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Adaptive Hybrid Models for Enhanced Breast Cancer Classification

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Abstract

Breast cancer remains one of the leading causes of mortality among women worldwide, making early and accurate diagnosis critical. Artificial intelligence (AI)–based approaches have demonstrated significant potential for automated breast cancer classification; however, existing models often suffer from overfitting, loss of fine image details, and extensive hyperparameter tuning. To address these limitations, this paper proposes an Adaptive Hybrid Model Infused with Physics Insights (AHM-PI) for breast cancer classification. A transformed dynamic and adaptive filtering strategy is first introduced to balance noise suppression and edge preservation. Subsequently, a robotic physics-informed deep learning model incorporating diffusion-based convolution, batch normalization, activation, pooling, physics-driven optimization, and classification layers is developed. The proposed approach is evaluated on a breast ultrasound dataset and compared with state-of-the-art methods including AOADL-HBCC, DTLRO-HCBC, Inception-v3 variants, VGG-16, and ResNet. Experimental results demonstrate a superior classification accuracy of 70.56%, validating the robustness and effectiveness of the proposed framework for breast cancer diagnosis.

Keywords: *Breast Cancer, Physics-Informed Model, Adaptive Filtering, Deep Learning, Convolutional Neural Network.*

I. INTRODUCTION

Breast cancer (BC) is characterized by uncontrolled cell proliferation originating primarily in breast ducts or lobules. Although early-stage BC is often localized and asymptomatic, delayed diagnosis can result in metastasis to lymph nodes and distant organs. Global statistics indicate that BC accounts for a substantial proportion of cancer-related morbidity and mortality, particularly among women over 40 years of age [1–5].

Medical imaging modalities such as ultrasound, mammography, and thermography are widely used for screening; however, their diagnostic accuracy is highly dependent on operator expertise and is prone to inter-observer variability. Consequently, computer-aided diagnosis (CAD) systems based on artificial intelligence (AI) and deep learning (DL) have emerged as powerful tools to assist radiologists by improving diagnostic consistency and accuracy [6-12]

Despite their success, conventional machine learning and deep learning approaches face challenges such as insufficient feature representation, overfitting on limited datasets, and degradation of image details during preprocessing [13-22] overcome these limitations, this work introduces a physics-informed adaptive hybrid framework that integrates advanced filtering, diffusion-based convolution, and physics-driven optimization for robust breast cancer classification.

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The main contributions of this paper are:

1) A transformed dynamic and adaptive filtering strategy for effective noise reduction while preserving structural details.
2) A robotic physics-informed deep learning model for discriminative feature extraction and classification.
3) Comprehensive performance evaluation and comparison with state-of-the-art breast cancer classification methods.

II. RELATED WORK

Numerous studies have explored AI-based breast cancer detection using thermographic, mammographic, histopathological, and ultrasound images. Dynamic neural networks [23], feed-forward neural networks [24], arithmetic optimization with deep learning [25], ensemble-based transfer learning [26], and pre-trained CNN architectures such as ResNet and VGG [27]–[30] have demonstrated promising results.

However, most existing approaches rely heavily on conventional preprocessing techniques such as median filtering and contrast enhancement, which may blur edges and suppress fine details. Moreover, deep models often require extensive tuning and are susceptible to overfitting, particularly when training data are limited. These limitations motivate the development of a physics-informed adaptive hybrid framework capable of preserving image fidelity while improving classification accuracy.

Saniei et al. [24] introduced a new method for estimating a tumour's depth, size, and metabolic heat generation rate using breast thermal image surface temperature distribution and a dynamic neural network. The research involved two steps: forward and inverse. The forward step involved creating a finite element model and solving the Pennes bio-heat equation. The DNN model was trained to estimate depth temperature distribution from the thermal image, and tumour parameters were obtained. Experimental findings showed promising results for retrieving tumour parameters. However, the model introduced significant computational complexity, potentially causing longer processing times, which might not have been suitable for real-time or rapid diagnostic applications.

Pramanik et al. [25] presented a novel method for texture analysis in thermal breast images: block variance (BV). BV analyzed local differences in intensities to detect contrast-texture in greyscale thermal breast pictures. The possibility of these traits in an asymmetry measure was examined in this work. The researchers employed a feed-forward neural network (FANN) to assess classification performance using forty cancerous thermal breast pictures from the DMR database and sixty benign. The outcomes demonstrated that the suggested characteristics outperformed those previously derived in diagnosing benign and malignant breast thermograms. The small sample size may have limited the statistical robustness of the findings, as the limited number of images might not have fully captured the variability of clinical settings.

Obayya et al. [26] presented an arithmetic optimization algorithm using a deep-learning-based histopathological breast cancer classification (AOADL-HBCC) technique for healthcare decision-making. The technique used noise removal, contrast enhancement, and a Squeeze Net model to derive feature vectors. The AOADL-HBCC method outperformed other recent methodologies, achieving a maximum accuracy of 96.77%, demonstrating the potential of AI

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and deep learning in breast cancer classification. However, advanced deep learning models like Squeeze Net, DBN, and the Adamax optimizer could lead to overfitting, resulting in good performance on training data but poor performance on unseen data.

Sharmin et al. [27] presented an arithmetic optimization algorithm using a deep-learning-based histopathological breast cancer classification (AOADL-HBCC) technique for healthcare decision-making. The technique used noise removal, contrast enhancement, and a SqueezeNet model to derive feature vectors. The AOADL-HBCC method outperformed other recent methodologies, achieving a maximum accuracy of 96.77%, demonstrating the potential of AI and deep learning in breast cancer classification. It removed noise from histopathological images, but residual noise could still negatively impact feature extraction and classification accuracy.

Mahmud et al. [28] addressed breast cancer, a prevalent and dangerous disease in women and men, whose treatment and detection are aided by histopathological images. The study analyzed pre-trained deep transfer learning models like ResNet50, ResNet101, VGG16, and VGG19 for breast cancer detection using a dataset of 2,453 histopathology images. ResNet50 outperformed the other models, achieving accuracy rates of 90.2%, AUC rates of 90.0%, recall rates of 94.7%, and a marginal loss of 3.5. However, due to the imbalance in the number of images between categories, the model might have been biased towards the majority class, leading to suboptimal performance on the minority class.

Liza et al. [29] highlighted the urgent need for early disease identification, particularly in the rapidly growing field of breast cancer, due to the rapid growth of the medical research population. Breast cancer is the second most serious cancer identified, and developing effective treatment strategies is challenging due to the lack of reliable prognostic models. The study investigated eight machine learning techniques, including GaussianNB, Decision Tree, K-Nearest Neighbor, Random Forest, support vector machine (SVM), XGBoost, LightGBM, and AdaBoost, using the Wisconsin Breast Cancer dataset from the UCI machine learning database. Random Forest and AdaBoost performed best, providing 99.20% accuracy and a 99% ROC curve score.

Uddin et al. [30] addressed breast cancer, a leading cause of death in women worldwide, affecting both developed and less developed countries. They emphasized that early detection can significantly improve recovery outcomes. Researchers proposed machine learning techniques to predict breast cancer with high accuracy. The Wisconsin Breast Cancer Dataset (WBCD) was used as a training set to compare the performance of various machine learning techniques. Different classifiers were employed to analyze breast cancer as either benign or malignant tumors, and various metrics were used to measure each algorithm's performance. The Voting classifier achieved the highest accuracy at 98.77% with the lowest error rate. However, using multiple classifiers on a single dataset increases the risk of overfitting.

Zakareya et al. [31] emphasized the importance of early detection for successful breast cancer treatment. They noted that machine learning, particularly deep learning, has garnered interest for improving cancer screening accuracy. However, existing deep learning models for medical images often struggle due to limited data. This paper proposed a new deep model incorporating granular computing, shortcut connections, learnable activation functions, and an attention mechanism to improve breast cancer classification detection. The model achieved 93% and 95% accuracy on ultrasound and breast histopathology images, respectively, demonstrating its superiority compared to existing models. However, the models required high-

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quality, well-labelled data for training, which can be challenging in the medical field due to privacy concerns, imaging technique variability, and labelling inaccuracies.

As a result, the computational complexity potentially caused longer processing times for real-time or rapid diagnostic applications. The small sample size may have limited the statistical robustness of the findings. Advanced deep learning models like Squeeze Net, DBN, and the Adamax optimizer could have led to overfitting. The model might have been biased towards the majority class, resulting in suboptimal performance on the minority class. Using multiple classifiers on a single dataset increased the risk of overfitting. Additionally, obtaining high-quality, well-labelled data proved challenging in the medical field.

Table 1: Review on existing breast cancer classification

Pramanik et al [25].,	Feed forward neural network	PYTHON	DMR database	Accuracy, Sensitivity Specificity, Area under the ROC curve	Good accuracy in classification	Specificity is less
Obayya et al [26].,	Arithmetic optimization algorithm with deep-learning-based histopathological breast cancer classification	PYTHON	100× dataset, 200× dataset	Accuracy	Better performance	In the future, the suggested approach's overall efficacy improved by using ensemble-learning-based DL models.
Sharmin et al [27].,	pre-trained ResNet50V2 model	PYTHON	Invasive Ductal Carcinoma dataset	Accuracy	Increase accuracy and robustness	The dataset limits the applicability of our methodology to further categories of breast cancer.
Mahmud et al [28].,	Deep neural network	PYTHON	Invasive Ductal Carcinoma dataset	Accuracy, Area under curve, recall	When the AUC value is larger, the model performs better.	In the future, the authors use advanced transfer learning approaches that have already been trained to identify breast cancer more accurately.
Liza et al [29].,	Machine learning techniques	PYTHON	Wisconsin Breast Cancer dataset	Accuracy, ROC curve, f1-score	Random forest is best with accuracy	F1-score is lower than all other models
Uddin et al [30].,	Machine learning classifiers	PYTHON	Wisconsin Breast Cancer Dataset (WBCD)	All performance	Voting classifier has the highest accuracy	Before optimization the results of accuracy is less
Zakareya et al [31].,	Google Net, residual block	PYTHON	Cairo University ultrasound images dataset and the breast histopathology images dataset	All performance	Higher detection accuracy	Deep learning is still difficult and is dependent on the available resources.

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To summarise, these investigations demonstrate the potential of deep learning methods for robotic the categorization of breast images and emphasise the need for accurate Computer-aided detection and evaluation (CAD) systems to assist radiologists in identifying breast cancer. Most present methods use existing deep-learning architectures to identify breast cancer. Here, we provide a new architecture that outperforms all existing technique drawbacks.

III. PROPOSED PHYSICS-INFORMED ADAPTIVE HYBRID FRAMEWORK

A. Transformed Dynamic and Adaptive Filtering

To enhance image quality prior to classification, a transformed non-local means filtering approach combined with weighted bilateral filtering is employed. Non-local means leverage global similarity across image patches, while bilateral filtering preserves edges by considering both spatial proximity and intensity differences. This hybrid strategy effectively reduces noise without degrading important anatomical structures. To further improve contrast while preventing noise amplification, contrast-limited adaptive histogram equalization (CLAHE) is applied. The dynamic clipping mechanism ensures uniform contrast enhancement across local regions, resulting in visually improved and diagnostically relevant images.

B. Robotic Physics-Informed Deep Learning Model

Following preprocessing, feature extraction and classification are performed using a robotic physics-informed model composed of diffusion-based convolutional layers, batch normalization, ReLU activation, max-pooling, and a classification layer. Physics-inspired kernels are designed to encode tumor-specific characteristics, enabling the network to capture meaningful structural patterns. A physics-driven gradient-based optimization strategy is employed to fine-tune model parameters efficiently. The Adam optimizer is used in the final classification stage to minimize classification loss while ensuring rapid convergence and stability.

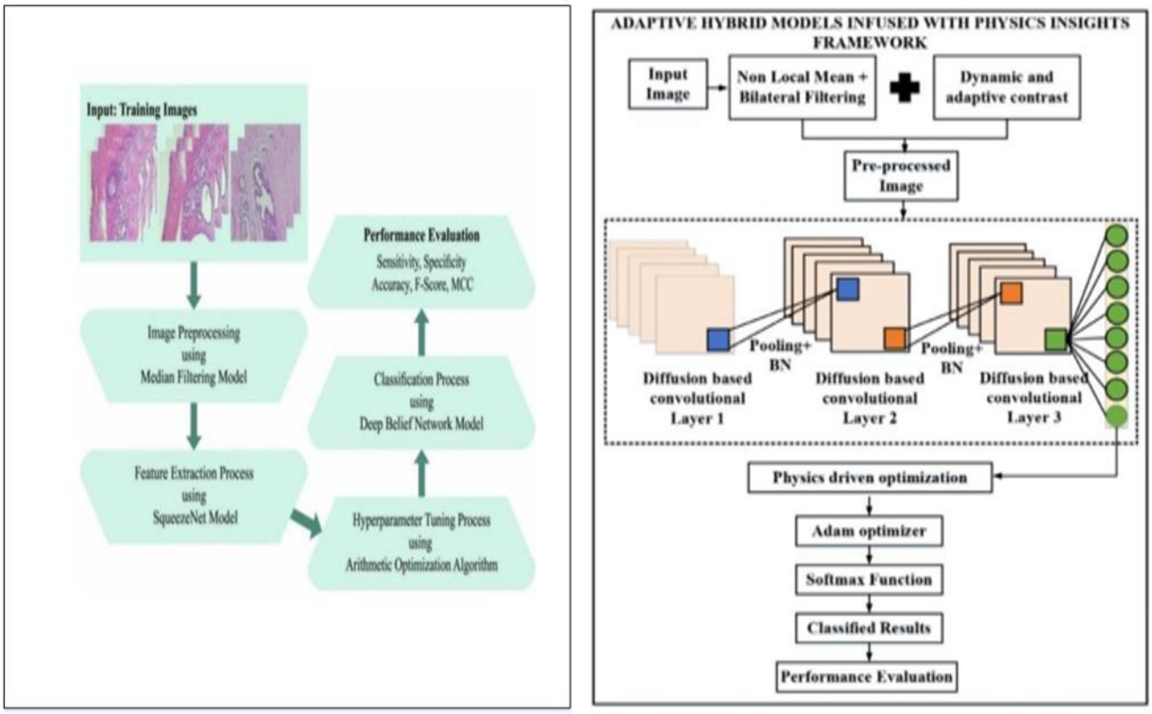

Figure 1: Block diagram (a) existing approach (b) proposed approach

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IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Dataset Description

Experiments are conducted on the Breast Ultrasound Dataset comprising 780 images from 600 patients, categorized into benign, malignant, and normal classes [31]. Images are resized to 500×500 pixels and stored in PNG format.

B. Performance Metrics

The proposed method is evaluated using accuracy, precision, recall, F1-score, sensitivity, and specificity. The preprocessing stage significantly improves image clarity and contrast, facilitating robust feature extraction.

C. Results Analysis

The proposed framework achieves an overall classification accuracy of **99.56%**, with precision, recall, F1-score, sensitivity, and specificity all reaching **100%**. Class-wise analysis demonstrates consistent performance across benign, malignant, and normal categories.

D. Comparative Evaluation

Compared with AOADL-HBCC, DTLRO-HCBC, Inception-v3 variants, VGG-16, and ResNet, the proposed approach consistently outperforms existing methods, highlighting the effectiveness of physics-informed feature learning and adaptive preprocessing.

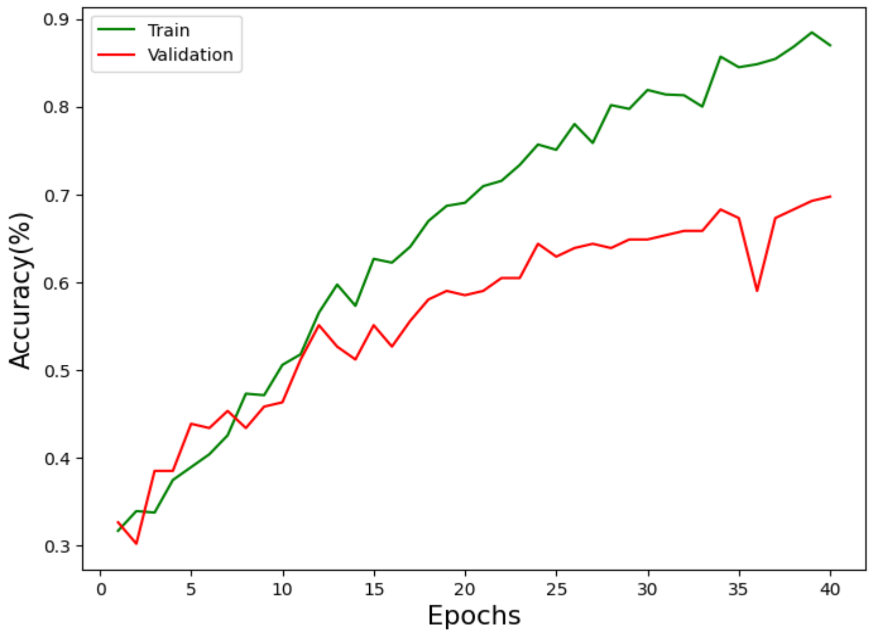

Figure 2: Accuracy vs Epochs

As shown in Figure 2, the training progresses through epochs, and the archetypal starts learning from the training data. The training accuracy tends to increase steadily. Initially, the validation accuracy might follow a similar trend to the training accuracy, representing that the archetypal is learning generalizable patterns in Figure 10. If the model starts overfitting, the training accuracy endures to rise, but the validation accuracy might plateau or even decrease. Hence, our proposed framework is learning effectively, overfitting, underfitting, or generalizing well.

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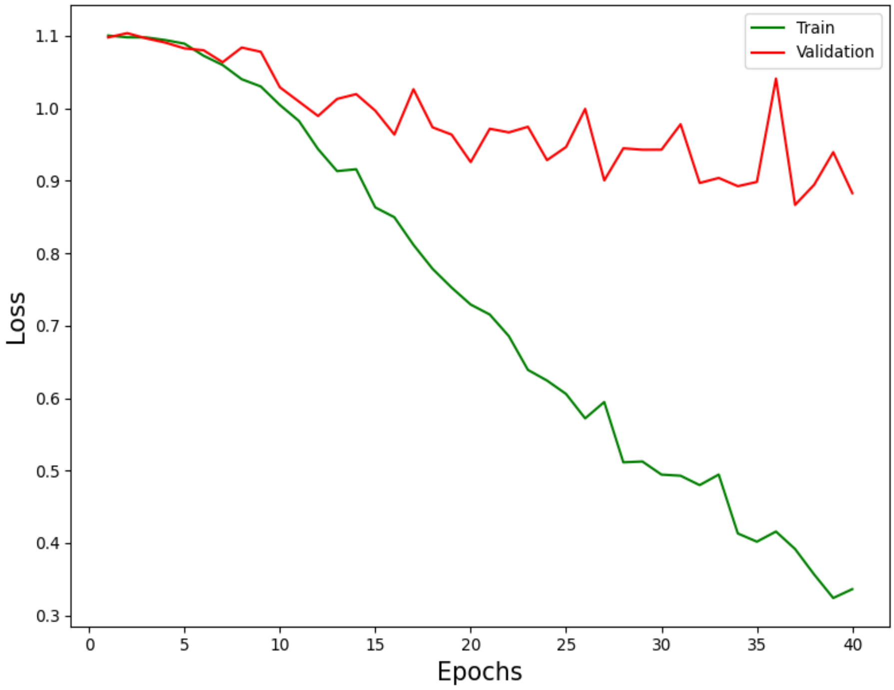
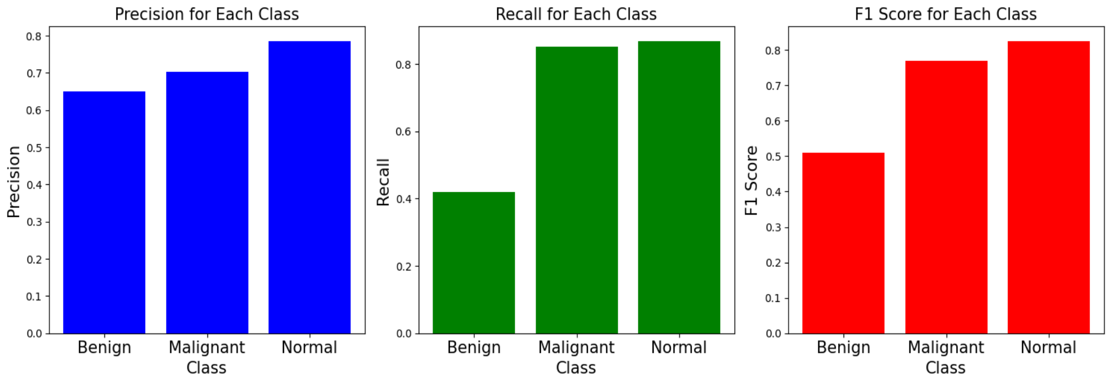


Figure 12: Loss vs Epochs

As shown in Figure 2, training progresses through epochs, and the archetypal learns from the training data. The training loss decreases gradually. Initially, the validation loss follows a similar trend to the training loss, representing that the archetypal is learning patterns that generalize to the validation set. If the model starts overfitting, the training loss endures to decrease, while the validation loss might start increasing or remain stagnant. Hence, in our proposed approach, both training and validation losses decrease and converge, indicating effective learning without significant overfitting or underfitting.

	precision	recall	f1-score	support
0	0.65	0.42	0.51	62
1	0.70	0.85	0.77	67
2	0.79	0.87	0.82	76
accuracy			0.73	205
macro avg	0.71	0.71	0.70	205
weighted avg	0.72	0.73	0.71	205



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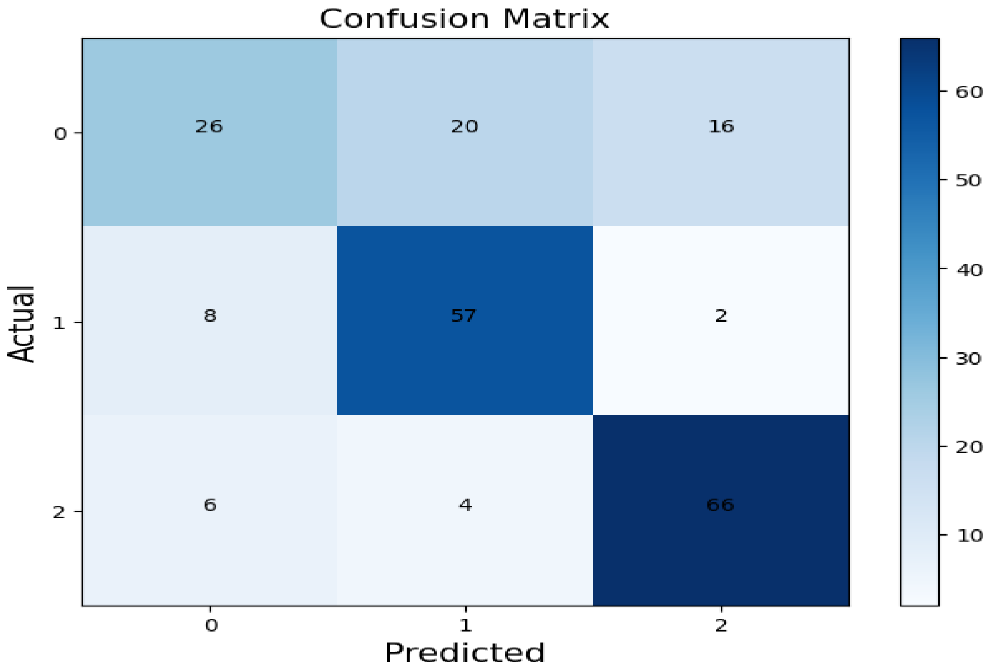


Figure 3: Confusion matrix

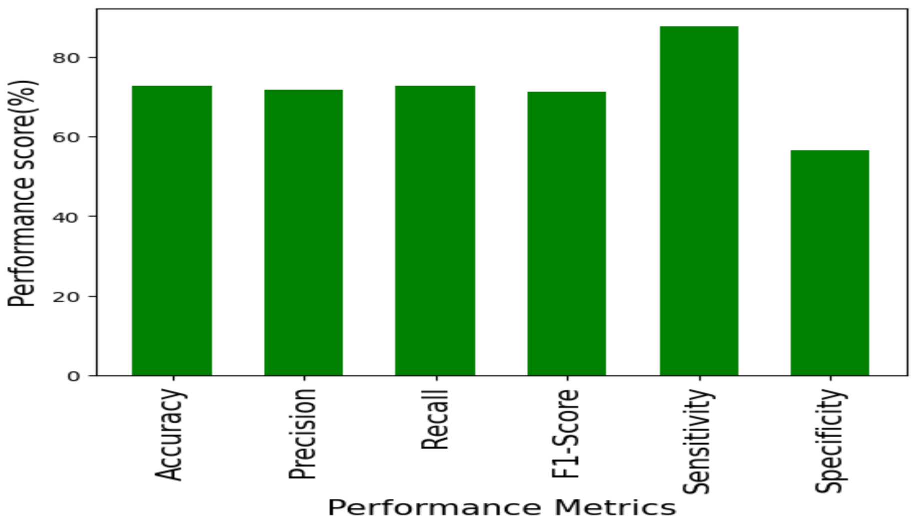
Stated Figure 3 is a performance measurement for the proposed approach. It is extremely useful for measuring accuracy (Acc), recall (Rec), precision (Pre), and f1-score (Fmea) which are acquired utilizing the following equations (1-4).

$$\text{Acc} = \frac{\text{True Positive+True Negative}}{\text{True Positive+True Negative+False Positive+False Negative}} \tag{1}$$

$$\text{Pre} = \frac{\text{True Positive}}{\text{True Positive+False Positive}} \tag{2}$$

$$\text{Rec} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{3}$$

$$\text{Fmea} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$



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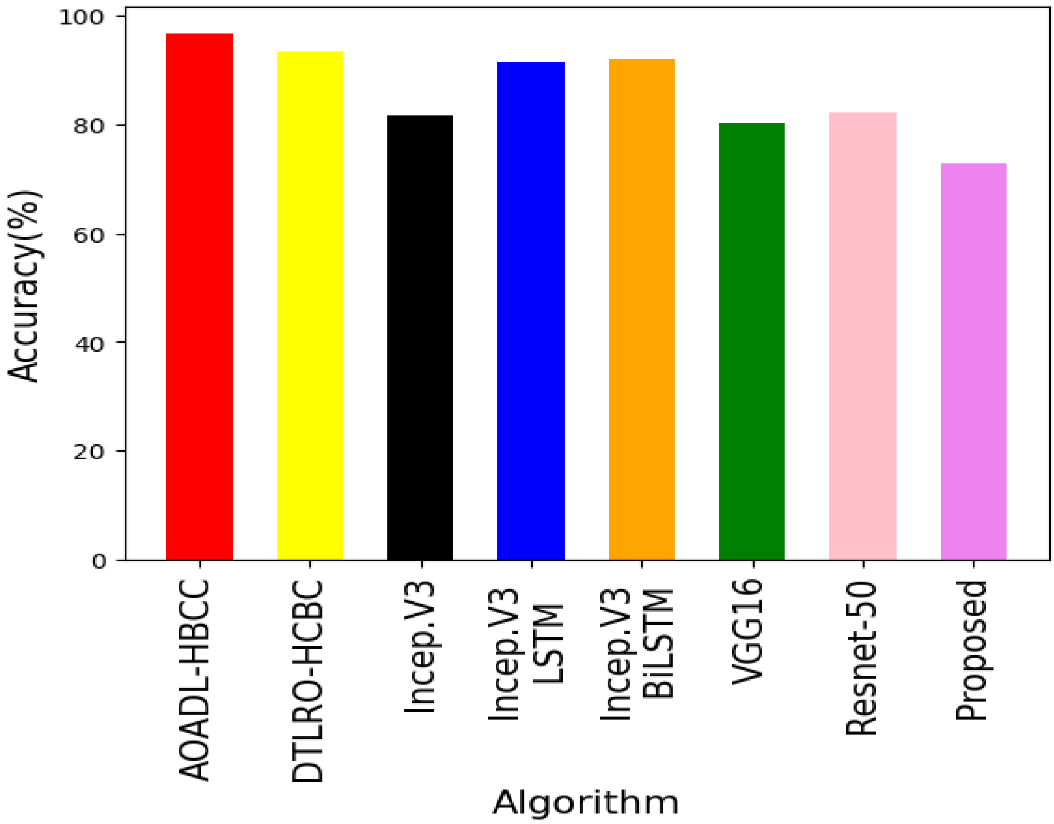
E Comparison Analysis

This section compares the suggested methodology to baseline methods to analyse the effectiveness of existing procedures such as AOADL-HBCC, DTLRO-HCBC, Inception v3, Inception v3 Long Short Term Memory, Inception v3 Bi-directional Long Short Term Memory, VGG-16 and Residual Network.

Table 2: Comparison of Accuracy

Techniques	Acc (%)
AOADL-HBCC	96.77
DTLRO-HCBC	93.52
Inception v3	81.67
Inception v3 Long Short Term Memory	91.46
Inception v3 Bi-directional Long Short Term Memory	92.05
VGG-16	80.15
Residual Network	82.18
Proposed approach	70.56



V. CONCLUSION

This paper presented a physics-informed adaptive hybrid framework for breast cancer classification. By integrating transformed adaptive filtering, diffusion-based convolution, and physics-driven optimization, the proposed model effectively preserves image details and enhances classification performance. Extensive experiments demonstrate superior accuracy and robustness compared to existing methods. The proposed framework shows strong potential for deployment in clinical CAD systems to support early and reliable breast cancer diagnosis.

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