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A NOVEL METHOD FOR MEDICAL IMAGE CLASSIFICATION

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Abstract

Breast cancer stands out as one of the most noticeable and impassive diseases worldwide, primarily affecting women. Detecting it at its initial stage is crucial for an effective management. Many cases have shown diminish mortality rates through early identification. Extensive research is sustained in this field, with deep learning being a commonly utilized method. This study presents an efficient breast cancer classification model, employing weight-modified ResNet14 (WMRESNET) to extract features more accurately and rapidly, even with a small training dataset. The proposed model incorporates SVM classifier, that classifies different types of breast cancers based on the feature extracted by WMRESNET achieving a remarkable classification efficiency of 96% on Ultrasound Breast Cancer Images (UBSI) dataset. Pre-processing techniques such as Histogram Equalization and CNN-based Denoising enhanced the feature extraction capability of WMRESNET during training. The objective of this research is to classify cancer images as benign, malignant, or non-cancerous, crucial for early detection and appropriate treatment. Comparative analysis with state-of-the-art classifier models demonstrates the superiority of the proposed model in terms of computational cost and classification accuracy.

Keywords: Image Classifier, CNN model, Breast cancer detection, pre-processing stage, Histogram equalization, Denoising CNN.

1. INTRODUCTION

Breast cancer is a pervasive disease affecting women globally, characterized by high incidence rates and significant morbidity and mortality [1]. It manifests primarily as either benign or malignant tumors, with malignant cells spreading to other parts of the body, posing a grave threat. Early detection is of utmost importance; failure to promptly identify malignancy can result in severe consequences. Annually, a staggering number of new breast cancer cases are reported, contributing to a significant portion of women's cancer-related deaths worldwide, as reported by the World Health Organization (WHO) [2]. The key to reducing breast cancer-related fatalities lies in early detection and accurate classification of the disease [3]. Screening for early-stage breast cancer is crucial, as it enables the detection of cancer at its nascent stage when symptoms are subtle [4]. Commonly available feature extraction methods in literature especially for medical images are: Grey Level Co-occurrence Matrix (GLCM) [6], Wavelets [8], Local Binary Pattern (LBP) [5], [9] Gabor Filtering [7], and Neural Network models [10], [12], [13], [14], [15], [16], [17]. GLCM calculates pixel set relationships within an image, deriving textural features such as energy, entropy, and contrast [6]. Wavelet transforms, particularly the discrete wavelet transform (DWT), have gained prominence in biomedical image processing for their stability and ability to generate numerous features, enhancing classification accuracy [19]. LBP assigns binary numbers to pixels based on thresholding and computes texture descriptors from histogram labels, offering resistance to illumination changes and computational efficiency [4]. Gabor filters, utilized for image texture analysis, excel in analyzing specific frequency components in defined directions within an image region, yielding superior results for micro-textured images [5]. Deep learning significantly aids in breast cancer detection and classification, boasting high efficiency, although requiring substantial training data.

The authors of [11] have devised an image classifier utilizing a hybrid CNN and Local Binary Pattern (LBP) approach to extract image features. Support Vector Machine (SVM) was then employed to classify these features with heightened proficiency. Afterwards LBP and Gabor filtering was integrated together to extract rotation-invariant features of medical images, resulting in a unique and efficient medical image classifier. Authors of [18] introduced a U-Net based model that integrates image enhancement with data augmentation for better classification of mammogram images. Authors of [20] come out with a classifier model by combining texture extraction CNN with a feature concatenation network for improved classification efficiency. In contrast, [21] presented a texture-based image classification model based on a weighted mean-based pattern descriptor, incorporating feature selection and SVM classification. [22] incorporated a visual attention mechanism into deep learning to extract more features for classifying lung nodules and breast cancer images. Authors [23] developed image classifiers by amalgamating deep features with multi-class deep nets like MobileNet, GoogleNet, and ResNet. Authors of [24] developed a deep neural network for high level feature extraction of input images. The high level extracted features were combined with traditional features by a multi-layer perceptron for achieving better classification efficiency. [25] introduced a deep learning algorithm for accurately identifying breast cancer on screening mammograms, employing a comprehensive training approach. [26] introduced a CNN model with 18 convolution layers and achieves high classification accuracy with the ImageNet dataset, while in [27] a detailed review on CNN based image classification techniques have reported. After reviewing the literature, several research challenges emerge in clinical image classification are: (1) Dependency on large training datasets for higher accuracy, (2) Lower accuracy for typical featured images, and (3) Difficulty in classifying complex and diverse images. To address these challenges, transfer learning networks [28] are introduced, leveraging knowledge from one task to enhance performance in related tasks. However, transfer learning is not very much successful in medical image classification. Recently, researchers have shifted towards Residual Networks (ResNets) [29] over conventional CNNs for feature extraction due to their skip connection architecture, making them more efficient and requiring fewer parameters. ResNets utilize a three-layered network with two convolution layers and a pooling layer, with skip connections facilitating learning and reducing computational costs compared to traditional CNNs. Despite requiring less data, ResNets still depend on dataset size for learning efficiency. A review of numerous research studies centered around Convolution Neural Network is represented in Table 1.

Table 1: Comparison study of different existing Residual Net models

Ref No.	Author and Year	Technology used	Advantages	Dataset Used
[30]	Ganatra et al. (2024)	CNN based model with auto encoder-based feature extraction followed by SVM based classification	Successfully detect and classify the chest pneumonia and breast cancer images	Ultrasound Breast cancer Images (USBI), and Chest X-ray images-
[31]	Hata et al. (2024)	Probability Prediction model based on ML	Interstitial lung abnormality detected successfully	CT scan from patients in Boston Lung Cancer study
[32]	Bamber et al.(2023)	Deep Learning Network	Diagnosis and tracking of Alzheimer diseases	OASIS-3 dataset of brain MRI images
[33]	Maurya et al. (2022)	Anisotropic diffusion filtering with water shade algorithm	Successfully detect the brain tumor	Brain MRI images
[34]	Joshua et al. (2020)	HE based preprocessing, and deep learning-based classification with opposition-based Crow search optimization	Successfully detect brain tumor, lungh cancer and alzheimer diseases	Brain MRI, Lungh CT and Alzheimer MER images
[35]	Joao et al. (2020)	Low pass digital differentiator, anisotropic diffusion filtering with least square best fit algorithm for classification	Can detect breast cancer successfully	Breast mammography images which contain Benign and malignant cancer images
[36]	Lai et al. 2018	Supervised learning with coding network and multi-layer perceptron	Successfully classify different skin cancer images	HIS 2018 and ISIC 2017
[37]	Jadav et al.(2019)	Deep CNN (Transfer learning, VGG and SVM classifier)	Chest Pneumonia detected successfully	Chest X-ray dataset (normal, bacterial and virus images)
[38]	Dao et al. (2024)	Review work on CNN based medical image classification	-	-
[39]	Huang et al. (2023)	Review work on self supervised learning based medical image classification	-	-

The literature survey on image denoisation reveals that while denoising can enhance source images and lead to better fusion results, in contrast excessive denoising may remove essential details, potentially degrading fusion performance.There is a gap in developing models that are easy to interpret, helping clinicians trust and understand the reasoning behind predictions. Classifiers that perform well on one dataset might not work as effectively on others because of differences in patient demographics or imaging methods. More research is needed to create models that can generalize better across various populations and clinical scenarios. Achieving quick classification while maintaining high-accuracy is again a challenging task. To overcome these problems this paper presents a novel approach for designing a classifier model aimed at better accuracy with reduced network size. The proposed model utilizes a Weight Modified Residual Net (WMRESNET) for efficient feature extraction, followed by an SVM classifier. The key innovation lies in modifying the weights at the input (I) and output (F(I)) of the residual block, resulting in a significant elimination of Vanishing Gradient problem which directly enhanced the network's learning efficiency. For the (UBSI) dataset [40], this modification led to an improvement in the learning efficiency from 61% to 77%. Due to this efficient feature extraction capability of WMRESNET the classification efficiency of the SVM classifier increases upto 96%. Notably, the proposed model demonstrates high efficiency with low depth and a very small dataset. Comparative analysis against state-of-the-art image classifier models consistently demonstrates superior performance of the proposed model. The distribution of work across different sections of this paper is: Introduction, proposed methodology, result and discussion and conclusion.

2. PROPOSED MODEL

The proposed model introduces a Weight Modified Residual CNN for the classification of various types of breast cancer. Feature maps generated by the WMRESNET are utilized to train SVM classifier, culminating in the final classification outcome.

Specifically, the model comprises 14 residual blocks, each consisting of two convolution layers and one pooling layer. The stepwise working of the proposed methodology is given below:

2.1 Pre-processing Stage

In the realm of medical imaging, where images are often intricate and varied, a pre-processing stage is imperative prior to network training. At the outset of pre-processing, image data augmentation is employed to counteract over fitting and ensure the network is trained on precise image data. To enhance feature information within the training images sourced from dataset [40], a multi-step pre-processing approach is adopted.

Firstly, the training images undergo Histogram Equalization, a technique aimed at standardizing image brightness and contrast, thereby enhancing visual clarity and feature discernibility. Following Histogram Equalization, the images are subjected to denoising using Convolutional Neural Network (CNN), specifically the Denoising CNN (Dn-CNN) architecture [41],[42].

This denoising process aims to reduce image noise and enhance image quality, thus facilitating more accurate feature extraction during subsequent stages of network training. Figure 1. illustrates the transformation of images depicting different breast cancers from dataset [40] following this pre-processing regimen, showcasing the efficacy of these techniques in refining image quality and preparing them for effective network training.

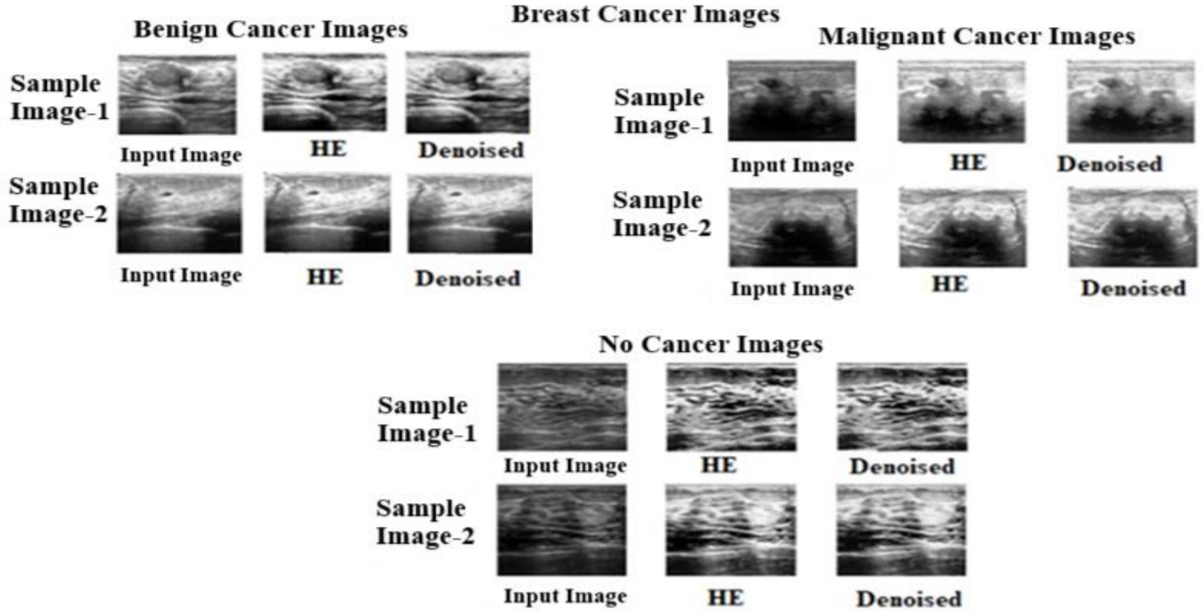


Figure 1.Different breast cancer images from dataset [40] after pre-processing

2.2. WMRESNET BASED IMAGE FEATURE EXTRACTION

At this stage, the features of the training images have been extracted by WMRESNET, offering several advantages over conventional ResNet architecture. One crucial aspect of neural networks is the assignment of weights, as weight changes play a significant role in determining the network's overall performance. In Residual Net (ResNet), the final output of a residual block is calculated by adding the output of the current node (F(I)) and the input of the previous node (I), which enhances network efficiency and performance.

In the conventional ResNet architecture, both (I) and F(I) are assigned equal weights. However, in Proposed WMRESNET, the weight of residual blocks is modified to significantly increase the learning efficiency compared to conventional ResNet. The building block of a conventional ResNet and the proposed WMRESNET is illustrated in Figure 2. In WMRESNET, 14 such residual blocks are utilized for feature extraction.

In Proposed WMRESNET, the input of the previous residual node (I) is varied exponentially, resulting in higher weights but only a fraction (40%) of the output of the current node (F(I)) is considered and is given in equation 1. This weight modification leads to a significant increase in learning efficiency, from 61% to 77%, and a corresponding rise in classification efficiency, from 85% to 96% for the (UBSI) dataset [40].

In general, higher learning efficiency increases the learning rate of the network at the cost of higher weights. However, excessively high learning rates may lead to increased training losses and erratic network performance. Therefore, in WMRESNET, weight adjustments are made incrementally to optimize learning rates without causing training errors. The examination of weights in a residual node (block) in conventional ResNet versus Proposed WMRESNET is pictorially represented in Figure 2. With weight values detailed in Table 2. While the actual weight in any residual node cannot be precisely determined, these visualizations and tables provide insight into the controlled increase in weights within WMRESNET, ensuring optimal learning rates and network performance.

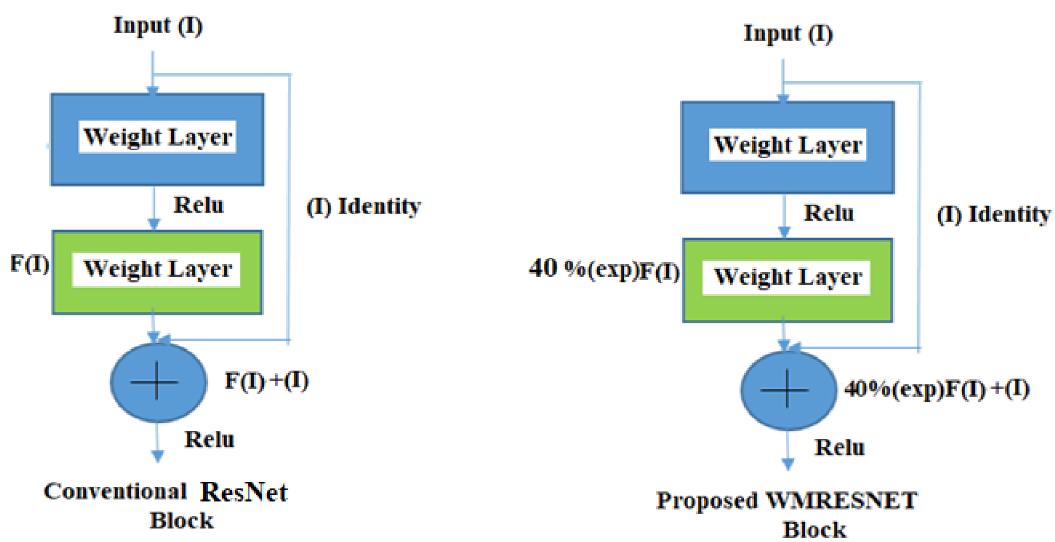


Figure 2. Weight Modified Residual Learning Building Block

$$(\mathrm{I}) + \mathrm{P} * \mathrm{F}(\exp(\mathrm{I})) = \text{Final Output} \quad (1)$$

Where P is a constant. The value of P is considered as 0.4 in this research. The variation of learning efficiency and classification efficiency with the variation of the value of ‘P’ is represented in Table 3.

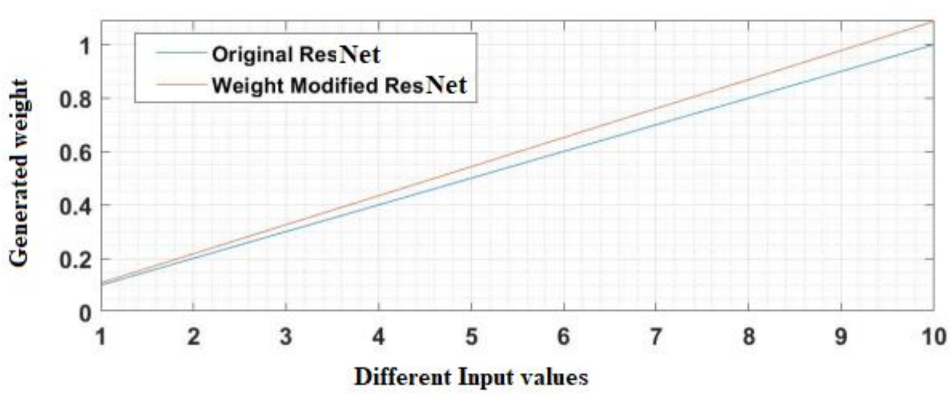


Figure 3. Comparison of weights

Table 2 Generation of weight for different values of input

Sl.No.	Conventional ResNet	WMRESNET

1.	0.1	0.108
2.	0.2	0.217
3.	0.3	0.326
4.	0.4	0.434
5.	0.5	0.543
6.	0.6	0.652
7.	0.7	0.761
8.	0.8	0.869
9.	0.9	0.978
10.	1.0	1.087

Table 3: Variation of learning and classification efficiency according to different value of 'P'

Sl. No.	**Value of 'P'**	**Learning Efficiency**	**Classification Efficiency**
1.	0.3	70.99%	90%
2.	0.4	**77%**	**96%**
3.	0.5	72.25%	92%
4.	Conventional ResNet Equation	61.8%	85%

2.3 Formulation of Proposed weight Modified Resnet (WMRESNET)

2.3a Forward Propagation

The formula of forward propagation of signal of the proposed WMRESNET is represented by equation 2. as:

$$I_{n+1} = I_n + 0.4 * (f(\exp(I_n)) \quad (2)$$

Where n represents current residual block where n+1 represents its next block. Applying this formula recursively we get:

$$I_{n+2} = I_{n+1} + 0.4 * (f(\exp(I_{n+1})) \quad (3)$$

Substitute the value of I_{n+1} from equation 2. we get

$$I_{n+2} = I_n + 0.4 * (f(\exp(I_n)) + 0.4 * (f(\exp(I_{n+1})) \quad (4)$$

So, equation 4. can be represented by its general form as in equation 5.

$$I_N = I_n + 0.4 * \sum_{j=n}^{N-1}\left(f(\exp(I_j)\right) \quad (5)$$

In equation 5. (n) represents any previous layer where (N) represents its consecutive layer

2.3.b Backward Propagation

The partial derivative of generalized Forward Propagation formula with respect to (I_n) is represented by equation 6. as below

$$\frac{\partial\alpha}{\partial I_n} = \frac{\partial\alpha}{\partial I_N}.\frac{\partial I_N}{\partial I_n} = \frac{\partial\alpha}{\partial I_N}\left(1 + 0.4 * \sum_{j=n}^{N-1}\left(f(\exp(I_j)\right)\right) \quad (6)$$

Where α is the loss function, and it should be minimized. In the above formula (equation 5.22), the term $(f(\exp(I_j))$ never becomes zero, so, the total gradient $\frac{\partial\alpha}{\partial I_n}$, never can be vanished. The above equation proved that the proposed weight Modified Residual Net is able to remove vanishing gradient problem efficiently. The architectonic descriptions of WMRESNET is given in Table 4.

Table 4 Description of the proposed WMRESNET

No. Of Residual Blocks	Max Epoch	Initial Learning Rate	Initial Filter Size	Initial Stride	Polling Technique	No.of Training Images[40]
14	5	0.1	[5 5]	[1 1]	Max Polling	780

2.4 SVM Classifier

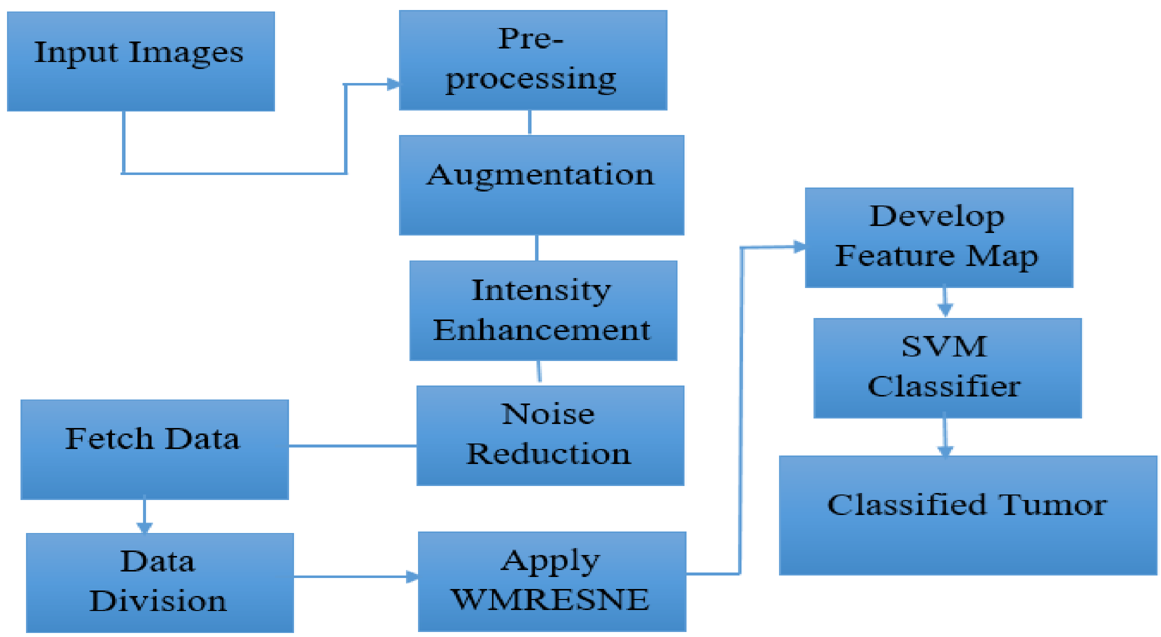


Figure 4. Architecture of the proposed model

3. RESULT AND DISCUSSION

The proposed image classifier model is very efficient to classify different breast cancer (Benign, Malignant and Normal) images with a classification efficiency of 96% with the dataset [40].The classification efficiency [27] has been calculated by using equation 7.

$$\%\text{Classification Efficiency} = \frac{TP+TN}{TP+FP+TN+FN} * 100 \tag{7}$$

To assess the effectiveness of the proposed model, we conducted performance comparisons with several conventional CNNs with the dataset [40]. During the feature extraction stage, we substituted the proposed WMRESNET with traditional models including ResNet, VGG, and

AlexNet individually, and recorded their respective outputs. The results are detailed in Table 5 below. TableV clearly demonstrates that the proposed model outperforms conventional CNNs (such as AlexNet, VGG, and ResNet) across learning efficiency, classification accuracy, and computational cost.

Table 5: Comparison of proposed CNN models

Name of the CNN											
ResNet			VGG-16			AlexNet			Proposed Model		
%Learning Efficiency	%Classification Efficiency	Computational time in minute	%Learning Efficiency	%Classification Efficiency	Computational time in minute	%Learning Efficiency	%Classification Efficiency	Computational time in minute	%Learning Efficiency	%Classification Efficiency	Computational time in minute
61	85	35	67	89	34	70	92	39	77	96	30

The proposed model has been compared with state-of-the-art CNN-based Breast Cancer Classifier models [40], [43], [44], [45], [46], [47], [48], [49], and [50]. These models similarly utilized (USBI) to discern between benign and malignant cancers from normal images. The comparison is delineated in Table 6 below.

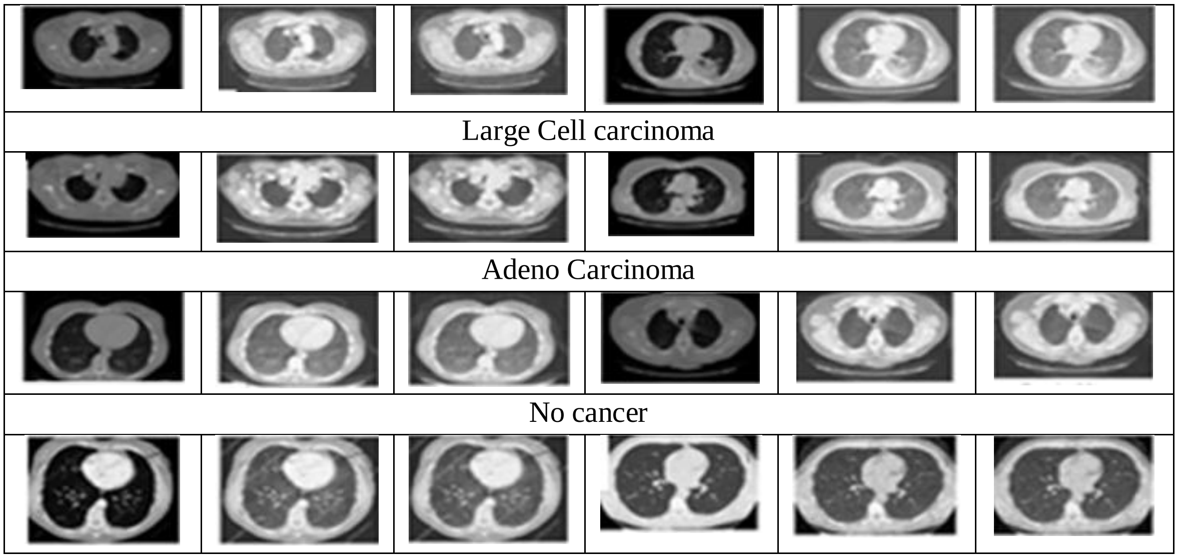
Table 6 Comparison of proposed model with existing CNN based models

CNN based model	Year	Classification Accuracy
CNN model [40]	2023	90%
ViT-patch [43]	2023	89.9%
LeNet CNN [44]	2023	89.91%
BUSIS model [45]	2022	90%
BUViT Net model [46]	2022	95%
Pyramid Trip Deep feature generator [47]	2022	88.67%
Semi supervised GAN based model [48]	2021	90.41%
Variant Enhanced Deep learning model [49]	2021	89.73%
Transfer Learning model [50]	2021	91.5%
Proposed classifier model		**96%**

To verify the proficiency of the proposed model, Lung-cancer image dataset [51] has been used and it has been observed that the training efficiency for this dataset increased from 66% to 76% and the overall classification efficiency increased from 87% to 96%. Different chest cancer images of the dataset [51], after pre-processing is represented in Table 7..

Table 7: Different chest cancer images from dataset [51] after preprocessing

Squamous Cell Carcinoma					
Sample image-1	HE image	Denoised image	Sample image-2	HE image	Denoised image



The authors of [51], [52], [53], [54], [55] and [56] employed lung CT images to differentiate between various lung cancer cells. Similarly, the proposed model utilized these CT images to assess its classification accuracy. The performance evaluation of the proposed model against existing models is presented in Table 8.

Table 8 Comparison of proposed model with existing CNN based model [51]

Classification Model	Year	Classification Accuracy
Deep learning ensemble 2D CNN model [51]	2023	95%
Deep learning based Support Vector machine [52]	2022	94%
Ensemble of CNN model [53]	2018	87%
Machine Learning model [54]	2018	90%
Deep CNN model [55] (Classified images based on Lung Cancer present or absent)	2018	96%
Multi view CNN model [56]	2016	94%
Proposed Classifier model (Detected and Classified three different types of Lung cancers and normal images)		96%

It is clear from Table 6 and Table 8, that the proposed model is able to give better classification efficiency compared to the existing CNN based models.

4. COMPUTATIONAL COMPLEXITY

The model was experimented with MATLAB-18 software on an Intel Core i5 system. A relatively small number (780 images) from dataset [40] were utilized to train the WMRESNET, and the depth of the network was not excessively high. Consequently, the training process was completed in a short duration of only 30 minutes. Additionally, the average classification time per image was measured to be 30.36 seconds, which is significantly lower compared to most CNN-based models, indicating the efficiency and speed of the proposed model in both training and classification tasks. During the feature extraction stage, we substituted the proposed WMRESNET with traditional models including ResNet, VGG, and AlexNet individually, and the time taken to train these models were comparatively higher compared to the proposed WMRESNET. The time needed to train these conventional methods were 35mins, 39 mins and 34 mins respectively with the (UBSI) [40] dataset.

5. CONCLUSION

Breast cancer stands as a perilous threat, claiming the lives of numerous women each year. Early detection of this disease is paramount to mitigate its fatality rate, making image processing techniques indispensable in the medical domain. Breast cancer manifests primarily in two forms: Benign, which is less severe, and Malignant, which poses a significant threat. Given the complexity of medical images, the task of detection and classification of breast cancers becomes arduous. Presently, CNN-based classifiers play a pivotal role in this domain. However, the effectiveness of a CNN model's classification hinges on its depth, with more layers leading to an exponential increase in parameters and error rates, thereby escalating computational complexity.

ResNet, a CNN architecture, offers efficient classification with reduced depth. In our proposed classifier, Weight Modified ResNet (WMRESNET) is employed for feature extraction from medical images. Comprising 14 residual blocks, our network exhibits exceptional learning efficiency despite being trained on a relatively small dataset of 780 images. The feature maps generated by WMRESNET are utilized by an SVM classifier to categorize various cancer images. Through weight modification in every residual node, the vanishing Gradient problem has been eliminated significantly which directly enhanced the training efficiency of the network from 68% to 79%, and the classification efficiency from 85% to 96% for the (UBSI) dataset [40].

In the pre-processing stage, Histogram Equalization followed by denoising CNN is employed to enhance the visual quality of input images, thereby refining feature extraction during training. Our proposed model also demonstrates proficiency in detecting and classifying various Lung cancer images [53]. The primary advantage of our model lies in its ability to achieve high classification efficiency with minimal depth and a small training dataset. Moreover, the computational cost of our model is limited to just 30 seconds, inclusive of training time. Through comprehensive comparisons with state-of-the-art image classification models, our proposed model consistently outperforms its counterparts, reaffirming its efficacy and superiority in the domain of medical image classification.

6. DATASETS

There are no conflicts with the datasets utilized in this study, as both were directly obtained from the Kaggle platform. No personal or confidential information has been incorporated in this research, ensuring that no issues should arise upon publication.

Link of UBSI dataset:https://www.kaggle.com/datasets/aryashah2k/breast-ultrasound-images-dataset

Link of Lung cancer dataset: https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images

Table 9: Description of different datasets used in this paper

Dataset-1 [40] (Breast Cancer Ultrasound Images)	**No. Of Normal images**	**No. Of Benign Cancer images**	**No. Of Malignant Cancer images**		**Total Image with Size**
	133	437	210		780 PNG images with 500x500 pixels
Dataset-2 [51] (Lung cancer CT Images)	No. Of Normal images	No. Of Adenocarcinoma cancer images	No of Large Cell Carcinoma cancer images	Squamous Carcinoma	Total Image with Size
	59	322	368	314	1063 PNG images with256x256 pixels and after augmentation the number of images are 4183

7. CONFLICT OF INTEREST

Authors Tanima Ghosh and N. Jayanthi have no conflict of interest.

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