. Features are extracted by several pre-trained convolutional neural network (CNN) models, and are then concatenated. The most useful characteristics are chosen on the basis of mutual knowledge with the target variable. A variety of machine learning algorithms, including as support vector machines (SVM), random forests (RF), k-nearest neighbours (kNN), and neural networks (NN), are then used to classify these attributes. With NN attaining 92% on the RSNA dataset, 94.5% on MIAS, and 96% on DDSM, the results demonstrate the efficacy of the approach with high accuracy.

Raaj et al [17] presented the use of hybrid deep learning architecture for Breast cancer detection and diagnosis in 2023. In this research, hybrid CNN architecture is proposed to classify mammography pictures into normal, benign and malignant classes. The system consists of a hybrid CNN model with data augmentation and radon transform. Once applied to spatial pixels, the radon transform gives us time frequency variability images, which are then enhanced to create a new dataset. A morphology based segmentation technique is used to identify cancer pixels. Experiments on MIAS and DDSM datasets show that the suggested approach provides high sensitivity, specificity, accuracy, and Jacquard index.

In 2022, Muduli et al. have presented automated diagnosis of breast cancer using multi-modal datasets: A deep convolution neural network approach [18]. Using ultrasound and mammography pictures, a deep convolutional neural network (CNN) model is suggested for automated breast cancer classification. Key features may be automatically extracted with fewer adjustable parameters thanks to the model's five learnable layers, which include four convolutional layers and one completely interconnected layer. The model performs better than contemporary state-of-the-art techniques, according to extensive simulation findings on mammography datasets (MIAS, DDSM and INbreast) and ultrasound datasets (BUS-1, BUS-2). To lessen over fitting, data augmentation is used; the resulting accuracies are 96.55%, 90.68%, 91.28%, 100%, and 89.73%, respectively.

In 2024, Ghadge et al. have presented, Analysis on machine learning-based early breast cancer detection [19]. A novel approach to breast abnormality diagnosis is proposed, utilizing feature extraction and dimensionality reduction from pre-trained Convolutional Neural Network (CNN) models to distinguish between malignant and non-cancerous cases. Machine learning algorithms (SVM, RF, KNN and NN) are employed for categorization by concatenating relevant features. The inclusion of age and various views contributes to the NN-based classifier achieving 92% accuracy on the RSNA dataset. With 94.5% accuracy on the MIAS dataset and 96% accuracy on the DDSM dataset, the method outperforms advanced approaches, demonstrating superior sensitivity and accuracy.

In 2023, Sahu et al. have presented, High accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets [20]. By incorporating the advantages of both networks, five novel deep hybrid convolutional neural network-based breast cancer detection frameworks have been created that outperform their respective base classifiers. For effective hybridization, a probability-

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based weight factor and threshold value is essential, with an optimal threshold chosen through experimentation enhancing speed and precision. Across several breast cancer datasets, the suggested ShuffleNet-ResNet scheme surpasses existing state-of-the-art techniques, obtaining abnormality and malignancy detection accuracies of 99.17%, 98.00%, 96.52%, and 93.18%, respectively.

In 2022, Houssein et al. have presented, an optimized deep learning architecture for breast cancer diagnosis based on improved marine predator's algorithm [21]. In order to help radiologists identify abnormalities more effectively, this research suggests a novel classification model for breast cancer diagnosis based on a hybrid CNN and an enhanced optimization approach that incorporates transfer learning. An opposition-based learning approach is used to improve the aquatic predator algorithm, which leads to the enhanced marine predation algorithm for CNN hyper parameter optimization. When tested on the MIAS and CBIS-DDSM datasets, the suggested IMPA-ResNet50 architecture surpasses cutting-edge techniques, attaining 98.88% accuracy on MIAS and 98.32% accuracy on CBIS-DDSM. When compared to other optimization techniques, IMPA performs better.

- **Problem Statement**

One of the most common cancers in the world today is breast cancer, and its rising incidence rate emphasizes the importance of early and precise detection in order to enhance patient outcomes and maximize treatment approaches. Despite improvements, the precision needed for thorough analysis is frequently not achieved by current diagnostic techniques. Despite their potential, traditional machine learning methodologies are usually limited by shortcomings in feature extraction and optimization methods. A unique technique Quasi Cross Bilateral Dual Domain Fourier Transforms Capsule Network with Sea Horse Optimization (QCB-DDFT-CNet-SHO) improves the accuracy of breast cancer detection systems by advanced deep vector feature concatenation.

3. PROPOSED METHODOLOGY

The Quasi-Cross Bilateral Dual Domain Fourier Transforms Capsule Network with Sea Horse Optimization (QCB-DDFT-CNet-SHO) approach is proposed for breast cancer detection, utilizing input data from DDSM dataset. Figure 1 depicts the QCB-DDFT-CNet-SHO approach, which begins with pre-processing input dataset using Quasi Cross Bilateral Filtering (QCBF).The next step involves segmentation of the breast cancer images using a Dual Domain Attention with GAN (DDA-GAN) method. With SHO hypothesis applied to images to optimize images to improve accuracy, the feature extraction method uses SPFT & Continuous Wavelet Transform (SPFT-CWT). Next, breast cancer type is classified through an Elastic Decision Gated Graph Capsule Network (EDGGCNet).

3.1 Image Acquisition

The Digital Database for Screening Mammography (DDSM) is among the most popular breast cancer research datasets. It is a very big publicly available mammography dataset (>2,500 instances) and is a good tool to develop and test machine learning models. The development and testing of diagnostic methods to identify and survey breast cancer is enabled by this dataset. The DDSM dataset is obtained via full field digital mammography devices which provide high resolution mammograms with overall views of breast tissue that can be used in the investigation of anomalies and improvements in the detection of breast cancer.

Pre-processing processes increased image quality and the images were made to allow further analysis. They are assumed to be in the next unit. Figure 1 is a proposed QCB-DDFT-CNet-SHO block diagram.

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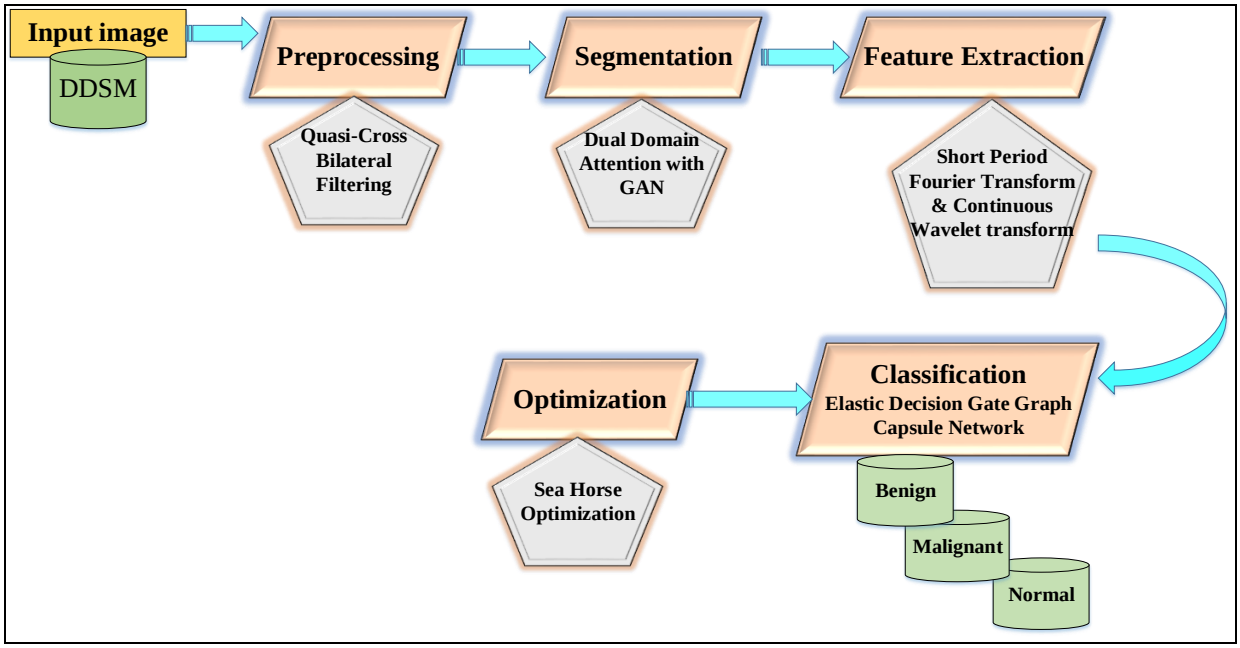

Figure 1: Block diagram of proposed QCB-DDFT-CNet-SHO

3.2 Pre-processing using Quasi Cross Bilateral Filtering (QCBF)

To lessen noise and blur in images used for breast cancer screening, the Quasi Cross Bilateral Filtering (QCBF) technique was created [22-23]. A multi-modal medical image fusion method based on QCBF is suggested, in which the original image is filtered using QCBF. This method breaks down the image into layers of energy and structure by utilizing the special qualities of complementary modalities. The final output shows noticeably better clarity, especially in the target region, as compared to conventional cross-bilateral filtering.

An image's Edge Likelihood (EL) is frequently determined by a smoothing procedure that usually includes filtering. Despite being widely used, a Gaussian filter can only smooth surfaces globally; it cannot smooth particular regions. Because of this restriction, it may become more difficult to distinguish between Edge Likelihood (EL) and Smooth Likelihood (SL) since intensity information along image edges may be lost. By smoothing other areas of the image and improving edge retention, the bilateral filter outperforms the Gaussian filter by taking into account both spatial closeness and gray-level similarity. Equation (1) can be used to determine the image following the use of bilateral filtering.

$$Q_S = \frac{1}{f_p} \sum_{n,m \in \Omega p} A_{bb}(\|(x,y)-(n,m)\|) A_{bb}(\|Q(x,y)-Q(n,m)\|) \times Q(x,y) \quad (1)$$

where, f_p is the normalization constant. A_{bb} denote the filtering kernel according to pixel size and spatial location. bb symbolizes the spatial location. $Q(n,m)$ symbolizes the neighbourhood pixel whose coordinates are $Q(x,y).\Omega$ symbolizes the image's applied filtration window Q. The QCBF methodology's improved bilateral filtering technique is intended to maintain the distinctive characteristics of the original mammography pictures, guaranteeing precise analysis for the identification of breast cancer.

In the case of breast cancer detection, Equation (2) can be used to determine the energy layer of the clinical picture and the outermost layer of the structural features.

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$$Q(x,y) = Q_v(x,y) + Q_S(x,y) \quad (2)$$

where, $Q(x,y)$ symbolizes the structure layer. $Q_S(x,y)$ symbolizes the energy layer.

To precisely identify the areas impacted by breast cancer, the pre-processed mammography images are further put through a feature extraction step and segmentation.

3.3 Segmentation using Dual Domain Attention with GAN (DDA-GAN)

To properly segment the region of interest for efficient cancer diagnosis, the segmentation block receives the pre-processed breast mammography image. A thorough analysis of the mammography image is necessary since segmentation is essential to guaranteeing the precision of next analyses. A Dual Domain Attention with GAN (DDA-GAN) is used to efficiently improve the feature maps, and segmentation heads produce the output for cancer diagnosis [24-25].

Enhancing the quality of breast cancer images can be thought of as a denoising procedure that aims to increase image clarity while maintaining a resolution similar to that found in healthy breast tissue. The goal is to use the data collection of healthy breast tissue to approximate the data distribution of malignant breast tissue (MBT), as indicated by Equation (3).

$$f(NBT) = UHBT \quad (3)$$

where, NBT is the normal breast tissue. $UHBT$ is the unhealthy breast tissue. The data distributions pertinent to the identification of breast cancer are simplified in equation (4).

$$\arg\min(\sum g(K_{\lambda K}(NBT), UHBT)) \quad (4)$$

where, The function responsible for calculating the variations between images is represented by g . K is a generator. λK is a parameter of layers. After that, the segment breast mammography picture is transmitted to the feature recognition and categorization module, where it undergoes thorough segmentation to help identify any possible anomalies or illnesses.

3.4 Feature Extraction using Short-Period Fourier Transform & Continuous Wavelet Transform (SPFT- CWT)

Here, features are extracted from segment breast mammography pictures using the SPFT-CWT model [26-27]. A thorough examination of the input images' structural elements is made possible by the feature maps produced by the SPFT-CWT, which capture hierarchical graphic representations of the images.

- **Short-Period Fourier Transform (SPFT)**

The certainty of mammography-based breast cancer detection is increased when changes are properly highlighted by a strong analysis method. Widely used in image processing, the time-frequency analysis approach, or SPFT, treats irregular mammography images as geographically stationary and uses a window function to convert them into the domain of time and frequency so that unique spectral information can be captured. SPFT is described by equation (5) as follows,

$$F(x,y) = \int g(x+\mu)h(\mu)\exp(-2i\Pi s\mu)b\mu \quad (5)$$

where, $g(x)$ is the signal to be considered. $h(\mu)$ is the sliding window function. x is the time and s is the frequency.

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Continuous Wavelet Transform (CWT)

Because real-valued wavelet transforms are sensitive to shifts and have limited directionality, they are ineffective at communicating phase information. Equation (6), which establishes the scaling equation, is a fundamental principle of multi-resolution evaluation in the scenario of breast cancer diagnosis, supporting accurate extraction of features and hierarchical picture representation.

$$\psi(x) = 2\sum_{h} a_h \psi(2x - h) \tag{6}$$

where, a_h is the parameter. The a_h can be both real and imaginary valued and $\sum a_h = 1$. After feature extraction, the Capsule Network is used to classify the information gathered from mammography breast cancer images, allowing for accurate breast cancer type diagnosis. This method improves diagnostic accuracy and early identification of and planning for efficient treatment of breast cancer through the use of sophisticated classification methods particular for breast cancer imaging.

3.5 Classification using Elastic Decision Gated Graph Capsule Network (EDGGCNet)

The Elastic Decision Gated Graph Capsule Network (EDGGCNet) breast cancer classification approach using images from the DDSM dataset outperforms the accuracy of breast cancer detection through the analysis of the mammographic features in identifying the cancerous patterns, thereby offering a safe way of making an early diagnosis and consequently better clinical outcomes with managing of breast cancer [29-30].

A Capsule Network (Caps Net) used for breast cancer detection is composed of several layers, each of which is a Capsule and each one captures a singular trait or attribute about a region of breast tissue in a certain location. The length of a capsule helps distinguish between malignant and non-cancerous cases by indicating the likelihood that the associated feature will be present. The prediction of Capsule is expressed in equation (7),

$$\hat{v}_{n/m} = H_{nm} v_n \tag{7}$$

where, $\hat{v}_{n/m}$ represent the prediction of Capsule n for Capsule m. v_n represent the instantiation parameter. H_{nm} represent the trainable weight matrix. The actual output of the Capsule is expressed in equation (8),

$$A_m = \sum_{n} d_{nm} \hat{v}_{n/m} \tag{8}$$

where, d_{nm} represent the score given to the predictions. A_m represent the actual output of the Capsule.

CapsNet Loss Function: Margin loss enforces the correct classification and penalizes incorrect predictions but not beyond this margin, while reconstruction loss tries to reconstruct the difference between the inputs and reconstruct image. The CapsNet (Capsule Network) loss function combines these two loss functions with the following formula (9) for total loss.

$$CapsNetLoss = L_t = L_m + \beta \bullet L_{re} \tag{9}$$

where, L_t is the total loss. L_m is the margin loss. β represent the scales reconstruction loss. L_{re} is the reconstruction loss. To improve its performance, the Sea Horse Optimization (SHO) algorithm is used to minimize the CapsNet loss function efficiently by identifying the parameters that lead to improved accuracy and convergence.

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3.6 Optimization using Sea-Horse Optimization (SHO)

A nature inspired optimization algorithm Sea Horse Optimization (SHO) is proposed. As iterative processes, it takes advantage of their movement patterns to solve complex optimization problem efficiently.

Step1: Initialization

The Sea Horse Optimization (SHO) technique is used to initialize a population of possible parameter settings for a deep learning model. These candidates are later assessed against a fitness function such as classification accuracy of the DDSM dataset. The SHO algorithm continuously updates the population in order to improve the efficacy of the model in detecting breast cancer.

Step 2: Random Generation

Each seahorse in the space is initialized to some random location and each is a solution in the search space for breast cancer. We break the breast cancer diagnosis job down to each dimension (feature or parameter with respect to the breast cancer diagnosis) and consider each seahorse's placement with respect to each dimension to be a feature or a classifier feature vector.

Step 3: Fitness function

For the Sea Horse Optimization (SHO) algorithm, the fitness function is essential toward the optimal answers when feature selection or hyper parameter tweaking occurs. Besides improving detection accuracy, it guarantees that the solution that has been chosen is one that meets important performance criteria such as computation time and resource consumption. In principle, this fitness function aims to maximize the classification accuracy in terms of diagnosis problem for breast cancer with various real world constraints including model complexity and computational efficiency. An expression for the fitness function as set forth in Equation (10).

$$FF = Min(CapsNetLoss) \tag{10}$$

where, $CapsNetLoss$ represent the Capsule Network loss function.

Step4: Seahorse movement behaviour

The normal distribution may be used to study seahorse behaviour, and the two case studies show how to best balance exploration and exploitation. In order to expand the locally-solvable issue space, the agent dynamically modifies the rotation angle as it spirals toward the Xelite. The following mathematical formula (11) relate to the first case:

$$M^{1}_{new}(S+1) = M_{n}(S) + Levy(\eta)(M_{best}(S) - M_{n}(S)) * x * y * z + M_{best}(S)) \tag{11}$$

where, $M^{1}_{new}(S+1)$ is represent the new weight for the $(S+1)$ iteration. $M_{n}(S)$ is represent the current weight of particle n in the S th iteration. $Levy(\eta)$ is represent the Lévy flight distribution with parameter η. $M_{best}(S)$ is represent the best solution found so far in the S th iteration. x represent the weighting factor. y and z represent the variables influencing the update.

Step 5: Termination

Instead, the termination process replicates or reinforces patterns or anomalies that the DDSM dataset provides through replication. Data processing ensures that overall the dataset contains positive and negative cases evenly spread throughout, meaning no one instance is overrepresented while not underrepresented either and thus providing balanced representation, having assured reliability of breast cancer detection.

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By refining model parameters, Sea Horse Optimization (SHO) improves feature selection and classification performance in breast cancer detection, increasing accuracy and efficiency and producing more accurate and dependable diagnostic results.

4. RESULT AND DISCUSSIONS

The research results and discoveries from the suggested approach are included in this section, which was implemented on the Python platform. The proposed approach is thoroughly tested and compared to different alternative strategies. The simulation parameters are displayed in Table 1.

Table 1: Simulation Parameters

Parameters	Description
Proposed Technique	QCB-DDFT-CNet-SHO
OS	Windows 10
Optimization	Sea-Horse Optimization (SHO)
Dataset	DDSM
Software	Python 3.7

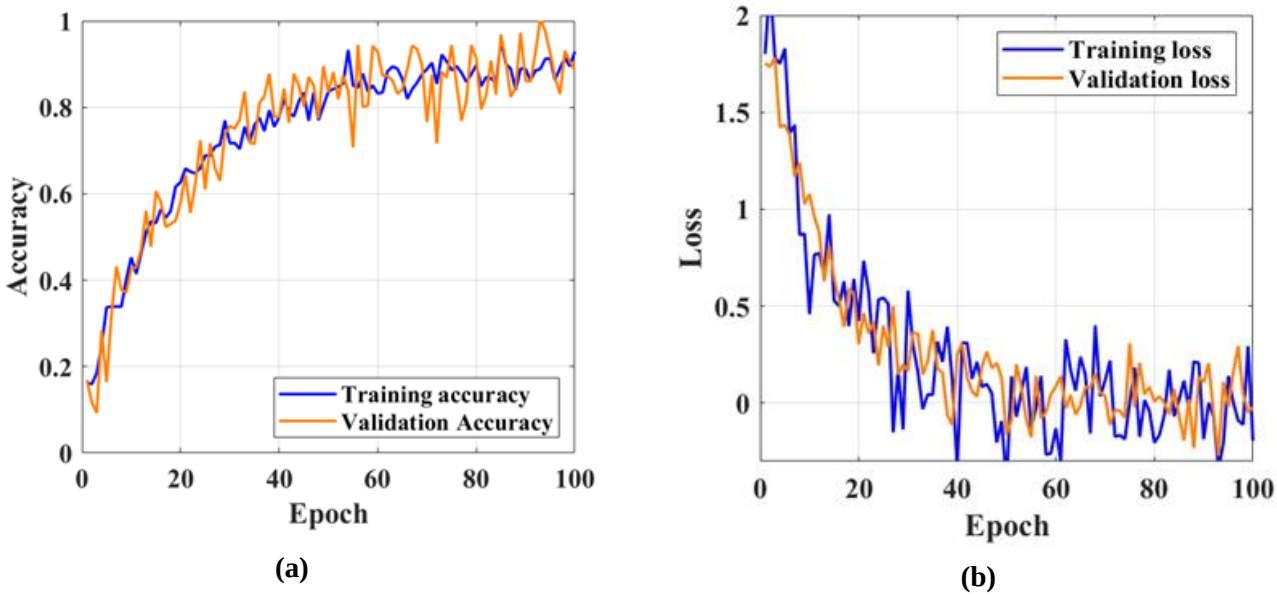
4.1 Dataset Description

The DDSM dataset, widely utilized for breast cancer identification, is described as follows:

- **DDSM (Digital Database for Screening Mammography) dataset**

The Digital Database for Screening Mammography (DDSM) is a freely accessible tool for investigating and identifying breast cancer. It comes with comments on mammograms and ground truth verified by biopsy on normal, benign, and malignant cases. The main goal of DSM is to create and test complex algorithms for diagnosis, segmentation and detection of breast cancer. The dataset also includes mammograms of varying density making research over difficult cases easier. DDSM helps to increase the accuracy and dependability of breast cancer detection and management systems by providing a variety of samples and comprehensive metadata that facilitate robust validation and training of machine learning models.

4.2 Comparison of DDSM dataset



(a) **(b)**

Figure 2: (a) Accuracy & (b) Loss function of DDSM dataset

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The DDSM dataset's training and validation accuracy and loss functions are shown in Figure 2. Accuracy over 100 epochs is displayed in Panel (a), where both training and validation accuracy gradually rise, signifying successful learning. The loss function is shown in Panel (b), where training and validation losses both decrease throughout the course of epochs, indicating that the model is minimizing mistakes and convergent. The accuracy and loss trends show that the model is working well and has little over fitting.

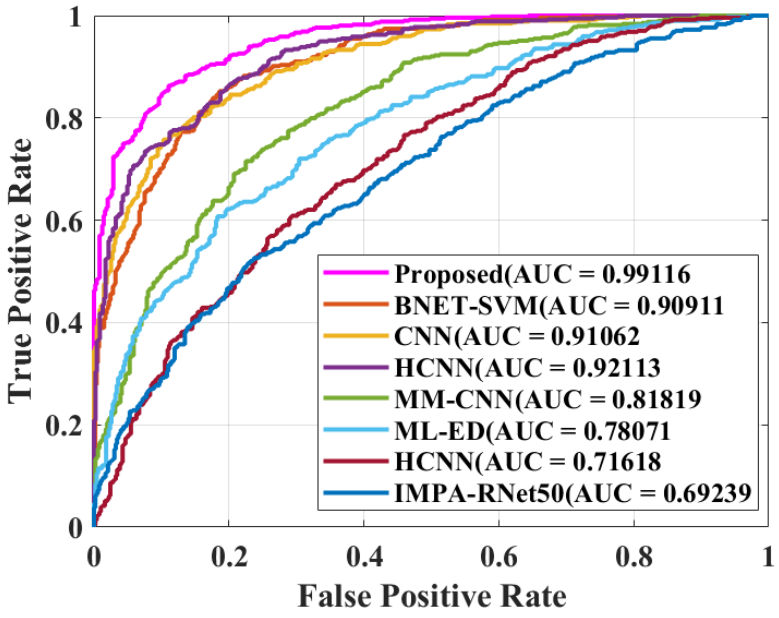

Figure 3: ROC curve of DDSM dataset

The performance of various models on the DDSM dataset for breast cancer detection is shown by the ROC curve in figure 3. With the greatest AUC of 0.99116, the suggested approach performs better than the others and shows remarkable classification accuracy. Competitive performance is shown by models like CNN (AUC = 0.91062) and BNET-SVM (AUC = 0.90911). While HCNN (AUC = 0.71618) and IMPA-RNet50 (AUC = 0.69239) have comparatively lesser accuracy, MM-CNN (AUC = 0.81819) and ML-ED (AUC = 0.78071) exhibit reasonable performance.

Table 2: Performance Comparison of the DDSM dataset

Metrics	Classes	(BNET-SVM) [8]	(CNN) [9]	(HCNN) [10]	(MM-CNN) [11]	(ML-ED) [12]	(HCNN) [13]	(IMPA-RNet50) [14]	Proposed Technique (QCB-DDFT-CNet-SHO)
Accuracy%	Benign	84.4	84.9	87.3	81.1	83.1	85.3	82.7	99.4
	Malignant	81.5	83.5	82.5	87.6	88.7	86.5	84.9	99.3
	Normal	85.8	89.4	87.5	86.9	83.6	87.3	85.7	99.6
Precision%	Benign	82.0	89.6	83.8	81.9	81.7	83.8	86.8	99.8
	Malignant	86.9	84.7	85.8	83.2	80.6	84.6	89.3	99.7
	Normal	84.4	84.9	87.3	81.1	83.1	85.3	82.7	99.4
Recall%	Benign	85.2	81.8	83.6	84.9	84.6	87.1	85.3	99.6

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	Malignant	84.6	87.1	85.3	83.2	80.6	84.6	89.3	99.4
	Normal	87.5	86.9	83.6	88.7	86.5	84.9	81.9	99.6
Sensitivity%	Benign	85.7	83.5	81.8	83.5	80.1	83.7	89.1	99.5
	Malignant	85.2	81.8	83.6	84.9	84.6	87.1	85.3	99.2
	Normal	85.7	83.5	81.8	83.5	86.9	84.7	85.8	99.4
Specificity%	Benign	86.9	84.7	85.8	83.2	80.6	84.6	89.3	98.9
	Malignant	83.8	86.8	81.8	83.6	84.9	84.6	83.5	99.1
	Normal	83.5	80.1	83.7	89.1	85.2	81.8	83.6	99.7
F1-score%	Benign	85.8	89.4	87.5	86.9	83.6	87.3	85.7	99.8
	Malignant	87.3	81.1	83.1	85.3	82.5	87.6	88.7	99.6
	Normal	84.9	87.3	81.1	83.1	85.3	81.7	83.8	99.8

The performance metrics of several models for DDSM dataset-based breast cancer detection are shown in the table 2. In every metric, the suggested method, QCB-DDFT-CNet-SHO, performs noticeably better than alternative models. With accuracy scores of 99.4% for benign instances, 99.3% for malignant cases, and 99.6% for normal cases, it produces findings that are almost flawless. With 99.8% accuracy for benign, 99.7% accuracy for malignant and 99.4% accuracy for normal categories, precision is likewise good. With a robust performance in recall-99.6% for benign patients, 99.4% for malignant cases, and 99.6% for normal instances the method demonstrates great sensitivity to each category. In order to 'nicely' diagnose benign cases, malignant ones, and normal control cases, the model had near perfect sensitivity and specificity metrics. The F1-score values for benign, malignant and normal are 99.8, 99.6 and 99.8 respectively showing balanced performance that illustrates the overall efficacy of the model in detecting breast cancer.

Table 3: Comparison of error rate and computational time

Methods	Error rate%	Computational time(sec)
(BNET-SVM) [8]	0.24	1.42
(CNN) [9]	0.46	1.65
(HCNN) [10]	0.32	1.64
(MM-CNN) [11]	0.29	1.75
(ML-ED) [12]	0.24	1.79
(HCNN) [13]	0.35	1.82
(IMPA-RNet50) [14]	0.38	1.78
Proposed Technique (QCB-DDFT-CNet-SHO)	0.1	0.2

A comparison of the calculation time and error rate for various approaches is shown in Table 3. With a computation time of 1.42 seconds, the BNET-SVM approach produced the lowest error rate of 0.24%. The CNN approach took 1.65 seconds to compute and had a little higher error rate of 0.46%. With an error rate of 0.1% and a computing time of only 0.2 seconds, the suggested method, QCB-DDFT-CNet-SHO, performs noticeably better than the other approaches, exhibiting both high precision and efficiency. This result shows how the proposed strategy performs when compared to existing methods.

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5. CONCLUSION

Early breast cancer identification is an important development with Quasi Cross Bilateral Dual Domain Fourier Transforms Capsule Network with Sea Horse Optimization (QCB-DDFT-CNet-SHO). The imaging processing technique of the method being developed, which also uses the DDSM (Digital Database for Screening Mammography) dataset, improves image quality by applying Quasi-Cross Bilateral Filtering (QCBF), which reduces noise and artefacts. While feature extraction makes use of the Short Period Fourier Transform and Continuous Wavelet Transform (SPFT-CWT) for dependable representation, Dual Domain Attention with GAN (DDA-GAN) guarantees accurate segmentation of cancerous patches. The Elastic Decision Gate Graph Capsule Network (EDGGCNet) is used for classification; its robustness and efficiency are increased by further optimizing it using the Sea Horse Optimization (SHO) technique. The model makes remarkable results with an accuracy of 99.9% and a recall rate of 99.8 % on the DDSM dataset. These results suggest that the compared QCB-DDFT-CNet-SHO achieved lower error and better efficiency in the early diagnosis of breast cancer compared to the baselines. Such a method promises much better early breast cancer screening and better outcomes for patients and better treatment strategies. The great precision and dependability of this technique makes it capable of changing the way breasts are diagnosed and treated for breast cancer, making it entirely possible.

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