RESEARCH PAPER

Adaptive Machine Learning Models for Breast Cancer Detection: Accuracy-Based Evaluation

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ABSTRACT
One of the most prevalent diseases among women globally is breast cancer, and early,Prediction and treatment outcomes are greatly enhanced by precise detection. Using tabular diagnostic data, this study gives an in-depth review of a number of popular machine learning methods for breast cancer detection. The methodology covers data preprocessing, feature engineering, model development, and evaluation protocols. Support Vector Machines, K-Nearest Neighbors, Decision Trees, Random Forests, Gradient Boosting, Multilayer Perceptron, and Logistic Regression are among the models that are analysed. Accuracy, precision, recall, F1-score, and ROC AUC are incorporated in stratified cross-validation to evaluate performance. In addition, analyse each model's benefits as well as drawbacks, highlight feature importance as well as interpretability aspects, and provide recommendations for selecting suitable models in clinical decision-support applications.

Keywords: Breast Cancer Detection, Machine Learning, Classification, Logistic Regression, Random Forests, Support Vector Machine.

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1. INTRODUCTION

Breast Cancer (BC) detection remains a pressing challenge in modern healthcare. Machine learning (ML) has become a potent strategy to support clinicians by identifying malignancies from both diagnostic data and medical imaging. Despite the wide adoption of ML algorithms for this purpose, no single method provides a universally optimal solution. The effectiveness of an algorithm depends on factors such as data modality, dataset size, interpretability requirements, and computational efficiency. This paper focuses on tabular diagnostic features commonly exemplified by the Wisconsin Breast Cancer dataset and related sources and presents a comparative study of several classical and ensemble ML methods for breast cancer detection [1].

Breast cancer is a serious worldwide health issue that arises from cells of breast. Significant investments in breast cancer breast cancer cognizance and research have advanced diagnostic capabilities and treatment strategies, contributing to reduced mortality rates. Prior finding, innovative therapeutic choices, and an improved considerate of disease progressionhave collectively enhanced survival outcomes. Within this research, we focus specifically on ML techniques to identify and classify breast cancer. [1].

Classifications ML process for assigning feature vectors to predefined classes varies across algorithms, and selecting the most suitable method requires careful consideration of data characteristics, interpretability, and computational demands. A critical challenge in early BC diagnosis deceits during distinctive between benign and malignant tumors. The benign tumors consist of noncancerous cells, while malignant tumors contain cancerous cells capable of spreading. Early and accurate classification can act as vital role in avoiding disease progression.

Heresuggestsa predictive model designed for rapid and accurate categorization of breast cancer cases in Human Computer Interaction (HCI) framework for diagnostic support. Previous studies have explored various HCI enterprise methods for cancer prediction [2], including evaluation of user interfaces in digital health systems [3]. Broader research in negotiation and cognitive HCI [4] has examined interaction patterns, though traditional classifications of sentimental, behavioural, and intellectual dimensions into productive, resistant, and non-engagement have been shown to introduce inconsistencies [5].

The current aims to evaluates multipleML approaches for cancer classification, with aim of identifying the most effective algorithm. Precision, recall, F1-score, ROC AUV, training time and accuracy are used to assess performance. Random Forests (RF), Decision Tree (DT), Extreme Gradient Boosting (XGBoost), Support Vector Machines and Artificial Neural Networks (ANN) are the classifiers that are taken into consideration. Experiments used Wisconsin Breast Cancer Diagnostic (WBCD) dataset [1].

Overarching aims of workto concern classifier-based supervised ML techniques to detect BC efficiently on WBCD dataset and to identify the most prognostic features. In section 2survey prior research on BC diagnosis. Section 3 presents methodology of proposed assessment. Reports with analyses measured results describe in section 4. Conclusively, section 5 concludes work and highlights key insights.

2. MOTIVATION AND CONTRIBUTION

Significant contributions of this study are as follows:

1. To establish aconsistent, clear and accurate reproducible experimental framework for evaluating machine learning classifiers on breast cancer diagnostic tabular data.
2. To comparative investigation of widely used ML methods, assessing their performance through evaluating criteria: precision, recall, F1-score, ROC AUV and accuracy.
3. To discuss critical aspects beyond accuracy, including model interpretability,computational efficiency, robustness, and practical considerations for deployment in clinical decision-support systems.

3. MATERIALS AND METHODS

Machine learning provides a diverse set of algorithms for breast cancer detection and diagnosis. Researchers use varied datasets to further their studies, examining different aspects of the disease and identifying topics for further investigation.

Das et al. [6] made a significant contribution by introducing expert system for BC prediction. Proposed system uses a DT and Undiluted Feature Set (UFS) method. UFS approach, improves accuracy through 0.59%, which can have a significant influence on a higher population. Maheshwar and Gautam investigated several categorization approaches as well as discovered that DT performed fine in terms of inclusive accuracy when used to BC predictions [7].

Anisha et al. [8] used a ML strategies called RFpredictive classifierBC.It splits information into several tree thenachieves impressive concluding accuracy of 98%, with additional factors like lumps size and the stage of BC are added.

In a major addition, Kamel et al. [9] improved efficiency of SVMs through extracting best features using Gray Wolf technique, consequently improving BC detection performance. They employed data mining for integrate GWO's feature selection approach and SVM. Furthermore, a recent technique uses Deep Convolutional Neural Networks (DCNN) to classify breast masses through mammography as benign, malignant, or normal categories [10].

Trivedi et al. [11] devoted an ensemble approach that that combines OTSU thresholding, CLAHE, and GLCM for efficient feature extraction.

Mahesh et al. [12] investigated effectiveness of XGBoost ensemble technique forBC classification. To address class disparities and data noise, used Synthetic Minority Oversampling method. The outcome showedXGBoost-RF outperformed another ensemble classifiers, with 98.20 % accuracy. Nasien et al. [13] used an artificial neural network (ANN) with backpropagation to solve complex pattern recognition issues. By numerical simulations, System achieved 96.92% accuracy.

4. METHODOLOGY

Our primary goal is to identify utmost exact and reliable methodto identifying BC. Data analysis method used for disease classification, clustering, anomaly detection, and association [14]. The proposed approach steps are outlined below. We examine the data and use five supervised ML techniques to produce truthful decision based on various parameters.

High-quality images are produced by imaging techniques like X-rays, MRIs, endoscopes, ultrasounds, and others, but they are injurious to human body and usage fewer energy, which results in images with underprivileged contrast and quality. A method for improving quality of imageas well as assessing mammography images for classify that they are benign or malignant is called Human Computer Interaction Diagnosis (HCID). An artificial intelligence diagnostic system that usages membership function to represent emotional level of patients and evaluates severity of patient's symptoms [15]. PD R-CNN was used by some to present a multi-feature illness fusion discriminating approach [16]. Methodology for diagnosing HCI that has been proposed:

Step 1: Load the Dataset

The dataset containing diagnostic information is loaded into working environment. This dataset includes features extracted from digital images of breast masses obtained through fine-needle aspiration (FNA).

Step 2: Data Preprocessing

The collected data is pre-processed to ensure accuracy and consistency. This involves cleaning missing or noisy values, normalizing feature values, and selecting relevant attributes from the digital images of breast tissue. Proper preprocessing enhances reliability of ML models.

Step 3: Apply Machine Learning Algorithms

Several ML algorithms such as DT, RF, SVM, XGBoost, and ANNare applied to the pre-processed dataset. Each algorithm is trained to classify breast tumors as benign or malignant based on the extracted features.

Step 4: Evaluate Model Performance

The performance of each classifier is assessed using key evaluation metrics, including:

- **Accuracy:**To Measures overall correctness of the model.

- **Recall (Sensitivity):** To Measures how effectively model identifies positive cases.
- **Precision:**To valuates how many of the predicted positives are correct.
- **Specificity:**To indicates how well model identifies negative cases.
- **F1 Score:** To balances precision and recall.
- **ROC AUC:**To represents classifier's ability to distinguish between classes.
- **Training Duration:**Time taken by each model to train.
- **Feature Importance:**Toidentifies which features most influence classification.

Step 5: Identify the Best Classifier

After evaluating all models, classifier that demonstrates highest accuracy, robustness, and optimal performance across evaluation metrics is selected as best-performing model for breast cancer detection.

Proposed approach demonstrates entire procedure for data categorization as well as assessment to determine the optimal classifier utilizing assessment parameters.WBCD datasetutilized to analysis this approach.

5. RESULT AND DISCUSSION

Cancer prediction by optimizing number for benign as well as malignant categories bymatrix of confusion for projected approaches after applying a ML technique to WBCD dataset. a examine of pre as well as postimage deal with methods for digital pathological images using a deep learning architecture [17].

The most crucial performance metric is accuracy, which is proportion for correctly projected observations to entirely observations. Proposed model is regarded as best if it is extremely accurate and makes use of every feature that is available. The projected and actual classes will be used to gauge accuracy [1].

$$ACCURACY = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

Here,
TP: True Positive,
TN: True Negative,
FP: False Positive,
FN: False Negative

Precision proportion is defined as fraction of positively imagined observations that were impeccably anticipated vs all projected observations. Precision correlates by low FP rates.

$$PRECISION = \frac{TP}{TP+FP} \tag{2}$$

Recall is ratio of correctly predicted observations to entire observations in class. This method will advantage from a value greater than 0.5.

$$RECALL = \frac{TP}{TP+FN} \tag{3}$$

The specificity of the model is measured by the percentage of TN that is correctly detected. Because they were initially misunderstood as positive results, the number of real negatives (false positives) will increase. The TNR is another name for this ratio. The specificity (real negative rate) and the FPR would always add up to one[1].

$$SPECIFICITY = \frac{TN}{TN+FP} \tag{4}$$

F1 score is a weighted average of accuracy and recall that accounts for both FP and FN. In cases where the distribution of classes is unequal, F1 is often additional treasured as compared to accuracy. While the costs of FP and FN are similar, accuracy is at its peak.

$$F1SCORE = \frac{2*(\text{RECALL} * \text{PRECISION})}{\text{RECALL} + \text{PRICISION}} \tag{5}$$

ROC (Receiver Operator Characteristic) curve is method pro determining accuracy of binary classification problems. By comparing TPR and FPR at several borderline, curve of probability can be used to distinguish between the "signal" and the "noise". Curve of ROC curve, summarystatistic, AUC, evaluates classifier's capacity for class distinction.

Table1: Percentage of accuracy for WBCD dataset.

Algorithm	Accuracy (%)
DT Classifier	94.15
RF Classifier	95.32
SVM	97.66
XGBoosting	95.91
ANN	97.07

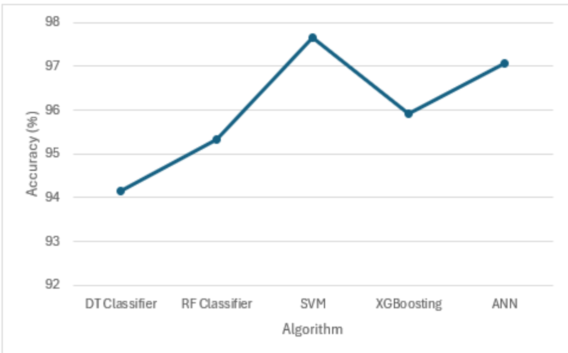
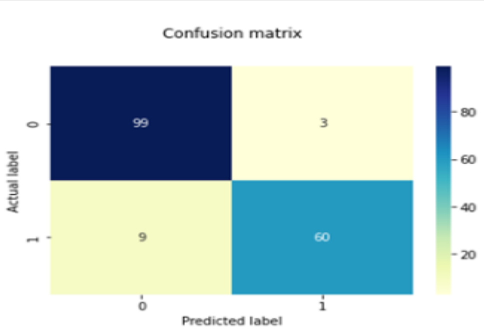
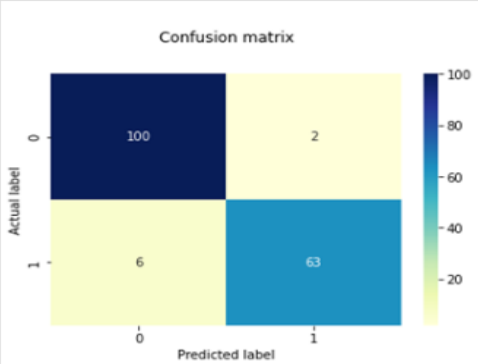
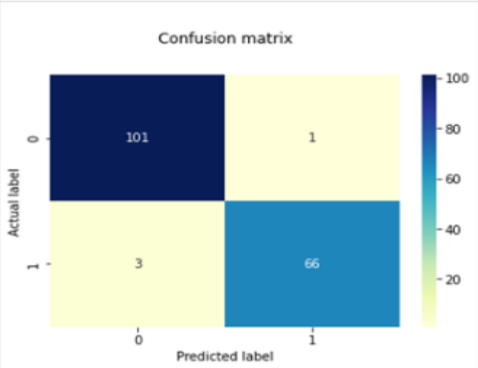
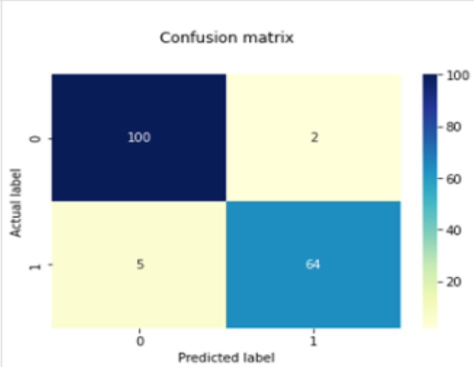
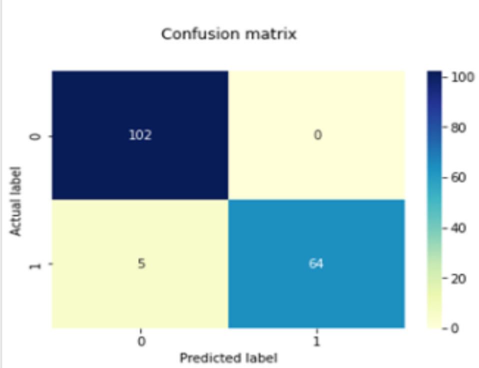


Figure 1: Comparative graph of classifier accuracies.

Table 1 and Figure 1 show the WBCD dataset's accuracy based on the training set findings. andaccuracy of each classifier varies, but SVM routinely outperforms others (97.66%) [1].

Human computer interactive diagnostic is utilized to improve cancer detection. HCID will transition to selfdiagnosis based on the symptoms found. System will be beneficial in future for initial diagnosis, improving patient survival, as well as saving lives. Some futuristic approaches have been proposed to improve detection methods, such as breath biopsy, which analyses breath samples to stratify biomarkers, and mammary ductoscopy, in order to observe the ductal epithelial lining and cell recovery, small endoscope is inserted obsessed by breast milk ducts [18]. An analysis of AI systems for skin cancer diagnosis based on digital images [19].

Table 2: Statistics of confusion matrix for classifiers.

Classifier	Confusion Matrix
DT Classifier	
RF Classifier	
SVM	
XGBoosting	
ANN	

Since confusion matrices, a useful tool for classifier evaluation, Table 2 shows classifier along with confusion matrix that results from testing dataset on all classifiers. Table 3 shows Performance metrics interpretation for benign and malignant diseases, including accuracy, recall, and specificity [1].

Support vector machines therefore perform more accurately than other categorization algorithms. SVM achieves well than other classifiers in relations of average precision(),recall (), specificity() andF1-score() for both classes, as indicated in Table 3[1].

Table 3: Performance metrics interpretation

Algorithm	Precision	Recall	Specificity	F1 Score	Class
DT Classifier	0.92	0.97	0.86	0.95	B
	0.95	0.87	0.97	0.91	M
RF Classifier	0.94	0.98	0.91	0.96	B
	0.97	0.91	0.98	0.94	M
SVM	0.97	0.99	0.95	0.98	B
	0.99	0.96	0.99	0.97	M
XGBoosting	0.95	0.98	0.92	0.97	B
	0.97	0.93	0.98	0.95	M
ANN	0.95	1.00	0.92	0.98	B
	1.00	0.93	1.00	0.96	M

Table 4: Changes in accuracy for DT

Algorithm	Change Acuuracy w.r.t. Decision Tree Accuracy Testing Set
RF Classifier	1.17
SVM	3.51
XGBoosting	1.76
ANN	2.92

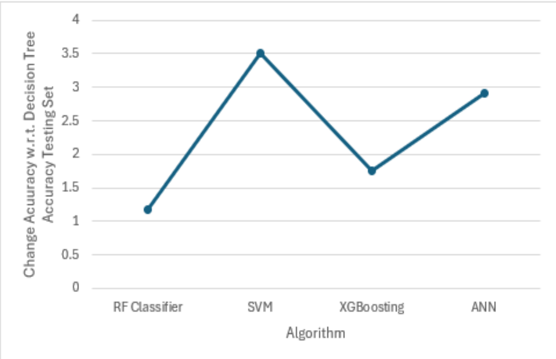


Figure 2: Accuracy change comparison w.r.t. DT

Table 4 and Figure 2 illustrate accuracy change by regard to a low-accuracyDT, SVM indicates that the change outperforms another classifier.

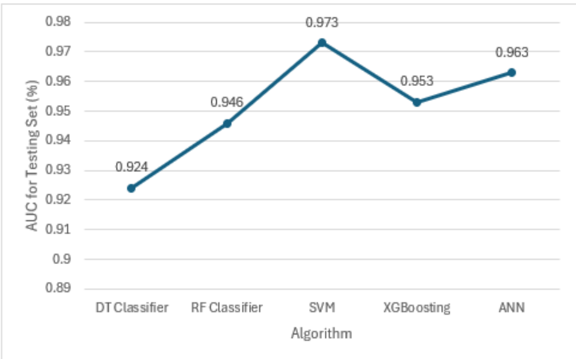


Figure 3: Comparative area of ROC AUC curve

Figure 3 shows ROC curves of all ML approach. ROC curve plays an important role in determining classifier effectiveness. The region under curve of ROC is referred to as AUC. Better classifier is where section is larger. SVM classifier has greatest AUC score (0.973), while DT classifier has worst (0.924), listed in Table 5.

Table 5: Area under Curve of ROC (AUC)

Algorithm	AUC for Testing Set (%)
DT Classifier	0.924
RF Classifier	0.946
SVM	0.973
XGBoosting	0.953
ANN	0.963

Table 6. Training time

Algorithm	Training Time
DT Classifier	0.015
RF Classifier	0.109
SVM	0.01
XGBoosting	0.094
ANN	1.84

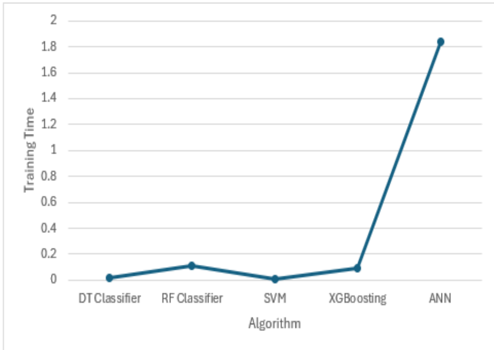


Figure 4. Training time

Table 6and figure 4 shows training time for all classifier, SVM takes significantly fewer time than additional classifiers, ANN takes longer due to the 100 epochs.

6. CONCLUSION

In this research, supervised ML techniques like DT, RF, SVM, XGBoostingand ANN are employed toward predict BC. Properly structured comparison investigation is given along through performance metrics recall, F1 score, accuracy, precisionand specificity obtained since the classificationon dataset of WBCD.Here, investigation moreover discussed relevance as well as exploitation of every attribute in dataset to establish furthermost exact, precise, and efficient ML algorithm. All accessible algorithms were developed by Anaconda framework through scikit-learn package through Python.After correctly comparing models,SVM exploited entirely features, gave a better accuracy of 97.66%. Precision, recallin addition F1 score measurement matrix all indicates that SVM performs well than other classifiers. SVMs take less time as well as have a greater area under curve than other classifiers. Lastly, SVM prove to be effective in predicting, diagnosing BC and attain better performance by employing evaluation measures. It proves, method is functional only on dataset of WBCD, constructed on methodscorresponding MRI, mammography, as well as US datasets may be employed in forthcoming, however, same approach and methods need to be implemented in order to test other databases. On bigger data sets where there are more classes, we can utilize a range of ML techniques with higher parameters to enhance accuracy.

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