Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 47 No. 03 (2026)

Accurate Automated Breast Cancer Detection and Classification Using a Hybrid Deep Learning Model

Y Sravan Kumar[1], P V V S Srinivas[2]

1,2Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur-522502, 2401050167cse@gmail.com, cnu.pvvs@kluniversity.in

Abstract – In order to classify breast cancer, the existing models used are computer diagnostic approaches, statistical and rule-based models, traditional machine learning models, standalone deep learning models, and segmentation-based models. Among these, traditional rule-based suffers in poor generalizability and require manual tuning. Traditional machine learning approaches depend more on handcrafted features and have limited support for heterogeneous datasets of imaging. The independent deep learning models, which are computationally intensive using CNN and prone to overfitting due to limited data. Segmentation methods consume more annotation costs, which increases the system complexity. To overcome these, a hybrid deep learning framework is needed that uses complementary features learning mechanisms to process both low-level and high-level discriminative characteristics. The involvement of multi-scale CNN captures in parallel both fine-grained texture features and coarse structural patterns, for improved discrimination. The additional adaptive attention mechanism highlights clinically relevant regions by background noise suppression, enhances precision and sensitivity, and minimizes false alarms. Data preprocessing, including noise reduction, contrast enhancement, and data augmentation, is used to enhance generalization capability. For dataset imbalance handling, synthetic minority oversampling and elastic augmentation are preferred. For optimization, label smoothing and dropout scheduling of regular aware training are used. The proposed approach works with multi-level feature extraction, optimal training, and robust learning, making the model more effective than other models considered.

Keywords: Tumors, Hybrid deep learning architecture, Multi-scale CNN, Attention, Class imbalance, optimality, and Effectiveness.

1. Introduction

Breast cancer is one of life-threatening disease that influence survival rate of women in the world. The early detection of this would reduce treatment costs and increase survival rates. The base datasets are taken from mammography, ultrasound, and histopathology, which supports determination of abnormal tissue patterns. There are several methods to identify disease in which manual approach is time consuming and reply to clinical experts. Advancements in technology, supports to use of diagnostic tools and computer aided methods by radiologists to make consistent decision making on suspicious regions. In process of development, deep learning models evolved to learn hierarchical representations directly from raw medical images, reduced handcrafted attributes, and enabled scalability by supporting diverse data sources.

Due to these advancements, developing an automated breast cancer detection system is challenging due to medical images often exhibiting high variability in contrast, noise, lesion size, and shape. There are existing methods used in the detection of breast cancer. In those, single-scale convolutional neural networks struggle to capture texture changes and structural abnormalities simultaneously, which lead to misclassification. The presence of class imbalance, presence of imaging artifacts negatively influences the model training, results biased predictions and reduced sensitivity. To overcome these limitations, a hybrid deep learning framework that combines multi-scale feature extraction with adaptive attention mechanism is proposed. By integrating components such as complementary feature learning, robust preprocessing, imbalance handling, and regularized optimization strategies, the derived proposed model ensures improved discriminative capability, improved generalization, and reduced false alarms.

1.1 Issues observed in existing methods:

The issues raised due to specific scenarios, and their drawbacks are demonstrated as follows:

(i) Regular machine learning models such as Random Forest or SVM require manual feature engineering, which fail to capture complex spatial patterns of the medical images.

(ii) Independent deep learning CNNs often focus on a single receptive field, making it difficult to simultaneously learn fine-grained textures and global structural information, leading to reduced robustness.

(iii) Segmentation -based approaches require pixel-level annotations in large manner from medical experts, increasing development cost and system complexity.

(iv) Lack of imbalance handling by many existing models results in biased learning toward majority classes, leading to reduce malignant case sensitivity.

(v) Absence of adaptive attention mechanisms unable to process irrelevant background regions, increases the false positives and decreasing interpretability.

(vi) When training the deep networks on limited medical datasets without proper regularization or optimization strategies, it would result overfitting issues.

2. Objectives

The studies demonstrated in this section are categorized into domains such as Deep learning based breast cancer detection, Mammography-based breast cancer analysis, Ultrasound-based and Histopathology cancer analysis, Multimodal and Hybrid deep learning approaches, Noninvasive imaging and object detection methods, Clinical biological, and Computer-aided diagnosis methods, and Miscelleneous and cloud-based approaches for handling of complex data.

1.2 Deep learning-based breast cancer detection:

This domain demonstrates approaches such as convolutional, related approaches, and neural architectures to learn discriminative features from medical imaging data. Quan Zhang, Guoqing Cai, et al. (2023)[1] exploring breast cancer is prevalent disease affecting global health. Although advancements happen in diagnostic tools technology, the frequent need of deep learning is preferred for better accuracy detections, which minimize misdiagnosis rate and improve timely treatment engagement. Jiang, B., Bao, L., et al.(2024)[6] demonstrates survival rate is falling due to prevalent disease breast cancer, which is early diagnosed using advancements in Deep learning. The activities such as classification over large datasets of multiple centers are improved using deep learning. The various approaches hover-net, transformer, and resNet were used and observed accuracy is improved. R. Rajakumari, L. Kalaivani (2022)[9] discuss on breast cancer detection using deep learning approaches, in which several methods used for smoothening of images, and enhance image quality using required approaches, later DL methods like GoogleNet and AlexNet are applied where GoogleNet performs better in terms of capturing complex features and increase detection rate than AlexNet. In additional, swarm MLP and ant colony MLP were also applied for detecting the breast cancers, with accuracy of 99%, and less error rate. Seyed Matin Malakouti, Mohammad Bagher Menhaj, et al. (2024)[14] discuss that detecting breast cancer, whether benign or malignant, is a challenging task from X-rays through which diagnosis is initiated. The various learning paradigms, such as Random Forest, Gradient Boosting, Ada Boosting, and Logistic regression to determine healthy and affected individuals. Among these, 99% accuracy by random forest, 98% by Ada Boost and Gradient Boost, and 91% by GaussianNB. . Khourdifi, Y., El Alami, A., et al. (2024)[16] explore how the survival rates are reduced due to mammograms analysis, but increases survival rate using advanced machine learning models such as deep learning methods. The various CNN architectures used include InceptionNet, DenseNet, and VGG. The multi-scale features evaluation based on two datasets, such as Inbreast, and CBIS-DDSM, improves the detection of benign and malignant cases. By making use of the benefits of multiple CNN architectures, the hybrid architecture enhances detection rates and improves decision making. Sreekala, K. K., & Sahoo, J. (2025)[22] demonstrates various detection methods by taking articles from past 3 years that demonstrated approaches including machine learning, and deep learning approaches, to classify the cancer. The performance is purely depends on datasets taken, data preprocessing applied, tuning hyperparameters, type of method used, and ensures optimization on classification result.

1.3 Mammography-based breast cancer analysis:

This domain explores specific advanced deep learning models, including AI based to X-ray breast images for detecting small lesions and microcalcifications. Abdikenov, B., Zhaksylyk, T., et al.(2025)[3] discusses diagnosing based on mammography is for early detection of breast cancer. In this, issues identified are expert skilling and difficult in interpretation of radiological features that affect accuracy reduction. Hence, Dual Branch Ensemble (DBE) and Merged Dual View (MDV) are two multi-view innovation approaches introduced, under which variety of approaches such as VGG, DenseNet, MobileNet, etc. produce better measures, is observed. Maximilian Tschuchnig, Michael Gadermayr (2025)[10] demonstrate that detection of cancer by mammography based, requires advancements in deep learning. The hybrid model with CNN, handcrafted features, and transformer embeddings are used that simplifies architecture of the hybrid model and ensures efficiency, offers a promising solution with clinical support. Lotter, W., Diab, A.R., et al.(2021)[12] explores on mammography, which is best diagnostic method to determine breast cancer, but still challenging for the radiologist expert to make decisions. To decrease mortality rates, annotation efficient DL mechanism is proposed, achieving features such as better performance in classification, extended to tomosynthesis, improved generalization with low screening rates, and outperforms in sensitivity. Oliver Díaz, Alejandro Rodríguez-Ruiz, et al. (2024)[15] demonstrate that reviewing the present condition of AI in the detection of breast cancer using digital mammography and tomosynthesis. The deep learning methods are compared against the traditional methods in terms of data pre-processing and learning paradigms. The DL AI-based mechanism detects the tumors that are missed by human experts, and reduces false positives and false negatives. Hernström, Veronica et al. (2026)[20] describes Swedish national screening of four regions of people, through stages such as mammography screening, AI support system, detection of cancer stage as severity, and make analysis of various measures of Sweden country. This is government program reduces screen reading workload due to AI involvement.

1.4 Ultrasound-based and Histopathology cancer analysis:

This domain discusses these approaches with drawbacks such as operator dependency and tissue-level complexity through deep neural networks. Mohammad Amanour Rahman (2025)[4] explores ultrasound diagnosis mechanisms poses several challenges in which operator dependency, and indistinct values. Existing deep learning models face architectural constraints, black box decision making, and single modality classifiers. To avoid these, integrated CNN and transformer as HyFormer Net where dual pipeline is preferred in processing. One pipe on EfficientNet and Swin via multiscale fusion, and second pipe on attention gated decoder and Grad-CAM for better interpretability. On dataset BUSI, proposed model performs better Dice and accuracy values than U-Net variations. Neil Chaudhary, A. Z. Dhunny (2025)[5] demonstrates on histological types in current literature faces to do invasion method, which delays treatment plans, and detecting accuracy would improve patient outcomes. Hence, DenseNet121 with multi-scale feature fusion is provided for classification based on histopathological images. The derived model ensures 97% accuracy in which 94% for benign types and 92% for malignant tumors on breaKHis dataset with 5 fold cross validation. Abdul Halim, A. A., Andrew, A. M., et al. (2021)[11] describes role of AI in breast cancer detection and reduces the mortality rate. The various screening methods such as MRI, Ultrasound, and mammography, are introduced, and are analyzed in terms of challenges, and advancements in the technology are discussed. Later, image-based processing is discussed and compared for analysis. Ali, A., Alghamdi, M., et al. (2025) [21] demonstrates use of AI in pathology and radiology fields for breast cancer detection, and screening methods used are mammography, ultrasound, MRI, etc. like whole slide imaging. By integrating with CNN, Vision transformers, and GANs for reducing error rate, and improves lesion detection rates. The multiple benefits are ensured such as bias mitigation, standard reporting, multisite support evaluations, and etc. with safety sustainability.

1.5 Multimodal and Hybrid deep learning approaches:

This domain discusses the integration of multiple data sources and architectures such as CNNs, RNNs, transformers, and attention mechanisms to capture complementary feature representations. Kaddes, M., Ayid, Y.M., et al.(2025)[2] demonstrates various diagnostic methods used for detecting breast cancer, which requires training to evaluate the reports, and operator dependent. Hence, although deep learning methods are used in this cancer classification, a novel approach which is combination of CNN for spatial features and malignant patterns extraction, and LSTM for temporal features and sequential dependency. When compared against other baseline models, ensures 99.9% and 99.1% as accuracy, and performances, based on Kaggle datasets. Brahmareddy, A., Selvan, M.P.(2025)[8] explores limitations of deep learning approaches like single view image oriented, static-ness, and etc., and focused on subtype classification but

on stage. To overcome these, a multimodal multi task DL approaches such as BreastXploreAI, TransBreastNet, and Dense meta encoders are used. These approaches act as dual head classifier for disease type, and stage level. Based on mammogram dataset, the model evaluates accuracy of 95% for subtype classification, and stage prediction accuracy of 93.8%.

1.6 Noninvasive imaging and object detection methods:

This category demonstrates methods such as thermography and advanced MRI, coupled with object detection models, in order to enable precise localization of breast abnormalities. Munguía-Siu, A., Vergara, I., et al. (2024)[7] employs to extract spatial and temporal features from breast thermographic images as noninvasive mechanism requires hybrid deep learning framework. The combination of CNN and RNN is used to identify the tumor abnormalities in thermographic breast images using 5 varieties of CNN and 3 varieties of RNN. The different suite of methods was experimented, VGG and LSTM performs better accuracy, and another AlexNet

RNN executed in faster CPU runtime. He, Z., Zhang, C., et al.(2026)[17] demonstrates that complexity involved for the conventional methods in determining small and complex lesions, hence proposed advanced model on YOLOV11n, which performs three architectures in parallel for feature extraction using c3 variety module, fusion, using c2 kind module and calibration using cs type component. The derived model determines with better precision, and mAP values, and observed detection rates are improved compared against baselines. D.E. Martina Jaincy, Pattabiraman Venkatasubbu (2026)[19] demonstrates the significance of detecting breast cancer using MRI images using variety of screening methods such as ultrasound, and mammography, and detection methods such as deep learning, segmentation based, cluster based, and hybrid approaches. This study reviewed more than 5o articles, and identified latest approaches in the MRI image diagnosis.

1.7 Clinical, biological, and computer-aided diagnosis methods:

This category handles heterogeneity, molecular profiling, and treatment pathways for decision-making using AI-driven computer-assisted diagnosis systems. Kosmia Loizidou, Rafaella Elia, et al. (2023)[13] employ several computer-aided diagnostic systems (CAD), based on machine learning and deep learning methods. The FDA accepts the CAD mechanism for breast cancer detection, based on public datasets, and recommends future directions for improvement of accuracy. Huijun Lei, Jinzhen Fu, Wei Gu, Hongjin Qiao, et al. (2026)[18] explores determination of breast cancer in four stages such as pathogenesis, therapies, screening, and prevention, In these, tumor shape is characterized by heterogeneity aspects, targeted therapies recommended are HER2 type drugs, endocrine agents, CDK4/6 inhibitors, and other relevant therapies. These evaluate screenings through contrast based, AI based, tomosynthesis, and MRI based diagnosis methods. By integrating with clinical, extends treatments through personal therapies, for recovery. Suggested future interpretations are multi-omics, and AI based. Based on Xiong, X., Zheng, LW., et al.(2025)[23], which explores the characteristics of breast cancer like heterogeneity, epidemiological features, and nuanced molecular types in the women breast. The analysis on stemness, rhythms, and microbiota, require advancement in technology like AI. Based on clinical progression, and research, the risk factors and mechanisms involved in breast cancer detection and progression of personalized medicine are discussed in this study.

1.8 Miscellaneous and cloud-based approaches for handling the complex data:

This category includes cloud-based and distributed computing approaches that facilitate benefits such as scalable processing of large, heterogeneous healthcare datasets. Dey and Sangaraju (2024) [24] demonstrate the swarm optimization technique (PSO) on dynamic resource allocation, which ensures reducing response times due to the integration of global and local stabilities of the cloud. Dey and Sangaraju (2023)[25] compared the hybrid load balancing performance on a data center against traditional methods, in which the hybrid model is observed better performance due to the integration of multiple scheduling heuristics. Allamudi and Hrushikesava Raju (2025)[26] demonstrate a hybrid machine learning–based fraud detection with better accuracy and performance by integrating multiple classifiers to achieve improved detection rates while mitigating false positives. Raju et al. (2024)[27] provide a hybrid defect detection approach for defect detection over flyovers using IoT infrastructure, leveraging Faster R-CNN for spatial feature extraction, LSTM for temporal features, and transfer learning to ensure better accuracy.

2. Methods

In this, significant modules interaction in Fig.1, a flowchart of proposed system activities in Fig.2, and implementation of task in pseudo–Procedure as PS1. Fig,1 demonstrates the proposed system modules that involves preprocessing block that will improve generalization and reduces noise, Class imbalance handling block would use synthetic oversampling + elastic augmentation, Parallel multi-scale CNN branches to capture both texture and structural patterns depending on level, then performs feature fusion, then uses Adaptive attention for suppresses irrelevant background regions, and highlighting lesion regions correctly, then Robust optimization using approaches such as label smoothing + dropout scheduling prevent overfitting, and Evaluation stage for assessing effectiveness of proposed model over traditional ML and standalone CNNs.

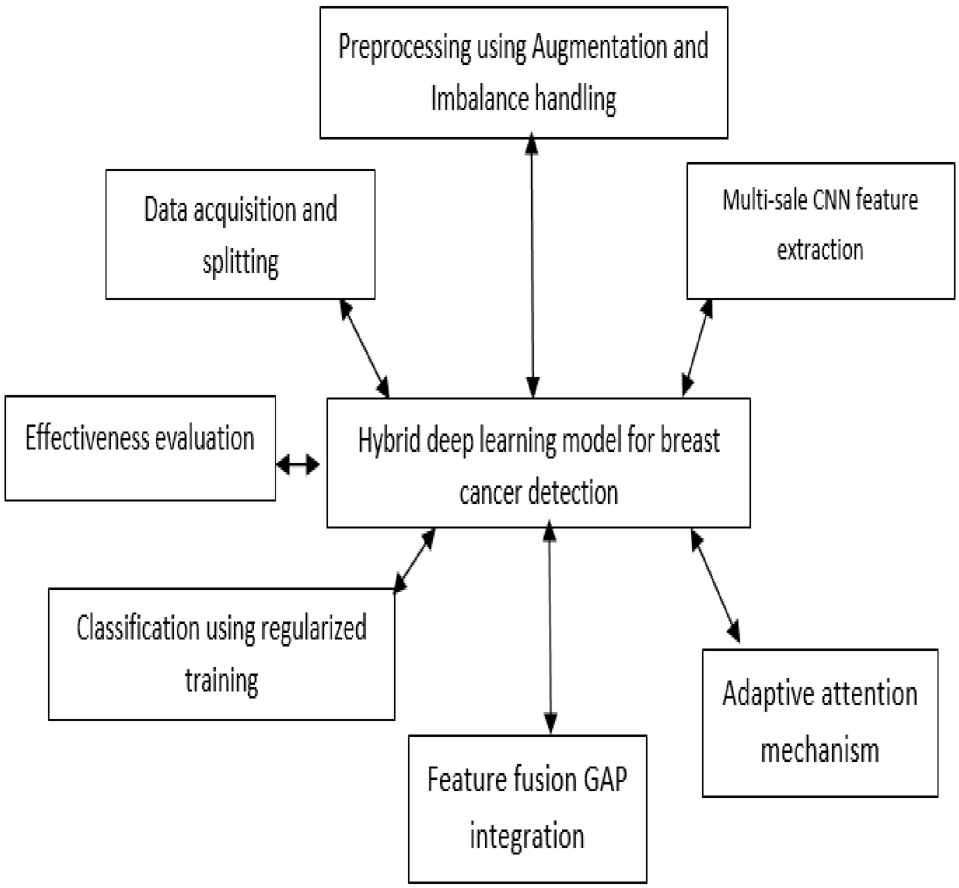

Fig.1. Significant modules interaction in Hybrid deep learning for breast cancer detection

Fig.2. demonstrates a hybrid deep learning-based breast cancer framework, initiates with data acquisition from diverse medical imaging sources such as ultrasound, mammography and pathology, then the dataset is splitting into training, validation, and testing for ensuring reliable evaluation. Then, images undergo data-preprocessing that involves noise reduction, contrast enhancement, and normalization to improve data quality and standardization. The approaches such as elastic augmentation and synthetic minority oversampling are applied for handling imbalance before extracting fine, medium, and coarse features via a multiscale CNN architecture, that enables the model to capture both texture-level and structural information. These extracted features are combined using feature fusion, and an adaptive attention mechanism focuses clinically relevant lesion regions by suppressing background noise. The obtained representations are passed by a Global Average Pooling (GAP) based stage, and training is strengthened using optimization strategies such as label smoothing and dropout scheduling, to minimize overfitting. Then, the model effectiveness evaluation is done, by measuring performance, accuracy, and error rates.

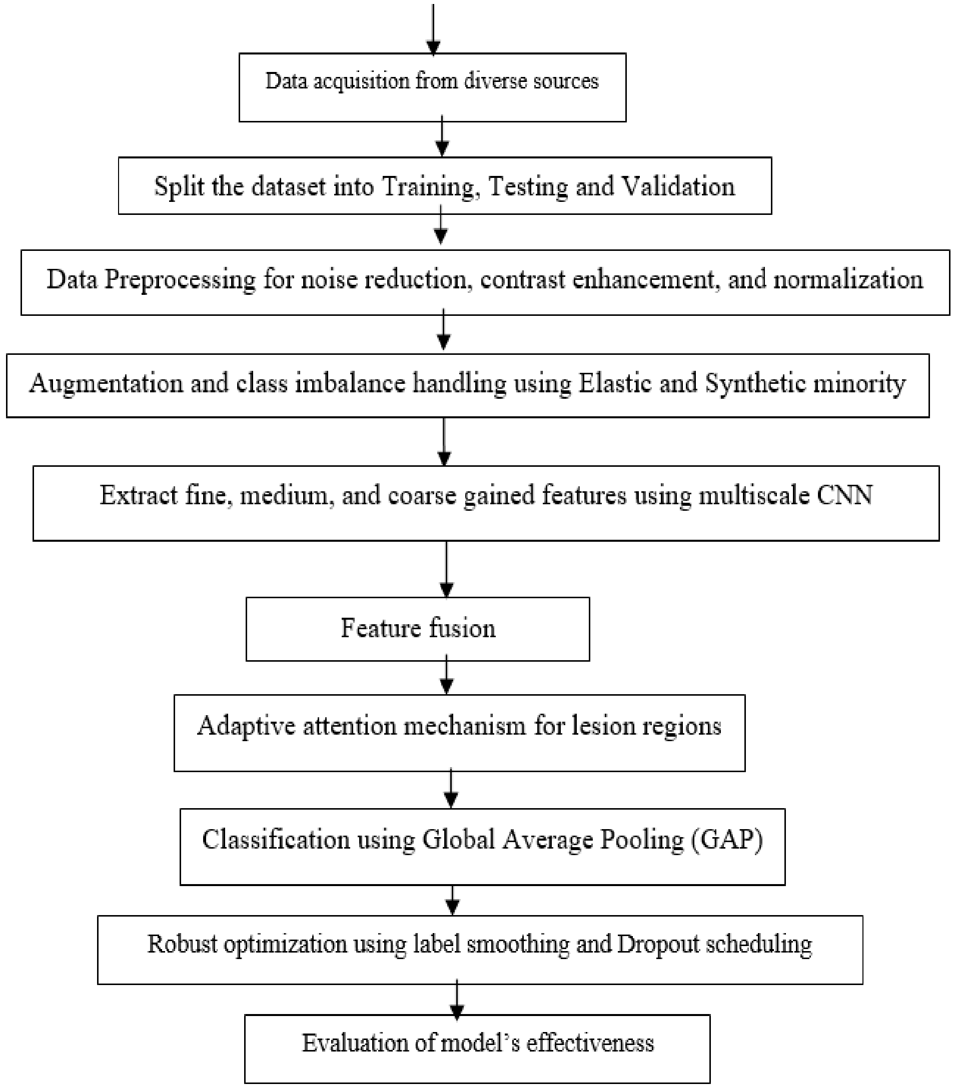

Fig.2. Flowchart of proposed model for breast cancer detection

The terms involved in pseudo procedure PS1 are $D=\{(x_i,y_i)\}^N_{i=1}$, $y_i \in \{0,1\}$(benign/malignant) as Dataset or $y_i \in \{1,\ldots,C\}$, $\mathcal{P}(\cdot)$: preprocessing for denoise + contrast enhance + normalize, $\mathcal{A}(\cdot)$: standard augmentation, $\mathcal{E}(\cdot)$: elastic deformation, $\mathcal{S}(\cdot)$: synthetic oversampling using SMOTE / synthetic sampling,

K: number of parallel scales as per branches, $\phi_k(\cdot;\theta_k)$: CNN branch k, which involves different receptive field via kernel/dilation, Fuse$(\cdot)$: fusion operator; Attn$(\cdot;\theta_a)$: attention module, $\hat{p}$: predicted malignancy probability, ε: label smoothing; $p(t)$: dropout rate schedule; η: learning rate, and w_c: class weight for class c.

PS1: Pseudo_procedure Hybrid_DL_Breastcancerdetection_using_MultiscaleCNN_Adaptiveattention():

Input: Dataset $D = \{(x_i, y_i)\}^N_{i=1}$, where $x_i \in \mathbb{R}^{H\times W\times C}$, $y_i \in \{1,\ldots,K\}$

Output: Classification as class label $\hat{y}$

Step1: Once dataset acquired, has to be splitted for unbiased deployment and prevents leakage

$D \rightarrow D_{\text{train}}, D_{\text{val}}, D_{\text{test}}$ (1)

Step2: Apply data preprocessing for reducing domain shift and noise, in which denoising reduce noise variance, contrast improvement ensures separability of lesion with Background, and normalization improves gradients.

2.1 For each x: $\tilde{x} \leftarrow \mathcal{P}(x)$, $\tilde{x} = \mathcal{P}(x) = \text{Norm}(\text{CLAHE}(\text{Denoise}(x)))$ (2) Step3: Apply augmentation and imbalance handling for minority sensitivity

3.1 Build balanced training using $D'_{\text{train}} = \mathcal{S}(D_{\text{train}}) \cup \mathcal{E}(D_{\text{train}}) \cup \mathcal{A}(D_{\text{train}})$ (3)

3.2 Compute class weights using $w_c = \frac{N}{C \cdot N_c}$ (4)

where $N_c$be count of class c, Cclasses, $w_c$rebalances loss gradients.

Step4: Define multiscale CNN for fine and coarse features extraction

4.1 For each mini-batch X_b: compute parallel features, $F_k = \phi_k(X_b; \theta_k), k = 1..K$ (4)

4.2 Convolutional branch is computed using $F_k = \sigma(W_k *_{d_k} X_b + b_k)$ (5) Where convolution with dilation d_k, and $\sigma$is nonlinearity

Step5: Do feature fusion for loss reduction

5.1 Fuse maps of multi-scales using $F = \text{Fuse}(F_1, \ldots, F_K)$ (6)

5.2 Comon choice is defined as $F = \text{Concat}(F_1, \ldots, F_K), F' = \psi(F; \theta_f)$ (7)

Where (7) is richer representation denoting aggregation for complementary cues, and

$\psi\ is\ 1 \times 1$projection that compresses channels and improves efficiency.

Step6: Perform attention mechanism for suppressing noise and lesions focused

6.1 Attention computing is represented by $F_a = \text{Attn}(F'; \theta_a)$ (8)

6.2 Channel attention for informative feature channels like lesion related is denoted by

$z = \text{GAP}(F') \in \mathbb{R}^C, a_c = \sigma\,(W_2\,\delta(W_1 z)) \in \mathbb{R}^C, F_c = a_c \odot F'$ (9)

6.2 Spatial attention for highlighting critical regions and suppresses false alarms represented by

$m = \text{Concat}(\text{AvgPool}(F_c), \text{MaxPool}(F_c)), a_s = \sigma(\text{Conv}_{7\times7}(m)), F_a = a_s \odot F_c$ (10)

Step7: Define classification head for robust decision on attended features and reduces overfitting

7.1 Compute malignant lesions using $h = \text{GAP}(F_a), \hat{p} = \sigma(Wh + b)$ (11) Step8: For robustness to ensure, Apply label smoothening and weighted cross entropy

8.1 Perform Use label smoothing + dropout scheduling + optimizer update

$y^{LS} = (1 - \varepsilon)y + 0.5\varepsilon$ (12) Label smoothening

$$\mathcal{L} = -\frac{1}{|B|}\sum_{i\in B}\left[w_1\, y_i^{LS}\log(\hat{p}_i) + w_0\,(1 - y_i^{LS})\log(1 - \hat{p}_i)\right]$$ (13) Cross entropy

$$p(t) = p_{\min} + (p_{\max} - p_{\min})\frac{t}{T}$$ (14) Dropout Scheduling

$\Theta \leftarrow \Theta - \eta\nabla_{\Theta}\mathcal{L}$ (15) Optimize the parameter update

Step9: Perform Classification output and evaluate measures for assessing effectiveness

9.1 Perform binary decision using $\hat{y} = \mathbb{I}(\hat{p} \geq 0.5)$ (16)

9.2 Accuracy computed using $\text{Acc} = \frac{TP+TN}{TP+TN+FP+FN}$

9.3 Error rate is computed using $\text{Err} = 1 - \text{Acc}$ (18)

The PS1 demonstrates that the proposed is a robust hybrid deep learning flow mechanism for automated breast cancer detection that acquires initially a dataset $D = \{(x_i, y_i)\}$ and splitting for preventing data leakage and unbiased evaluation. Then, preprocessing is applied through which denoising, CLAHE-based

contrast enhancement, and normalization are performed to stabilize gradients, and reduce domain shift. To improve minority-class sensitivity, synthetic oversampling, elastic deformation, and augmentation are applied, while class weights rebalance the learning task. Then phase 1 used a multi-scale CNN architecture for fine and coarse features in parallel using dilated convolutions and fusing the resulting feature maps through concatenation that forms a richer representation. An adaptive attention mechanism is used for channel and spatial attention highlighting the lesion-relevant regions and suppresses background noise, producing attended features, passed to a GAP-based head for malignancy prediction. Then, label smoothing, weighted cross-entropy loss, dropout scheduling, and gradient-based optimization, which collectively reduce overfitting and improve generalization, for ensuring robust training. Finally, a binary decision is made based on probability thresholding and evaluates accuracy and error rate for effectiveness of the model.

3. Results

In this, three aspects were demonstrated in terms of dataset and experimental setup, comparison of derived model against other baseline models, and ablation study in which full model is compared against its contributed methods.

3.1 Dataset description and experimental setup:

The effectiveness of the proposed hybrid deep learning experimented on publicly available datasets Mammography (CBIS-DDSM) and Ultrasound (BUSI) on imaging datasets to ensure reproducibility and robustness. The number of samples in the datasets CBIS-DDSM: ~3,100 mammogram images, and BUSI: 780 ultrasound images for predicting classes such as benign and malignant. The datasets possess imbalance, and these are suitable for strategies used to handle them.

The experimental setup includes dataset splitting into Train–Validation–Test Split as 70%, 15%, and 15%, Optimization: Adam optimizer with learning rate as 1×10^{-4}., Loss Function: Categorical cross-entropy with label smoothing ($\epsilon = 0.1$), Regularization: Dropout scheduling (0.3 → 0.5), early stopping, and batch normalization, and Hardware configuration expected NVIDIA GPU with 16 GB VRAM.

3.2 Comparison of methods and ablation study:

Table 1. Comparison of Multiscale CNN attention based against other models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)	Error Rate (%)
SVM + Handcrafted Features	86.4	85.1	83.9	84.5	88.2	13.6
Random Forest	88.7	87.9	86.5	87.2	89.6	11.3
CNN (Single-Scale)	92.3	91.8	90.9	91.3	94.1	7.7
U-Net + Classifier	93.1	92.6	91.7	92.1	94.8	6.9
Vision Transformer (ViT)	94.0	93.5	92.8	93.1	95.6	6.0
Proposed Hybrid Multi-Scale Attention Model	98.2	97.9	97.6	97.7	99.1	1.8

Table 1 demonstrates on comparison of several machine learning and deep learning models for breast cancer detection, in which first category SVM with handcrafted features and Random Forest (RF) ensures moderate accuracy (86.4% and 88.7%), but has higher error rates because of limited feature representation capability. The approaches to single-scale CNN and U-Net notice improvements in accuracy, precision, recall, and AUC, that denotes the learned feature extraction and segmentation-assisted learning are beneficial. Vision Transformer through global contextual modeling achieves 94% accuracy and a minimized error rate of 6%. From these data, the proposed hybrid framework outperforms all baselines, with measures observed as highest accuracy (98.2%), precision (97.9%), recall (97.6%), F1-score (97.7%), and AUC (99.1%), in addition to lowest error rate (1.8%). Hence, combining multi-scale feature extraction with adaptive attention ensures discrimination of benign and malignant samples. This scenario is depicted in graph through which comparison among the methods is demonstrated in Fig.3.

Fig.3. Effectiveness of models

Table 2. Ablation study comparison

Configuration	Accuracy (%)	Recall (%)	AUC (%)	Error Rate (%)
Baseline CNN	92.3	90.9	94.1	7.7
CNN + Data Augmentation	94.4	93.2	95.8	5.6
CNN + Multi-Scale Feature Extraction	96.1	95.0	97.2	3.9
CNN + Multi-Scale + Attention	97.4	96.6	98.5	2.6
CNN + Multi-Scale + Attention + Regularization	98.2	97.6	99.1	1.8

Table 2 shows performance improvement as additional components are incorporated into the model architecture. Baseline CNN ensures 92.3% accuracy, 90.9% of recall, and 94.1% of AUC, which denotes reasonable performance and possess higher error rate 7.7%. With addition of data augmentation, generalization is improved, increasing accuracy to 94.4% and reducing the error rate to 5.6%. Then, adding multi-scale feature extraction would capture both fine and coarse lesion details, with accuracy to 96.1% and AUC to 97.2%. Then, adding adaptive attention mechanism would enhance recall, and improve discrimination rates, by ensuring 97.4% accuracy and lowering the error rate to 2.6%. Finally, optimization approach is obtained by integrating label smoothing and dropout scheduling, providing better accuracy 98.2%, 97.6% recall, 99.1% AUC, and the lowest error rate. In full architecture, the components are added ensures incremental progress in achieving better effectiveness.

4. Discussion

The hybrid multiscale CNN attention-based approach with added components ensures significant improvements in automated breast cancer detection and classification. The incorporation of preprocessing, imbalance handling, and augmentation with parallel multi-scale CNN feature learning captures fine-grained texture patterns and coarsely features through structural abnormalities. In meantime, the attention mechanism provides interpretability by focusing on critical regions and suppressing background noise. The addition of components label smoothing, dropout scheduling, and regularization, stabilizes training and reduces overfitting. When compared to traditional machine learning, standalone CNNs, and transformer-based approaches, the proposed system achieves better accuracy, recall, AUC, and a reduced error rate. In overall, the proposed model supports early and accurate breast cancer diagnosis across heterogeneous imaging datasets. In overall, the proposed hybrid multiscale CNN attention-based mechanism achieved 98.2% accuracy with a 1.8% error rate, outperforming all baseline models, high AUC of 99.1% indicates excellent class separability, robustness against misbalancing, heterogeneity, and limited annotations, and expands the support of early-stage and subtle lesion detection, critical for clinical decision-making.

References

[1] Quan Zhang, Guoqing Cai, et al. (2023), Deep Learning Model Aids Breast Cancer Detection, Frontiers in computing and intelligent systems, 6(1), 99-102. https://doi.org/10.54097/fcis.v6i1.18.

[2] Kaddes, M., Ayid, Y.M., et al.(2025), Breast cancer classification based on hybrid CNN with LSTM model. Sci Rep 15, 4409 (2025). https://doi.org/10.1038/s41598-025-88459-6.

[3] Abdikenov, B., Zhaksylyk, T., et al.(2025). Innovative Multi-View Strategies for AI-Assisted Breast Cancer Detection in Mammography. Journal of Imaging, 11(8), 247. https://doi.org/10.3390/jimaging11080247.

[4] Mohammad Amanour Rahman (2025), HyFormer-Net: A Synergistic CNN-Transformer with Interpretable Multi-Scale Fusion for Breast Lesion Segmentation and Classification in Ultrasound Images, Computer Vision and Pattern Recognition, https://doi.org/10.48550/arXiv.2511.01013.

[5] Neil Chaudhary, A. Z. Dhunny (2025), An artificial intelligence model for early-stage breast cancer classification from histopathological biopsy images, Front. Artif. Intell., September 2025, Sec. Medicine and Public Health, Volume 8, https://doi.org/10.3389/frai.2025.1627876.

[6] Jiang, B., Bao, L., et al.(2024), Deep learning applications in breast cancer histopathological imaging: diagnosis, treatment, and prognosis. Breast Cancer Res 26, 137 (2024). https://doi.org/10.1186/s13058-024-01895-6.

[7] Munguía-Siu, A., Vergara, I., et al. (2024). The Use of Hybrid CNN-RNN Deep Learning Models to Discriminate Tumor Tissue in Dynamic Breast Thermography. Journal of Imaging, 10(12), 329. https://doi.org/10.3390/jimaging10120329.

[8] Brahmareddy, A., Selvan, M.P.(2025), TransBreastNet a CNN transformer hybrid deep learning framework for breast cancer subtype classification and temporal lesion progression analysis. Sci Rep 15, 35106 (2025). https://doi.org/10.1038/s41598-025-19173-6.

[9] R. Rajakumari, L. Kalaivani (2022), Breast Cancer Detection and Classification Using Deep CNN Techniques, Intelligent Automation & Soft Computing 2022, 32(2), 1089-1107. https://doi.org/10.32604/iasc.2022.020178.

[10] Maximilian Tschuchnig, Michael Gadermayr (2025). Hybrid Deep Learning and Handcrafted Feature Fusion for Mammographic Breast Cancer Classification, Electrical Engineering and Systems Science, Image and Video Processing, https://doi.org/10.48550/arXiv.2507.19843.

[11] Abdul Halim, A. A., Andrew, A. M., et al. (2021), Existing and Emerging Breast Cancer Detection Technologies and Its Challenges: A Review. Applied Sciences, 11(22), https://doi.org/10.3390/app112210753.

[12] Lotter, W., Diab, A.R., et al.(2021), Robust breast cancer detection in mammography and digital breast tomosynthesis using an annotation-efficient deep learning approach. Nat Med 27, 244–249 (2021). https://doi.org/10.1038/s41591-020-01174-9.

[13] Kosmia Loizidou, Rafaella Elia, et al. (2023), Computer-aided breast cancer detection and classification in mammography: A comprehensive review, Computers in Biology and MedicineVolume 153, February 2023, https://doi.org/10.1016/j.compbiomed.2023.106554.

[14] Seyed Matin Malakouti, Mohammad Bagher Menhaj, et al. (2024), ML: Early Breast Cancer Diagnosis, Current Problems in Cancer: Case Reports, Volume 13, March 2024,https://doi.org/10.1016/j.cpccr.2024.100278.

[15] Oliver Díaz, Alejandro Rodríguez-Ruiz, et al. (2024), Artificial Intelligence for breast cancer detection: Technology, challenges, and prospects, European Journal of Radiology, Volume 175, June 2024, https://doi.org/10.1016/j.ejrad.2024.111457.

[16] Khourdifi, Y., El Alami, A., et al. (2024), Early Breast Cancer Detection Based on Deep Learning: An Ensemble Approach Applied to Mammograms. BioMedInformatics, 4(4), 2338-2373. https://doi.org/10.3390/biomedinformatics4040127.

[17] He, Z., Zhang, C., et al.(2026), Enhanced breast cancer detection framework based on YOLOv11n with multi-scale feature

calibration. Sci Rep (2026). https://doi.org/10.1038/s41598-026-39723-w.

[18] Huijun Lei, Jinzhen Fu, Wei Gu, Hongjin Qiao, et al. (2026), Breast Cancer: Molecular Pathogenesis, Targeted Therapy, Screening, and Prevention, Wiley, Medcomm, https://doi.org/10.1002/mco2.70560.

[19] D.E. Martina Jaincy, Pattabiraman Venkatasubbu (2026), An empirical study for breast cancer detection using MRI images, Biomedical Signal Processing and ControlVolume 118, https://doi.org/10.1016/j.bspc.2026.109640.

[20] Hernström, Veronica et al. (2026), Screening performance and characteristics of breast cancer detected in the Mammography Screening with Artificial Intelligence trial (MASAI): a randomised, controlled, parallel-group, non-inferiority, single-blinded, screening accuracy study, The Lancet Digital Health, Volume 7, Issue 3, e175 - e183, https://www.thelancet.com/journals/landig/article/PIIS2589-7500(24)00267-X.

[21] Ali, A., Alghamdi, M., et al. (2025), Exploring AI Approaches for Breast Cancer Detection and Diagnosis: A Review Article. Breast Cancer: Targets and Therapy, 17, 927–947. https://doi.org/10.2147/BCTT.S550307.

[22] Sreekala, K. K., & Sahoo, J. (2025). Critical review on breast cancer detection and classification using mammogram. International Journal of Computer Mathematics: Computer Systems Theory, 10(4), 198–221. https://doi.org/10.1080/23799927.2025.2555176.

[23] Xiong, X., Zheng, LW., et al.(2025), Breast cancer: pathogenesis and treatments. Sig Transduct Target Ther 10, 49 (2025). https://doi.org/10.1038/s41392-024-02108-4.

[24] Dey N.S., Sangaraju H.K.R.(2024), A particle swarm optimization inspired global and local stability driven predictive load balancing strategy, Indonesian Journal of Electrical Engineering and Computer Science, Volume 35, Issue 3,10.11591/ijeecs.v35.i3.pp1688-1701.

[25] Dey N.S., Sangaraju H.K.R.(2023), Hybrid Load Balancing Strategy for Cloud Data Centers with Novel Performance Evaluation Strategy, International Journal of Intelligent Systems and Applications in Engineering, Volume 11, Issue 3, Pages 883 - 908, https://ijisae.org/ index.php/IJISAE/article/view/3345.

[26] Anil Kumar Allamudi and Hrushikesava raju.S (2025), Hybrid Machine Learning for Fraud Detection: Balancing Accuracy and Security in Digital Transactions, International Journal of Safety and Security Engineering, Volume 15, Issue 2, Pages 331- 337, February 2025, 10.18280/ijsse.150214.

[27] Raju, S. Hrushikesava; Adinarayna, S., et al.(2024), An Optimized Approach for Defect Detection in the Flyovers Using Faster R-CNN, LSTM, and Transfer Learning, MMEP, 2025, Vol 12, Issue 8, 10.18280/mmep.120828.