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Article

Performance Evaluation of Hybrid Meta-Heuristic Optimization Techniques in Multilayer Perceptron-Based Breast Cancer Detection

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Abstract: Breast cancer is a prevalent malignancy in women worldwide. Mammography screening is an effective method for early detection, and timely diagnosis is essential for improving treatment outcomes and survival rates. Medical imaging techniques, especially mammography, are frequently used for detecting breast cancer and monitoring tumour progression. However, this diagnostic technique has a low positive predictive value for breast biopsies, often resulting in unnecessary procedures for abnormal findings. The Breast Imaging Reporting and Data System (BI-RADS) was developed as a standardized diagnostic technique for reporting mammographic results. It categorizes abnormal findings related to breast cancer into specific groups, facilitating the assessment of breast biopsies and the identification of tumours. In this research, ensemble models are integrated with optimization techniques to enhance the detection process in mammography. The initial step involves pre-processing using a Gaussian Bilateral Filter (GBF) to reduce noise and improve image quality. Following this, the region of interest (ROI) is identified employing the Adaptive Histogram Thresholding and Contour Clustering (AHT-CC) algorithm. Feature extraction is conducted utilizing the Convolutional VGG-16 (ConV-16) model. The extracted features are then fed into a Hybrid Bayesian Genetic Optimized Multilayer Perceptron (HBGOMLP-EnML) for precise identification of breast cancer based on BI-RADS categories. The analysis reveals that the proposed model achieves an accuracy of 98.6%, precision of 97.1%, recall of 97.2%, and F1-score of 97.2% across different classifiers. The results indicate that the proposed method is competitive with existing classification models in the literature, presenting a practical and beneficial solution.
Keywords: Gaussian Bilateral Filter, Bayesian optimization, Histogram Thresholding, Genetic algorithm, Multi-layer perceptron.

1. Introduction

[1,2] Breast cancer remains a significant global health issue, with its incidence and effects differing by country and ethnic background. According to the World Health Organization (WHO), approximately 2.3 million women were diagnosed with cervical cancer in 2020, leading to 685,000 deaths worldwide. [3] By the end of the year, 7.8 million women diagnosed with breast cancer within the last five years continue to fight the disease. This underlines breast cancer's significance as a global health issue, demonstrating that women across all nations tend to be diagnosed at older ages, with risk escalating with age. While predominantly affecting women, breast cancer is not solely confined to this demographic. [4,5] Breast cancer is the most common cancer among women worldwide. Screening mammography is instrumental for early detection, which leads to better and less costly treatment. However, a significant limitation of current screening methods is the high false positive rate, resulting in repeat testing, unnecessary biopsies, and short-term follow-up recommendations.

[6] A study by the American College of Obstetricians and Gynecologists found that after 10 years of annual screening, 61% of women aged 40 to 59 will have at least one negative recurrence, while 9% will have at least one negative recurrence after a positive breast cancer biopsy. This highlights the significance of breast ultrasound as a widely used diagnostic tool in monitoring breast health, reducing radiation exposure compared to other screening methods.[7,8] Breast ultrasound (US) is a widely used diagnostic tool that complements non-invasive mammography, facilitates the evaluation of visual findings, and assists in guiding breast biopsy procedures. Its advantages over other imaging techniques include being low-cost, lacking ionizing radiation, and allowing for immediate interpretation of images. Despite promising results, ultrasound interpretation remains challenging due to its operator dependency, leading to a high false-positive rate and low predictive value. This issue is particularly significant in the context of breast cancer, including cases of Ductal Carcinoma In Situ (DCIS), where accurate diagnosis is crucial for effective treatment and management.

[9, 10] Ductal carcinoma in situ (DCIS) is a precancerous form of breast cancer that originates in the breast tissue without spreading to adjacent tissues. In contrast, invasive ductal carcinoma (IDC), which comprises 80% of breast cancer cases, is characterized by its ability to invade surrounding breast tissue. [11] Invasive lobular carcinoma (ILC) is a type of breast cancer that arises in the mammary gland, comprising 15% of all cases. The most prevalent forms of breast cancer include invasive ductal carcinoma (IDC) and ductal carcinoma in situ (DCIS). While IDC is more common, DCIS is characterized as a slow-growing condition that typically does not interfere with a patient's daily life.

[12] Breast cancer primarily manifests in two forms: invasive ductal carcinoma (IDC) and invasive lobular carcinoma (ILC). Invasive ductal carcinoma originates in the breast ducts and has the potential to metastasize to surrounding areas within the breast. [13] Inflammatory lobular carcinoma (ILC) originates in the lobules of the breast and has the potential to spread to adjacent areas within the breast. It is noteworthy that only 1-4% of women diagnosed with breast cancer will experience ductal carcinoma in situ, which is classified as a form of Paget disease of the breast. The association between Paget disease, women, and breast cancer emphasizes the need for further understanding of these conditions and their implications on the spread of cancer.

[15] Noncancerous breast cells are localized within the affected area of the breast, avoiding proliferation to adjacent lobules or ducts. Radiologists play a crucial role in this process, meticulously scrutinizing mammography images and documenting their observations of any detected abnormalities through the Body-Based Imaging and Data Reporting System (BI-RADS). [16] -scale analyses are essential for supporting cultural studies of women, but this approach faces significant practical challenges in developing countries like Ethiopia, primarily due to the shortage of electricians, which complicates implementation.

[17] The development of a machine learning (ML) model aimed at detecting breast abnormalities significantly enhances the performance of cancer diagnosis by providing valuable insights that assist radiologists. This advancement allows radiologists to concentrate on critical areas, thereby improving diagnostic accuracy in breast cancer detection through the application of artificial intelligence. [18] Machine learning (ML), an essential part of artificial intelligence, has attracted significant interest recently due to its effectiveness in image processing. Its application in cancer diagnosis and detection is expected to improve the performance of radiologists and address the gaps in experience and proficiency among novice practitioners. [19]AI assistance significantly enhances radiologists' performance in breast ultrasound, yielding a 37.3% reduction in false negative rates while ensuring 27.8% fewer biopsies are conducted, all within the context of CAD (Computer-Aided Detection) systems used in mammography for breast cancer diagnosis.

[20] Breast cancer remains a leading cause of mortality among women, making timely detection crucial for lowering mortality rates and enhancing life expectancy. Mammography serves as an established screening method for radiologists. Recent advancements in deep learning have led to the development of computer-aided diagnosis (CAD) systems designed to assist radiologists in accurate diagnosis. This paper presents an optimized machine learning model for breast cancer detection utilizing BI-RADS categories and mammography images.

1.1 Problem statement

Breast cancer remains a leading cause of mortality among women, with survival rates significantly enhanced through early detection via mammography. The mammogram interpretation process is challenging and predominantly relies on radiologists, risking missed cancer signals and resulting in false positives or negatives. Implementing machine learning (ML) in breast cancer diagnosis could improve and automate mammography, leading to a more accurate and efficient approach.

Existing models for breast cancer detection encounter limitations related to dataset issues, high computational complexity, and delays in timely result predictions. The proposed hybrid model aims to address these issues by utilizing advanced classification techniques, enhancing accuracy, scalability, and reducing time complexity.

1.2 Objective

To improve breast cancer detection, advanced machine learning algorithms should be employed to analyse mammograms, thereby reducing human error and enhancing diagnostic accuracy. This approach aims to identify patterns and ultimately improve patient outcomes.

For this;

- researcher introduced a novel model along with optimization for the effective breast cancer detection using BI-RAD score in mammographic images.
- To evaluate and compare a proposed model with existing mammography imaging techniques for breast cancer detection.

2. Review of Literature

In a study by Ozsahin et al [21], a six standalone machine learning model was introduced utilizing a breast cancer mammogram dataset with BI-RADS-based classification. The classifiers included Naive Bayes, random forest, artificial neural network, SVM, K-nearest neighbor, and logistic regression. SVM achieved the highest accuracy at 80.6% and precision of 76.8%, while logistic regression had an AUC of 84.6%. The model aims to enhance the accuracy of breast cancer diagnosis and assist the medical industry.

Developed a machine learning approach Kalpana et al. [22] for cancer detection in mammogram images, involving preprocessing steps like noise removal and normalization. Features were extracted using probabilistic PCA, with Naïve Bayes and integrated CNN networks utilized for classification. Firefly binary grey optimization and moth flamelion optimization were employed for classification outputs. Experimental results showed the suggested models achieved accuracies of 95% and 98%, outperforming other methods.

Avci et al. [23]examined whether various preoperative techniques could enhance the classification of benign and malignant breast tumors using mini-MIAS data. A combination of median filter (MF), contrast-limited histogram equalization (CLAHE), and undetectable mask (USM) was employed to reduce artifacts and improve image quality. K-means integration was utilized for classifying suspicious regions, followed by the implementation of machine learning algorithms to categorize images as normal/abnormal and benign/malignant. The integration of MF, USM, and CLAHE resulted in improved accuracy, with support vector machine, random forest, and neural network yielding the best outcomes.

Sarvestani et al. [24] in this research, a machine learning model for diagnosing breast microcalcifications in mammogram images was developed. Two enhancement methods were applied: a fuzzy system-based ROI method and Gabor filtering. The decision tree algorithm was used to isolate microcalcification lesions, followed by segmentation to mask suspicious patterns. An artificial neural network (ANN) was employed to differentiate between benign and malignant ROI groups. Trained on the DDSM dataset and implemented in MATLAB, the system achieved an accuracy of 93%, outperforming previous methods.

In this study, eight classification models were evaluated for breast cancer prediction. Five selection methods optimized the data, retaining 17 weights. The multilayer perceptron (MLP), support vector machine (SVM), and clustering algorithms showed high accuracy, with SVM achieving the highest at 97.7%. SVM had low errors, recording 0.029 false negatives (FN) and 0.019 false positives (FP), making it the best model for this task.

3. Proposed Methodology

In this paper, an optimized model HBGOMLP-EnML is proposed for detecting breast cancer based on BI-RADS categories. The work flow includes 4 stages are pre-processing, ROI identification, feature extraction, classification. Figure 1 illustrates the workflow of proposed model.

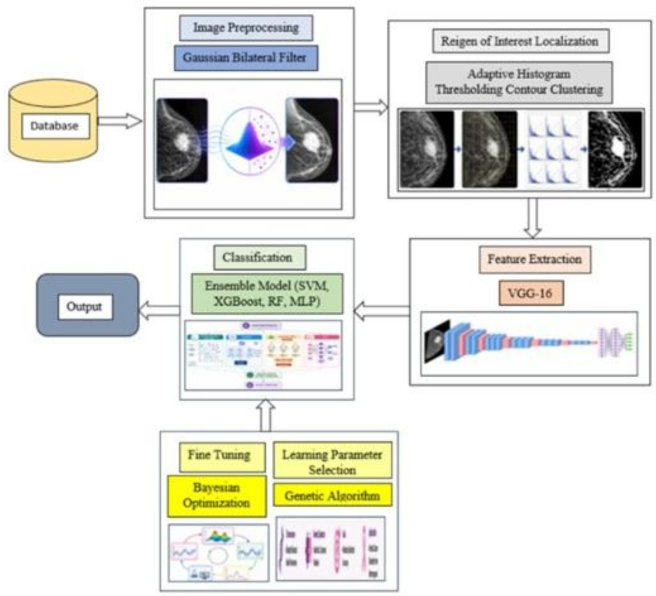


Figure 1: Workflow of proposed approach

Initially, data are collected from the Breast cancer mammogram dataset, followed by a pre-processing phase utilizing a Gaussian Bilateral Filter (GBF) to eliminate noise and improve image quality. Subsequently, the region of interest (ROI) is identified using the Adaptive Histogram Thresholding and Contour Clustering (AHT-CC) algorithm. This approach merges AHT with contour clustering techniques that focus on structured patterns and boundaries, effectively minimizing the impact of noise and artifacts. Higher-level deep features are then extracted using the Convolutional VGG-16 (ConV-16) model. Ultimately, the Hybrid Bayesian Genetic Optimized Multilayer Perceptron (HBGOMLP-EnML) is applied to classify breast cancer into BI-RADS categories. This model incorporates ensemble techniques, such as Support Vector Machine (SVM), XGBoost, and Random Forest (RF), leveraging Genetic Algorithms (GA) and Bayesian Optimization (BO) alongside the Multilayer Perceptron (MLP) to enhance the accuracy of breast cancer classification.

4. Results and Discussion

4.1 Performance metrics

This section offers a comprehensive evaluation of different performance metrics. The metrics associated with the model were evaluated using Accuracy, Precision, Recall, F1-score, Intersection over union (IOU), Dice similarity score (DSC).

4.2 Dataset description

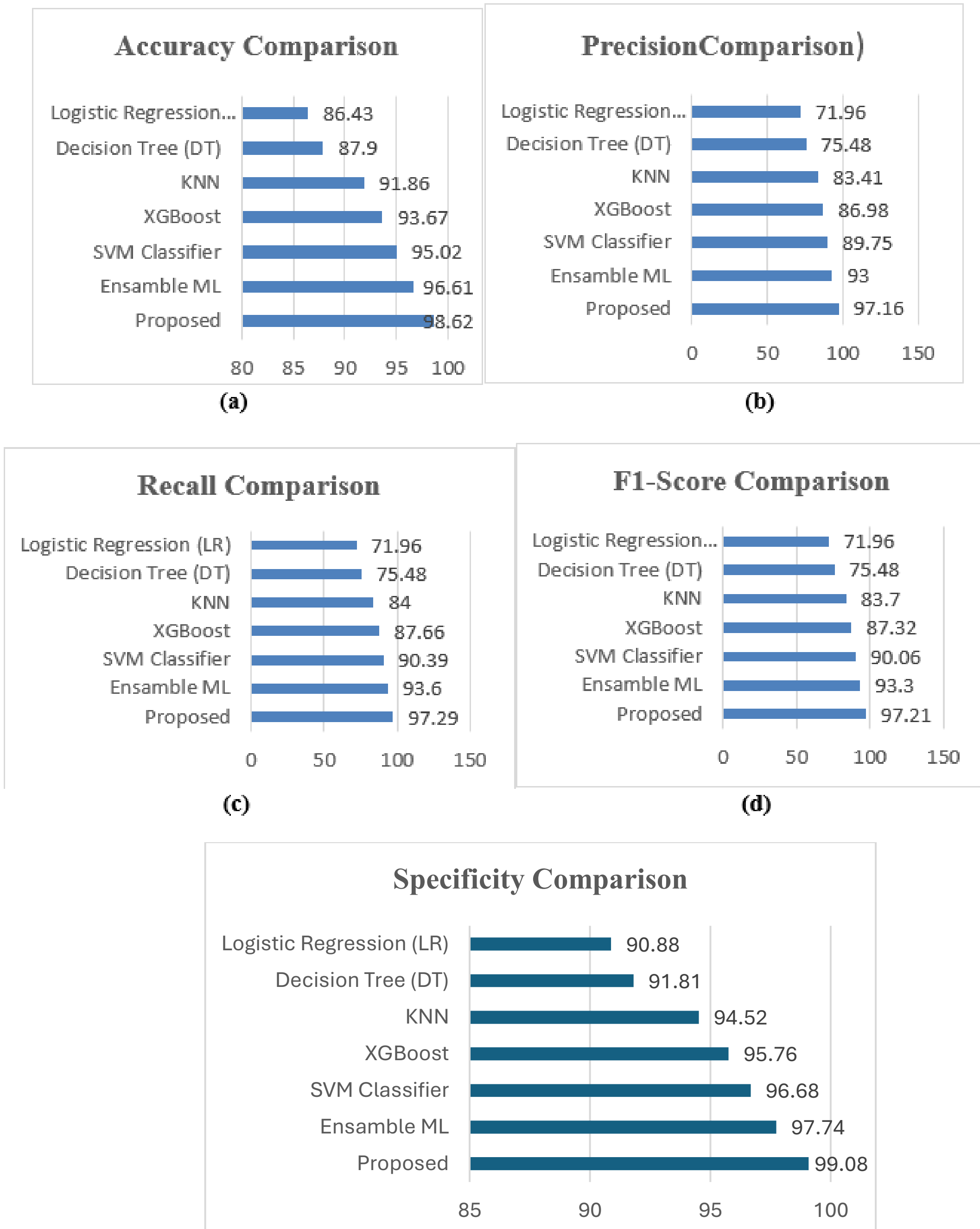
The proposed work uses Breast cancer mammogram dataset. The link of the dataset is,

https://www.kaggle.com/datasets/asmaasaad/king-abdulaziz-university-mammogram-dataset

The inaugural digital mammogram dataset for breast cancer in Saudi Arabia that applies BI-RADS categories to address the scarcity of local public datasets. This initiative involves the collection, categorization, and annotation of mammogram images to enhance the medical field by equipping healthcare professionals with a variety of diagnosed cases, particularly within Saudi Arabia. The dataset includes featuring images captured from two different views (CC and MLO) for both the right and left breasts, resulting in a total of 5,662 mammogram images. The dataset is categorized into five levels that follows the BI-RADS classification system. The dataset contains total 2206 samples. Among that, 1764 samples taken for training and 442 samples taken for testing. Figure 8 shows the outcomes using the proposed model.

4.3 Performance evaluation with existing approaches

The proposed model is analysed with existing models includes Ensemble ML, SVM, RF, XGBoost, k-nearest neighbour (KNN), decision trees (DT), and linear regression (LR).



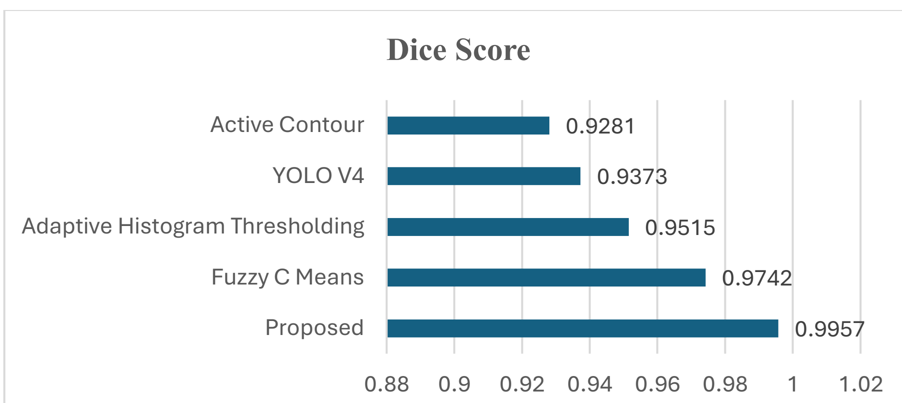
(e)

Figure 2 (a)-(e): Performance comparison with existing models in terms of accuracy, precision, recall, F1-score, specificity

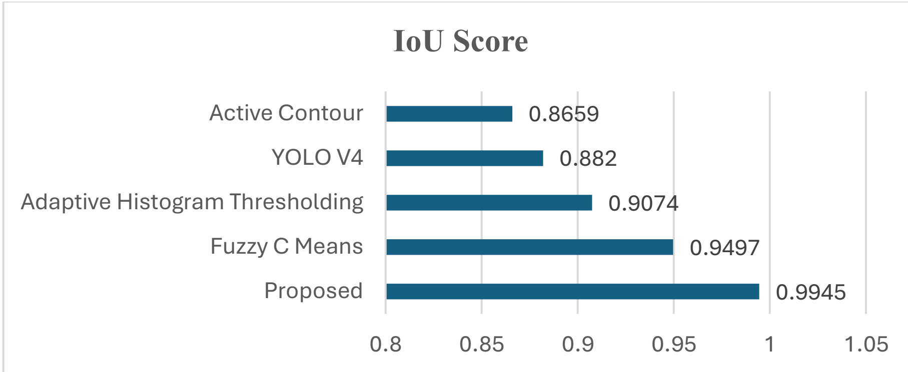
The proposed model evaluates the classification capability for breast cancer detection with various assessment metrics that provide a comprehensive insight into the model effectiveness based on BI-RAD score. Understanding the performance of the proposed model through these evaluation metrics enables informed decision-making in breast cancer detection. Accuracy is recognized as a crucial factor in the precise classification of benign and malignant samples. Figure 2 (a) defines the accuracy of the proposed model with existing methods for breast cancer classification, emphasizing the superior accuracy of the proposed model compared to previous designs. The proposed model effectively extracts features from the region of interest (ROI), leading to improved classification results. The existing model faces issues in extracting the features and achieves low accuracy. Figure 2 (b) presents a precision analysis comparison between the proposed model and existing techniques for the automatic detection of breast cancer. The proposed model demonstrates superior performance over earlier models for breast cancer identification. The recall performance of the proposed model, along with existing architectures for breast cancer detection is illustrated in Figure 2 (c). Figure 2 (d) presents the evaluation of the f-measure generated by both the existing classifiers and the proposed model for breast cancer detection. The proposed model demonstrates a strong capability in accurately predicting the given inputs. Additionally, the f-measure incorporates parametric input to define precise positive rates derived from various mappings of distinctiveness. This improvement is attributed to the model ability to create well-defined decision boundaries and automatically optimize weights, leading to enhanced f-measure values. The comparison of specificity between the proposed model and existing architectures for the automation of breast cancer detection is illustrated in Figure 2 (e). This graphical representation effectively quantifies a classification model proficiency in accurately classifying negative instance. This parameter is crucial in breast cancer detection. A higher specificity indicates a lower rate of false positives, which is important for minimizing unnecessary treatments for individuals without cancer. Moreover, assessing the specificity of different classification models in breast cancer detection has provided significant insights into their ability that decreases the false positive outcomes. The proposed model is particularly beneficial in clinical environments as it lowers the risk of misclassifying patients who do not have cancer. Table 1 shows the values of proposed and existing approaches.

Table 1: Performance analysis with existing and proposed models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Specificity (%)**
Proposed	98.62	97.16	97.29	97.21	99.08
Ensamble ML	96.61	93	93.6	93.3	97.74
SVM Classifier	95.02	89.75	90.39	90.06	96.68
XGBoost	93.67	86.98	87.66	87.32	95.76
KNN	91.86	83.41	84	83.7	94.52
Decision Tree (DT)	87.9	75.48	75.48	75.48	91.81
Logistic Regression (LR)	86.43	71.96	71.96	71.96	90.88



(a)



(b)

Figure 3 (a-b): DSC, IOU comparison

Figure 3 (a) denotes the DSC comparison. Figure 10 (b) defines the IOU comparison. A widely recognized metric for evaluating the effectiveness of ROI localization tasks in breast cancer detection from mammography images, is the Dice similarity score (DSC), Intersection over Union (IoU), also known as the Jaccard Index. In summary, the metrics measures the degree of overlap between the ground truth region and the predicted region. Analysing the variations in IoU scores across different ROI localization methods can provide valuable insights into the efficacy of various strategies based on BI-RAD score. The proposed model improves the breast cancer detection process. In contrast, existing architectures such as AHT, fuzzy c-means, Yolov4, and the active contour model report minimum IoU values due to various complexities. However, the proposed model provides an innovative solution to the challenges faced by the existing approaches. Table 2 illustrates the segmentation values with existing approaches.

Table 2: Segmentation values

Segmentation Method	IoU	Dice Score
Proposed	0.9942	0.9956
Fuzzy C Means	0.9497	0.9742
Adaptive Histogram Thresholding	0.9074	0.9515
YOLO V4	0.882	0.9373
Active Contour	0.8659	0.9281

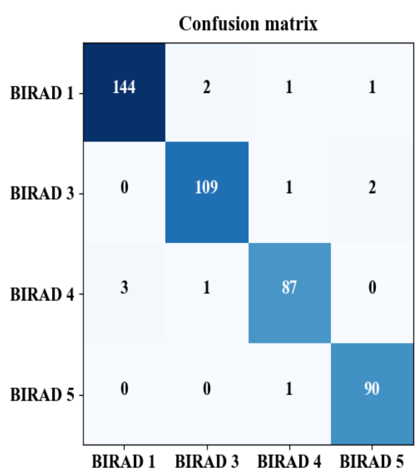


Figure 4: Confusion matrix of proposed model

The confusion matrix for the proposed model, depicted in Figure 4, illustrates the classification performance across 442 instances. Within this dataset, 144 samples were utilized to predict BI-RAD 1, resulting in 4 misclassifications. For BI-RAD 3, 109 instances were analyzed, yielding 3 misclassifications. Additionally, during the prediction of BI-RAD 4 from 87 instances, only 4 samples were misclassified. Finally, for BI-RAD 5, predictions were based on 90 instances, where merely 1 was misclassified. Overall, this detailed representation underscores the accuracy and reliability of the predictive model in distinguishing between various BI-RAD categories.

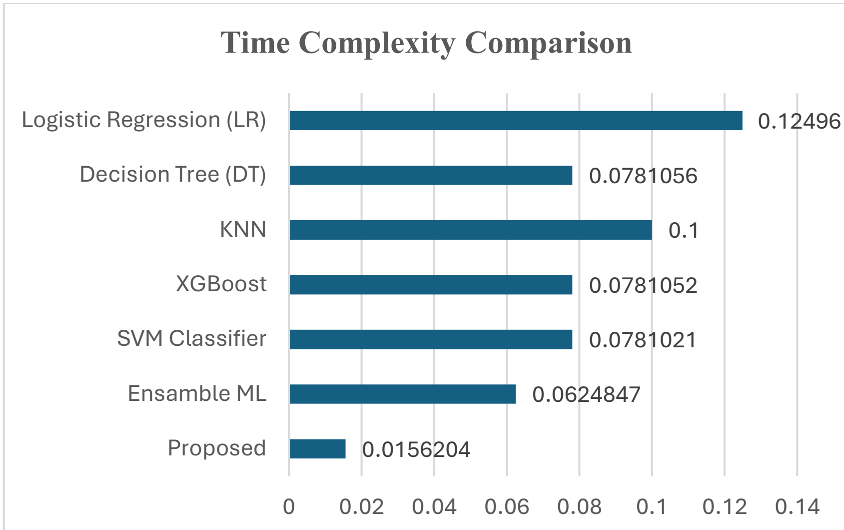


Figure 5: Time complexity

Figure 5presents a comparative analysis of the time complexity between the proposed model and existing models in breast cancer detection. The existing model exhibits a longer time in delivering results, which could potentially impact patient outcomes adversely. In contrast, the proposed model demonstrates a significantly reduced time complexity, offering a more efficient and scalable approach to breast cancer detection. This enhancement in efficiency is crucial in the medical field, as it aims to improve patient outcomes. Correspondingly, Table 3 details the specific time complexity values associated with both models.

Table 3: Time complexity

Model	Time Complexity
Proposed	0.0156204
Ensamble ML	0.0624847
SVM Classifier	0.0781021
XGBoost	0.0781052
KNN	0.1
Decision Tree (DT)	0.0781056
Logistic Regression (LR)	0.12496

5. Conclusion

The newly proposed HBGOMLP-EnML classification techniques have exhibited significantly improved accuracy in the detection of breast cancer. This enhancement is particularly notable when applied based on the BI-RAD classifications derived from mammography images. The implementation of these advanced classification methods marks a promising advancement in the field of diagnostic imaging for breast cancer, potentially leading to better patient outcomes through earlier and more precise detection.The proposed model enhances the assessment of breast lesions by emphasizing their shape and boundaries. It prioritizes these essential characteristics through a modification of the semantic mask, which excludes the tumor center, and by normalizing pixel values. By focusing on the informative areas, the combination of convolutional neural networks with VGG-16 architecture adeptly discern and evaluate key characteristics associated with lesions. This classifier plays a crucial role in the overarching methodology, providing vital insights into the classification of breast cancer.

The proposed approach significantly decreases response time while enhancing patient outcomes through timely detection and informed decision-making. Experimental analysis reveals that the model achieves an accuracy of 98.6%, precision of 97.1%, recall of 97.2%, and an F1-score of 97.2%. In the future, it is crucial to conduct more research that incorporates larger, multi-institutional datasets. This should be accompanied by external validation and assessments to fully understand the additional benefits of the proposed methodology prior to its implementation in clinical environments. Moreover, enhancing prediction capabilities through optimization algorithms rooted in reinforcement learning will further refine the model's effectiveness.

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