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Enhanced Deep Learning Frame Model for an Accurate Segmentation of Cancer Affected Part in Breast

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Enhanced Deep Learning Frame Model for an Accurate Segmentation of Cancer Affected Part in Breast

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Abstract Breast cancer is one of the primary causes of death occurring in females around the world. So, the recognition and categorization of breast cancer in the initial stage is necessary for helping the patients to have suitable action. In this research, a novel Spider Monkey-based Convolution Model (SMCM) is developed for detecting breast cancer cells in an early stage. Here, breast Magnetic Resonance Imaging (MRI) is utilized as the dataset trained to the system. Moreover, the developed SMCM function is processed on the breast MRI dataset to primarily detect and segment the affected part of breast cancer. Additionally, segmented images are utilized for tracking in the dataset that has identified the possibility of breast cancer. Moreover, the simulation of this approach is done by Python tool and the parameters of the current research work are evaluated with prevailing works. Hence, the outcomes show that the current research model produces improved accuracy for breast cancer segmentation than other models.

Keywords Breast cancer • Magnetic Resonance Imaging • Medical Image Processing • Spider Monkey Optimization • convolution model • segmentation

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1 Introduction

Digital image analysis is a trending topic to specify and predict diseases in an accurate manner (Kathale P, Thorat 2020). The health condition of a person by the medical checkup may not be accurate in some cases, especially in harmful disease prediction (Du et al. 2020). So the Digital image process is introduced to figure out the disease risk in a specific person (Perre et al. 2021). Bioresearch has become a trending topic in today's modern world, in which the research of cancer detection attracts the focus of researchers (Terada et al. 2020). Especially, breast cancer has become a serious threat globally (Broberg et al. 2020), so early recognition of breast cancer is very significant for reducing the death rate (Ginsburg et al 2020). Besides, the scheme mammogram x-ray helps to identify the risk features in the breast (Sundarambal et al. 2020). At last, in result the attained false positive rate address the poor condition of the patient and follow the doctor suggestions (Latif et al. 2020). Moreover, interpretation of a mammogram is more difficult to identify the affection (Sharma et al. 2021), because the abnormalities have only happened in a small specific area in the earlier stage that is measured as 0.5% (Hakim and Awale 2020).

The most benefit of using a deep learning model in MRI images or entire medical image analysis is that it can train large amounts of data for disease prediction (Gonzalez-Hernandez et al. 2019). The frame of the medical image processing model is defined in fig. 1. Also, the hyper parameter in the deep learning approach leads to attaining better accuracy of disease prediction than the ML model (Jasbi et al. 2019). Moreover, the labeled data in training can reduce the training error by avoiding data over fitting (Ting et al. 2019). Furthermore, the enhanced version of machine learning is deep learning (Benard et al. 2004), thus the approach of deep learning attained the best accuracy than machine learning. In addition, solving the deep learning model is easy considering other rule based mechanisms (Aribal et al. 2019). Because the function of the deep learning model is processed with the use of several control layers. The model deep learning itself has a memory and control mechanism to carry on the process in a better way (Aribal et al. 2019).



Several models such as auto fluorescence (Waaijer et al. 2021), improved fuzzy (Dhanaseelan et al. 2021), etc were implemented to segment the affected part and to regulate the severity of disease by earlier stage prediction. So to reduce the death rate and to bring the recovery confidence measures to women, a hybrid deep learning model with an optimization approach should be implemented in an effective manner. That proposed model has the capability for detecting and segmenting the breast cancer affected part.

The paper arrangement is ordered as; the literature review of this paper is discussed in the session 2. Also, the analyzed problem and system model is elaborated in Session 3. The developed novel technique is explained in the Session 4. Subsequently, the attained results and comparative analysis are mentioned in Session 5. The conclusion about the work is detailed in Session 6.

2 Related Work

Recent works of literature related to this work are described as follows,

Artificial Intelligence (AI) strategies are introduced in medical image processing for accurate disease prediction in a short time. Thus, it is capable of early disease prediction to reduce the disease severity measure of each patient. So, Celika et al (2020) proposed a deep ResNet model to recognize the disease in an earlier stage that utilizes the Break His dataset. Consequently, to measure the effectiveness of the projected model, it is compared with other existing approaches and has attained good diagnosis accuracy. But in the case of complex data, it has achieved a very less accuracy rate while detecting the affected part and it takes more time to complete the process.

The common type of cancer in women is known as breast cancer, it affects aged women a lot. Thus, Ibrahim et al (2020) proposed a chaotic-based swarm intelligence model, also a mastology dataset is utilized to execute the proposed model. Subsequently, the measure of robustness is compared with recent works, and assessments are evaluated. However, in the case of complex data, it attains a very low classification rate and has high training error. Also, the classified images have high noise than other methods.

Worldwide, several doctors and scientists made researches to discover effective medicines to cure breast cancer and to improve women's health. But it met several issues because the prediction of cancer in an earlier stage is very difficult. So Patil et al (2020) proposed a mammogram with clustering approach to classify the cancer types and to reduce the training error. Thus, it attained high accuracy because of reduced training error. However, it takes more time to process and the attained images had a poor resolution.

Dhanaseelan et al (2021) described that the growth of malignant tumors in women is termed breast cancer. A novel improved fuzzy frame was developed to extract the affected part accurately; here the extraction process is performed based on specific rules. Also, this methodology is based on frequent pattern mining (FPM) that can analyze the important factors of breast cancer. Moreover, if the training data is complex then it has pertained to poor performance and it requires a large period for the training process.

To attain the clear cut of detected images, an auto fluorescence scheme is used which is also adaptable for real-time applications. Waaijer et al (2021) made a deep study based on the auto fluorescence scheme and its detection performance. In addition, an endoscopic identification is represented by white light and the proposed method processed on both breast cancer and high-risk patients. In some rare cases, the identification resulted negative in the auto fluorescence method, without classifying the breast cancer types. It decreases the performance of the entire model.

Thus, a novel deep learning approach is developed to segment breast cancer using MRI images that increased the performance. The key roles of this proposed model are summarized as,

- > Initially, the MRI breast image dataset is utilized for training the system.
- Subsequently, a novel Spider Monkey based Convolution Model (SMCM) was developed to detect the affected part.
- The Spider Monkey (SM) fitness module is works in the Convolution Model (CM) pooling layer that is used to segment and track the affected part images.
- Hence, the developed SMCM segments the affected part of breast cancer with high performance.
- Finally, the segmented images are utilized to track the dataset for identifying the possibility of breast cancer.
- Moreover, the developed approach is validatedusing recent prevailing approaches in terms of detection accuracy, specificity, sensitivity, recall value, F-measure, and error rate.

3 System Model and Problem Definition

One of the primary cancers in women is breast cancer that creates severe risk. Also, the highest mortality in women happens because of breast cancer. Thus, it attracts scientists and researchers to make awareness about breast cancer and to separate the affected part. In addition, the prediction of cancer in an earlier stage is not at all easy and in some cases it is impossible. Moreover, recognition and segmentation of the breast cancer in the early stage, and differentiation of malignant and benign types is more difficult. Several approaches were developed for detecting breast cancer such as machine learning, logistic regression, support vector machine, etc. However, these approaches have not attained an accurate level for predicting and classifying tumors.

Here, the symptoms of breast cancer, detecting classifiers, and the attained problems are detailed in fig. 2. Additionally, the breast images are attained by X-ray, mammography, Positron emission tomography (CT), blood test, bone scan, Computerized tomography (CT), and breast MRI for detecting breast cancer.

However, the diagnostic tool like X-ray is processed manually that provides misdiagnosed results and create errors. Also, the mammography images provide very less sensitive that create abnormalities in the breast images. Hence, this research develops a novel deep learning approach to detect and segment the affected part of breast cancer. Also, this method utilized the MRI breast images for processing because it is more sensitive than other diagnostic tools.



4 Proposed SMCM Methodology

Breast cancer is the category of malignant tumor that easily affects women than men. Due to this reason, the affected persons die in the range of 1:3; so the early prediction is necessary. To cure breast cancer, identification of the affected part is more significant since without knowing the affected part treatment measure is impossible. So, the exact identification of the affected part is required with high accuracy to make the control measures. To address this problem, the current article has projected a novel Spider Monkey based Convolution Model (SMCM) for the exact recognition of the affected part. The proposed methodology is shown in fig. 3.



Fig. 3 Proposed SMCM Methodology

In this approach, the SM module is updated in the convolution model to enhance the efficiency of segmentation. Thus, it detects and segments the breast cancer affected part using MRI breast images. Lastly, the outcome of the planned approach is compared by existing approaches.

4.1 Data Acquisition

Normally, MRI is very sensitive and efficient than mammography that can identify breast cancer effectively. Also, breast MRI is employed to evaluate the extent of breast cancer. The MRI breast images are required for classifying the diseases for that, several MRI images from various patients are collected. In this research, a breast MRI dataset is utilized for training and testing, which is attained from a net source. The attained breast cancer dataset is called the Kaggle dataset that contains more number of patients breast MRI.

4.2 Process of SMCM to segment the affected part

In this approach, the SMCM mechanism is developed for detecting and segmenting breast cancer. The developed SMCM is the combined form of Spider Monkey Optimization (SMO) (Sharma et al. 2019) and Convolution Neural Network (CNN) (Horiuchi et al. 2020). The behavior of the SMO function is initiated in the CNN pooling and dense layer that can enhance disease detection.

In SMO, the spider monkeys survive in a group and every group has one leader, which takes the better decision searching for food. In the current research, the SMO function is utilized for identifying the exact part of the disease. Initially, the MRI breast image dataset is trained to the system. Primarily, the breast MRI data is collected for various patients (n) initiated using eqn. (1),

$$P_i = P_{Min.i} + \tilde{U}(0,1) \times (P_{Max.i} - P_{Min.i})$$
⁽¹⁾

Where, $P_i(i = 1, 2, ..., n)$ denotes the n^{th} patient data, $P_{Max.i}$ and $P_{Min.i}$ are the limits of highly affected patients and poorly affected patients and $\tilde{U}(0,1)$ the equally distributed arbitrary number in the sort [0, 1].

Additionally, the collected datasets are trained to the system based on the local fitness function. The expression for perturbation rate (p_r) is calculated for individual patients as expressed in eqn. (2),

$$pr_{iter+1} = P_i + \left(\frac{0.4}{Tn_i}\right) pr_{iter}$$
⁽²⁾

Here, pr_{iter} is the present iteration value of (p_r) and Tn_i is the total count of iterations (patients). Also, the finest fitness function of the SM is calculated using eqn. (3),

$$prb_i = 0.9 \times \frac{fitness_i}{Max_fitness} + 0.1$$
⁽³⁾

Where, *fitness*_i is the i^{th} fitness value of individuals and *Max_fitness* is the maximum

fitness of total data.



Fig. 4Process of SMCM Network

The convolution network has performed using several layers that involve the input, convolution, pooling, dense, and output layer. These layers are performed in separate functions that are represented in fig. 4.

• Pre-processing and feature extraction

In this, the MRI breast image dataset is given to the input layer and the noise, as well as errors in the MRI, is removed in the next layer. Moreover, the convolution layer acts as an extractor and performs pre-processing and feature extraction processes on MRI breast images. The extracted non-linear operations are mentioned in eqn. (4),

$$P_i d = f\left(fk_d * P_i s\right) \tag{4}$$

Where, $P_i s$ is the input image, $P_i d$ is the extracted output, and non-linear operation is represented as f(.).

• Classification and segmentation

Subsequently, the extracted output is given to the pooling layer that performs the classification process. In this layer, the fitness function of the SM is utilized to enhance the classification. Also, it reduced the spatial resolution employed to obtain the spatial invariance to falsification and input translations. Moreover, this layer classifies the patients who are affected with breast cancer. Afterward, the classified output is given to the dense layer that is able to segment the affected part. Hence, the segmentation and classification processes are done using SMCM that is represented in eqn. (5),

$$P_{i}d^{cl} = f \left[\sum_{k \in A_{l}} P_{i}d^{cl-1} * KN_{kl}^{cl} \operatorname{Pr} b_{i} + AB_{l}^{cl} \right] \operatorname{Pr}_{iter+1}$$
(5)



Fig. 5 Flow chart of proposed SMCM approach

Where, cl is the convolutional layer, cl-1 represents the down sampling layer, the input characteristics of this layer are mentioned as $P_i d^{cl-1}$, kernel maps and additive bias are denoted as KN_{kl}^{cl} and AB_l^{cl} , pr_{iter} is the iteration value, Prb_i is the fitness of SM utilized for classification, selection input maps for segmentation is A_l , input and output are denoted as k, l. Finally, the output layer provides the segmented output using a multilayer network. Here, the affected part is segmented using the proposed SMCM approach that is detailed in algorithm 1.

Algorithm:1 Process of SMCM	
Input: MRI breast dataset	
Output: Segmented images	
Start	
1	
// perform the operation of Spider Monkey (SM)	
$int(P_i)$ // initialize the dataset	
// perform dataset training process	
for $(i = 1, 2, 3, \dots, n)$ // number of patients	
Calculate Prb _i // fitness function	
end for	
// perform the operation of convolution model (CM)	
testing breast MRI for $(i = 1, 2, 3, \dots, n)$ //input layer	
error removing and feature extraction process	//convolution layer
$U_{pdate} \operatorname{Pr} b_i$	
Categorize the disease	// pooling layer
Calculate $P_i d^{cl-1}$ using eqn.5	//dense layer
Update $P_i d^{cl-1}$ for $(i = 1, 2, 3,, n)$ //classification and seg	ementation
end	
Track the images using segmented output// output layer	
Output best solution	
}	

Therefore, the developed SMCM manner is processed on the breast MRI dataset that has segmented the affected part of breast cancer. Also, the segmented images are utilized to track the dataset for identifying the possibility of breast cancer.

5 Results and Discussion

The developed SMCM replica is processed using Python; the success rate of the projected model is assessed by current existing mechanisms in the terms of accuracy, sensitivity, F-measure, precision, and recall. In this approach, MRI breast images are utilized for detecting breast cancer. Here, the proposed SMCM approach classifies breast cancer from MRI images and segments the affected tumor part. Hence, the developed model attained high performance in classification and segmentation.

5.1 Case study

Stop

Normally, breast cancer is denoted as the most hazardous category of cancer, especially in women. An initial detection is necessary from time to time and the diagnosis of cancer should be very sensitive and effective to save the lives of women. Initially, the breast MRI dataset is trained to the system and the proposed SMCM model is processed on the dataset. The sample MRI breast input images for five patients are given in fig. 6 (a) to (e). Moreover, the pre-processing and filter extraction function is processed on the dataset that removes the unwanted errors in the images.



(e) **Fig. 6**MRI breast Input images

The filtered input images are performed with the feature extraction process that removes the unwanted errors in the images, which are done in the convolution layer of the proposed model.

• Segmentation

Subsequently, the affected part is segmented using the dense layer of the proposed model. In that, the fitness function of the optimization approach is initiated to enhance the accuracy of the developed approach. Thus, the segmented outputs of the given samples are given in fig. 7.





(c)





(e) **Fig. 7**Segmented output images

The affected part of breast cancer has been segmented by the proposed SMCM approach. Subsequently, the developed model was utilized to check the possibility of breast cancer. In this, the segmented output is taken as the testing that can identify the possibility of breast cancer in a given dataset.

• Tracking results

Finally, the possibility of breast cancer is calculated using the segmented images from the proposed model. Here, the segmented images are taken as the input images and the dataset images are considered as the testing images. The developed SMCM model is performed on these images that identify the possibility of the disease.

Number of sample input segmented images	Possibility of breast cancer in percentage (%)
10	30%
20	50%
30	55%
40	69%
50	83%

Table 1 Tracking results

Here, the input images are considered as 50 numbers and the possibility of breast cancer is 83% that is attained using the proposed SMCM model, which is detailed in table.1. Thus, the proposed model traces out the affected part of the breast cancer.

5.2 Performance metrics

The implementation work of the developed SMCM approach is done by Python tool and the parameters like accuracy, sensitivity, recall, specificity, F1-measure, and precision is calculated. Moreover, the developed approach is validated using existing methods like convolution Neural Network (CNN) Breast Net (Toğaçar et al. 2020), firefly updated chicken based CSO with convolution recurrent neural network (FC-CSO-CRNN) (Patil et al. 2021), and Radial-Function Neural Network (RBFNN) (Osman et al. 2020).

5.2.1 Accuracy measurement

Accuracy is defined as the degree of calculation of the efficiency of the proposed model functioning. Also, it is the fraction of properly expected observance to the entire observations that are expressed in eqn. (6),

$$A = \frac{T_{p} + T_{n}}{T_{p} + T_{n} + F_{p} + F_{n}}$$
(6)

Where, T_p is the true positive that denotes the accurate prediction and exact segmentation, T_n is the true negative that denotes the accurate prediction and incorrect segmentation, F_p is the false

positive that involves inaccurate prediction and exact segmentation, and F_n is the false negative that denotes inaccurate prediction and incorrect segmentation of affected part.

Table 2 Validation of Accuracy

No. of samples	Accuracy (%)			
rio. or sumples	CNN-	FCCSO-	RBFNN	SMCM
	BreastNet	CRNN		[Proposed]
10	97.99	93.59	98.4	98.82
20	97.84	92.34	97.76	98.5
30	98.51	91.78	97.35	98.37
40	95.88	87.56	96.87	97.58
50	92.67	83.74	96.36	97.08

The accuracy of the proposed SMCM model is calculated and validated using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches that attained values as mentioned in table 2.



The existing approaches have achieved lower accuracy and the proposed technique has obtained a high accuracy value of 99.76% than others, which proves the effectiveness of the proposed approach. Also, the comparison of the accuracy measurement is shown in fig. 8.

Sensitivity is utilized to calculate the amount of true positives that are predicted precisely. Also, it is the probability of segmenting the affected part of cancer that is measured using eqn. (7),

$$S_N = \frac{T_p}{T_p + T_n} \tag{7}$$

Table 3 Validation of Sensitivity			
CNN-Breast Net	FC-CSO-CRNN	RBFNN	SMCM
			[Proposed]
97.68	97	98.87	99.6
97.21	96.35	97.68	98.97
97.70	95.46	97.45	98.56
95.16	92.67	96.89	97.68
93.56	90.98	95.46	97.37
	Table CNN-Breast Net 97.68 97.21 97.70 95.16 93.56	Table 3 Validation of Sensi Sensit CNN-Breast Net FC-CSO-CRNN 97.68 97 97.68 97 97.21 96.35 97.70 95.46 95.16 92.67 93.56 90.98	Table 3 Validation of Sensitivity Sensitivity (%) CNN-Breast Net FC-CSO-CRNN RBFNN 97.68 97 98.87 97.21 96.35 97.68 97.70 95.46 97.45 95.16 92.67 96.89 93.56 90.98 95.46

The sensitivity of the proposed SMCM model is calculated and validated using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches that are described in table 3.



The existing approaches have achieved lower sensitivity of almost 98% only. Also, this SMCM method has achieved99% high sensitivity value than other methods, which proves the effectiveness of the developed model. Also, the comparison of sensitivity is graphically represented in fig. 9.

5.2.3 Specificity measurement

Specificity is defined as the degree that is utilized for identifying the amount of true negatives that are recognized accurately. Also, specificity is employed for calculating the efficiency of tracking breast cancer using the segmented images, calculated using eqn. (8),

 $S = \frac{T_n}{T_n + T_n}$

		$I_p + I_n$		(8)
Table 4 Validation of Specificity				
No. of samples	Specificity (%)			
i tor or sumpres	CNN-BreastNet	FC-CSO-CRNN	RBFNN	SMCM
				[Proposed]
10	96.56	92.21	95.67	99.04
20	94.35	91.96	94.87	98.56
30	91.93	87.89	93.69	97.97
40	87.38	86.57	92.92	97.65
50	85.47	84.76	92.06	97.09

The specificity of the proposed SMCM model is calculated and validated using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches that attained values as mentioned in table 4.



Here, the existing approaches achieved lower sensitivity of almost 96%. Subsequently, the developed approach has achieved 98.89% high specificity value than other methods, which proves the

effectiveness of the developed model. Also, the comparison of specificity is graphically represented in fig. 10.

5.2.4 Precision measurement

This process has been evaluated for identifying the number of correct positive estimates alienated by the overall positive estimates. Also, precision is the proportion of precise diagnosis of cancer affected region, which is computed using eqn. (9),

$$P = \frac{T_p}{T_p + F_p} \tag{9}$$

Table 5 validation of Precision				
No. of samples	Precision (%)			
i tor or sumpres	CNN-BreastNet	FC-CSO-	RBFNN	SMCM
		CRNN		[Proposed]
10	97.68	83.33	89.67	98.11
20	97.08	82.45	87.56	97.98
30	96.89	80.78	86.97	97.63
40	95.16	78.45	86.46	97.08
50	94.67	76.98	86.07	96.76

The precision of the proposed SMCM model is calculated and validated using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches, and attained values are mentioned in table 5.



Here, the existing approaches have achieved lower precision of almost 97% only. Additionally, the developed SMCM approach has obtained 98.56% high precision value than other methods and the comparison of precision as represented in fig. 11.

5.2.5 Recall measurement

The recall is utilized for calculating the total amount of correct positive forecast to the overall true positives and false negatives. It expresses the proportion of predictions that have been correctly diagnosed as cancer and is calculated using eqn. (10),

$$R = \frac{T_p}{T_p + F_n} \tag{10}$$

No. of samples		Recall	(%)	
ito. or samples	CNN-Breast Net	FC-CSO-CRNN	RBFNN	SMCM [Proposed]
10	98.57	90.67	96.57	100
20	98.97	89.78	94.87	99.98
30	97.69	88.69	93.47	98.73
40	94.75	86.37	91.84	97.36
50	93.65	85.08	91.09	97.07

 Table 6 Validation of Recall

The calculation of the recall by SMCM technique is compared using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches are described in table 5.



Also, the existing approaches attained a lower recall of almost 96% only. Subsequently, the recall value of the SMCM approach is higher than other methods. It has achieved 98.56% recall value and the comparison of recall is represented in fig. 12.

5.2.6 F1-score measurement

The calculation is based on the precision and recall measurements for recognizing the efficiency of tracing the images, which is measured using eqn. (11),

$$F1 - score = 2\left(\frac{P*R}{P+R}\right)$$
(11)

Where, P denotes the calculated precision value and R represents the calculated recall value.



The F1-score of the proposed SMCM model is calculated and validated using prevailing methods like CNN-Breast Net, FCCSO-CRNN, and RBNN approaches, and the attained values are mentioned in table 7.

Table 7 Validation of F1-score

Proposed]
.04
.98
.65
.79
.08

Here, the existing approaches achieved a lower F1-score and the proposed model has attained a high F1-score value of 98.37% than other methods as represented in fig. 13.

Additionally, the efficacy of the SMCM approach is identified by calculating the metrics like Intersection over Union (IOU), Dice Index (DI) Coefficient, mean Average Precision (mAP), and mean Average Recall (mAR), which are calculated using eqns.(12) to (15),

$$IOU = \frac{T_p}{T_p + F_p + F_n}$$
(12)

$$DI = \frac{2T_p}{2T_p + F_p + F_n} \tag{13}$$

$$mAP = \frac{\sum_{k=1}^{n} Ap_{k}}{n}$$
(14)

$$mAR = \frac{\sum_{k=1}^{n} AR_{k}}{n}$$
(15)

Where, Ap_k denotes the average precision value of k segmented images with (n) the number of input images and AR_k represents the average recall value. Thus, the attained values are detailed in table 8.

No. of samples	IOU (%)	DI (%)	mAP (%)	mAR (%)
10	98.11	99.04	98.6	100
20	98.06	99	98.08	99.96
30	97.95	98.96	97.94	99.85
40	97.86	98.75	97.85	99.49
50	97.63	98.48	97.58	99.07

Table 8 Performance metrics of proposed SMCM

Additionally, the proposed SMCM approach has attained better outcomes in IOU, DI, mAP, and mAR parameters that are represented in fig. 14.

Thus, the proposed SMCM approach is utilized for segmenting the breast cancer affected part in an accurate manner. Here, the proposed technique has achieved high performance for segmenting and tracking processes in breast cancer using MRI breast images.



Fig. 14 Performance metrics representation

Conclusion 6

A novel SMCM approach is developed in this work for detecting and segmenting the affected part of breast cancer. Here, the MRI breast images are taken as input images that are trained to the system. The proposed SMCM model involves the processes like pre-processing, feature extraction, classification, segmentation, and tracking. Moreover, the developed model is processed on an MRI dataset and finally, the affected parts of the breast cancer are segmented. Furthermore, the segmented images are employed to identify the possibility of breast cancer. Additionally, the proposed model has attained better results of accuracy, sensitivity, specificity, precision, and recall. Thus, it has achieved a98.82% accuracy for segmenting breast cancer affected parts while comparing with existing models.

Acknowledgement

None

Compliance with Ethical Standards

1. Disclosure of Potential Conflict of Interest:

The authors declare that they have no potential conflict of interest.

- 2. Statement of Human and Animal Rights
 - i. Ethical Approval

All applicable institutional and/or national guidelines for the care and use of animals were followed.

ii. Informed Consent

For this type of study formal consent is not required.

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