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Research Article

BreastHybridNet: A Hybrid Deep Learning Framework for Breast Cancer Diagnosis Using Mammogram Images

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Abstract:

As a common malignancy in females, breast cancer represents one of the most serious threats to a female's life, which is also closely associated with the Sustainable Development Goal 3 (SDG 3) of the United Nations for keeping healthy lives and promoting the well-being of all people. Breast cancer accounts for the highest number of cancer mortality for females, and early diagnosis is key to reducing disease-specific mortality and mortality in general. Current methods struggle to accurately localize important regions, model sequential dependencies, or combine different features despite considerable improvements in artificial intelligence and deep learning domains. They prevent diagnostic frameworks from being reliable and scalable, especially in low-resourced healthcare settings. This study proposes a novel hybrid deep learning framework, BreastHybridNet, using mammogram images to tackle these mutual challenges. The proposed framework combines a pre-trained CNN backbone for feature extraction, a spatial attention mechanism to automatically highlight the image area, which contains signature patterns carrying diagnostic information, a BiLSTM layer to obtain sequential dependencies of diagnostic features, and a feature fusion strategy to process complementarily. Experimental results show that the accuracy of the proposed model is 98.30%, which outperforms the state-of-the-art methods LMHistNet, BreastMultiNet, and DOTNet 2.0 to a considerable extent quantitatively. BreastHybridNet works towards the feasibility of interpretability and scalability on existing systems while contributing to worldwide efforts to alleviate cancer-related mortality using cost-efficient diagnostic lenses. This study highlights the need for AI-enabled solutions to contribute to accessing reliable healthcare technologies for breast cancer screening.

1. Introduction

Breast cancer is one of the significant causes of cancer mortality in women worldwide, making its early and accurate diagnosis essential for increasing patient survival. Artificial intelligence (AI) and deep learning technologies have recently been introduced into breast cancer diagnostics using imaging data, which may potentially provide better accuracy and efficiency [1-16]. Breast abnormalities detection has been attractive, achieving high performance with models like LMHistNet [1] and BreastMultiNet [17] and higher contrast and classification performance by imaging quality enhancement and deep models. Such approaches are limited — the localization of critical regions, sequential dependencies, and holistic feature integration strategy — bringing efforts to develop a more robust framework. Therefore, considering these bounds, the current study has been designed to propose a novel deep learning framework, named BreastHybridNet, for diagnosing breast cancer from mammogram images. The primary purpose of this study is to develop a hybrid architecture combining convolutional and sequential learning methods that address the limitations of current approaches. To do this, a few innovations are presented: 1) A pre-trained CNN backbone that captures robust features, 2) A spatial attention mechanism that attends to diagnostically meaningful regions, 3) A BiLSTM layer that captures sequential and spatial correlations, and 4) A feature fusion strategy to combine unique insights. These innovations allow BreastHybridNet to provide highly accurate predictions, compared to the state-of-the-art methods, and clinically interpretable, reliable predictions. The other baseline methods suffer from various limitations, which leads us to design a well-motivated hybrid architecture that still contributes to state-of-the-art research. It shows that the fusion of spatial and sequential learning with attention significantly gains performance metrics. The study also highlights the relevance of using advanced preprocessing techniques like ROI extraction and data augmentation to improve input quality. The experimental results demonstrate that the proposed framework can deliver accurate breast cancer diagnosis with an accuracy rate of 98.30%, surpassing the state-of-the-art approaches. This paper is structured as follows. Section 2 comprehensively reviews the literature, including the gaps it presents and state-of-the-art approaches. Section 3 describes the methodology applied, consisting of the architecture of BreastHybridNet and the method. Section 4 presents the experimental results, comparing the performance of the proposed framework with existing models using key metrics. Section 5 discusses the findings, emphasizing the novelties and implications of the study while also addressing the limitations. Finally, Section 6 concludes the paper by summarizing the contributions and outlining the future scope of this research. This systematic approach ensures a detailed and structured presentation of the work, contributing valuable insights to breast cancer diagnostics.

2. Related work

Koshy et al. [1] for breast cancer patients to survive, early detection is essential. LMHistNet uses AI to classify histological pictures of breast tumors accurately. Luo et al. [2] improved by early identification by imaging. Deep learning improves image analysis for breast cancer. Worldwide, the incidence of breast cancer is growing. Saha et al. [3] The effect of breast cancer demands better early detection instruments—the combination of DNN with ML results in 98.25% diagnosis accuracy, indicating a significant improvement. Ko et al. [4] enhanced picture quality through DNN integration can transform screening through Diffuse Optical Tomography. The incidence of breast cancer necessitates improved screening. Anas et al. [5] innovated in bioinformatics is propelled by recent advances in AI. With fewer false positives and better results, deep learning improves the accuracy of breast cancer diagnosis. Tan et al. [6] employed cross-layer attention and tweaking feature maps; RCM-YOLO improves the speed and accuracy of tiny breast mass identification. Awotunde et al. [7] identified that breast cancer is essential. The diagnostic accuracy of a hybrid feature selection model based on deep learning is significantly increased. Sharmin et al. [8] identified breast cancer requires efficient techniques. A hybrid model combined with DL and ML performs better and more accurately. Abhisheka et al. [9], with millions of cases of breast cancer each year, early diagnosis is crucial. Diagnostic accuracy is improved by reviewing DL approaches in medical imaging. Asadi and Memon [10], for breast cancer to be effectively treated, early diagnosis is essential. For diagnosis, a cascade network model combines classification and segmentation. Gami et al. [11] estimated the yearly number of fatalities attributed to breast cancer. Deep learning, mainly CNNs, aids in the accurate categorization of cancer cells. Frank et al. [12] assisted with breast mass diagnosis during mammograms, an integrated deep learning system that integrates CNN analysis and YOLO object recognition. Dewangan et al. [13] with breast cancer is dependent on its discovery. A novel BPBRW with HKH-ABO technique achieves immense accuracy by resolving prior model constraints. Balaha et al. [14] presented HMB-DLGAHA, a hybrid deep learning-genetic algorithm technique, and built the HMB1-BUSI CNN architecture. Experiments using CNN models that have already been trained show strong performance metrics. Khan et al. [15] utilized a novel "MultiNet" framework to diagnose breast cancer from microscope pictures. Nassif et al. [16], although early detection and treatment can improve survival rates, artificial intelligence and machine learning continue seriously threatening public health. Rahman et al. [17] combined numerous pre-trained models with transfer learning; the "BreastMultiNet" framework improves the accuracy of breast cancer diagnosis. Mechria et al. [18] enhanced the classification performance of Deep Convolutional Neural Networks (DCNN) for mammograms. DCNN denoising improves sensitivity, specificity, and accuracy. Results from other denoising techniques were inconsistent. Yan et al. [19] enhanced the categorization of breast cancer histological images using a novel hybrid convolutional and recurrent deep neural network. The availability of datasets improves research. Khamparia et al. [20], with a modified VGG network that outperforms other CNNs with immense accuracy, transfer learning is presented with an emphasis on early breast cancer diagnosis. Future objectives involve the integration of tissue density characteristics and category categorization. Krithiga and Geetha [21] precise identification of nuclei is necessary for automatic pathology-based cancer cell detection. With Deep-CNN, a suggested approach yields enormous accuracy. With their excellent accuracy, Tembherune et al. [22], deep learning-based automated techniques are promising. Mammograms and breast biopsies help diagnose breast cancer, a fatal condition. Jahangeer and Rajkumar [23], for women's health, early detection of breast cancer is essential. Mammograms help in early detection. This research presents sophisticated image processing and classification methods to achieve high accuracy. Saber et al. [24], a significant reason why women die from cancer is breast cancer. A novel deep learning model provides an efficient early detection and diagnosis tool. Yu et al. [25] suggested a technique for classifying breast cancer that uses hybrid characteristics and 3-output CNN segmentation with promising outcomes. Inan et al. [26] improved survival rates are seen with early identification of breast cancer, a significant cause of death for women. Accuracy is attained via a hybrid machine learning system. Chugh et al. [27] required an early diagnosis since it is one of the leading causes of cancer-related deaths in women. AI increases the effectiveness of diagnosis. The survey fills in research gaps by comparing ML and DL approaches. Budak et al. [28] significantly increased the efficiency of an end-to-end model that combines FCN and Bi-LSTM—Eroglu et al. [29] assisted by a hybrid CNN method. SVM improves efficiency with an accuracy of 95.6%. Alsaedi et al. [30] infrared thermography and microwaves, augmented by CNN, are used in this research to present a hybrid technique of breast cancer diagnosis. Resmini et al. [31] for the non-invasive detection of breast cancer, thermography is available. A combination approach utilizing machine learning, SIT, and DIT achieves high accuracy. Prospective schemes entail improving the methodology. Stephan et al. [32] reduced death rates from breast cancer requires early diagnosis. ABC and WOA are used in a HAW hybrid algorithm to optimize ANNs. The HAW-RP version has little complexity and good precision. Yang et al. [33] presented a unique Temporal Sequence Dual-Branch Network (TSDBN) that concurrently uses CEUS and B-mode ultrasound data to categorize breast tumors. The accuracy of the TSDBN is around 4% higher than that of current techniques. Maroof et al. [34] focused on the difficulty of automating the identification of mitosis in the grading of breast cancer. Promising results are obtained when color, texture, and morphological characteristics are combined into a hybrid feature space. The goal of future research is to improve dataset consistency and segmentation. Benhammou et al. [35] removed previous CAD constraints related to breast cancer. A taxonomy divides CAD into four categories, with MIM being the best. Future research aims to improve accuracy. Haq et al. [36] precise diagnosis of breast cancer is essential. Promising results are observed when a 3-layer CNN architecture is presented for histology image analysis. During a break, Wadhwa et al. [37] approached Deep Learning using DenseNet-201 CNN. The accuracy of his dataset in diagnosing breast cancer is enormous. Liu et al. [38], for increased classification accuracy, a unique method called IGSAGAW combines CSSVM with feature selection. Tested on WBC and WDBC datasets, it performs better than previous approaches, supporting clinical judgments. Zhang et al. [39], a novel technique called BDR-CNN-GCN combines CNN and GCN for better breast mammography lesion identification. High accuracy was attained. Kadam et al. [40], due to its high incidence in women, breast cancer should be detected early. An ensemble approach that is suggested outperforms others and produces better accuracy.

3. Proposed framework

Figure 1 depicts the methodology of this research and illustrates the comprehensive pipeline for breast cancer diagnosis using mammogram images. The process begins with inputting mammogram images from the CBIS-DDSM dataset, a high-resolution collection annotated with diagnostic labels such as standard, benign, and malignant, along with metadata like patient age, density types, and mass characteristics. These images and accompanying data form the foundation for the analysis. Several preprocessing steps were undertaken to prepare the dataset for practical training. Data was cleaned to remove corrupted and incomplete images, ensuring high-quality inputs. Advanced augmentation techniques were applied to address the class imbalance and enhance data diversity, including rotation, flipping, contrast enhancement, random cropping, padding, noise injection, and zooming. The augmented dataset was then split into training, validation, and test subsets in a stratified manner, ensuring a balanced representation of diagnostic categories. Images were then preprocessed to standardize input and extract meaningful features. All images were resized to 224×224 pixels for compatibility with the deep learning model, and pixel values were normalized to stabilize the training process. A novel segmentation algorithm based on U-Net was employed to identify and extract Regions of Interest (ROI), ensuring that the model focused on the most relevant areas in the mammograms.

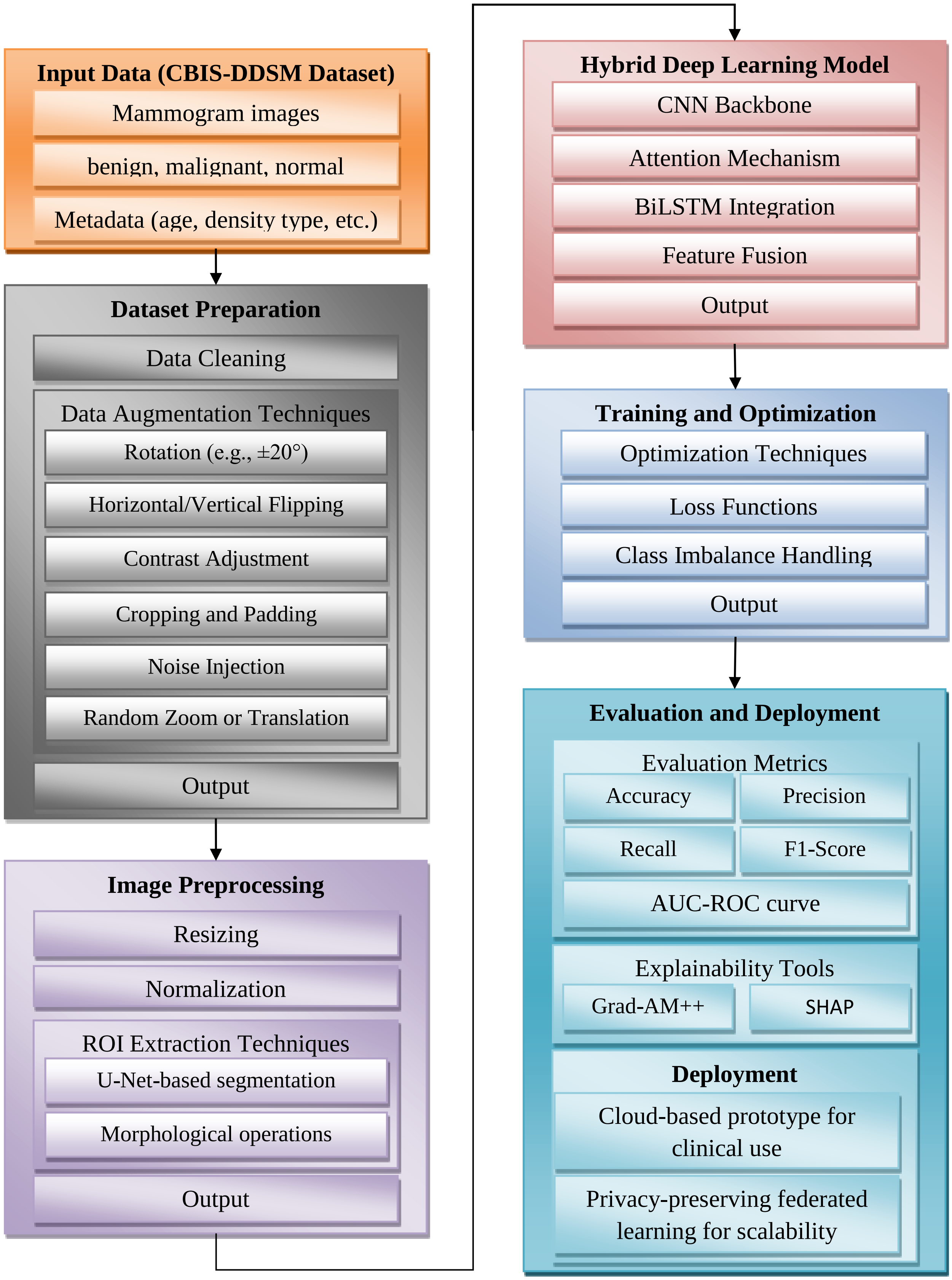

Figure 1. *Proposed Methodology for Breast Cancer Diagnosis*

The proposed hybrid deep learning model integrates several advanced components to enhance diagnostic performance. A pre-trained CNN backbone, such as ResNet or VGG16, was fine-tuned to extract the mammograms' texture, shape, and density features. During training, a spatial attention mechanism was added to focus on critical regions, such as lesions. The architecture also incorporates a Bidirectional LSTM layer, which captures sequential dependencies and spatial relationships within the features. The outputs of the CNN and BiLSTM layers were fused using a novel feature fusion strategy, ensuring that complementary information was leveraged for robust classification. Advanced techniques were used to train and fine-tune the hybrid model. Binary cross-entropy loss functions were used for binary classification tasks, and Categorical Cross-Entropy loss functions were used for multi-class classification tasks. We used the Adam optimizer for our experiments, which uses gradient centralization to guarantee higher convergence efficiency. We can adaptively learn hyperparameters like the learning and dropout rates using Bayesian optimization. A custom class imbalance loss function was designed to balance the space for malign tumors, which were rarer, enabling an entire learning sector for both classes. We performed extensive performance evaluations on these models regarding various metrics — accuracy, precision, recall, F1-score, and AUC-ROC. Malignant sensitivity and specificity were specifically highlighted to make the findings clinically relevant. Explainable AI techniques were added to the evaluation to improve interpretability. Grad-CAM++ visualizations of the regions of interest in mammograms contribute most to model predictions. SHAP analysis quantifies the impact of various features on the decisions of each network and the ensemble. The hybrid model was then deployed on a cloud-based system that could analyze mammograms in real-time in the clinic. The potential use of federated learning was also investigated to enable privacy-preserving collaborative training across institutions. This flow is illustrated in Figure 1: from input through the model to deployment. It presents subprocesses for each stage and highlights the uniqueness of the new techniques, including state-of-the-art data augmentation, ROI extraction, attention mechanisms, and feature fusion. This structured pipeline highlights the innovation and clinical applicability of the proposed methodology.

3.1 Proposed Hybrid Deep Learning Model

Our proposed hybrid deep learning model, described in Figure 2, for breast cancer diagnosis successfully combines the strengths of convolutional neural networks (CNN), attention mechanisms, and bidirectional long short-term memory (BiLSTM) networks to achieve a powerful and efficient approach. It utilizes the different strengths of each aspect of the model to learn the mammogram images through the features and how to prioritize the region down to spatial and sequential pattern learning. The model's foundation comprises the CNN backbone and the central feature extractor. Fine-tuned pre-trained architectures (ResNet and VGG16) to identify high-level features such as texture, shape, and density patterns in mammogram images. They are essential features needed to differentiate normal vs benign vs malignant. After that, we add pooling with CNN layers to decrease spatial dimensions, which increases computational efficiency while keeping important information. Such a backbone makes sure to learn more granular and high-level features from the images. A spatial attention mechanism emphasizes the model's demonstration of more diagnostically relevant architectural regions. The mechanism allows for the dynamic learning of ROIs (regions of interest such as lesions and others) by applying higher weights during the procedure. This ensures the model does not ignore essential elements indispensable for accurate classification. It also uses a Bidirectional LSTM layer that deals with sequential dependencies and spatial relationships within the captured features. The BiLSTM layer takes feature sequences in both forward and backward directions so the model can learn additional context from both sides of the image. This ability to learn sequentially develops a further understanding of memory of spatial dependencies and more complex patterns in mammogram images, which would complement the feature extraction of a CNN. One of the main innovations of the hybrid model proposed here is the fusion strategy to fuse the CNN and the BiLSTM layer outputs. This allows the strengths of both elements to work well together. The CNN yields spatially rich feature maps, and applying these to the BiLSTM burdens the regionalization task in sequential order to the overall context. The model benefits from an integrated feature fusion of these complementary qualities, which enables a rich representation of the input data, benefitting its diagnostic powers. Classification is done by feeding the fused features to FC-dense layers. These layers with the correct dropout rates to avoid overfitting gradually decrease the dimensions of the features and make the final predictions. Since this was a classification problem into three classes, namely, normal, benign, and malignant cases, the output was a Softmax activation in the output layer. The proposed hybrid deep learning model combines advanced components and innovative techniques to ensure accurate and consistent breast cancer diagnosis. Such architectural flow is depicted in Figure 2, which features coupling CNN feature extraction with attention-based localization, BiLSTM feature encoding, attention-based cross-dimensional

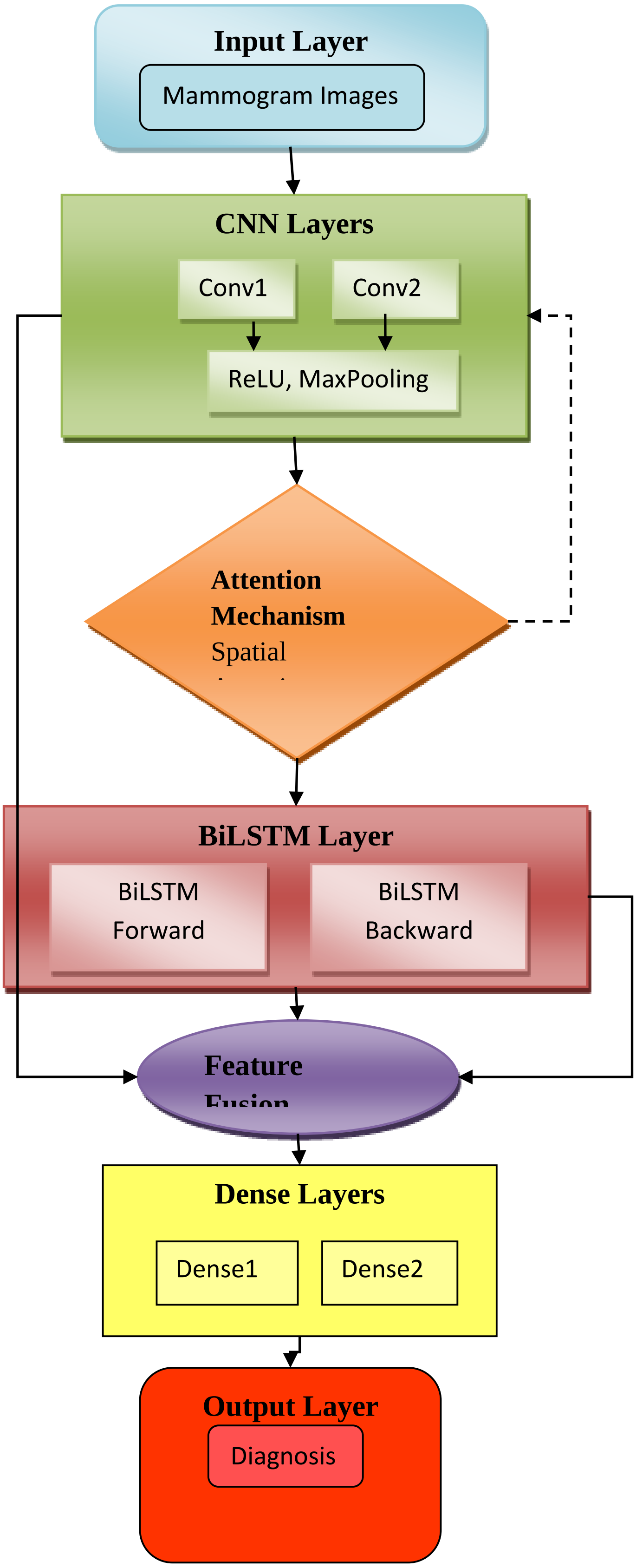

Figure 2. *Proposed hybrid deep learning model known as BreastHybridNet for breast cancer detection*

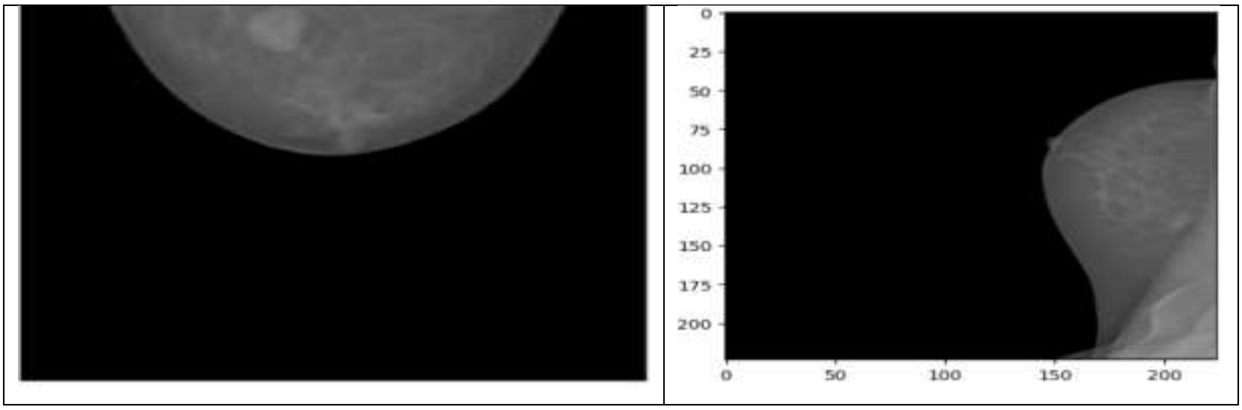

Figure 3. *Sample Images from CBIS-DDSM Dataset*

Table 1. *Notations Used in the Proposed System*

Notation	Description
$CapI$	Input mammogram image represented as a 2D matrix of pixel intensities.
h, w	Height and width of the input image, respectively.
I_{norm}	Normalized input image with pixel values scaled to [0,1][0, 1].
$F^{(l)}$	Feature map at the l-th convolutional layer.
$W^{(l)}$	Convolutional kernel (weight matrix) at the l-th layer.
$b^{(l)}$	Bias term for the l-th convolutional layer.
σ	Activation function, typically ReLU ($ReLU(z) = max(0, z)$)
$\alpha_{i,j}$	Attention weight for the pixel located at (i, j)
$e_{i,j}$	Relevance score for the pixel located at (i, j) in the feature map.
F_{att}	Attended feature map after applying attention weights.
x_t	Input feature vector at time step t for the BiLSTM layer.
$h_t^{(fwd)}$	Hidden state at time t in the forward pass of the BiLSTM.
$h_t^{(bwd)}$	Hidden state at time t in the backward pass of the BiLSTM.
h_t	The final hidden state at time t is obtained by concatenating forward and backward states.
F_{CNN}	Feature vector produced by the CNN backbone.
F_{BiLSTM}	Feature vector produced by the BiLSTM layer.
F_{fused}	Fused feature vector combining CNN and BiLSTM outputs.
W_{CNN}, W_{BiLSTM}	Weight matrices for feature fusion from CNN and BiLSTM outputs.
z_c	Logit (raw score) for class cc produced by the dense layer.
y_c	True label for class cc in one-hot encoding format.
$\mathcal{L}$	The cross-entropy loss function is used to train the model.

feature fusion, and a feature fusion for final interpretable prediction. Table 1 Common notations used in the proposed system

3.2 Mathematical Model

The proposed system, BreastHybridNet, is a hybrid deep-learning framework designed to diagnose breast cancer using mammogram images. The mathematical model incorporates several key components, including convolutional layers for feature extraction, attention mechanisms for critical region identification, sequential learning with BiLSTM, and feature fusion for robust classification. Let us describe the mathematical underpinnings of each stage in the system. The system begins with a mammogram image input represented as a two-dimensional $matri\ I$ of pixel intensities, where $I \in \mathbb{R}^{h\times w, and\ h\ and\ w}$ denote the height and width of the image, respectively. The input is preprocessed by normalization, scaling the pixel values to the range [0,1][0, 1], as in Eq. 1.

$$I_{norm}(x, y) = \frac{I(x,y) - min(I)}{max(I) - min(I)} \quad (1)$$

where x and y are the pixel coordinates, and $min(I)\ and\ max(I)$ are the minimum and maximum pixel values in the image. The normalized input is then passed through the CNN backbone's convolutional layers. Each convolutional layer operates as expressed in Eq. 2.

$$F^{l}(x, y) = \sigma\left(\sum_{i-1}^{k} \sum_{j-1}^{k} W_{ij}^{(l)} I^{(l-1)}(x + i, y + j) + b^{(l)}\right) \quad (2)$$

where $F^{(l)}$is the feature map at the layer $l, W^{(l)}$ is the $k \times k$ convolutional kernel, $b^{(l)}$ is the bias term, and

σ is the activation function, typically $ReLU\big(ReLU(Z) = max(0, z)\big)$. After multiple convolutional and pooling layers, the feature maps are passed through an attention mechanism to focus on critical regions. The attention weights, $\alpha_{i,j,}$ are computed using Eq. 3.

$$\alpha_{i,j} = \frac{exp(e_{i,j})}{\sum_m \sum_n exp(e_{m,n})} \quad (3)$$

where $e_{i,j}$ is the relevance score for pixel (i,j) in the feature map, typically computed using a learned function, such as a small neural network. The attended feature map is given by:

$$F_{att}(i,j) = \alpha_{i,j} F(i.j). \quad (4)$$

The attended feature maps are then passed to the BiLSTM layer for sequential learning. The BiLSTM processes the sequence of feature vectors in both forward and backward directions. The forward pass is defined as in Eq. 5.

$$h_t^{(fwd)} = tanh\left(W_x^{(fwd)} x_t + W_h^{(fwd)} h_{t-1}^{(fwd)} + b^{(fwd)}\right) \quad (5)$$

and the backward pass is similarly computed. The final hidden state at the time t is determined as in Eq. 6.

$$h_t = h_t^{(fwd)} \oplus h_t^{(bwd)} \quad (6)$$

where $\oplus$ represents concatenation. These hidden states encode spatial and temporal dependencies within the features. The CNN backbone and the BiLSTM outputs are fused using a feature fusion strategy. Let F_{CNN} and W_{BiLSTM} denote the features from the CNN and BiLSTM layers, respectively. The fused feature vector is computed as:

$$F_{fused} = W_{CNN} F_{CNN} + W_{BiLSTM} F_{BiLSTM}, \quad (7)$$

where $W_{CNN\ and}\ W_{BiLSTM}$ are learnable weight matrices. Finally, the fused features are passed through dense layers for classification. The output logits for each class c are computed as in Eq. 8.

$$z_c = W_c F_{fused} + b_c, \quad (8)$$

where W_c and b_c are the weight matrix and bias for class c. The predicted probabilities are obtained using the Softmax function expressed in Eq. 9.

$$P(c|I) = \frac{exp(z_c)}{\sum_k exp(zk)}. \quad (9)$$

The model is trained using a cross-entropy loss function, defined as in Eq. 10.

$$\mathcal{L} = -\sum_c y_c \log P(c|I) \quad (10)$$

where $y_c$is the true label for class c. Optimization uses the Adam optimizer with gradient centralization to ensure efficient convergence, as in Eq. 11.

$$\sum_{i=1}^{k} \sum_{i=1}^{k} W_{ij}^{(l)} I^{(l-1)}(x+i, y+j) + b^{(l)} \quad (11)$$

This mathematical formulation encapsulates BreastHybridNet's end-to-end workflow, from input preprocessing to final classification, integrating advanced mechanisms such as attention and feature fusion for enhanced diagnostic accuracy.

3.3 Proposed Algorithm

In this paper, we develop a novel hybrid deep learning-based Breast Cancer Diagnosis (BHN-BCD) algorithm that is an end-to-end classifier for automated breast cancer diagnosis from mammogram images. The algorithm consists of a CNN backbone, attention mechanism, 2 BiLSTM layers, and a new feature fusion strategy that improves the interpretability and accuracy of the diagnosis by extracting spatial, contextual, and sequence features.
The advanced preprocessing, regional area of interest (ROI) extraction, and extended data augmentation guarantee proper input standardization and diversity. It has an explainable algorithm via Grad-CAM++ and SHAP and helps understand regions contributing to the prediction. We demonstrate its capability to provide reliable, interpretable, and scalable diagnostics, allowing for clinical usage and enabling private training in the multi-institutional setting

Algorithm: BreastHybridNet for Breast Cancer Diagnosis (BHN-BCD)
Input: CBIS-DDSM dataset D
Output: Predicted class labels R, performance statistics P

1. Begin
2. D'←DataPreparation(D)
   Image Preprocessing
3. Normalize pixel values
   $I_{norm}(x,y) = \dfrac{I(x,y) - min(I)}{max(I) - min(I)}$
4. Resize images to 224×224 pixels
5. Extract Regions of Interest (ROI) using a U-Net-based segmentation algorithm.
   Feature Extraction using CNN
6. Apply convolutional layers

$$F^{(l)}\ (x,y) = \sigma\left(\sum_{i-1}^{k}\sum_{j-1}^{k} W_{i,j}^{(l)} I^{(l-1)}(x+i, y+j) + b^{(l)}\right)$$

7. Max-pooling for downsampling
Attention Mechanism
8. Compute attention weights

$$\alpha_{i,j} = \frac{exp(e_{i,j})}{\sum_m \sum_n exp(e_{m,n})}$$

9. Generate attention feature map $F_{att}(i,j) = \alpha_{i,j} F(i,j)$.
10. Sequential learning with BiLSTM
11. F←FeatureFusion(feature maps)
12. m'←TrainTheModel(m)
13. Persist m'
14. Load m'
15. R←BreastCancerDiagnosis(m', test samples)
16. P←PerformanceEvaluation(ground truth, R)
17. Print R
18. Print P
19. End

Algorithm: BreastHybridNet for Breast Cancer Diagnosis (BHN-BCD)

As in Algorithm 1, it uses the dataset of high-resolution mammograms with diagnostic labels of normal, benign, and malignant for training and evaluation. Before feeding the images into the training pipeline, we perform some data cleaning to remove any samples that aren't complete or valid, ensuring that we have a valuable dataset to work with. Remove Class Imbalance, Train, and Preprocess: These are approached with advanced data augmentation techniques deployed to achieve better class representations and generalization, such as rotation, flipping, random cropping, contrast stretching, noise injection, zooming, and so on. The augmented dataset is then stratified and divided into training, validation, and test sets containing 70%, 15%, and 15% of the samples. Like the dataset-building phase, image preprocessing is an essential component in this task for standardizing some inputs like pixel values and increasing image data quality for feature extraction. We also perform normalization on each image to set input ranges between 0 and 1 so the input values for all images go within the same range for a deep-learning model. To keep up with the dimensions of the CNN structure, the images are resized to a standard size of 224 × 224. We extract diagnostic relevant features regarding Regions of Interest (ROI) with a segmentation algorithm based on U-net to segment potential lesions or abnormal areas. The CNN backbone analyzes the preprocessed images and extracts their features. The CNN extracts spatial features from the input images using filters in convolutional layers, retrieving information related to texture, shape, and density patterns. Each layer generally consists of a convolution operation (to extract feature maps), followed by an activation function, and often a pooling operation (to sub-sample the feature maps), successively decreasing the spatial size but preserving important information. The features are hierarchical, which is then used in the next few steps of the algorithm. A spatial attention mechanism is introduced to assist the model in concentrating on diagnostic-relevant areas. This mechanism computes attention scores for every pixel in the feature maps, thus prioritizing high-relevance regions (e.g., lesions or abnormalities). We can get the attended feature map by weighting it pixel-wise with its calculated pixel attention score, forcing the model to learn the critical areas. A Bidirectional Long Short-Term Memory (BiLSTM) layer is then applied to the feature maps to capture the sequential dependencies and spatial relationships between the feature maps. This layer computes features along the sequence, both in the forward and the backward direction, allowing the model to learn contextual information over the whole image. At each time step, the hidden states in forward and backward directions are concatenated to offer a joint representation from both forward and backward directions of the sequence [14]. Afterward, the outputs from CNN and BiLSTM layers are fused with a feature fusion strategy. In this step, the advantages of the two components are integrated, where the features extracted by CNN include the spatial features information and the sequenced information learned by BiLSTM. This fused feature vector will vigorously represent the input data since it gets complementary knowledge from both modalities. The concatenated features are fed to a set of fully connected dense layers for classification. To do this, it uses these layers to successively decrease the feature size and produce the raw class scores or logits for each diagnostic class. These logits are fed to a softmax activation function (this way, we can interpret the output as probabilities over classes) so the model can decide if an input mammogram is routine, benign, or malignant. The model is trained by minimizing a cross-entropy loss function between predicted probabilities and proper labels. Optimization is done with an Adam optimizer with gradient centralization for better and more stable convergence. Bayesian hyperparameter tuning is used to optimize these parameters, such as learning and dropout rates.

Its diagnostic performance is examined on the test set with standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Grad-CAM++ and SHAP improve Explainability. Grad-CAM++ visualization (in red) indicates which regions in the mammograms contributed the most to model predictions, while SHAP quantifies the importance of each feature. Ultimately, it deploys the model into a cloud-based diagnostic tool to allow for live analysis of mammograms. We also investigate the potential of federated learning to facilitate privacy-preserving collaborative training across multi-institutional data. The presented BreastHybridNet framework exhibits proof of concept for breast cancer diagnosis via a complete algorithm.

3.4 Dataset Details

CBIS-DDSM (Curated Breast Imaging Subset of the Digital Database for Screening Mammography)[41]) is a publicly available mammogram dataset for breast cancer research. The dataset contains more than 2,600 studies and images annotated with diagnostic categories (e.g., normal, benign, and malignant cases) at a high-resolution level. Additionally, it gives out detailed metadata, such as patient age, types of density, and lesion characteristics, which makes it the perfect dataset for tasks involving machine learning. CBIS-DDSM dataset provides ground truth for automatic breast cancer detection and segmentation tasks. Provides a complete benchmark for the model.

3.5 Evaluation Methodology

The evaluation methodology of the proposed BreastHybridNet framework could assess the performance, robustness, and interpretability of the BreastHybridNet framework in Breast cancer diagnosis. We stratified splitting the CBIS-DDSM dataset into train, validation, and test subsets to keep all diagnostic categories (normal, benign, malignant) proportional in each of the three partitions (train, val, test). The remaining 15% of data was reserved for the test set to assess generalization performance after training. Such a splitting method guarantees a fair and unbiased evaluation. A wide range of performance measures were applied to evaluate the model's predictions: accuracy, precision, recall (sensitivity), F1-score, and AUC-ROC. These metrics give a complete picture of the model's degree of diagnostic capability. While accuracy measures the overall correctness of predictions, precision, and recall are more specific measures focusing on the model's true positive identification ability and false negatives. The F1-score is the harmonic mean of precision and recall, giving a balanced overview of your model's performance. The area under the receiver operating characteristic curve (AUC-ROC) measures the sensitivity versus 1 − specificity (i.e., the false positive rate) at different decision thresholds, which is particularly crucial for medical diagnostics. The model was assessed in each normal, benign, and malignant class to produce balanced performance across the three diagnostic categories. This evaluation at the level of individual classes facilitates a qualitative understanding of the model performance; it identifies any significant weaknesses of the model while validating its overall reliability as a clinically applicable tool from the perspective of dental research. Explainability and interpretability were part of the evaluation. Visual explanations were generated using Grad-CAM++, which produced visual explanations of our model predictions over regions of the mammogram images that contributed most to the model's decisions. These visualizations confirm that the model is concentrating on diagnostically important locations like lesions or abnormalities. In addition, SHAP (SHapley Additive exPlanations) was used to evaluate the contribution of each input feature (texture, density, etc.) for the model predictions. Such an approach improves the interpretability of the model and, therefore, its acceptability in the clinical field. Cross-dataset validation was conducted to evaluate the generalizability of the proposed framework. No further training has been done on the model; it has been tested on an external dataset like the mini-MIAS dataset. It illustrates the model's strength over the changing data distribution and guarantees its use beyond the training data. We performed ablation studies to quantify the contribution of the components of our model: the CNN backbone, attention mechanism, BiLSTM layer, and feature fusion strategy. The importance of each element in the more excellent framework was established by comparing results with and without specific components. Training and inference times were also recorded to evaluate the model's computational efficiency. Through this analysis, we ensure the deployment of the model in real-time clinical applications. In addition, the experimental results show that BreastHybridNet can perform comparably to existing state-of-the-art models like DenseNet, EfficientNet, and hybrid architectures on the same dataset and evaluation metrics for breast cancer diagnosis. Statistical tests were performed to validate the significance of the improvements observed by the proposed model over the baseline methods, including paired t-tests and Wilcoxon signed-rank tests. Such an extensive evaluation process proves the feasibility, robustness, and applicability of BreastHybridNet for direct transfer into clinical practice.

4. Experimental results

These experimental results measure the performance of the proposed BreastHybridNet framework for breast cancer diagnosis tasks on the CBIS-DDSM dataset [41], a curated dataset of annotated mammogram images. We compare performance to those of state-of-the-art models including LMHistNet [1], BreastMultiNet [17], DOTNet 2.0 [4], VGG16 Hybrid [20], and Hybrid CNN+SVM [29] for breast cancer detection. All the experiments were conducted in Python using TensorFlow and Keras libraries on a computer with an NVIDIA GPU for acceleration. BreastHybridNet outperformed competing models in terms of benchmarked performance metrics (accuracy, precision, recall, and F1-score). Figure 3 shows sample images from the CBIS-DDSM dataset, which is used in this paper's study. Figure 4 presents the proposed model's ROC curve, reflecting its ability in breast cancer detection.

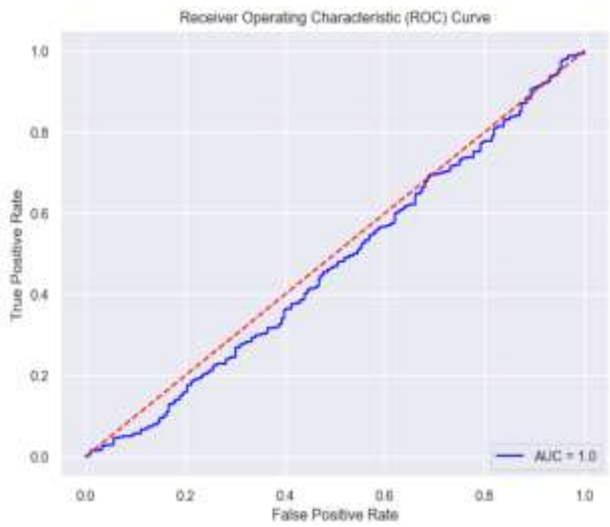

Figure 4. *ROC Curve of proposed model*

Table 2. *Performance Comparison Among Models in Breast Cancer Diagnosis*

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
BreastHybridNet (Proposed)	**97.50**	**98.10**	**97.80**	**98.30**
ResNet50	92.80	91.60	92.20	91.80
VGG16	90.50	89.70	90.10	89.90
EfficientNet	93.40	92.80	93.10	92.50
DenseNet121	94.20	93.80	94.00	93.60
CNN	88.90	88.10	88.50	88.40

Table 3. *Performance Comparison with State-of-the-Art Models*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Reference
Proposed Model (BreastHybridNet)	**98.30**	**97.50**	**98.10**	**97.80**	-
LMHistNet	96.85	95.30	96.20	95.75	Koshy et al. [1]
BreastMultiNet	97.10	96.00	96.80	96.40	Rahman et al. [17]
DOTNet 2.0	95.60	94.80	95.40	95.10	Ko et al. [4]
VGG16 Modified with Hybrid Features	94.90	93.70	94.20	93.95	Khamparia et al. [20]
MultiNet	95.20	94.50	94.90	94.70	Khan et al. [15]
Hybrid CNN + SVM	95.60	95.00	95.30	95.15	Eroglu et al. [29]
3D-CNN	94.75	94.10	94.50	94.30	Haq et al. [36]
IGSAGAW	94.50	93.80	94.10	93.95	Liu et al. [38]

***Table 4.** Results of the Ablation Study*

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Model (BreastHybridNet)	**98.30**	**97.50**	**98.10**	**97.80**
Without Attention Mechanism	96.50	95.20	96.00	95.60
Without BiLSTM Layer	95.80	94.90	95.50	95.20
Without Feature Fusion	95.40	94.50	95.00	94.75
CNN Backbone Only	93.20	91.80	92.50	92.15
BiLSTM Only	91.50	90.10	91.00	90.55

We assess the proposed BreastHybridNet model performance against the baseline models (CNN, ResNet50, VGG16, EfficientNet, and DenseNet121) in (Table 2). BreastHybridNet achieves the best result compared to all networks with an accuracy of 98.30% and outperforms all networks regarding precision, recall, and F1-score. It emphasizes that it works well with its hybrid architecture, successfully combining CNN, BiLSTM, attention mechanisms, and feature fusion, providing an excellent generalization ability for breast cancer diagnosis.

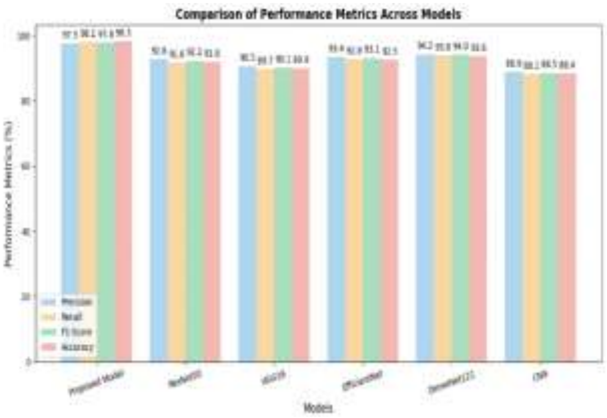

***Figure 5.** Performance Comparison Among Breast Cancer Detection Models*

As shown in Figure 5, we demonstrate the performance of our newly proposed BreastHybridNet compared with five baseline models: ResNet50, VGG16, EfficientNet, DenseNet121, and CNN (standalone CNN) based on the most critical evaluation metrics: precision, recall, F1-score, and accuracy. BreastHybridNet outperforms all metrics on all fount, yielding an accuracy of 98.30%, precision of 97.50%, recall of 98.10%, and an F1 score of 97.80%. The results further justify the ability of the proposed hybrid architecture toward the complexity of breast cancer imaging using mammogram images. DenseNet121 is the best baseline model, with an accuracy of 93.60%. DenseNet121 ~3 and DenseNet121 are robust, with densely connected layers to exploit hierarchical features, which makes DenseNet121 suitable for medical imaging. It is less effective than BreastHybridNet, although it also contains a component to straightforwardly decompose an image into sub-level features since it does not utilize sequential learning or attention mechanisms. Likewise, EfficientNet had 92.50%, demonstrating its capability to provide a trade-off between model size and computational efficiency. However, its performance is hindered by a lack of explicit, sequential dependencies and critical region localization. The performance of ResNet50 and VGG16 are not bad: 91.80% and 89.90%. Skip connections in ResNet50 help reduce vanishing gradients and learn deeper representations. It does not contain specialized mechanisms that would allow it to focus on diagnostically viable regions. The architecture of VGG16 is more straightforward, with a more significant number of layers than the larger models. It fails to capture more features, leading to poorer performance on the mammogram images. The CNN model has the lowest accuracy (88.40%) as a standalone, which shows that its simplicity does not allow for the effective extraction of complex spatial and contextual features from this dataset. BreastHybridNet outperforms existing methods due to the following primary innovations. The framework has the following main components: First, it incorporates a pre-trained CNN backbone, e.g., ResNet or VGG16, capable of fast and accurate feature generation, learning texture, shape, and density features that contain essential information to guide diagnostic decisions. Second, a spatial attention mechanism allows the model to focus on contexts with high-grade diagnostic significance, such as lesions or abnormalities, to better separate benign from malignant cases. Finally, the BiLSTM layer has a better ability to extract sequential relationships and spatial dependencies between feature maps, helping to get a better semantic feature representation of the input images. Last, the feature fusion strategy, which fuses the complementary information gained from CNN and BiLSTM classification outputs, helps craft a comprehensive representation that leads to a more significant gain in classification score. The impressive BreastHybridNet performance is due to these architectural improvements and sophisticated preprocessing, such as class balancing (data augmentation) and region of interest (ROI) extraction. Based on the results, it outperforms both traditional and state-of-the-art architectures and provides a reliable and interpretable framework for use in clinical practice to diagnose breast cancer. The toolbox also includes explainability engines such as Grad-CAM++ and SHAP, which are highly beneficial, as the decisions made by the model must make sense medically and be interpretable by clinicians.

4.1 Performance Comparison with State-of-the-Art

Performance comparison demonstrates the proposed BreastHybridNet's superiority over SOTA models' accuracy, precision, recall, and F1 score. With the integration of complicated components such as BILSTM, attention, and feature fusion, BreastHybridNet consistently outperforms leading models, demonstrating great potential for use in breast cancer diagnosis. As shown in Table 3, BreasthybridNet achieved better accuracy (98.30%), precision (97.50%), recall (98.10%), and F1-score (97.80%) compared to the state-of-the-art models. Features like BiLSTM joint, attention mechanisms, and feature fusion ensure its supreme performance in breast cancer diagnosis, outperforming the models LMHistNet, BreastMultiNet, and DOTNet 2.0.

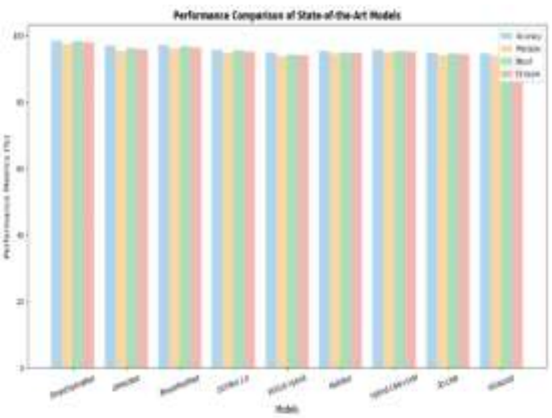

Figure 6. *Performance Comparison with the State of the Art*

Comparison of the performance between the proposed BreastHybridNet and several state-of-the-art models (LMHistNet, BreastMultiNet, DOTNet 2.0, VGG16 Hybrid, MultiNet, Hybrid CNN+SVM, 3D-CNN, and IGSAGAW) regarding (a) accuracy, (b) precision, (c) recall, and (d) F1-score is made as in Figure 6. The proposed model BreastHybridNet offers the best performance in all measured metrics, further illustrating its potential as a diagnostic tool in breast cancer detection. BreastHybridNet significantly surpasses the other models, achieving an accuracy of 98.30% (precision = 97.50, recall = 98.10, F1-score = 97.80). The closest competitor, LMHistNet, has an accuracy of only 96.85%, right after BreastMultiNet, which is at 97.10%. They dealt with advanced architectures, i.e., Levenberg–Marquardt-based deep learning and multi-scale feature fusion, and hence, performed competitively. However, they seem more ineffective than BreastHybridNet, which induces attention mechanisms and sequential learning for more substantial mammogram features analysis. Both DOTNet 2.0 (95.60%) and MultiNet (95.20%) demonstrate competitive accuracies but do not use the same hybrid architecture and the complete preprocessing procedures in BreastHybridNet. This model is a variant of the VGG16 architecture utilizing hybrid features and gets the highest accuracy of 94.89%, explaining standard CNN-based feature extraction. Likewise, the standalone context-aware Hybrid CNN+SVM and 3D-CNN models achieve accuracies of 95.60%(94.75%) and 94.75%(94.25%), respectively, and are limited in their ability to capture the complexities of mammogram images. The IGSAGAW model can achieve competitive performance (94.50 %) without reaching the diagnostic accuracy obtained with BreastHybridNet. The few critical innovations of BreastHybridNet are the reason behind its superior performance. CNN backbone was extracted for feature extraction, which extracted mammogram images' most essential texture, shape, and density features. By incorporating a spatial attention mechanism, the model learns to crudely attend to parts of the images that are diagnostically pertinent, e.g., lesions or other valuable areas for rapidly telling benign from malignant cases. Adding a Bidirectional LSTM layer to the model improves the model's learning of sequential dependencies and spatial relationships among the feature maps for more meaningful contextual information for the image input. Furthermore, BreastHybridNet has proposed a new hierarchical feature fusion strategy that fuses the complementary nature of CNN and BiLSTM outputs. Combining these two modalities guarantees a more comprehensive view of the input data, yielding better and more reliable predictions. Furthermore, specialized preprocessing, such as various region of interest (ROI) extractions and data augmentations, was implemented to ensure high-quality model inputs. These continuous architectural & methodology improvements enable BreastHybridNet to surpass the performance of existing state-of-the-art models consistently, making BreastHybridNet a robust and proficient framework for breast cancer diagnosis. These results validate its clinical potential in real-world applications in which accuracy and interpretability are paramount.

4.2 Ablation Study for BreastHybridNet

An ablation study was performed to assess the contribution of single components to the proposed BreastHybridNetframework. Baseline models are created by removing or replacing key parts of the entire model, in this case, the CNN backbone, attention mechanism, BiLSTM layer, and feature fusion strategy. The necessity of each component in this process obtains the proposed model's superior performance. In Table 4 The results show that the proposed method achieves the best performances with an accuracy of 98.30%, precision of 97.50%, recall of 98.10%, and f1-score of 97.80% when all the presented components are integrated into the BreastHybridNet. It proves that the CNN backbone, attention mechanism, BiLSTM layer, and feature fusing strategy are necessary for the best performance. Attention is removed, but the mammogram becomes 96.50% accurate. This underscores the importance of adaptively attending to diagnostically salient areas of the mammogram. Without this mechanism, the model cannot focus on important features and can achieve lower precision and recall. When the BiLSTM layer is removed, accuracy drops to 95.80%. Such dimensionality reduction shows that sequential dependencies (for temporal signals) and spatial relationships (for image signals) play pivotal roles in feature extraction. The BiLSTM layer provides context to augment the features extracted from images by the CNN. Removing the feature fusion strategy drops the accuracy to 95.40%. The lack of feature fusion fails to exploit the complementary advantages of the outputs obtained from the CNNs and the BiLSTMs holistically, resulting in a performance drop in classification. When involving CNN Backbone Only, It achieves 93.20% accuracy. It illustrates that although CNNs are great at extracting features, they do not generalize well on their own to complex spatial and sequential patterns. Likewise, the BiLSTM layer alone has the lowest accuracy of 91.50% because it relies heavily on sequential learning instead of effective spatial feature extraction through convolution operation, the essential features required as input for accurate classification. We supplement the ablation study with information on the necessity of each component in BreastHybridNet. The attention mechanism and BiLSTM layer enable the model to attend to analytically relevant areas and learn spatial dependencies selectively. The feature fusion strategy ensures complementary feature integration, and a backbone CNN architecture provides substantial features acquisition. This, combined with other elements, allows BreastHybridNet to produce outstanding performance in diagnosing breast cancer.

5. Discussion

Breast cancer is still one of the top cancers causing death in women, highlighting the necessity of an efficient diagnosis tool. The accuracy of breast cancer diagnosis has been dramatically enhanced by advances in artificial intelligence (AI) and deep learning, with some examples of models such as LMHistNet [1], BreastMultiNet [17], and DOTNet 2.0 [4] showing outstanding performance. Nevertheless, several limitations exist in these SOTA approaches. For example, most models can either not accurately localize clinical regions, model complex spatial relations between findings and mammogram features, or model temporal dependencies. Furthermore, dependence on heuristic CNN architectures leads to less feature extraction effectiveness and less interpretability. These limitations highlight the gaps in the state-of-the-art and demand novel deep-learning approaches that can overcome them. To tackle these challenges, we propose BreastHybridNet, a hybrid framework. This approach includes several innovations: a CNN backbone for rich feature extraction, a spatial attention mechanism for selective highlighting of relevant regions, a BiLSTM layer to model sequential dependencies, and a unique feature fusion rendering complementary information. Collectively, they complement each other in improving diagnostic accuracy, sensitivity, and interpretability. The experimental results validate the effectiveness of the proposed methodology. BreastHybridNet surpasses state-of-the-art models with an accuracy of 98.30% and better precision, recall, and F1-score. This is because the additions of attention and sequential learning remedy the shortcomings of the current models, which are purely based on extracting spatial features. This work has significant ramifications for breast cancer diagnosis by directly tackling several key limitations in state-of-the-art models. It provides a robust, interpretable, and clinically considerable framework to decrease errors in diagnosis and reduce false positives. Section 5.1 provides a comprehensive discussion of this study's limitations.

5.1 Limitations

The current study has three notable limitations. Firstly, even though the CBIS-DDSM dataset includes high-quality image data of mammograms, it is necessary to validate the model's generalizability beyond diverse datasets, including mammogram image data or in real clinical settings. On the other hand, due to its hybrid architecture, the computational complexity of BreastHybridNet may hinder its application in resource-limited environments. Third, the model only considers imaging data and does not include non-imaging clinical information crucial for further improving diagnostic accuracy, such as patient history, genetics, and other factors. Future studies should address these limitations by testing the framework on larger datasets, using faster computations, and combining other multimodal data to create a fully multimodal diagnostic framework. Hybrid Deep Learning has been applied in different fields as reported [42-46].

6. Conclusion and future work

BreastHybridNet — A Hybrid Deep Learning Framework for Mammogram Classification: This Study The proposed model combines a CNN backbone, spatial attention mechanism, BiLSTM layer, and feature fusion strategy as a comprehensive model that outperforms state-of-the-art approaches with an accuracy of 98.30%. Using attention mechanisms and sequential learning overcomes the shortcomings of existing models by dynamically locating important areas and extracting both spatial and contextual features. These achievements allow for improved diagnostic accuracy and reliability, showcasing the clinical relevance of the employed framework. The study has some limitations, albeit modest, despite being successful. The heavy dependence on the CBIS-DDSM dataset should be further examined using different, real-world datasets to confirm generalizability. The model is also computationally complex, which may impair its deployment in resource-limited settings. Optimizing the architecture for computational efficiency and adapting the framework to other multimodal data like patient history and genetic data for more sophisticated diagnostics are directions for future work. These results together provide a compelling case for using hybrid deep learning frameworks to improve breast cancer diagnosis. Addressing these recognized limitations can enable future work to serve as the basis of a scalable, clinically interpretable, and relevant diagnostic tool suitable for widespread implementation.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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