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Breast Cancer Diagnosis Improvement Based Deep Learning

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Abstract: Background: Globally, Breast cancer is the utmost predominant cancer and it affects millions of women every year. Dynamic Contrast Enhanced Magnetic Resonance Imaging (DCE-MRI) has been familiar as an efficient modality for diagnosing breast cancer. In spite of DCE-MRI modality being majorly utilized for the classification of breast cancer, the diagnostic performance is still deficient and misclassification occurs.

Method: This research proposes the Deep Learning (DL) approach of Dual Attention Deep Convolutional Neural Network (DADCNN) for the classification of breast cancer into two types named benign and malignant. Initially, the DCE-MRI, Rider Breast MRI and Breast MRI datasets are utilized for estimating the effectiveness of the classifier. After collecting the dataset, pre-processing is performed by utilizing data augmentation technique. Then, the augmented data is input for the feature extraction process, which is performed by using DenseNet-121 and ResNet-101 architectures. Then, the extracted features are concatenated by using the feature fusion model and finally, classification is performed to categorize the breast cancer. The DADCNN approach deals with the long input features to selectively focus on the most relevant parts in breast cancer, so it enhances the results. The presented DADCNN approach significantly outperforms the existing methods like MUM-Net-joint prediction, UDFS + SVM, XGBoost, Multivariate Rocket and BI-RADS. The greater accuracy of the proposed DACNN approach suggests DL approach to effectively enhance the classification accuracy in breast cancer.

Results: The experimental results establish that the proposed method attains greater results in all performance metrics as compared to the exiting methods like Multi-modality Network (MUM-Net) and Multivariate Rocket algorithm, The suggested DADCNN approach attains the maximum accuracy of 0.931, specificity of 0.924, sensitivity of 0.925, AUC of 0.962, PPV of 0.853 and NPV of 0.902 in breast cancer classification, which denotes that the DACNN effectively classify the cancer into benign and malignant.

Concluding Remarks: The DADCNN approach deals with the long input features to selectively focus on the most relevant parts in breast cancer, so it enhances the accuracy, specificity, sensitivity, AUC, PPV and NPV in breast cancer classification.

Index Terms: Breast cancer, DenseNet-121, Dual attention deep convolutional network, Dynamic contrast enhanced magnetic resonance imaging and ResNet-101

1. Introduction

Breast cancer is the most significant cancers in the globe and the number of deaths caused by it have been increased every year [1]. As stated by the World Health Organization (WHO), over 2.3 million breast cancer cases were diagnosed in 2020 with 6.85 lakh deaths. Hence, it is significant to detect breast cancer in early period to reduce the mortality percentage [2]. Breast cancer can be divided into binary categories as benign and malignant. The benign (noncancerous) is non-destructive towards nearby muscles and does not feast throughout the chest. Whereas, malignant are cancerous as well as hostile, due to which feast as well as harm the nearer parts [3, 4]. Magnetic Resonance Imaging (MRI), Ultrasound (US) images, Histopathology and Mammogram are some of the various modalities to identify cancers employed by doctors and expert radiologists [5, 6, 7]. Manual diagnosis process may reason to produce maximum False Positive Rate (FPR) and False Negative Rate (FNR) [8]. So, in nowadays, Computer Aided Diagnosis Systems (CAD) is widely utilized for supporting radiologists at the time of decision making for cancer identification. The CAD systems potentially minimize the radiologists' efforts, alongside reducing FPR and FNR in diagnosis [9, 10].

The traditional CAD approaches cannot easily attain functional features architectures of breast cancer image [11, 12]. Whereas nowadays, with the development of Artificial Intelligence (AI) approaches, the chances of achieving superior outcomes in addressing the existing problems of CAD approaches have increased [13], hence, the dependability on Machine Learning (ML) and Deep Learning (DL) approaches for segmentation and classification of breast cancer [14, 15]. Some approaches are comparatively having lower effectiveness because of the extraction of deficiency manual features of the breast cancer [17, 18]. During the preceding years, researchers have introduced many DL approaches to facilitate the diagnosis process of breast cancer [19, 20]. For breast cancer identification, the MRI image features are manually extracted and later the extracted features are provided to the classification algorithms for categorization [21, 22, 23]. However, achieving accurate classification of breast cancer cells with MRI systems still remains challenging due to minimum contrast, noise, blurred boundaries and various tumour shapes and sizes in the images [24]. Also, the diagnostic performance is still deficient and often leads to misclassification [25]. Thus precise research question or hypothesis is how to motivate this research to effectively overcome the above-mentioned limitation. Hence, this research aims to propose the novel DL approach which results in accurate breast cancer classification. The contribution of this research in its proposed Dual Attention Deep Convolutional Neural Network (DADCNN) algorithm for the classification of breast cancer into binary class like benign and malignant. In the classification based on DADCNN, an attention module determines the particulars by activating the highlighted regions of breast tumour which contribute to the diagnosis, as a result, enhancing the accuracy results. The significant contributions and novelty of this article are including in the following:

- The data collected from DCE-MRI is pre-processed by using data augmentation technique to enhance the number of input samples through rotating and flipping. This helps to enhance the accuracy performance through enhancing the learning capability of breast tumours.
- Feature extraction is performed by using the pre-trained CNN architectures of DenseNet-121 and ResNet-101 to extract the relevant features, wherein the extracted features are fused through the Feature Fusion (FF) approach. It extracts meaningful features from breast cancer images and enables the classifier to effectively train the features.
- The DADCNN classifier is utilized for the classification process for categorizing breast cancer into either benign or malignant. The dual attention module helps in focusing on the most informative breast features and regions, leading to high classification accuracy and minimum NPV.

This paper is arranged in four sections in the subsequent way: Section 2 provides the literature survey; Section 3 presents the proposed method, while the experimental results are discussed in Section 4 and Section 5 summarizes the paper.

2. Literature Review

The recent researches on breast cancer classification approaches on MRI datasets are discussed in this section.Qiao et al. [26] introduced the MRI-US Multi-modality Network (MUM-Net) for the classification of breast tumours into various subtypes according to 3D MR as well as 2D US images. The Discrimination Adoption Module (DAM) was initially utilized for feature decomposition into modality-agnostic as well as modality-specific ones with min-max training plans. Afterwards, the FF approach was developed to enhance a modality-agnostic feature density by the help of attraction matrix with the Nearest Neighbour selection. By focussing on the relevant breast regions and combining the information from multiple-scales, MUM-Net led to better classification results. The introduced approach obtained joint predictions according to the two modalities as well as loss functions, even when the data for individual modality were applicable.

Militello et al. [27] presented and estimated the radiomic approach capable for the prediction of malignant breast cancers through 3D radiomic feature extraction from DCE-MRI. The Support Vector Machine (SVM) was introduced for classification of breast lesion. Feature calibration and pre-processing techniques like normalization as well as quantitative imaging map development were utilized for the identification of robust non-redundant features. The presented approach obtained efficient results in overall metrics. However, the large number of features extracted from 3D images led to high-dimensional feature space, making it challenging to select the most relevant features.

Vamvakas et al. [28] developed the Boosting ensemble approach for classification of the breast cancer. The boosting ensemble approach was utilized for the enhancement of diagnosis effectiveness of multiparametric MRI (mpMRI) radiomic models. The hierarchical clustering on Spearman’s rank correlation coefficient was developed for the selection of final feature subset. The Adaptive Boosting (AdaBoost), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost) as well as Light Gradient Boosting Machine (LightGBM) was utilized for estimation of categorizing the breast lesions. Nevertheless, the feature extraction step was not performed and so, it focused on irrelevant features which led to suboptimal learning.

Prinzi et al. [29] presented the time series-based approach of Multivariate Rocket model for the classification of breast cancer. The multi-instants feature selections as well as univariate time series classification approaches were utilized for the identification of various supportive features for the radiomic time series classification. After that, the most significant features were combined through the voting approach for the execution of Multivariate Rocket Model. A utilization of the radiomic extracted features from entire sequence of DCE-MRI mimicked a radiologist's diagnostic procedure. Nevertheless, this approach varied based on the contrast agent utilization, and did not inherently consider long-term dependencies in the data.

Debbi et al. [30] introduced the Random Forest (RF) approach for the classification of breast mammary masses through the utilization of DCE-MRI. Two efficient radiologists specialized in breast imaging classified the mammary masses on breast MRI based on the BI-RADS classification. The breast cancer images were post-processed through the utilization of the breast's cape software package and later, the features were selected by the utilization of the Boruta approach alongside the BI-RADS classification being recorded from the two radiologists. Nonetheless, the introduced approach lacked external validation on autonomous cohorts collected from other centres.

Domiziana Santucci et al. [31] presented the three various CNN architecture for the analysis of various tumour bounding options for the prediction of Lymph Node Status (LNS). The impact of the 2D and 3D features extracted from an input data and the impact of the health tissue in the conditions of the multimodal and multicentre tumours were analysed. The presented CNN approaches were varied based on the characteristics of the volumes focussed as inputs. Nevertheless, the presented CNN architecture was resulted in less sensitive values as compared to the specificity.

Roa'a Khaled et al. [32] introduced the automated approach of 3D patch-based U-Net model for the segmentation of breast lesion. The modified Un-Net architecture which incorporated the residual basic blocks. Furthermore, the utilization of various inputs was examined and introduced the ensemble approach which integrated various models; each uses various combinations of the inputs. The 3D U-Net courses volumetric data, captured high spatial context than 2D models, leads to more accurate segmentations of complex structures in breast lesions. However, independent segmenting patches lead to artefacts at the boundaries of patches, significantly affecting an overall segmentation quality.

Chuanbo Qin et al. [33] developed the two-stage breast cancer image segmentation approach called TR-IMUnet. The U-Net network approach enabled the uneven definition of breast region in the collected images and removed an impact of the distinct parts on the segmentation of the breast tumour. The developed TR-IMUnet was enhanced through embedding the multi-scale fusion block and the transformer module in a model coding path, thus acquired a multiscale and global attention data. However, the data augmentation was not performed to improve the number of data to solve overfitting problems, leads to poor performance.

Muhammad Umar Nasir et al. [34] presented the fine-tuning approach by the utilization of AlexNet in the neural network for the feature extraction from breast images. In the presented fine-tuned AlexNet model, the first and final three layers of the AlexNet were updated for the detection of normal and abnormal areas of the breast cancer. The presented approach obtained the fast and efficient results in the training and testing phase. However, the AlexNet architecture does not have the capability to capture complex features as effectively.

Ali M. Hasan et al. [35] developed the Long Short-Term Memory (LSTM) approach for the classification of breast cancer. The fully automated and effective deep feature extraction approach like T2-Weighted with Turbo Spin Echo (T2W-TSE) and Short Inversion time (STIR) MRI sequences were developed to extract the features. The Fractional Integral Entropy (FIE) approach was utilized in the pre-processing step to minimize the effects of the intensity differences among MRI images. The extracted features were effectively enhanced the effectiveness of LSTM. Nevertheless, T2W-TSE and STIR sequences produced complex data which is challenging to interpret correctly by automated systems without pre-processing.

Ying-Ying Guo et al. [36] introduced the CNN with SVM (CNN-SVM) approach for the classification of breast cancer. In the testing stage, the labelled output of the CNN and the test grey scale image were forwarded to the SVM for an accurate segmentation process. The introduced CNN-SVM approach had adapted to the variations and segmentation in breast tumours effectively and accurately. SVMs obtained the robust decision boundaries, often leading to improved classification performance when combined with CNNs. But the presented CNN architecture was resulted in less sensitive values as compared to the specificity.

Yang Zhang et al. [37] developed the Mask Reginal-CNN (R-CNN) for the detection of abnormal lesions, pursued through the ResNet50 for the estimation of malignancy probability in breast cancer. The subtraction and pre-contrast image of the right and right breasts were utilized as inputs in the pre-processing step to examined symmetry of the data/ the detected distrustful region was characterized through the ResNet50 by the utilization of multiple DCE parametric maps as inputs. However, Mask R-CNN produced false positives and negatives, leading to potential misdiagnosis.

Kranti Kumar Dewangan et al. [38] introduced the Back Propagation Boosting Recurrent Wienmed (MPBRW) approach with the Hybrid Krill Herd African Buffalo Optimization (HKH-ABO) approach for the detection process. Initially, the Wienmed filter was developed for the removal of noise from the MRI data in the pre-processing step. The introduced MPBRW approach effectively fine-tuned the predictions through iteratively adjusting the weights, leads to better performance in detecting breast cancer. However, boosting's capability to reduce overfitting, improper handling or excessive boosting led to overfitting.

Wei Wang and Yisong Wang [39] implemented the modified YOLACT approach for the classification and diagnosis of breast cancer from MRI images. The difficult-sample mining approach was developed to enhance effectiveness YOLACT. The implemented modified YOLACT approach effectively obtained the superior accuracy and classification effectiveness. However, the YOLACT does not extract the most relevant features for breast cancer diagnosis, leads to poor performance.

Ali M. Hasan et al. [40] presented the SVM approach for the classification of molecular subtypes of the breast cancer. Initially, the dataset was pre-processed by applying Region of Interest (ROI) through the radiologist experienced in breast MRI data. Then, the CNN approach was utilized for the extraction of the deep features. SVM had efficiently handled high-dimensional data, making them appropriate for the deep features extracted through the CNN. However, SVM was sensitive to noise and outliers in the training data, which affected the classification performance.

Maria Colomba Comes et al. [41] developed the CNN approach for the automatic feature extraction of the breast cancer. The prediction approach was developed with the optimal subset of the CNN features and estimated the two sets of the patients from the collected dataset. The fine-tuned data was initially utilized for the identification of the optimal feature subsets and the independent test, whose patients does not been performed in the feature selection process. However, the data augmentation was not performed to improve the number of data to solve overfitting problems, leads to poor performance.

Ahmed Iqbal and Muhammad Sharif [42] developed the Breast Tumour Segmentation and the Swin Transformer (BTS-ST) approach for the classification of breast cancer. The BTS-ST approach combined the ST into CNN-based U-Net approach for enhance the global modelling capabilities. The Spatial Interaction Block (SIB) was utilized to enhance the feature representation capability of the irregular shape features. The Relationship Aggregation Block (RAB) was introduced as the concatenation among the dual encoders to integrate the global dependencies features. Nevertheless, the implemented approach does the extracted the meaningful features from the pre-processed data to extract the relevant features, leads to poor performance.

Xiaoming Zhao et al. [43] introduced the DCE-MRI dataset named BreastDM for the process of the segmentation and classification. The introduced data solved the problematic of shortage of large, publicly available DCE-MRI datasets for breast tumour segmentation and classification. The Local-Global Cross Attention Fusion Network (LG-CAFN) approach was introduced for the interactive fusion of extracted local and global data for the segmentation and classification of breast cancer. However, independent segmenting patches lead to artefacts at the boundaries of patches, significantly affecting an overall segmentation quality.

Monu Verma et al. [44] implemented a prediction model for breast cancer to neoadjuvant systemic therapy based on deep learning approach. For automatic prediction, an efficient multi-modal and 3D-CNNmethod used to predict breast cancer at early diagnosis. A cross-kernel feature fusion module was incorporated to make the model more learnable by extracting spatiotemporal features. However, the developed approach was sensitive to noise, which affected the accuracy result, leads to unreliable results.

Navved Urr Rehman et al. [45] designed a model to enhance breast tumour in MRI analysis based on DCNN method. An enhanced segmentation approach of edge U-Net was utilized to improve tumour localization and classification of breast tumour in MRI data. The main advantage of designed model was a loss function included to EEU-Net method increased the learning process for more precise results. However, due to imbalance data, the designed model face challenges to predict breast tumours effectively.

From this section, the following limitations are drawn which lead out to the research question or hypothesis: The feature extraction step was not formed, and did not inherently consider long-term dependencies in the data. These limitations caused poor performance and had the chance to misclassification. To overcome these challenges, this research proposes a novel DADCNN method for the accurate classification of breast cancer. Additionally, the feature extraction step is performed to select the relevant features. It enhances the feature representations through generating more informative features in breast cancer. The detailed information of this approach is provided step-by-step below.

3. Proposed Methodology

This research proposes the classification of the breast cancer into two categories of benign and malignant by using the novel DL approach. This section comprises of various steps: Initially, the data is collected by using DCE-MRI dataset. Then, pro-processing is performed by the utilization of data augmentation technique. After pre-processing, the features are extracted by using the two pre-trained architectures, employing DenseNet-121 and ResNet-101. Then, the feature fusion model is deployed to concatenate the different feature extraction models, and finally, classification is employed. Figure 1 shows the working steps of the proposed method.

3.1 Data Collection

The primary focus in this model is to collect the breast cancer image dataset to estimate the efficacy of the model. This research utilizes three breast cancer diagnosis datasets such as Dynamic Contrast Enhanced Magnetic Resonance Imaging (DCE-MRI) [46]; Rider Breast MRI [47] and Breast MRI [48] are used to estimate the effectiveness of the model. The DCE-MRI dataset consists of 226 image samples collected from Signa HDxt; GE Healthcare, Barrington, IL, USA. Table 1 shows the DCE-MRI dataset characteristics. Generally, the DCE-MRI dataset contains minimum data which is not sufficient for accurately classifying breast cancer. This dataset consists of four classes such as BC, MC, BM and MM. The Rider Breast MRI involves 2400 DCM format data pieces of 288×288 size was chosen as an experimental training data. Hence, pre-processing is performed to enhance the raw data. The collected dataset is then fed to the pre-processing stage for achieving better classification performance. Figure 2 depicts the samples images of the utilized datasets.

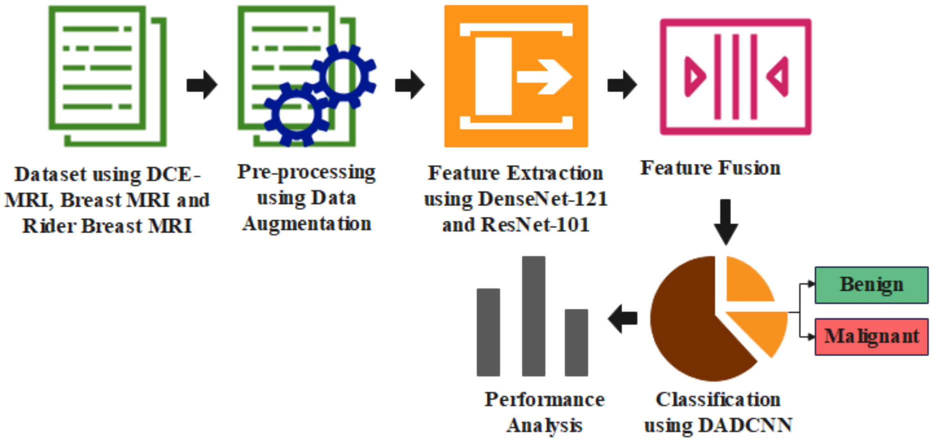

Fig. 1. Working steps of the proposed method

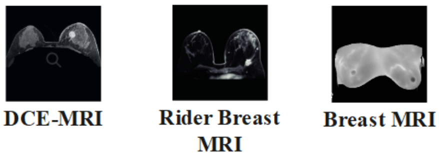

Fig. 2. Sample images of the utilized datasets

Table 1. DCE-MRI dataset characteristics

DCE-MRI characteristics	Value
Dimensional size	512×512 pixel
Pixel spacing	$0.6875 - 0.7422mm$
Spacing among slices	1 to 1.5 mm
Scanner Model	GE signal HDxt (1.5T)
Flip angle	10°
Slice thickness	$2 - 3mm$

3.2 Pre-processing

Before providing DCE-MRI data for classification, the pre-processing must be performed before the feature extraction and classification in breast cancer. The collected DCE-MRI data contains only a limited amount of data samples. So, it leads to misclassification problems. Hence in this step, the data augmentation technique is utilized to enhance the input image samples. The detailed explanation of this technique is described in the subsection.

3.2.1 Data Augmentation

Data augmentation [49] is an efficient and majorly utilized technique for ignoring the overfitting problem through creating the extended data. Before inputting the data to augmentation, the input image data are improved by preventing the noise as well as resizing them to 224×224 resolution. Then, augmentation is performed to enhance the training sets, generalization, as well as improve the convergence speed, performed only with the training data in breast cancer. The data augmentation is performed by random reflection, rotation, zooming and shearing to augment the input breast image data. 90-degree and 180-degree rotations and flipping are employed in the augmentation while keeping the actual image features [14]. The augmented image sizes are minimized with respect to the improved accuracy, speeding up the process. The augmented data is then fed to the feature extraction process. Table 2 gives the information about data augmentation parameters.

Table 2. Data augmentation parameters with their values

Parameters	Values
Brightness	Up to 0.35
Contrast	Up to 0.5
Hue	Up to 0.1
Saturation	Up to 0.1
Horizontal flip	90° and 180°
Vertical flip	90°
Image rotation	0.2

3.3 Feature Extraction

In this step, the augmented DCE-MRI data are extracted by the pre-trained CNN architectures. The most common goal of feature extraction is to minimize high dimensionality of features, alongside data compaction. In this feature extraction process, the DenseNet-121 and ResNet-101 are the two architectures utilized to extract the breast features. The pre-trained DenseNet-121 and ResNet-101models act as a feature extractor. For every image, the model extracts feature from various layers. Because of the dense connectivity of the DenseNet-121, features from all layers are used. In ResNet, features are extracted through residual blocks. The detailed information of these models is provided below.

3.3.1 DenseNet-12 1

In comparison to the other pre-trained models, the DenseNet-121 and ResNet-101 architectures accept the feature maps from the previous layers, allowing it to reuse the breast image features more effectively. Breast cancer classification often requires identifying subtle patterns and textures in images, which DenseNet-121 deep architecture with dense connectivity is well-suited to handle. DenseNet-121 [50] is the Fully Connected Feedforward Neural Network (FCFNN) which is majorly employed as the feature extractor. The actual DenseNet-121 architecture preserves minimum features as compared to other convolutional networks as it connects each feature map with the dense block. Consequently, DenseNet-121 is the supportive model for enabling an efficient extraction of the breast cancer features. This architecture involves multiple layers such as input (Conv 1), multiple dense blocks as well as transition. A Conv1 filter size of is 7×7 and a size of feature map is minimized by the 3×3-max pooling layer. The multiple dense layers involve 6, 12, 24 and 16 block layers, while the transition layers merge every block among the dense blocks. The DenseNet-121 includes SE blocks as well as Global Average Pooling (GAP) layers associated to final layers of every dense layer for extracting the feature vectors of size$1 \times 1 \times C$. A multi-scale feature maps acquired from pooling layers are moved towards SE blocks as well as GAP layers; the feature vector includes 256, 512, 1024 and 2048 channels which are acquired as outcomes. An extracted feature vectors from all SE blocks are associated with the course of channel, and eventually are minimized to 1024 dimensions by the FC layer with similar dimensions. DenseNet-121 is pre-trained by utilizing every breast DCE-MRI dataset by extending 1-dimensional FC as well as output layer. DenseNet-121 have the capability to capture intricate details in images and learn hierarchical features, making it well-suited for tasks where subtle patterns or abnormalities like identifying potential tumours or abnormalities in breast tissue require to be detected.

3.3.2 ResNet-101

The ResNet-101 [51] has the network's capability to specify well to unknown data, is important for reliable breast cancer classification. ResNet-101 or Deep Residual Neural Network (DRNN) is one of the most-pre-trained models that using the Image Net. Figure 3 depicts the ResNet-101 architecture. Two or more layers of the ResNet are straight associated to the next layers by utilizing the Rectified Linear Unit (ReLU) activation function. The ResNet architecture utilizes the forward and backward propagation approaches. The residual connection is utilized to manage the minimum-level features which are vanished while the input image forwards to its layers. The ResNet-101 architecture is assumed as the supportive network of the proposed method. Multiple SE blocks as well as GAP layers are substituted to the final layers in residual blocks. SE blocks apply the weight to every channel in input feature maps, while the size of the feature vector $1 \times 1 \times C$ is developed by GAP layer. The multi-scale feature maps are forwarded to the SE blocks, GAP layers as well as outcome feature vectors. A channel involved in the feature vectors are 256, 512, 1024 as well as 2048, while residual blocks are associated with a channel’s direction. These feature vectors are eventually forwarded to FC layer earlier minimized to 1024 dimensions. ResNet-10 in breast cancer has residual connections, efficient training, transfer learning capabilities, generalization to unseen data, and interpretability. These factors make it a compelling choice for researchers working on automated breast cancer detection systems using MRI images.

The features of breast cancer are efficiently extracted by utilizing the two pre-trained architectures of DenseNet-121 and ResNet-101. Then, the extracted features are fused before the classification process. The detailed information about the fusion model is described in the subsections below.

3.4 Feature Fusion

In this section, the extracted features are concatenated before the classification by using Feature Fusion (FF) approach. Through fusing the features from the different extractor, the FF approach designs the most discriminative representation of breast cancers. The concatenation of the features by the FF approach frequently leads to enhanced classification performance, as compared to using the other fusion approaches in the context of breast cancer classification. FF is the process of concatenating different input modalities into individual feature vectors before providing into the classifier for training. The FF approach [52] collects extracted feature vectors obtained from sub-networks and employs classification as it is complex to classify the data only by utilizing individual network. This approach assigns the learning-based feature-level fusion approach by utilizing the FC layers. In this FFA approach, only the utilized feature vectors are extracted, unlike the decision values obtained from every sub network. Furthermore, through learning a nonlinear FC layer, an optimal weight of feature vectors in sub networks must be identified. In FF approach, two 1024-dimensional extracted feature vectors from DenseNet-121 and ResNet-101 are initially associated in a channel direction. While working the feature-level fusion, the dimensions of feature vector are associated systematically, so as to maintain both DenseNet-121 and ResNet-101 architectures. Eventually, the integrated 2048-dimensional feature vectors are forwarded by 1-dimensional FC as well as sigmoid layers, hence classifying input features into benign and malignant. The advantage of the FF approach is the detection of correlated feature values produced through various biometric approaches, thereby determining the compressed set of salient features which enhance the classification accuracy. The fused feature is then forwarded to the classification process.

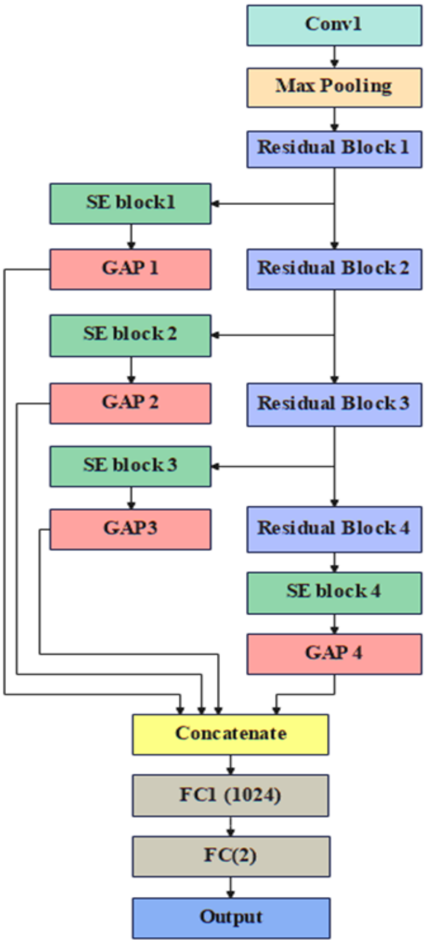

Fig. 3. ResNet-101 architecture

3.5 Classification

In the classification process, the extracted features are utilized as input to classify the breast cancer into two categories such as benign and malignant [53, 54]. The DL-based classification approach utilizes only minimum amount of training samples, as well as gives better performance. As compared to other methods, CNN is better for breast cancer classification using MRI datasets [55] due to their ability to efficiently and effectively capture spatial hierarchies, reduce the number of parameters, and process high-dimensional image data. Hence in this research, The CNN classifier is utilized for categorizing breast cancer [56] and the detailed information of this classifier is provided below.

3.5.1 Convolutional Neural Network

CNN is widely utilized for classification and recognition of medical diagnoses [57, 58, 59]. The CNN architectures comprise multiple layers such as input, convolutional, max-pooling, FC and output layer [60, 61, 62, 63, 64]. The DCNN's input images are provided to the initial two-dimensional convolutional layers. The input height $n_h$and width n_w of the initial two convolutional layers are 128 while the stride (s) value is 1. The initial max-max-pooling layer is developed to minimize an initial convolutional layer's dimensions. An outcome of the max-pooling layer's dimension is expressed in (1).

$$Dimension(Pooling(n,k) = \left(\left[\frac{n_w - f_w}{s} + 1\right], \left[\frac{n_h - f_h}{s} + 1\right], n_c\right) \tag{1}$$

Where,n_h n_w and n_c represent the height, width and channel of input$n$;f_h, f_w are height and width of filters the max-pooling layer; s is stride of pooling operation. An outcome of this layer is then provided to the convolutional layer. It utilizes the individual-step stride to assign a kernel value to an input data and ReLU activation function is utilized for the convolutional layers. The ReLU activation function is formulated in (2).

$$ReLU(x) = Max(0, x) \tag{2}$$

Furthermore, the flatten layer is developed after the convolution and pooling layers, and then it minimizes the 3-dimensional data into 1-dimensional data for the actual NN approach. The flatten layer converts the maxpooling layer as the outcome. Then, the initial dense layers are developed after the flatten layer and then enhance the input value for 512 to 2048 values. The single neuron output (z_j) of the first dense layer is expressed in (3).

$$z_j = ReLu\left(0, \sum_i^{512} b_j + x_i w_i\right) \tag{3}$$

Where, x_i and w_i are the value and weight of the ith input of jth output, and b_j is the bias value of jth node. A dropout layer is utilized among first dense and second dense layer in DCNN to prevent the overfitting problem. Likewise, the second dense layer's input is 2048, whereas the output of NN is 59. Furthermore, this layer utilizes a softmax activation function for the classification of breast cancer. The softmax function (σ) value of ith dense layer's neuron is formulated in (4).

$$softmax\left(\sigma(z_j)\,\right) = \frac{e^{z_i}}{\sum_{j=1}^{59} e^{z_j}} \tag{4}$$

Where, z_i is ith element of an input vector$z$; $\sum_{j=1}^{n} e^{z_j}$ represents sum of exponentials of all elements in input vector z; An output class of an input image is determined by the following (5).

$$\text{Output Class } (z_{out}) = max(z_1, z_2, \dots z_{59}) \tag{5}$$

The output value from z_1 to z_{59} describe the number of non-cancerous diseases. The outcome of this approach is then provided to the dual attention model to effectively classify breast cancer.

3.5.2 Dual Attention DCNN

The CNN has some drawbacks naming requiring a large number of labelled data to train a model [65, 66, 67]. Hence, the dual attention model is proposed with the CNN to effectively train the classifier and allow the model to effectively consider on the relevant features. The integration of dual attention mechanisms enhances the model's capability to focus on relevant features, improving classification performance. The DACNN outperforms traditional CNNs by better capturing both spatial and channel-wise importance, leading to higher classification accuracy. The dual attention module comprises two attention networks such as Position Attention (PA) as well as Channel Attention (CA) network for breast classification. The PA is equivalent to self-attention model and it utilizes various strategies for the development of the attention map. The DA involves the channel attention network which employs the binary multiplication operations such as softmax and addition. The DA operation is mathematically formulated in (6). The PA and CA operations are expressed in (7) and (8).

$$DA(x) = PA(x) + CA(x) \tag{6}$$

$$PA(x) = U(x) + In(x) = R(x).S(x) + In(x) = Soft\left(P(x)^t.Q(x)\right).S(x) + In(x) \tag{7}$$

$$CA(x) = N(x) + In(x) = soft\left(M(x)\right).In(x) + In(x) = Soft\left(In(x)^T.In(x)\right).In(x) + In(x) \tag{8}$$

Where, $DA(x)$, $PA(x)$ and $CA(x)$ are the feature maps of the DA, PA and CA, $In(x)$ are the input feature maps, $P(x)$, $Q(x)$ and $R(x)$ are the feature maps of multiple parallel convolutional operations, $S(x)$ represents a feature map after softmax operation, $U(x)$ represents the multiplied feature maps of $S(x)$ and $R(x), N(x)$ represents the multiplied feature map of $softmax(M(x))$ and input feature map, $M(x)$ refer to the multiplied feature maps of reshaped as well as transposed feature maps, **.** and $+$ represent the feature map's element-wise product and multiplication, respectively. Attention is a natural extension and it eliminates the redundancy in spatial dimension, making it as computationally efficient. In this breast cancer classification process, binary cross-entropy loss function and Adam optimizer is utilized for developing the output classification. Particularly, the loss function of the DADCNN approach makes the training as well as testing curves together, alongside exceeding overfitting effectively in the breast cancer. Algorithm 1 represents the CNN classifier with Dual Attention. Table 3 shows the training hyperparameters of the classifier used for breast cancer. The experimental configurations of the proposed approach are provided in the below section.

Table 3. Training hyperparameters of the DADCNN classifier

Hyperparameter	Values
Batch size	32
Optimizer	Adam
Learning Rate	0.001 (default)
Epoch	100

Algorithm 1: CNN Classifier with Dual Attention

Input: Training data, Testing data, Training Label, Testing Label
Hyperparameters (num_epochs, batch_size, learning_rate)
Output: Trained CNN model, Evaluation metrics, Predictions
1. Initialize the CNN model
2. Add the convolutional layers with filters, kernel size and activation
3. Add dual attention mechanism
4. Compute channel attention
5. Flatten the output from convolutional layers
6. Add fully connected (dense) layers
7. Add the output layer
8. Train and evaluate the model
9. Evaluate the model
10. Make predictions
11. Return the trained model, evaluation metrics, and predictions

4. Results

In this section, an achievement of the proposed approach is implemented through utilizing Python 3.8 environment with the system specification by Windows 10 OS, Intel Core i7 processor, 16GB RAM. The successful of the proposed method is validated based on various assessment metrics of accuracy, specificity, sensitivity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV) with 5-fold cross validation to address the overfitting problem. The mathematical formula of every metric is described in the following (9-14).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$Specificity = \frac{TN}{TN+FP} \tag{10}$$

$$Sensivity = \frac{TP}{TP+FN} \tag{11}$$

$$AUC = \frac{\sum R_i(I_I)-I_I(I_I+I)/2}{I_I+I_f} \tag{12}$$

$$PPV = \frac{TP}{TP+FP} \tag{13}$$

$$NPV = \frac{TN}{TN+FN} \tag{14}$$

Where, TP is True Positive, TN is True Negative, FP is False positive, FN is False Negative, I_I is the number of positive images, I_f is the number of negative images, and R_i is the rate of ith image.

4.1 Quantitative and Qualitative Analysis

To estimate the effectiveness of the proposed DADCNN approach for the breast cancer, different evaluation metrics are applied in the DCE-MRI dataset and the outcomes are statistically determined. Table 4 illustrates the performance analysis of feature extraction techniques with the FF approach. Table 5 illustrates the performance analysis of the classifier techniques. Table 6 displays the performance analysis of DADCNN with K-fold values. Figure 4; depict the graphical representation of the classification performance.

The results shown in Table 4 and Figure 3 present the performance analysis of the feature extractor with FF approach. The effectiveness of the fused DenseNet-121 and ResNet-101 architectures are validated by various evaluation metrics on the DCE-MRI dataset. The performance of DADCNN is compared with various classifiers such as Multilayer Perceptron (MLP), Generative Adversarial Network (GAN), CNN and DCNN. The obtained results show that the DADCNN attains superior accuracy of 0.931, specificity of 0.924, sensitivity of 0.925, AUC of 0.962, PPV of

0.853 and NPV of 0.902. These results prove that the DADCNN attains more significant results as compared to other models.

Table 4. Performance analysis of feature extraction techniques with FF approach

Methods	Accuracy	Specificity	Sensitivity	AUC	PPV	NPV
VGG-19	0.873	0.852	0.835	0.894	0.804	0.834
ResNet-50	0.893	0.864	0.884	0.912	0.812	0.856
DenseNet-121	0.901	0.884	0.892	0.932	0.831	0.875
ResNet-101	0.922	0.913	0.905	0.943	0.842	0.891
DenseNet-121 + ResNet-101	0.931	0.924	0.925	0.962	0.853	0.902

Table 5. Performance analysis of classifier techniques

Methods	Accuracy	Specificity	Sensitivity	AUC	PPV	NPV
MLP	0.853	0.846	0.858	0.891	0.805	0.824
GAN	0.887	0.874	0.863	0.915	0.821	0.852
CNN	0.905	0.897	0.890	0.932	0.837	0.871
DCNN	0.925	0.903	0.913	0.956	0.845	0.894
DADCNN	0.931	0.924	0.925	0.962	0.853	0.902

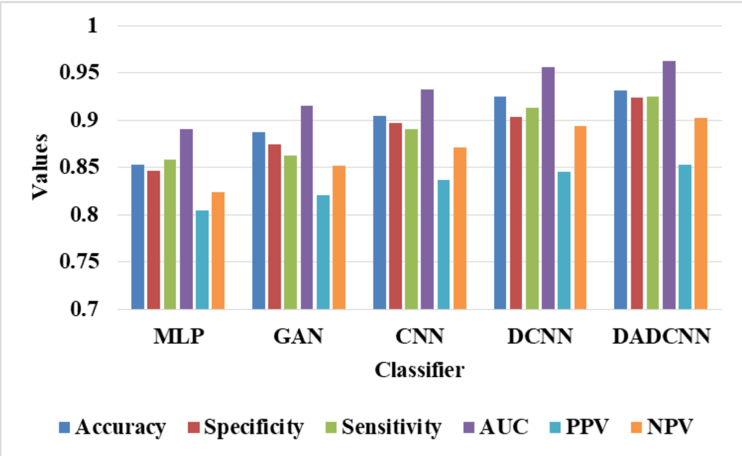

Fig. 4. Graphical representation of classification performance

The results displayed in Table 5 and Figure 3 exhibit the performance analysis of classification performance. The effectiveness of the DADCNN is validated by various evaluation metrics on DCE-MRI dataset. The performance of fused DenseNet-121 and ResNet-101 architectures is compared with the individual pre-trained models with feature extractors such as VGG-19, ResNet-50, DenseNet-121 and ResNet-101. The obtained outcomes evidence that the fused DenseNet-121 and ResNet-101 architecture attains superior accuracy of 0.931, specificity of 0.924, sensitivity of 0.925, AUC of 0.962, PPV of 0.853 and NPV of 0.902. These results prove that the fused approach accomplishes commendable outcomes as compared to other models.

Table 6. Performance analysis of DADCNN with K-fold values

Methods	Accuracy	Specificity	Sensitivity	AUC	PPV	NPV
2	0.862	0.862	0.844	0.894	0.807	0.832
3	0.875	0.885	0.861	0.901	0.819	0.851
5	0.931	0.924	0.925	0.962	0.853	0.902
8	0.902	0.891	0.885	0.923	0.828	0.879
9	0.921	0.912	0.912	0.941	0.834	0.891

The outcomes presented in Table 6 depict the classification results with different K-fold values of the proposed method using various performance metrics on the DCE-MRI dataset. The feature extractor with the FF approach and DADCNN classifier achieves better results when the K-fold value is 5, in contrast to the K-fold values of 2, 3, 8 and 9.

4.2 Comparative Analysis

The comparison of the proposed method with previous approaches is demonstrated with various performance metrics in this section. Table 7 shows the DCE-MRI characteristics of 4 different scenarios. The different scenarios like 1, 2, 3 and 4 are represented as MUM-Net-joint prediction [26], UDFS + SVM [27], XGBoost [28] and Multivariate Rocket [29] respectively. These different scenarios are compared with the proposed DADCNN approach for the estimation of effectiveness of the model. Table 8 represents the comparative analysis of the proposed method with different scenarios using various performance metrics.

Table 7. DCE-MRI characteristics based on different scenarios

Characteristics	Scenarios			
	1	2	3	4
Scanner model	GE Signa HD×t (1.5T)	GE Signa HD×t (1.5T)	GE Signa HD×t (3.0T)	GE Signa HD×t (1.5T)
Dimensional size	NA	512×512	512×512	452×452
Slice thickness	NA	2-3mm	4.0mm	0.8mm
Flip angle	NA	10°	90°	10°
Duration	2027 to 2020	2019 to 2020	NA	Apr 2018 to Mar 2020

Table 8. Comparative Analysis of proposed method with different scenarios

Scenarios	Methods	Performance Metrics					
		Accuracy	Specificity	Sensitivity	AUC	PPV	NPV
1	MUM-Net-joint prediction [26]	0.775	0.912	0.637	0.870	N/A	N/A
	Proposed DADCNN	0.834	0.932	0.784	0.902	0.862	0.912
2	UDFS + SVM [27]	N/A	0.741	0.709	N/A	0.72	0.75
	Proposed DADCNN	0.931	0.924	0.925	0.962	0.853	0.902
3	XGBoost [28]	0.88	0.90	0.91	0.95	N/A	N/A
	Proposed DADCNN	0.91	0.92	0.93	0.97	0.872	0.912
4	Multivariate Rocket [29]	0.852	0.823	0.882	N/A	0.833	0.875
	Proposed DADCNN	0.873	0.856	0.912	0.96	0.865	0.892

5. Discussion

This research aims at introducing a stepwise breast cancer model framework to enhance the classification performance, as well as to avoid the misclassification rate of breast cancer. From the overall analysis, the success of the proposed method is compared with the different approaches like MUM-Net-joint prediction [26], UDFS + SVM [27], XGBoost [28] and Multivariate Rocket [29]. The existing methods have limitations like: MUM-Net-joint prediction [26] approach had obtained joint predictions according to the two modalities as well as loss functions, even when the data for individual modality were applicable. UDFS + SVM [27] extracted the large number of features from 3D images led to high-dimensional feature space. In XGBoost [28], the lack of extracting the meaning features. Multivariate Rocket [29] approach varied based on the contrast agent utilization, and did not inherently consider long-term dependencies in the data. To overcome these limitations, this research proposes the DADCNN approach for breast cancer classification which establishes proficient in enhancing the model's performance with completely different dataset or across different imaging modalities. The two feature extractors, DenseNet-121 and ResNet-101 architectures are utilized for extracting relevant features and it is fused through the FF approach to concatenate different input modalities into an individual feature vector. The DADCNN enhances the feature representations through generating more generalized informative features in breast cancer. The suggested DADCNN approach attains the maximum accuracy of 0.931, specificity of 0.924, sensitivity of 0.925, AUC of 0.962, PPV of 0.853 and NPV of 0.902 in breast cancer classification, which denotes that the DACNN effectively classify the cancer into benign and malignant. These results prove that the presented DADCNN approach significantly outperforms the existing methods like MUM-Net-joint prediction [26], UDFS + SVM [27], XGBoost [28], Multivariate Rocket [29] and BI-RADS [30]. The greater accuracy of the proposed DACNN approach suggests DL approach to effectively enhance the classification accuracy in breast cancer. This helps the significant inclination of utilizing DL in medical image diagnosis to improve medical results. This research highlights the significance of DACNN to effectively improve the diagnosis of breast cancer by improving the accuracy. This research represents that the proposed DACNN enables the early detection and diagnosis to enhance the results of the better patients.

5.1 Limitations

The proposed breast cancer classification is constrained through the relatively small dataset used in this research, which does not completely represent the wide population. Furthermore, validated the results by using only MRI diagnosis tool without various diagnosis tools. The lack of integration of multiple diagnostic tools potentially impacts the robustness and generalizability of the findings of the model.

6. Conclusion

The DL approach achieves significant successes in the classification of the breast cancer and diagnosis for the various CAD systems. In this research, breast cancer classification is proposed by utilizing the DADCNN approach. The experimental validation evidences that the proposed DADCNN accomplishes the maximum accuracy of 0.931 and AUC of 0.962 respectively. The strong synthesis of the findings can be summarized through applying a dual attention model in CNN; the DACNN focuses more on parameters by greater weights and enhances the system performance. The two feature extractors are fused through the FF approach to make the individual feature which can be actionable improved through different fusion approach and types of feature extractor selection. Finally, classification is performed to categorize breast cancer into two types. The DADCNN enhances the feature representations by generating more informative features in breast cancer. In the future directions, the proposed method will be expanded to utilize different modalities for the classification of breast cancer to improve the generalizability.

Data availability

The dataset generated during the current study are available in the [DCE-MRI] dataset repository: https://www.kaggle.com/datasets/kaillashkumar/dce-mri-breast-cancer-dataset.

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