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CLASSIFICATION TECHNIQUES ANALYSIS AND COMPARISON FOR DIAGNOSING THE BREAST CANCER BY USING MAGNETIC RESONANCE IMAGES

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ABSTRACT
Breast cancer is characterized by the uncontrolled growth of abnormal cells that invade surrounding tissues to support tumor progression. This study presents a framework for Breast cancer MRI image classsification , incorporating pre-processing ,Segmentation, Feature extraction, Optimization, and classification stages. Image quality is enhanced using a Median filter, while OTSU's Thresholding is employed for accurate tumor segmentation.Texture features are extracted using the Gray Level Co-Occurrence Matrix and optimized through Weighted Particle Swam Optimization (WPSO). The Optimized features were classified using Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression Models. Performance evaluation based on accuracy,Sensitivity, Specificity, F1-score and False negative rate showed that the Random classifier outperformed the other models, achieving an accuracy of 98.98%, demonstrating its effectiveness and reliability for differentiating Malignant and Normal Breast MRI Images.

KEYWORDS: Breast cancer detection, Magnetic Resonance Imaging, Feature extraction, Feature selection, Weighted particle swarm Optimization

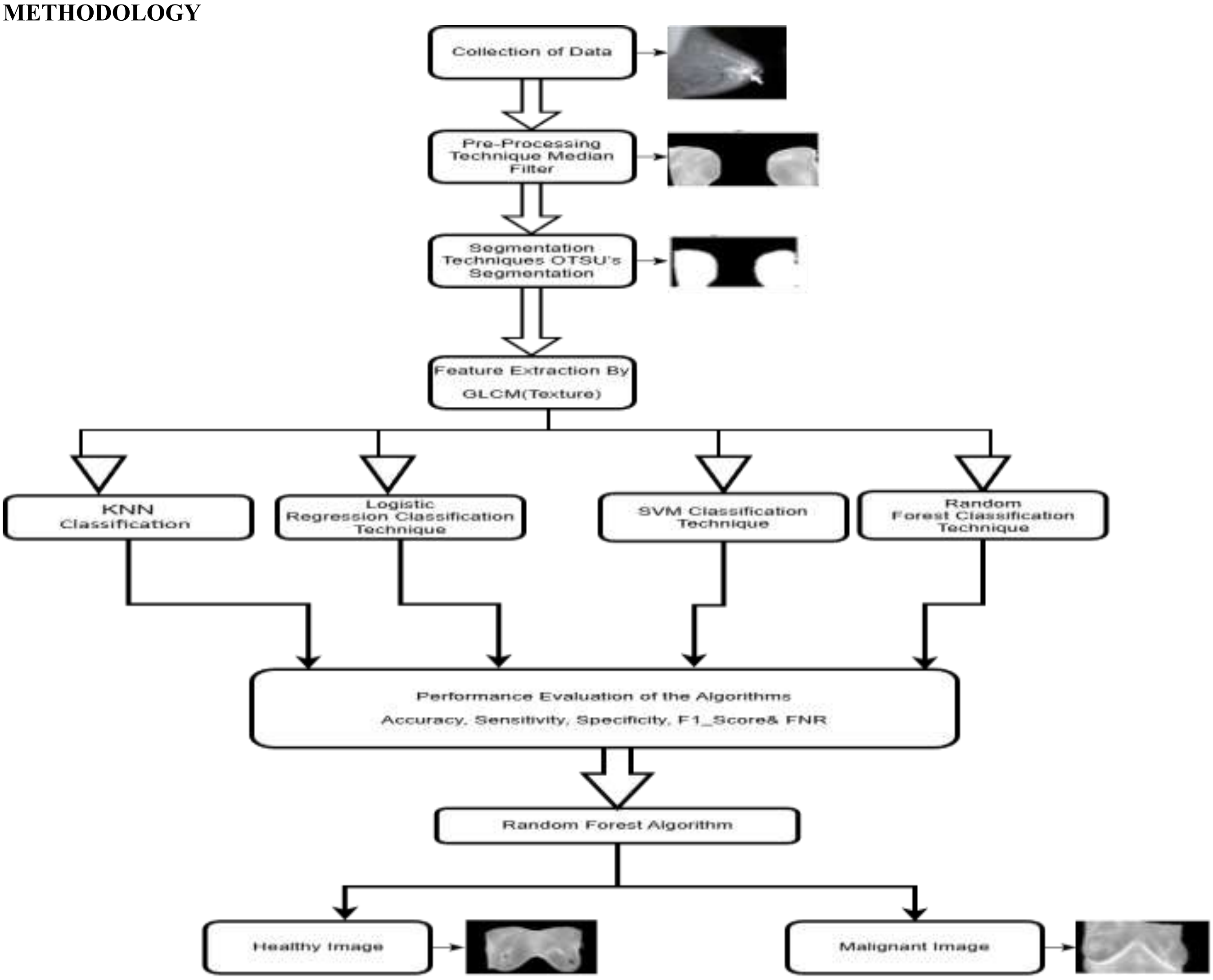
INTRODUCTION

In International level breast cancer is one of the main cause of death for women. Since early detection of breast cancer can improve patient survival, it is one of the most crucial concerns that needs to be addressed globally [1]. In 140 out of 148 nations worldwide, breast cancer is the most common cancer and the second most common cancer among women, according to the American Institute for Cancer Research [2]. Breast cancer is the leading cause of death for women in the 20–59 age range. Currently, 88% of women with breast cancer have a 10-year life expectancy. Recent years have seen a rise in the number of women dying from breast cancer, according to numerous scholars [3]. According to estimates from the World Health Organization (WHO), more than 627,000 women lost their lives in 2018.This group also estimates that by 2030, there may be 2.7 million people on the planet [4]. Breast cancer is currently the most common malignant tumour worldwide, surpassing lung cancer, and its incidence is continually rising [5]. The primary causes of this disease's poor survival rate include complicated procedures and delayed diagnosis. Thus, early identification of breast cancer is essential for implementing appropriate treatment and reducing the chance of cancer growing in other tissue cells [6]. First off, the screening phase mostly uses imaging methods, which necessitate highly qualified radiologists to accurately identify breast cancer. Second, core needle biopsy or fine-needle aspiration biopsy is used extensively for qualitative diagnosis of breast cancer in patients with high-risk imaging criteria [7] .The scientific community consequently proposed an automated method called CAD (Computer-Aided Diagnosis) for better tumour categorization, accurate results, and speedy execution without the need for radiologists or professionals [8].Researchers have focused a lot of emphasis on the use of AI technology in medical image analysis, particularly in breast cancer screening, as it has shown great promise [9] .These images can help a radiologist understand the tumour and its local spread. The radiologist assesses and examines them by hand before working with other experts to decide the result [10] .The results of this lengthy process mostly depend on the staff's level of experience. Furthermore, experts are not available everywhere in the world. The scientific community consequently proposed an automated method called CAD (Computer-Aided Diagnosis) for better tumour categorization, accurate results, and speedy execution without the need for radiologists or professionals [11].

RELATED WORK

Features like density, texture, morphologic, form, and size can be computed from the mass region [1]. Mahyar Nirouei .et .al has applied Chaos analysis for describing the Non linear and Complex systems. And they have applied Fuzzy C-Mean Segmentation method. In their work they have extracted Chaos and fractal features from the breast tumour [12]. Menasha Devi .et.al. Has performed the feature extraction and Classification on BCD Net and researcher has proposed the RPAOSM-ESO to optimize the weights to enhance the Classification techniques [13].Wang Zhenfei .et.al. Proposed a Ensemble Residual-VGG-16 model with the Deep Residual Network (DRN) and VGG-16 architecture. And they have achieved very good accuracy, precision, F1 Score [14] .Yiran Sun et.al. Has applied the feature extraction with EfficientNetB0 before the classification technique. The second model proposed in his work Hybrid CNN Model with the architecture of Mobile Net and Inception V3 and also the author implemented the Attention U- net for automated Tumour segmentation [15] .Heather M Whitney has applied the CNN feature extraction and VGG19 Model pertained on the Image Net dataset was used [16].

METHODOLOGY



Flow Chart

The Proposed methodology is designed to classify breast cancer MRI Images in to healthy and Cancerous categories using image pre-processing, segmentation, feature extraction, feature selection and classification techniques. The workflow begins with acquiring breast MRI images from the data-set, followed by pre-processing to enhance image quality. A Median filter is applied to remove noise while preserving important structural and edge information within the images. After noise removal image segmentation is performed using Otsu's thresholding technique to isolate the breast region and extract the Region of Interest(ROI).

Following segmentation, feature extraction is carried out using the Gray level Co-occurance Matrix (GLCM), a texture analysis technique that captured the spatial relationships between the neighboring pixels, From the segmented ROI's texture features such as contrast, correlation energy, homogeneity, entropy, and dissimilarity are extracted.

To Improve classification performance and reduce feature redundancy , weighted Particle Swarm Optimization (WPSO) is employed for feature selection. WPSO identifies the most informative features by optimizing the feature subset while eliminating irrelavant and redudant attributes.The optimized feature is then divided into training and testing datasets and used to train multiple machine learning classifiers, such as Random Forest (RF), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM).

The Performance of each classifier is evaluated using metrics such as accuracy, precision , recall , sensitivity, Specificity, F1-score, and False Negative Rate(FNR). Based on the comparative analysis of these performance measures, the best-performing classifier is selected for the final classification task.Finally, the processed Breast MRI images are passed through the chosen model to classify them as either healthy or cancerous images.

Pseudo-code for the proposed Breast cancer MRI image detection.

BEGIN

Input: Breast cancer image dataset

STEP 1 : LOAD DATASET
images <--- load_all_images_from _dataset()
STEP 2: Pre- processing (Noise Removal)
BEGIN
INPUT: Breast cancer image dataset
STEP 2: PRE-PROCESSING (NOISE REMOVAL)
FOR each image IN images Do
Filtered -image <---- apply_median_filter (image)
Store filtered _image in filtered_images_list
END FOR
STEP 3: SEGMENTATION (OTSU THRESHOLDING)
FOR each filtered _image IN filtered_images_list DO
segmented- image <---apply_otsu_thresholding (filtered _image)
ROI<---extract_region_of_interest (segmented _image)
store ROI in roi_list
ENDFOR
STEP 4: FEATURE EXTRACTION (GLCM)
FOR each roi_list DO
Features<---extract_glcm_features(roi)
Store features in feature_dataset
END FOR
FOR each roi IN roi_list DO
features ← extract_glcm_features(roi)
store features in feature_dataset
END FOR
STEP 5: SPLIT DATA SET INTO TRAINING AND DATA SETS
train -features, test- features, train_labels, test _labels<------Split_dataset (feature_dataset)
Step 6: TRAIN CLASSIFICATION MODELS
Classifiers<---{ Random Forest, KNN, Logistic Regression, SVM}
FOR each model using (train_features, train_labels)
Predictions<----model -predict(test_features)
Metrics <---evaluate_performance(predictions, test_labels)
Store metrics for model
END FOR
STEP 7: SELECT BEST PERFORMING MODEL
best_model<---model_with _highest_accuracy_or_f1score (classifiers)
STEP 8: CLASSIFICATION USING BEST MODEL
FOR each new_processed_image DO
New_features <---extract_glcm_features(new_processed_image)
Class_label<----best_model.predict(new_features)
IF class_label == 0 THEN
Print " Healthy Image"
ELSE
Print "cancerous Image"
ENDIF ENDFOR END

Procedure for executing the Proposed Methodology:

Step1: Collection of the Breast cancer MRI Images from the Kaggle
Step 2: Pre-process the Images using the Median filter
Step 3: Obtain the Region of Interest from the OTSU's Segmentation Techniques.
Step 4 : Features are extracted from the GLCM Feature extraction Techniques like Texture
Step 5: Importing of Libraries (Random Forest Classifier, K- Nearest Neighbors Classifier, Logistic Regression, SVM)
Step 6 : Import Confusion _matrix, accuracy_score, Recall_Score, f1
Step 7 : Import pandas for the analysis purpose
Step 8: Extracting the Dataset (Processed Images)
Step 9 : Splitting the images to Train Dataset and Test Dataset
Step 10 : Define the models for Random Forest Classifier, K- Nearest Neighbors Classifier, Logistic Regression, SVM Classifier
Step 11 : Evaluating the Functions like Confusion Matrix, True Negative, False Positive, False Negative and True Positive
Step 12 : Computation of macro averages , Accuracy, Sensitivity, Specificity, F1 and FNR
Step 13 : Train and Evaluate the Models
Step 14 : Compare the Classification Models
Step 15: Obtain the Comparison graph for each macro averages Accuracy, Sensitivity, Specificity, F1 and FNR
Step 16 : Obtained the best classification technique as Random Forest Classifier .

Step 17 : Classification of the images as Normal and Cancerous images by using the Random Forest classification Technique.

A. Dataset

The initial method of medical image analysis is the acquisition of images. The proposed method uses images as input from Kaggle Dataset. The dataset divided into two datasets the 4096 images for the Training and 1486 data for the testing. The images are in the DICOM formats are used to analysis and comparison of the algorithms.

B. Image Pre-processing

Unknown noise, poor picture contrast, in homogeneity, unconnected sections, and weak borders will impact the image's content are common features of medical imaging. To remove noise and improve images, median filtering uses contrast enhancement and open morphological operation. The contrast of the each region calculated with respect to its individual background. A Median filter is a nonlinear filter is removing salt and pepper noise [17].

C. Segmentation

Medical professionals frequently utilize manual segmentation (traditional) to find cancers in the breast ROI. However, the number of instances of breast cancer rises annually, and manual diagnosis is laborious and necessitates the expertise of medical professionals. As a result, medical professionals are overworked and may misclassify breast cancers. There is a chance of over segmentation and inaccurate breast tumour detection if segmentation is done in first stage without doing pre-processing i.e. from raw images which is having noise and low contrast [18].

D. Feature extraction

Feature set of breast cancer lesions that can reliably differentiate between benign and malignant is the goal of feature extraction and selection. Extracting and choosing the most useful characteristics is crucial because the feature space may be quite big and complicated. Both the false positive (FP) and false negative (FN) rates should be little for a good detection strategy [19] [20]

E. Classification Techniques

This technique uses the Statistics methods to classify the Variables and objects. The basics of the classification are based on the performance attributes. To assess the classification results accuracy, Sensitivity, Specificity, F1-Score and FNR are used.

Support Vector Machine

Support Vector Machine is popular because the results obtained are accurate, robust and reliable. To get Maximum margin Hyper plane the method uses two classes of data. The hyper plane is the result of distance from the hyper plane and to the immediate data points on either side called the support vectors

Random Forest Classifier

Random Forest is one of the advanced group learning algorithm. This method is flexible and it depends on the combination of the different decision trees. Multiple –level Randomizations are used in the Random Forest classifier. Stability can be enhanced by increasing the number of decision trees. The RF technique uses a recursive methodology.

K-Nearest Neighbor

The KNN Classifier uses data metrics to compare the data samples to other data samples. The distance metric can be used to increase the distance between two data samples and decrease the distance between two identical data. The Euclidean distance is applied to calculate the distance between the two data samples

Logistic Regression

In Machine learning Logistic Regression is widely used Classification Model. It is a statistical model. The Linear regression paradigm is transformed into classifiers and various regularization techniques via logistic regression. Ridge and Lasso regularizations techniques are the widely used. Over fitting is reduced by using these two models.

RESULTS AND DISCUSSION

Classification Techniques are trained by using the Feature extraction technique. Features are extracted using the Feature extraction Techniques. Gray Level Co-occurance Matrix (GLCM) extracts important features from breast cancer images, while Particle Swarm Optimization (PSOoptimizes feature selection but may suffers from premature convergence. Weighted Particle Swarm Optimization (WPSO), an improved version of PSO with adaptive weights .Overall, GLCM provides features, PSO improves selection and WPSO achieves the best optimization and performance. The features extracted are saved in the CSV File, for CSV file different classifications are applied SVM, RF, KNN and Logistic Regression. Table.2 shows the comparison of classification algorithm and each method is analyzed on the various attributes like Accuracy, Specificity, F1-Score and FNR. Fig. 2, Fig. 3, Fig. 4, and Fig. 5 showing confusion Matrix for SVM, Random Forest, KNN and Logistic Regression respectively

Table 1. Performance Comparison of PSO and WPSO

Methods	Accuracy	Precision	Recall	Selected Features
Particle Swam Optimization	92.34	93.40	90.83	73
Weighted Particle Swam Optimization	92.79	93.60	92.20	65

Table2. Comparison of classification algorithms in relation to their performance attributes.

Methods	Accuracy	Sensitivity	Specificity	F1- Score	FNR
SVM	90.2027	90.2027	90.2027	90.1999	0.097973

Random Forest	98.9865	98.9865	98.9865	98.9865	0.010135
KNN	97.6315	97.6315	97.6315	97.6349	0.023649
Logistic Regression	91.5541	91.5541	91.5541	91.5532	0.084459

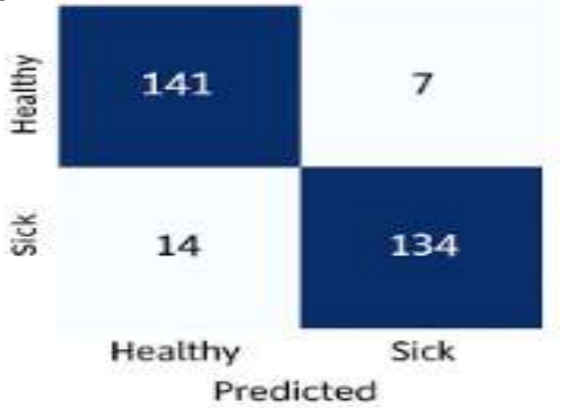


Fig. 1: Confusion Matrix for SVM Classification

Fig. 2: Confusion Matrix for Random Forest classification

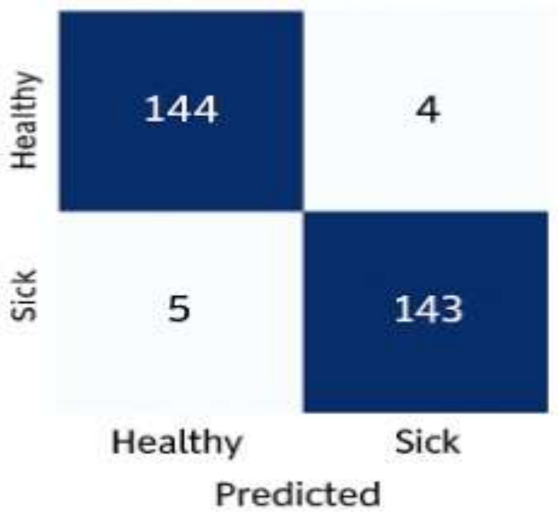


Fig.3: Confusion Matrix for KNN Classification

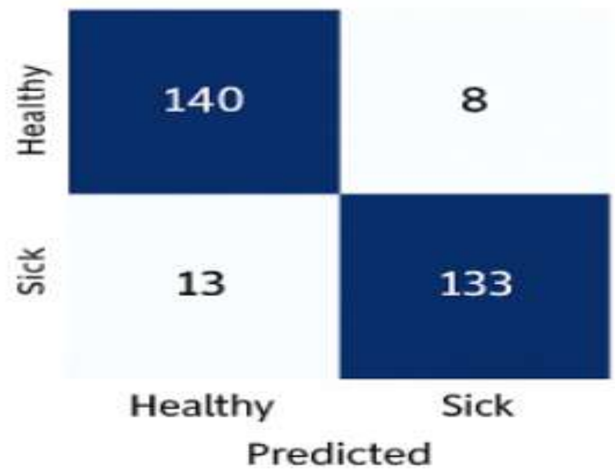


Fig.4: Confusion Matrix for Logistic Regression Classification

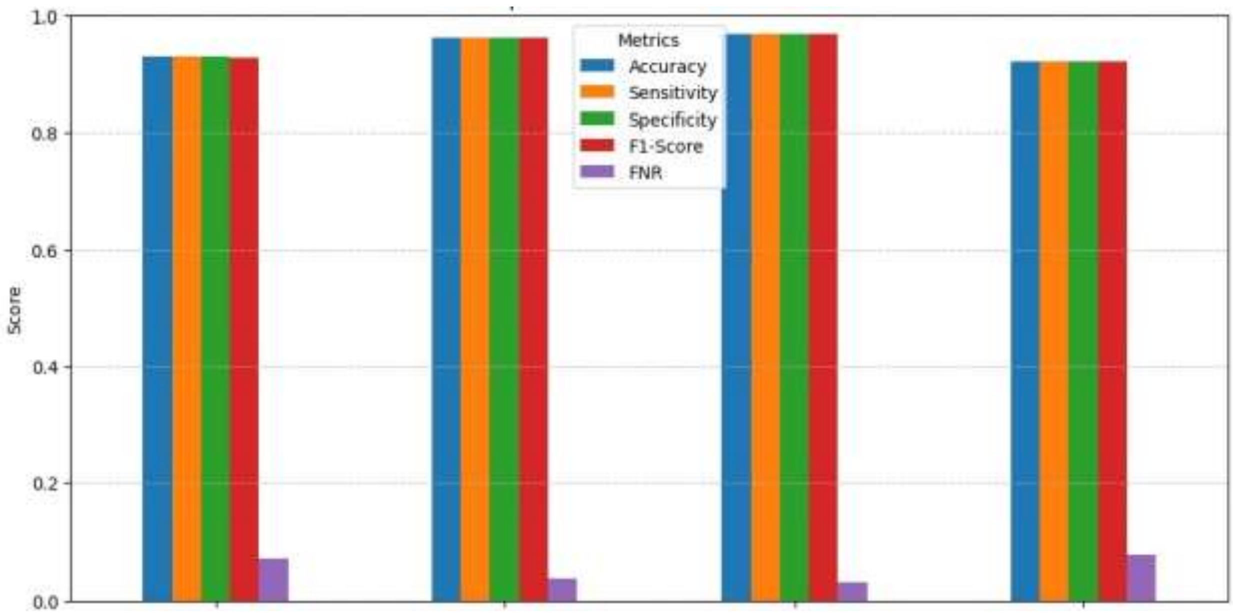


Fig. 5: Comparison of SVM, Random Forest, KNN and Logistic Regression in terms of Accuracy, sensitivity, Specificity,F1-Score and FNR attributes

The performance of the conventional Particle Swarm Optimization (PSO) and the Weighted Particle Swarm Optimization (WPSO) techniques was evaluated using accuracy, Precision , recall and the number of selected features.As shown in Table 1. WPSO achieved a classification accuracy of 92.79% which is higher than the 92.34% obtained using PSO. In addition , WPSO attained a recall of 92.20% outperforming the recall value of 90.83% achieved by PSO. The precision of PSO (93.40%) was marginally higher than that of WPSO(93.06%), WPSO selected only 65 features compared to 73 features selected by PSO. The reduction in the number of selected features indicates that WPSO eliminated redundant and less informative features.

The Proposed methodology conducted on the Breast cancer images to classify the Breast cancer images as Malignant or Normal images. Various performance metrics are applied to find the suitable algorithm for the classification of the MRI Breast Images. In this work four classifiers SVM, Random Forest, KNN and Logistic Regression are analyzed and Random Forest has given good accuracy of 98.98

Accuracy: This is the primary statistics for evaluation of the classification models. This model will measures the percentage of the machine learning models total predictions that are accurate.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total Number of Predictions}} = \frac{TN+TP}{TN+FN+TP+FP} \quad (1)$$

Sensitivity or Recall: Sensitivity or the Recall quantifies the proportion of real positive cases that the model accurately detected.

$$\text{Sensitivity} = \frac{TP}{FN+TP} \quad (2)$$

FNR: It describes the proportion of true positive cases were labeled as Negative cases.

$$\text{FNR} = \frac{FP}{FP+TN} \quad (3)$$

Specificity: This describes the Ratio of number of True negatives divided by the total number of actual negatives.

$$\text{Specificity} = \frac{TN}{FP+TN} \quad (4)$$

F1-Score: F1- score is a balance measure of the classification model's accuracy by combining the Precision as well as the recall.

$$\text{F1-Score} = \frac{2*(\text{Precision}*\text{Recall})}{\text{Precision}+\text{Recall}} \quad (5)$$

The Confusion Matrices in Figures 1-4 collectively summarizes the performances of four classifiers such as SVM, Random Forest, KNN and Logistic Regression on Malignant and Normal breast cancer MRI images. Figure. 1 shows the SVM classifier's confusion matrix, where strong diagonal values represent correct predictions (true positives and true negatives) and off –diagonal values indicates miscategorization (false positives and false negatives), providing insight into the model's sensitivity and Specificity. Figure.2 represents the confusion matrix for the Random Forest classifier, whose prominent diagonal elements highlight its ability to accurately distinguish between malignant and normal cases, confirming its high reliability and overall accuracy. Figure .3 displays the confusion matrix for the K-Nearest Neighbors classifier, summarizing how many images were correctly classified versus misclassified, which helps in understanding the model's strength and weaknesses in differentiating the two image categories. Finally Figure.4 shows the confusion matrix for Logistic Regression, where correct predictions appear along the diagonal and misclassifications of the diagonal; as a linear classifier, Logistic Regression may show limitations in capturing complex texture –based features in medical images, which can affect its classification performance.

Considering the outcomes shown in Figure.5, the Random Forest model demonstrated superior performance among all classification techniques, achieving the highest accuracy of 98.98%, followed by KNN at 97.63%, Logistic Regression at 91.55%, and SVM at 90.02%. The empirical data also confirm that Random Forest obtained the highest sensitivity and Specificity values, both at 98.98%, outperforming the KNN (97.63%), Logistic Regression (91.55%), and SVM (90.02%). Likewise, the F1-score results indicate the Random Forest again achieved the highest value of 98.98%, while KNN obtained 97.63%, Logistic Regression recorded 91.55%, and SVM achieved the lowest F1-score of 90.19%. Analysis of the Confusion matrix further reveals that the Random Forest classifier has the lowest False Negative Rate (FNR) of 1.01%, compared to KNN (2.36%), Logistic Regression (8.44%), and SVM (9.79%). Based on all performance metrics of accuracy, sensitivity, specificity, F1-score and FNR it is concluded that the Random Forest classifier provides the most effective and reliable identification of Breast cancer MRI images as cancerous or normal, achieving an overall accuracy of 98.98%.

After comparing four classification techniques based on the performance attributes it is concluded that the Random Forest classifier identifies the images as cancerous or Normal image with an accuracy of 98.98 %.Among the evaluated models The Random Forest classifier achieved SOTA Performance achieving the highest accuracy , sensitivity, specificity and F1-Score (98.98%)while also exhibiting the lowest false-negative rate (0.0101). This superior performance is attributed to its ensemble learning capability, which effectively captures complex non-linear feature interactions and reduce variance, resulting in highly robust predictions.

CONCLUSION

In this study, two optimization techniques particle Swarm optimization and Weighted Particle swarm optimization (WPSO) for feature selection.Weighted Particle swarm optimization (WPSO) selected only 65 features whereas PSO selected 73 features. This reduction indicates that WPSO was more effective in eliminating the redundant and less informative features. And also study evaluated four machine learning classification models such as SVM, Random Forest, KNN and Logistic Regression for the identification of malignant and Normal breast cancer MRI Images. The confusion matrices presented in Figures 1-4 provided a detailed understanding of each models strengths and limitations in terms of true and false classifications. Among the evaluated models, the Random Forest classifier consistently outperformed the others across all key performance metrics, including accuracy, Sensitivity, Specificity, F1-score and False Negative Rate. With an overall accuracy of 98.98% , and lowest FNR of 1.01%, The Random Forest model demonstrated presuming robustness, reliability and effectiveness in distinguishing cancerous and normal Breast cancer images. These results validate the potential of Random Forest as a strong and dependable classifier for Medical image analysis, particularly in breast cancer detection using MRI images. The current work can be extended in several directions to further enhance accuracy. A larger and more diverse data-set can be incorporated to improve model generalization and reduce potential biases.Integrating multi-modal imaging data could significantly improve diagnostic performance. Optimization techniques like hyper parameter tuning, feature selection and other approaches may be further investigated to improve the models.

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