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Breast Cancer segmentation & Classification of image using ResNet

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Abstract
Cancer is one of the deadliest disease, which leads living things to death, and there are nearly 18 million cases, which includes 9.5 million men and 8.5 million women. Breast cancer is one of the most common cancer globally in women. Considering such devastating statistics of breast cancer, early detection is needed, in past several researcher have tried to detect in the early stage, however the main disadvantage of these models were its complexity since the detection comprises many phases such as segmentation and classification. Furthermore classification plays an eminent role in early detection as it detects the cancer type i.e. benign or malignant. In this paper, we have proposed a novel classifier M-ResNet (Modified ResNet) to classify the cancer types. At first, we develop a learning framework and selects the optimal kernel. Further, we employ the M-ResNet (Modified ResNet) and classify the cancer based on its Bi-Rads score. Furthermore, our model is evaluated by considering the performance metric such as Accuracy, sensitivity and specificity. Our model achieves the accuracy of 96.43.

***Keywords:** Breast Cancer, Classification, M-ResNet*

1. Introduction

Breast cancer is abnormal cells growth in the breast tissue; it is one of the common cancer type among the women. It is considered one of the dreadful disease, which causes the death of women, especially 20 to 59 years old women [1]. Furthermore, it is observed that there has been massive growth in breast cancer in last few years; however, the death rate has been decreased.

Meanwhile the death rate degradation has been observed in the developed countries, especially where the early detection of breast cancer has been achieved through the MIA (Medical Image Analysis) and if the disease is detected in early stage the survival rate is

Also, up to the 80% [2]. Moreover, there are two types of diagnosing methods for the breast cancer detection i.e. Biopsy and mammography.

Mammography is examination process normally used for screening; it detects the non-palpable tumors, which results in breast cancer [3]. Furthermore, masses anomalies are detected in the anomalies, a mass is nothing but the thick area developed whenever there is

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any changes takes place in the breast. In mammography, specific breast image are used for detecting the early symptoms, biopsy is another method where the tissue sample from the affected images is observed through the microscope to detect and classify the tumor.

Further Mammogram is the effective as well as reliable technique to detect the cancer especially at early stage; Mammogram is nothing but the X-ray image of breast. Mammography detects two type of changes in the breast i.e. benign, which is non-cancerous, and cancer. Further depending on the characteristics of much detected the probability of being malignancy is established, meanwhile the characteristics considers are shape, size and border arrangement. Mass detection is very complex task due to its process. Mammography detects the mass whether it is fatty, dense or granular, further in all these the tough task is detection of dense types. Normally radiologists look for the abnormality in the mammogram through the visual inspection; however, there is high probability that radiologists may overlook the abnormality and fail to detect the cancer.

Hence, CAD (Computer Aided detection) were developed to help in detecting the breast cancer. Computer Aided Detection constitutes three major steps i.e. Preprocessing, image segmentation and classification. Segmentation is an initial and eminent step in mammogram analysis. Moreover, method link DuSAT [4], meanshift [5] has been proposed for mass selection Moreover our previous research work has segmented the image using the CNN.

Motivation and Contribution of this research work

Deep learning is the part of machine learning technique where the classification task takes place by directly learning from the text, sound, image (in this research work we consider image). Moreover, the model is trained on the huge number of dataset on the CNN architecture that contains multiple layer. Nevertheless, in medical image machine learning is used for the automated cancer detection. Hence, in this research work we use the CNN architecture named modified Resnet for classification. Further the contribution of this particular research work has been highlighted through the below points.

- We develop a framework whichis CNN architecture based Modified Resnet.
- Modified ResNet gives us advantage to go deeper in order to extract the highly distinguishable feature.
- Modified Resnet is further optimized to reduce the classification error and improvises the hidden layer transparency.
- Further our model Modified Resnet is evaluated by considering the standard dataset named InBreast by computing the Bi-Rads Score which classifies for Benign and Malignant
- Comparative analysis has been performed by considering the various performancemetrics.

This classification research is organized in an ideal manner; here first section starts with breast cancer stats and importance of early detection. Further, we discuss the technique used for detection and their drawbacks. In second section, existing methodologies for breast cancer classification has been surveyed. Third section discuss the proposed M-ResNet along with mathematical equation. Fourth section evaluates the proposed methodology which shows the outcome of our model.

2. Literature Survey

Several researchers have been introduced various solutions for the classifications of automated cells for cancer identification in the images of breast cryptology. To provide significant information to the cell information into malignant and benign [6], some of the researches have worked on the analysis of nuclei by removing the features with the help of nuclei. The clustering-based methods with different statistical features and circular Hough Transform are exploited for the nuclei classification and segmentation [7]. In the analysis of the medical image, algorithms for the histopathological images is been maximizing but still, it is highly demanded to the automatic system and obtain highly and efficient accurate outcomes [8]. Therefore, these types of methods are needed that provide the right direction towards the qualitative products for the diagnosis and gives the uniform outcomes in the process of observation and maximize the objectivity. The complex tasks like segmentation, FE (Feature Extraction), pre-processing are in the classical ML (Machine Learning) methods that degrade the performance of the system concerning accuracy and efficiency. To overcome the issues of traditional ML-methods, the DL (Deep Learning) has been represented to remove the significant data from raw-images and utilize it efficiently for the process of classification [9]. In DL, the features are manually not adjusted instead the learning process can be performed through data sets with the help of a learning approach [10]. Lately, DL based CNN (Convolutional Neural Network) has obtained great success in the analysis of biomedical images like quantization of mass in mammograms [11], identification cells from microscopic images [12], skin disease and its classification [13], tumor detection +7, classification of immune cells [14]. Although, on the larger dataset CNN works very well and it fails on the smaller dataset to obtain the import outcome. To obtain the high detection accuracy and minimize the computational-costs, the transfer learning concept is exploited to maximize the individual performance of CNN-architecture by integrating their-knowledge [15, 16], in this fact, the feature set is removed from the generic image of datasets by utilizing the trained-DCNN (Deep-CNN) and applied directly for the specific domain and small-dataset [17]. The context-based learning method provides novel direction to transfer the learning in that CNN will be trained in two sets as single and overlapping patches and well performed the classification and detection of breast cancer. The integration of multi-CNN architecture boosted the transfer learning performance and then replace the utilization of a single model of CNN architecture. Likewise, the correlation of InceptionV3, ResNet50 and InceptionV2 are trained on the Image-Net that produced as an accurate and fast model for the cell-based image-classification [18, 19].

3. Proposed Methodology

3.1 Preliminaries

Let us consider two domain i.e. source domain and the destination domain and it is depicted in the given below equation. Equation 1 indicates the source domain and equation 2 indicates the destination domain

$$\mathbb{E}_t = \left\{\left(\mathbb{Y}_j^T, \mathbb{Z}_j^T\right)\right\}_i^{o_t} \quad (1)$$

$$\mathbb{E}_u = \{\mathbb{Y}_k^u\}_{k=1}^{\mathbb{O}_u} \quad (2)$$

Moreover the above two equation are characterized through the probability distribution which can be denoted as $\mathbb{Q}$ and $\mathbb{R}$ respectively.

Here we construct the neural network that can be used for the cross-domain and design a classifier.

$$\mathbb{V} = \omega(\mathbb{Y}) \quad (3)$$

The above equation denotes the classifier that can further reduce the risk, similarly the below equation is for risk

$$\mathrm{A}_v(\omega) = Pr_{(\mathbb{Y},\mathbb{Z})\sim r}[\theta(\mathbb{Y}) \neq \mathbb{Z}] \quad (4)$$

Hence

$$\mathbb{E}_a = \left\{\left(\mathbb{Y}_j^b, \mathbb{Z}_j^b\right)\right\} \quad (5)$$

Moreover, through this research work the main intention is to develop and construct modified RESNET that can learn the features.

3.2 Optimal Kernel Selection

Learning is difficult task as it contains the only limited information, hence optimal kernel selection is important task in this section we select the optimal kernel.

Let $\mathbb{I}_l$ be the reproduced kernel with the Kernel$\mathbb{I}$, further mean embedding is calculated through $\mathbb{Q}$ in $\mathbb{I}_l$ such that it should satisfy the particular equation given below.

$$\mathbb{F}_{\mathbb{Y}\sim\mathbb{Q}} func(\mathbb{Y}^T) = \left(func(\mathbb{Y}^T), \vartheta_l(\mathbb{Q})\right)_{\mathbb{I}_l} \quad \forall func \in \mathbb{I}_l$$

$E_l^2(\mathbb{Q}, \mathbb{R})$Is learning modeland Distribution between $\mathbb{Q}\, and\, \mathbb{R}$ is defined as the reproduced kernel space distance between the Mean Embedding.

$$E_l^2(\mathbb{Q}, \mathbb{R}) \triangleq \left\|\mathbb{F}_{\mathbb{Q}}[\sigma(\mathbb{Y}^T)] - \mathbb{F}_{\mathbb{Q}}[\sigma(\mathbb{Y}^T)]\right\|_{\mathbb{I}_l}^2 \quad (3)$$

Later $\mathbb{Q}$= $\mathbb{R}$, if and If and only if and only if $E_l^2(\mathbb{Q}, \mathbb{R})$is equal to zero, hence activation map associated with characteristic kernel is presented in the below equation.

$$\sigma, l(\mathbb{Y}^3, \mathbb{Y}^u) = \langle\sigma\left(\mathbb{Y}^t, \sigma(\mathbb{Y}^u)\right)\rangle \quad (4)$$

Moreover, the characteristics kernel associated with the activation map is depicted through below equation

$$l \triangleq \left\{l = \sum_{v=1}^{n} \varepsilon_v l_v : \sum_{n=1}^{n} \varepsilon_v = 1, \right\} \quad \varepsilon_v \geq 0, \forall v \quad (5)$$

ε_vIs the COC (Constraints on Coefficient), In order to guarantee the characteristics kernel β_u is imposed so that the multi- kernel l is derived. Furthermore, it is

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observed that mean map of $\mathbb{Q}$ and $\mathbb{R}$ fails to provide the least test error; hence, multi-kernel is used for the ideal kernel selection.

3.3 M-RESNET (Modified RESNET)

RESNET is nothing but a network based on the CNN and has the deep architecture, the main advantage of RESNET is that here the problem is addressed through training in deep.

Residual Block Formulation

The ResNet possesses the lower convergence if overfitting is avoided, residual connection helps in accelerating the deep layer convergence. Moreover, huge number of layers are added to maximize the performance and avoid the overfitting. Hence we form the residual block which is given in the below equation. Here $\mathbb{I}_m$ is input block and $\mathbb{I}_{m+1}$ is the output block, w_l is parameter, $f(.)$ indicates mapping function

$$\mathbb{I}_{m+1} = \mathbb{V}(\mathbb{I}_m + func(\mathbb{I}_m, \mathbb{X}_m)) \quad (6)$$

Moreover if $func(\mathbb{I}_m, \mathbb{X}_m)and\mathbb{I}_m$ are not it then $\mathbb{B}_m$ is used for dimension matching and the above equation are written as:

$$\mathbb{I}_{m+1} = Relu(\mathbb{B}_m \mathbb{I}_m + func(\mathbb{I}_m, \mathbb{X}_m)) \quad (7)$$

These blocks have the convolution layer and contains the neurons with bias and learnable weights. The weights keeps on updating while training

$$\mathcal{Z}_k^j = \tau\left(\sum_{n=1}^{N} \mathbb{X}_{kn}^j * \mathcal{Z}_n^{j-1} + \mathbb{C}_k^j\right) \quad (8)$$

$\mathbb{X}_{kn}^j$is feature map weight in the given layer, $\mathbb{C}_k^j$ is jth bias in the i-th layer, further$\tau(.)$ is non-linear activation function of convolution layer. $\tau(\mathbb{Y}) = \max(\mathbb{Y}, 0)$ is the activation function.

Further the residual block is optimized to reduce the cost along with its dimensions and it is presented in the below equation.

$$\mathbb{I}_m = \mathbb{I}_m + \sum_{i=1}^{M-1} func\left(\mathbb{I}_j, \mathbb{X}_m\right) \quad (9)$$

L Indicates the RU (Residual unit) and computed as the sum of the mapping and unit. Further we derive the back-propagation from the above equation and depicted in the below equation. Since the optimization in Resnet mainly depends on the back-propagation algorithm.

$$\frac{\partial \theta}{\partial \mathbb{I}_j} = \frac{\partial \mathbb{I}_j}{\partial \mathbb{I}_j}(1 + \frac{\partial}{\partial \mathbb{I}_j}\sum_{i-1}^{L-1} func(h_i, w_i)) \quad (10)$$

4. Performance Evaluation

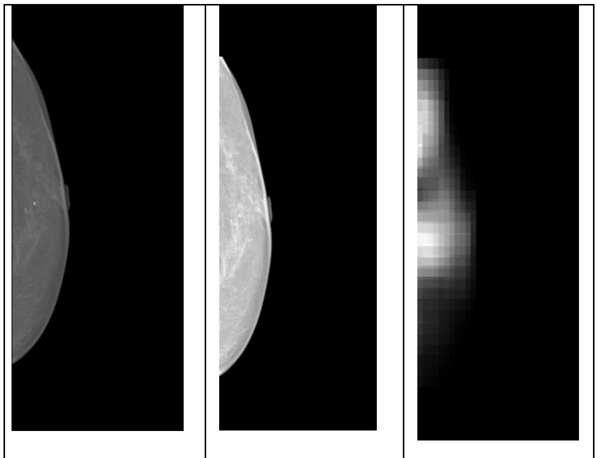
In this section proposed model M-ResNet is evaluated, furthermore the evaluation is

Dataset Description

In order to evaluate the M-ResNet we have used the InBreast dataset, it is publicly available, includes the 112 breast images, further these images are cropped into the pixels size of 256X 256, and contains the ROI (Region of Interest). Moreover according to the BI-RADS (Breast Imaging Reporting and Data system), there are 75 mass with the BI-RADs, the value of 4,5 and 6 indicates that it is malignant whereas left 37 masses are value of 2 and 3 and it is classified as benign. Further, there are two different view namely CC and MLO.

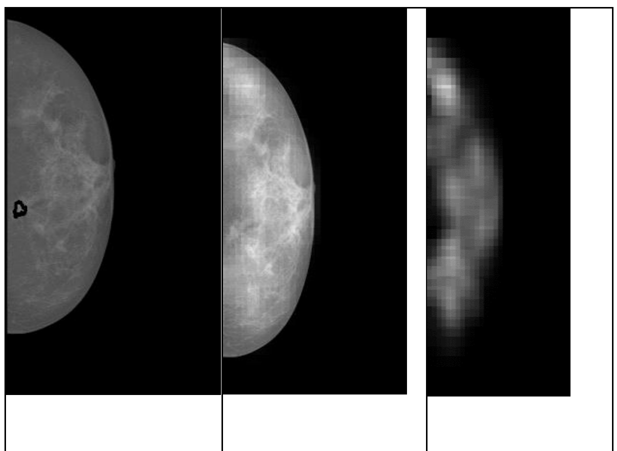
5. Result and Analysis

The classification performance of proposed M-ResNet is evaluated by considering the three important measuring metrics namely Accuracy, Sensitivity and specificity and all three metric are compared with various existing technique and it is depicted in below table 1. Furthermore, Figure 1 and Figure 2 presents the classification using M-ResNet.



Ground_Truth	Original_Image	Benign

Figure 1 benign detection using M-ResNet



Ground Truth	Original _Image	Malignant detected

Figure 2. Malignant Detection using M-ResNet

Table 1: Comparison of various technique with M-ResNet

Methodology	**Accuracy**	**Sensitivity**	**Specificity**
MS-FCN-8S[20]	86.76	87.80	85.19
MS-SegNet[21]	88.24	85.37	92.59
MS-U-Net[22]	80.88	78.05	85.19
Ms-U-SegNet[23]	88.24	95.12	77.78
MS-ResCU-Net[24]	94.12	97.56	88.89
M-ResNet(Proposed)	96.43	98.99	87.50

Accuracy

In general, accuracy is referred as the measured value to the standard value, in below table first column shows the different methodologies, second column presents the accuracy. Higher value of the model suggest that the model has better classifier. Here we observe that MS-FCN-8S, MS-SegNet, MS-U-Net, MS-U-segNet achieves the accuracy of 86.76, 88.24, 80.88, 88.24, 80.88, 88.24 and 94.12 respectively whereas in comparison proposed model i.e. M-ResNet achieves the accuracy of 96.43 (all these values are observed in percentage).

Sensitivity

Sensitivity is the statistical measure of binary classification test performance, it measures the actual proportion identified correctly, and thevalue shouldbe higher. In table two third column shows the sensitivity of different methodology, in here MS-FCN-8S, MS-SegNet, MS-U-Net, MS-U-segNet achieves the value of 87.80, 85.37, 78.05, and 95.12 respectively whereas proposed model M-ResNet achievesthe value of 98.79.

Specificity

Specificity is the measure of actual negative, which is identified correctly, in here MS-FCN-8S; MS-U-Net, MS-U-segNet achieves the value of 85.19, 85.19 and 77.78 respectively. Proposed model achieves the 87.50; here it is observed that existing model achieves the higher value of 88.89. Moreover, MS-SegNet achieves the highest of all i.e. 92.59.

6. Conclusion

In this research work, we develop a classification technique named M-ResNet (Modified) for the breast cancer detection. Furthermore M-ResNet. In here, we develop mechanism, which connects the hidden layer. This in terms helps in improvising the learning feature of model and further improvises network performance, computational complexity. Proposed M-ResNet evaluated considering various performance metric such as sensitivity, specificity, and accuracy, through the comparative analysis it is observed that our model achieves the value of 96.43, 98.99 and 87.50 respectively and outcast the entire existing model till this research work is carried. However our model does underperform in terms of specificity. Classification technique is one of the complex technique, hence still there are several aspect that needs to be looked such as considering the more number of parameter and further optimization can be done by considering the hidden layer.

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