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Breast Cancer detection using Transfer Learning enabled CLAHE-ResIn model

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Abstract

Backgrounds & Objective: Breast cancer is the most prevalent disease diagnosed in the women community. The mortality rate could be reduced significantly if this disease is diagnosed at an early stage. This paper focuses on development of a model for breast cancer prediction as an aiding model for women community.

Methods: Histopathological biopsy images have been used to detect tumor of breast. It is done by adapting pre-trained framework of Deep Learning. It is also known as transfer learning. Developed model receives an enhanced image as an input, find the region of interest, extract the features using convolutional neural network for better prediction of breast cancer. Images used with different magnification factors viz 40x, 100x, 200x, and 400x and Image enhancement is performed by Contrast Limited Adaptive Histogram Equalization (CLAHE) technique.

Results: The accuracy of this model for image with 400x magnification factor is 99.1%. This level of accuracy is better than some other existing models, which are using various hybrid approaches for breast cancer prediction.

Conclusion: Hybridization of Inception and Resnet architecture with image enhancement using CLAHE technique and Machine Learning (ML) classifiers provides better prediction than some other existing hybridization models. This difference in prediction results is due to missing of either CLAHE or ML classifier with deep learning in some existing hybridization models.

It is suggested that results may improve more by applying different other existing image enhancement techniques like Gaussian Filter etc. Different architecture of transfer learning may also be tested to improve the results.

Keywords: Breast cancer, CNN, Deep Learning, Histopathology, Transfer Learning, Inception_ResNet Architecture

I. Introduction

As per the report of cancer statistics'19, WHO's International Agency of Research on Cancer estimated that cancer was responsible for 606,880 million deaths. The mortality rate as per WHO for breast cancer in women exhibits alarming situation. Around 14% of all registered cancer cases is the breast cancer found in women in India (Siegel, R. L et al. 2019). The process of research for cancer prediction begins with data collection and proceeds for preprocessing the dataset, understanding the information in the dataset, analyzing the image dataset, finding the abnormality in the image dataset, detecting the accuracy of tumor for breast cancer. This involves a Deep Learning (DL) Technique where Convolutional Neural Network (CNN) plays a vital role, where mathematical theorem like gaussian filter, image processing, edge detection is used.

Normally the cancer progresses in four stages. The chances of recovery from cancer lie in stage I and stage II. when cancer reaches to stage III or IV, there are less chances of survival of a patient. The breast cancer can be detected at an early stage if screening test of the women breast is examined periodically and can be cured before it reaches to higher stages. Lots of work have been done in breast cancer prediction and presented below.

Use of Transfer Learning is one of the trivial techniques in use for such type of research. Transfer Learning is a pre-trained architecture model and a new training dataset is passed to the model to learn more features for the prediction of new dataset called test dataset. In most cases, BreakHis, A Histopathological dataset of breast cancer is used, and different transfer learning model is applied by different scholars. Sharma S. et al. (2020) proposed a CNN model based on VGG16 pretrained model ensembled with SVM linear kernel achieved accuracies of 93.97%, 92.92%, 91.23% and 91.79%. Vidyathi A et al. (2019) used CLAHE techniques and LeNet architecture for prediction of breast cancer in BreakHis image dataset with 90.36% accuracy. Ahmad H. et al. (2019) used transfer learning to classify the cancerous tumor of breast histopathological images dataset. The work has resulted in 85% accuracy in case of ResNet transfer learning. Jiang Y. et al. (2019) proposed a novel CNN model based on ResNET called Small SE-ResNet along with improved technique of learning rate on BreakHis image dataset and achieved accuracy of 98.87%, 99.04%, 99.34% and 98.99% for different image magnificent dimension 40x, 100x, 200x, and 400x. Wei B. et al. (2017) proposed a BiCNN model to reserve to reserve edge feature of cancerization region under AlexNet architecture. The accuracies from 97.02% to 97.50% were achieved for 40x, 100x, 200x, and 400x image magnification dimension. Kahya et al. (2017) proposed a feature extraction technique on histopathological images using three competitors such as ASSVM, SSVM-SCAD, SSVM-Lasso and SVM. ASSVM (Adaptive Sparse Support Vector Machine) alleviated with weighted L1-norm was the best performer ensembled with Wilcoxon rank sum test to identify the feature weighted. Chattoraj S. et al. (2018) employed Deep Neural Network aided discriminative ensembled for sub-space embedding and hashing based local shallow signature. This model achieved 95.8% accuracy pertinent to multi-classification on Lobular Carcinoma sub-type of beast cancer.
Nawaz M. et al. (2018) used DenseNet architecture transfer learning for multi-class breast cancer classification. This model achieved average of 95.4% accuracy for the subclass of tumor. Zhu C. et al. (2019) implemented a hybrid deep CNN based on Google's Inception architecture on two different datasets viz. BreakHis and BACH image datasets. The author has achieved the accuracy in different magnification factors for 40x, 100x, 200x and 400x were 85.2%, 83.5%, 84.1% and 79.3%. Alom M. et al.(2019) proposed a powerful model IRRCNN on two types of images datasets viz. BreakHis and Breast Cancer Classification Challenge 2015. This model combines the strength of Inception Network, ResNet and RCNN and showed the result as improved error rate by 2.14% on BreakHis image datasets and accuracy 99.05% on Breast Cancer Challenge datasets 2016. Yan R. et al. (2019) collected histopathological images of 3771 from publicly website http://ear.ict.ac.cn/?page_id=1616 and applied hybrid convolutional and recurrent deep neural network based on a pretrained model Google's Inception-V3 architecture and achieved accuracy of 91.3%.

Deep Learning and Convolutional Neural Network are implemented for the image datasets by the scholars for predicting the result in the medical images. Bardou D. et al. (2018) proposed a model CNN ensembled handcrafted features and was able to achieve the accuracy between 96.15% to 98.33% for image factors 40x, 100x, 200x, and 400x. Nahid A. et al (2018) focused on hybrid model combination of CNN and LSTM and achieved the accuracy of 91.00% accuracy on 200x datasets, the best precision value of 96.00% was achieved on 40x dataset, and comparatively the best F-measure were achieved on both the 40x and 100x datasets. Nahid A.A. et al. (2018) developed a DNN model with RBM of 'scaled conjugate gradient' backpropagation to classify histopathological breast cancer image. The researcher performed the image enhancement technique using RBM and Gaussian filter. As a result, the accuracies using RBM technique were achieved as 88.7% for 40x, 85.3% for 100x, 88.6% for 200x and 88.4% for 400x magnification factor of the images. Dabeer S. et al. (2019)

implemented CNN model by splitting the data into 80-20 portion to get accuracy 99.86%. the author suggested in the future scope that instead of reducing image size manually, one can implement autoencoder to regenerate 90% of original image.

Including first section this paper has four sections. First section describes about breast cancer cases and how world is deviating from healthy population to mortality population due to occurrence of breast cancer. It also includes the previous work performed by the esteemed scholars in the same domain. Section two has detailed about the technologies used in this presented research work for detecting tumor in the dataset. A description of proposed model has been developed to any cancer image dataset and will detect tumor of cancer with better accuracy. Third section presents an experimental setup for preparing training datasets and will be validating by test data. Fourth section shows the result obtained from developed model and presents the comparison of results obtained from proposed model with results provided by other existing models. Last section includes the conclusion and future works in this domain.

II. Materials and methods

This section presents about data source and type of data used in this research work. It also presents the technology used for the purpose and described the proposed model named "CLAHE-ResIn".

Data Source

BreakHis Image dataset (Benhammou. Y. et al 2020) is used for this research work and is available at https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/. Images are in different formats like histopathology, mammography, MRI, CT-scan, sonography, thermography etc. In this research paper, Histopathological images have been used. The image dataset used is composed of 9,109 microscopic images of breast tumor tissue collected from 82 patients using different magnifying factors (40x, 100x, 200x, and 400x). Input data set is shown in Figure 1 (Nawaz M. et al. 2018). This data set includes all subtypes of tissues such as benign has Adenosis (A), Fibro Adenoma (F), Phyllodes Tumor (PT), Tubular Adenoma (TA) whereas Malignant has Ductal Carcinoma (DC), Lobular Carcinoma (LC), Mucinous Carcinoma (MC), Papillary Carcinoma (PC). Distribution of used image datasets based on magnification factor and category of the cancer viz Benign and Malignant is given below in table 1.

Table 1: Distribution of Image datasets

Magnification	Benign	Malignant	Total
40x	652	1370	1995
100x	644	1437	2081
200x	623	1390	2013
400x	588	1232	1820
Total	2480	5429	7909

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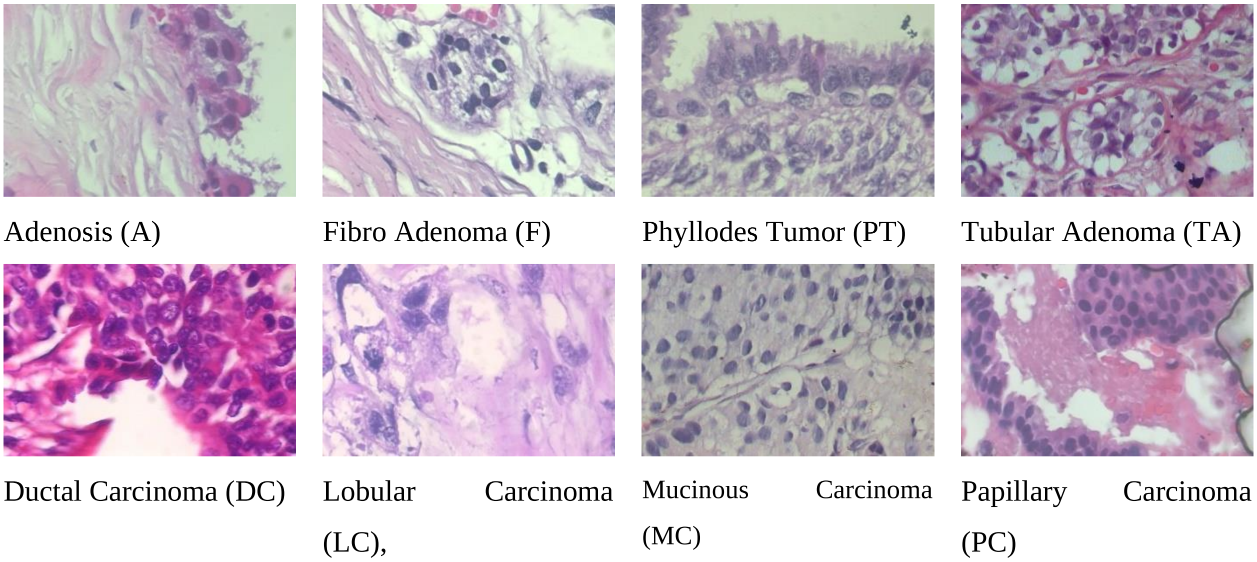

Figure 1: Types of tumor tissues of breast cancer used for Analysis

Data Augmentation

Data augmentation is done for increasing the number of samples and for enhancing quality of raw image for better segmentation of the tumor region. This process includes noise reduction, image scaling, color space conversion, detect abnormalities, enhancement of local contrast. There are many methods to enhance quality of the image using histogram equalization technique.

For the above said purpose BreakHis image dataset taken is converted into RGB first and then converted into grayscale image. CLAHE is Contrast Limited Adaptive Histogram Equalization (Ma. J et al 2017), which is an improved version of AHE (Adaptive Histogram Equalization). CLAHE works on a small region of the whole image for improving contrast. Before proceeding, CLAHE divides the image into grid or tiles. In divided small tiles, noises can be reduced by making histogram equalization.

Deep Neural Network (DNN)

DNN refers to any neural network with several hidden layers. Convolutional Neural Network (CNN) is a specific type of DNN which are especially useful for image processing. DNN with CNN is also known as Deep Convolutional Neural Network (DCNN). Some important mathematical formulas used during processing are given below (Alom M. 2019).

Mathematically CNN (Albelwi. S 2017) can be specified as feed forward neural network *'C'* composed of *'L'* layers C1, C2, C3, ……. C_L, that maps an input vector 'x' to an output vector 'y' i.e.

$$\begin{aligned} y &= f(x: w_1, w_2, .., w_L) \\ &= f_L(; w_L) \,.\, f_{L-1}(; w_{L-1}) \ldots\ldots. f_1(x; w_1) \end{aligned}$$

Where 'w_L' is the weight and bias vector for the L^{th} layer f_L.

ReLU

Rectified Linear Unit (ReLU) is an activation function used in hidden layer of DCNN. It allows for faster and more effective training, by mapping negative value to zero and maintaining positive values in the stride step, to filter the feature from the image. ReLU (Albelwi, S 2017) is given by the function *f(x)* as below.

$$f(x) = max(0, x)$$

$$OR$$

$$f(x) = \begin{cases} 0, & for\ x < 0 \\ x, & for\ x \geq 0 \end{cases}$$

Softmax function (Lee H. et al. 2017) is used to classify the output on account of probability $\boldsymbol{p} \in \{0,1\}$, where $\boldsymbol{p}$ is the probability for each output category, can be given by the following formula.

$$p_i = \frac{e^{a_i}}{\sum_{k=1}^{N} e^{a_k}}$$

$$where\ N\ is\ the\ number\ of\ neurons\ in\ the\ output\ layer\ and$$
$$e^{a_i}\ denotes\ each\ unnormalized\ output\ from\ the\ previos\ layer\ in\ the\ network$$

Steps for setting up a DNN like for defining a neural network, initialization of the number of hidden layers to train the data, to define the learning rate and bias value for every node, maxpooling(Alzubaidi L. 2020), define the number of epochs, training the network for given set of training data, Passing the test data in the network to find the classification rate of the model, Train the network until the number of epochs is completed and calculating the accuracy of the model using evaluation metric.(Ragab A.D. et al 2019)

Transfer Learning (TL)

Transfer Learning is a pre-trained image architecture model acquired from training dataset processing. There are many TL architecture available (Alzubaidi L. 2020), ResNet & Inception hybridization are used in this research work and are given below in brief.

ResNet Architecture

ResNet (Residual Network) architecture is used in image recognition (He et al. 2016). This model has multiple layers to filter the image and it follows feedforward neural network with “shortcut connection”. Shortcut connections are simply skipping one or more layers with some identity x. the output of this skipping layers is added to the final output in the stacked layers. The weights are added in each subsequent layer to compensate the learning rate. Residual Network equation is given by the following equation:

$$Y = f(x, \{W_L\}) + W_s x$$

Where Y is the output, $f(x)$ is the residual function for input x, W_L is weight in each layer, L indicates no. of layers, W_s is the square matrix of the input image pixel.

Inception Architecture

Previously known as LeNet network and was proposed by Google in 2014. This architecture takes multiple convolutional layers along with the filter concepts of maxpooling for optimized features from the image. (Szegedy et al. 2017)

CLAHE-ResIn Model

The proposed model for this research work is titled as CLAHE-ResIn model and is given in Figure 3. Other than input and output, the model is divided into four parts. Parts of the model are according to the stages of processing before the final prediction results. The four parts (Shorten et al. 2019) are data augmentation, features identification, optimized feature extraction using transfer learning, and machine learning classifier. Original histopathological images are used as input to this model. The images are processed using CLAHE technique (Ma. J et al 2017) for improving the image quality for data augmentation. CLAHE technique divide the image into small grids called 'tiles' and pixels of each tile are forwarded into the process for all possible features identification in each pixel. These features become the input to the CNN network. The following workflow diagram is mentioned below in figure 2.

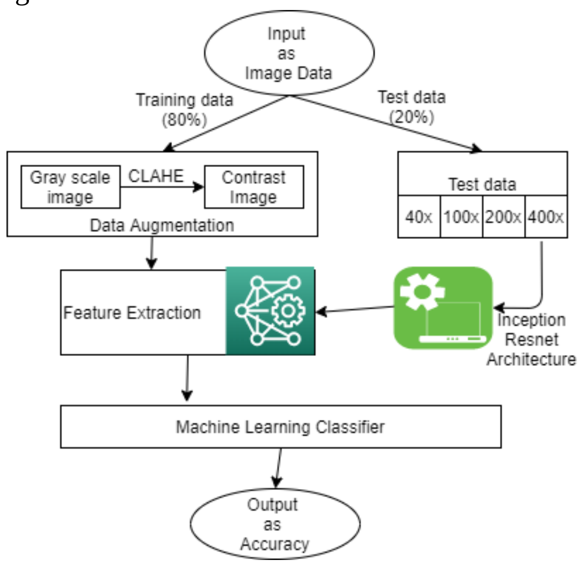

Figure 2: Workflow diagram of proposed model

There are convolutional, sub-sampling and activation layers in this CNN for optimization of features extraction. Last layer of network of layers is termed as Softmax layer. It provides the final data for cancer prediction. Sub-sampling layers of CNN optimizes the number of computations and learning parameters. It also reduces the spatial size of network. Network efficiency is improved by activating few nodes in each cycle and is done by Activation layer. In the medical domain, data annotation using CNN technique is somewhat challenging due to limited number of samples in the image. To address this challenge, Transfer Learning (TL) is introduced which extract the most significant features from the sample.

The proposed model consists of total 20 convolutional layers with different filter sizes that can extract the features such as color, shape, edges etc. The model starts with 7x7 filter size and stride 2x2 for the usage of maxpooling to reduce size of the input image of dimension 115x175x3 with 3 channels without losing information. The convolutional layers in the model are followed by Batch Normalization (BN) and ReLU (Bardou, D.2018). At the end, there is a concatenation layer to concatenate the output of the block that is the concatenation of all extracted features. After this all processing softmax gives the malignant dataset for further processing to get the accuracy level for predicting the cancer using ML classifier techniques.

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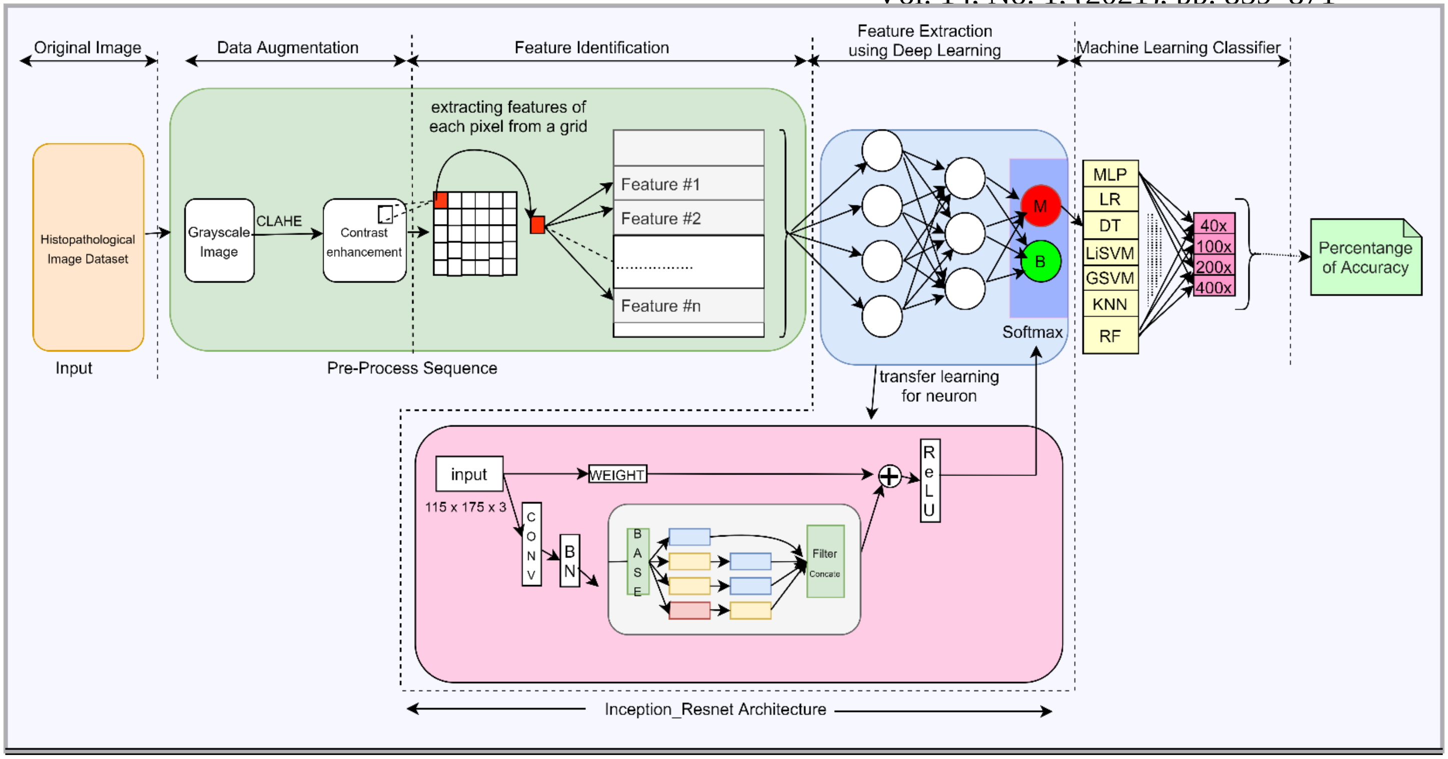

Figure 3: CLAHE-ResIn model

III. Experiments

The experimental setup is configured through Google's Colab platform where Graphics Processing Unit supports are there to run the image-based work using Python with machine learning and deep learning libraries. Colab platform dynamically provides all the configuration facilities required during the experiments. This experiment is done using histopathological image dataset took more than two hours to complete the processes.

Input and Pre-Processing

In this experiment images are used as input. The dataset shown in the figure 1 is used as input for preprocessing purpose. Preprocessing includes the task of data augmentation and feature extraction. Data Augmentation includes the contrast enhancement with many other orientations for improving the useful features extraction from the images. Contrast enhancement is done using CLAHE method (Jadoon, M. M et al. 2017) for all input images. CLAHE implementation steps result at different stages have been shown for a sample image of DC type tissue, as it is most prone to cancer.

Data Augmentation

The original image has been augmented by converting it into grayscale for better input to the model. Later, the grayscale image contrasted for better feature extraction and thereby better prediction. The value of brightness in original image ranges from 0 to 255 on an optimal proportion of RGB (Nahid A.A. et al 2018). Below figure 4 shows original image conversion into grayscale and then grayscale image conversion into contrasted one. All the three types of images have been shown in the form of histogram also.

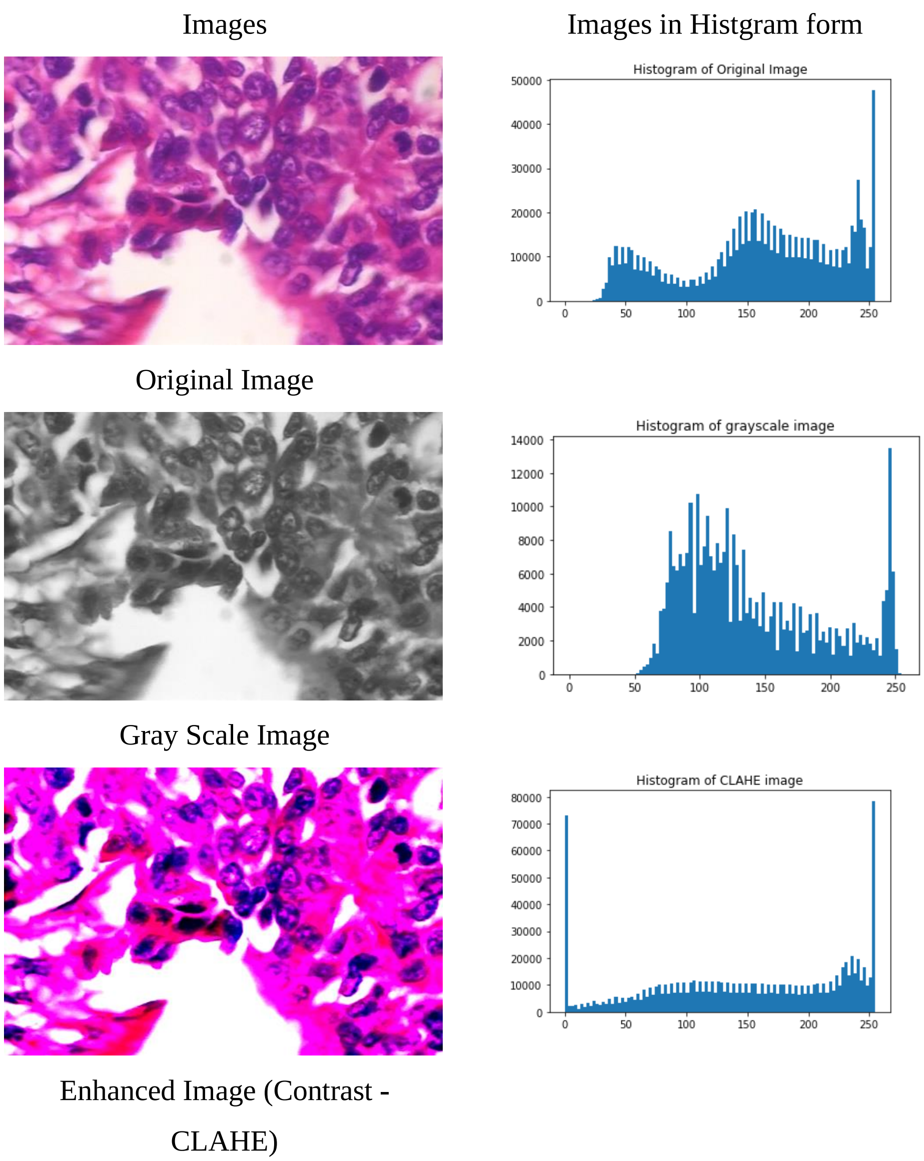

Figure 4: CLAHE implementation on the image

Histogram form of the images represents cumulative distribution function (CDF) for each pixel in the image. It is clearly visible from the figure 3 that in original image histogram, CDF is not equally distributed and in the grayscale image histogram, CDF has some variation. Whereas in CLAHE image histogram, the beginning pixel coordinate point and the end pixel coordinate points are fixed, and All the pixel values are lying within this range which provides an easy platform for better feature extraction (Jadoon, M. M et al. 2017)

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Processing in CLAHE-ResIn model

The model is trained using 2480 benign and 5429 malignant sample of dataset. Specification of the used image is: 700x460 pixels, 3-channel RGB, 8-bit depth in each channel and PNG format. Input to this presented CLAHE-ResIn model is, contrasted images produced after CLAHE application, over the original images of 40x, 100x, 200x, and 400x magnification factor. Following table 2 shows the results by the model for training dataset, which is 80% of the total dataset, based on Inception_ResNet architecture (Xie J. 2019). Table represents epoch, learning rate and accuracy for the datasets of different dimensions. Training model provided the best accuracy of 91.52% for the image of 40x dimension with 31 epoch and 0.55 learning rate. The minimum accuracy of 85% is observed for the image of 400x dimension with 22 epoch and 0.47 learning rate.

Table 2: Result shown by the model for training dataset

Image dimension	**Epoch**	**Learning Rate**	**Accuracy**
40x	31	0.55	91.52%
100x	27	0.34	88.2%
200x	21	0.36	87%
400x	22	0.47	85%

After the model is trained, test data, which is 20% of the total dataset, is applied with 10-fold Cross-Validation (CV) (Ryu S. 2020) with various machine learning classifiers mentioned in table 3. It is observed that among all 7 machine learning classifiers, Linear SVM classifier gives best accuracy 90.3% on magnification factor 40x, Logistic Regression gives best accuracy 92.2% and 95.0% on 100x and 200x magnification factor, respectively. While Gaussian SVM outperform among all classifiers for 400x magnification factor with accuracy 99.1%.

Table 3: Result shown by the model for test dataset with machine learning classifiers

Machine Learning classifier	**Accuracy after 10-fold CV**			
	40x	**100x**	**200x**	**400x**
Multi layered Perceptron	84.5%	87.7%	94.0%	98.7%
Logistic Regression	90.2%	**92.2%**	**95.0%**	98.6%
Decision Tree	64.3%	71.1%	78.9%	93.4%
Linear SVM	**90.3%**	91.3%	94.0%	98.6%
Gaussian SVM	72.0%	81.6%	90.5%	**99.1%**
k-Nearest Neighbor	87.2%	89.2%	92.6%	98.6%
Random Forest	73.8%	79.3%	88.0%	98.0%

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In the above table 3, the experiment shows that the accuracy of the training data sample varies from dimension to dimension of image. However, when the data samples are distributed on 10-fold cross validation. The accuracy of the test data samples changes variably.

IV. Results & Discussion

The experiment is performed on BreakHis histopathological image datasets of different magnifying factor images. The complete dataset processing during the training needs different epochs to maximizing the learning rate i.e. minimizing the error rate. There are different epochs control for images of different magnifying factors, shown below in figure 5, where the epochs are controlled with an early stopping for constant learning rate for a duration. Early stopping concept is applied to train the model CLAHE-ResIn at the point when performance of the model starts to degrade.

The graph is plotted for notifying the early stopping point for different images using python script. The figure 5 (a), fig 5 (b), fig 5 (c) and fig 5 (d) show the number of epochs performed for improving the learning rate.

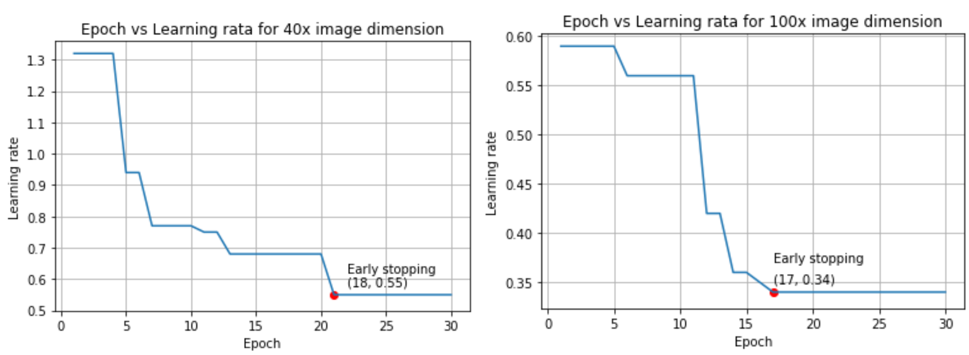

Figure 5(a) & 5(b): Early stopping plot graph for 40x image and 100x image

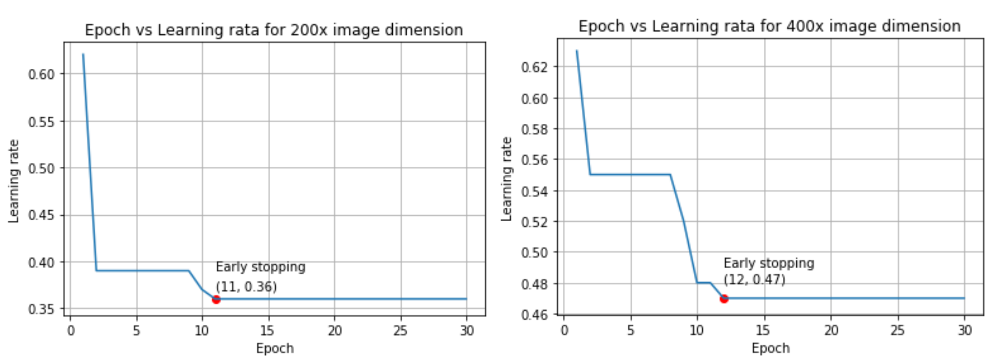

Figure 5(c) & 5(d): Early stopping graph plot for 200x image and 400x image

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With these above given epochs, the model is trained well. With that trained model, the result obtained from the testing datasets are shown in the table 3. The graphical representation of result given in table 3 are shown in figure 6. These results get compared with other models used for breast cancer prediction. The comparative results are shown in the table 4. Presented model CLAHE-ResIn has outperformed than many others for the image 400x magnification factors with the accuracy 99.1%.

Table 4: Comparison of our model with existing model

Method	**Dataset**	**Accuracy on magnification factor images**			
		40x	**100x**	**200x**	**400x**
AS-SVM (Kahya et al. 2017)	BreakHis	94.97%	93.62%	94.54%	94.42%
BiCNN (Wei et al. 2017)	BreakHis	97.89	97.64	97.56	97.67
DNN + CSML (Chattoraj et al. 2018)	BreakHis	99.1	98.7	99.3	98.4
Ensemble CNN model (Bardou et al. 2018)	BreakHis	98.33	97.12	97.85	96.15
DCNN + Gaussian Filter + RBM (Nahid A.A. et al 2018)	BreakHis	88.7	85.3	88.6	88.4
BHCNet-3 + ERF (Jiang et al. 2019)	BreakHis	98.87	99.04	99.34	98.99
VGG16 + SVM (L, 1) (Sharma S. et. Al. 2020)	BreakHis	93.97	92.92	91.23	91.79
DenseNet + CNN (Nawaz M. et al. 2018)	BreakHis	93.64	97.42	94.67	95.4
'CLAHE-ResIn' proposed model	BreakHis	90.3%	92.2%	95.0%	**99.1%**

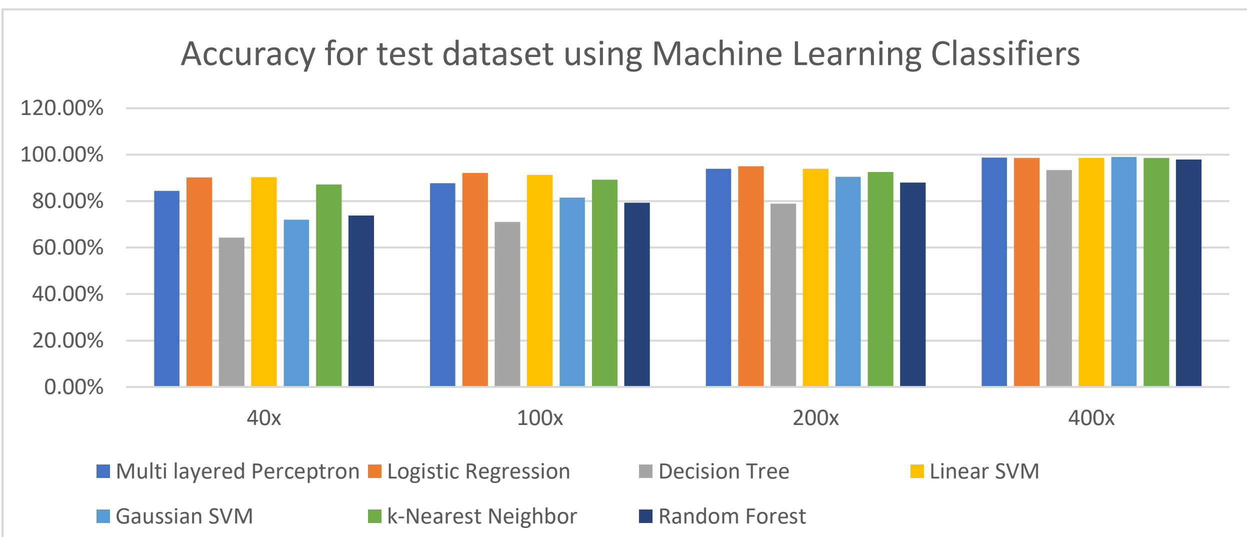

Figure 6: Accuracy of prediction for test dataset using Machine Learning Classifiers

V. Conclusion & Future Work

The model named "CLAHE-ResIn" is the model which predicts the breast cancer from histopathological images. Input images get contrasted using CLAHE and Deep learning process with Inception and ResNet architecture, for classification to get malignant dataset separated from benign datasets. In this model Machine Learning classifier techniques are applied over malignant datasets for finding the value of parameter accuracy in percentage. Presented model CLAHE-ResIn has outperformed than many others for the image 400x magnification factors with the accuracy 99.1%.

In future, we intend to improve the results more by applying different other image enhancement techniques like Gaussian Filter etc. Other approaches for feature extraction using optimization techniques like Restricted Boltzmann Machine, Genetic Algorithm, Ant Bee Colony, Particle Swarm Optimization etc. may also improve the results for cancer prediction. Different architecture of transfer learning may also be made to improve the results.

VI. Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

VII. Reference

1. Ahmad, H. M., Ghuffar, S., & Khurshid, K. (2019). Classification of Breast Cancer Histology Images Using Transfer Learning. *Proceedings of 2019 16th International Bhurban Conference on Applied Sciences and Technology, IBCAST 2019*, *March*, 328–332. https://doi.org/10.1109/IBCAST.2019.8667221
2. Albelwi, S., & Mahmood, A. (2017). A framework for designing the architectures of deep Convolutional Neural Networks. *Entropy*, *19*(6). https://doi.org/10.3390/e19060242
3. Alom, M. Z., Yakopcic, C., Nasrin, M. S., Taha, T. M., & Asari, V. K. (2019). Breast Cancer Classification from Histopathological Images with Inception Recurrent Residual Convolutional Neural Network. *Journal of Digital Imaging*, *32*(4), 605–617. https://doi.org/10.1007/s10278-019-00182-7
4. Alzubaidi, L., Al-Shamma, O., Fadhel, M. A., Farhan, L., Zhang, J., & Duan, Y. (2020). Optimizing the performance of breast cancer classification by employing the same domain transfer learning from hybrid deep convolutional neural network model. *Electronics (Switzerland)*, *9*(3). https://doi.org/10.3390/electronics9030445
5. Bardou, D., Zhang, K., & Ahmad, S. M. (2018). Classification of Breast Cancer Based on Histology Images Using Convolutional Neural Networks. *IEEE Access*, *6*(May 2018), 24680–24693. https://doi.org/10.1109/ACCESS.2018.2831280
6. Benhammou, Y., Achchab, B., Herrera, F., & Tabik, S. (2020). BreakHis based breast cancer automatic diagnosis using deep learning: Taxonomy, survey and insights. *Neurocomputing*, *375*(October), 9–24. https://doi.org/10.1016/j.neucom.2019.09.044
7. Chattoraj, S. (2019). *Manifold Learning & Stacked Sparse Autoencoder for Robust Breast Cancer Classification from Histopathological Images*. arXiv:1806.06876v2, 2018.
8. Dabeer, S., Khan, M. M., & Islam, S. (2019). Cancer diagnosis in histopathological image: CNN based approach. *Informatics in Medicine Unlocked*, *16*(August), 100231. https://doi.org/10.1016/j.imu.2019.100231
9. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2016-December*, 770–778. https://doi.org/10.1109/CVPR.2016.90
10. Jadoon, M. M., Zhang, Q., Haq, I. U., Butt, S., & Jadoon, A. (2017). Three-Class Mammogram Classification Based on Descriptive CNN Features. *BioMed Research International*, *2017*. https://doi.org/10.1155/2017/3640901
11. Jiang, Y., Chen, L., Zhang, H., & Xiao, X. (2019). Breast cancer histopathological image classification using convolutional neural networks with small SE-ResNet module. *PLoS ONE*, *14*(3), 1–21. https://doi.org/10.1371/journal.pone.0214587
12. Kahya, M.A., W. A.-H. and Z. Y. A. (2017). Classification of Breast Cancer Histopathology Images based on Adaptive Sparse Support Vector Machine. *Journal of Applied Mathematics & Bioinformatics*, *7*(1), 49–69.
13. Lee, H., & Kwon, H. (2017). Going Deeper with Contextual CNN for Hyperspectral Image Classification. *IEEE Transactions on Image Processing*, *26*(10), 4843–4855. https://doi.org/10.1109/TIP.2017.2725580

ISSN: 2233-7857IJFGCN

14. Nahid, A. Al, Mehrabi, M. A., & Kong, Y. (2018). Histopathological breast cancer image classification by deep neural network techniques guided by local clustering. *BioMed Research International*, *2018*. https://doi.org/10.1155/2018/2362108
15. Nahid, A. Al, Mikaelian, A., & Kong, Y. (2018). Histopathological breast-image classification with restricted Boltzmann machine along with backpropagation. *Biomedical Research (India)*, *29*(10), 2068–2077. https://doi.org/10.4066/biomedicalresearch.29-17-3903
16. Nawaz, M., Sewissy, A. A., & Soliman, T. H. A. (2018). Multi-class breast cancer classification using deep learning convolutional neural network. *International Journal of Advanced Computer Science and Applications*, *9*(6), 316–322. https://doi.org/10.14569/IJACSA.2018.090645
17. Nawaz, W., Ahmed, S., Tahir, A., & Khan, H. A. (2018). Classification of Breast Cancer Histology Images using *AlexNet*. *Springer Nature 2018*, ICIAR 2018, LNCS 10882, pp 869–876. https://doi.org/10.1007/978-3-319-93000-8_99
18. Ma, J., Fan, X., Yang, S. X., Zhang, X., & Zhu, X. (2017). *Contrast Limited Adaptive Histogram Equalization Based Fusion for Underwater Image Enhancement*. *March*, 1–27. https://doi.org/10.20944/preprints201703.0086.v1
19. Ryu, S. M., Seo, S. W., & Lee, S. H. (2020). Novel prognostication of patients with spinal and pelvic chondrosarcoma using deep survival neural networks. *BMC Medical Informatics and Decision Making*, *20*(1), 1–10. https://doi.org/10.1186/s12911-019-1008-4
20. Siegel, R. L., & Miller, K. D. (2019). *Cancer Statistics , 2019*. *69*(1), 7–34. https://doi.org/10.3322/caac.21551
21. Sharma, S., & Mehra, R. (2020). Conventional Machine Learning and Deep Learning Approach for Multi-Classification of Breast Cancer Histopathology Images—a Comparative Insight. *Journal of Digital Imaging*. https://doi.org/10.1007/s10278-019-00307-y
22. Shorten C, & Khoshgoftaar T.M. (2019). A survey on Image Data Augmentation for Deep Learning. *J. Big Data*, *2019*, *6:60*, *https://doi.org.10.1186/s40537-019-0197-0*
23. Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. A. (2017). Inception-v4, inception-ResNet and the impact of residual connections on learning. *31st AAAI Conference on Artificial Intelligence*, *AAAI 2017*, 4278–4284.
24. Vidyarthi, A., Shad, J., Sharma, S., & Agarwal, P. (2019). Classification of Breast Microscopic Imaging using Hybrid CLAHE-CNN Deep Architecture. *2019 12th International Conference on Contemporary Computing*, *IC3 2019*, *September*, 1–5. https://doi.org/10.1109/IC3.2019.8844937
25. Wei, B., Han, Z., He, X.,Yin, Y., (2017). *Deep Learning Model Based Breast Cancer Histopathological Image Classification.* IEEE Int. C. Cloud Computing and Big Data Analysis. 348–353. https://doi.org/10.1109/ICCCBDA.2017.7951937
26. Xie, J., Liu, R., Luttrell, J., & Zhang, C. (2019). Deep learning based analysis of histopathological images of breast cancer. *Frontiers in Genetics*, *10*(FEB), 1–19. https://doi.org/10.3389/fgene.2019.00080
27. Yan, R., Ren, F., Wang, Z., Wang, L., Zhang, T., Liu, Y., Rao, X., Zheng, C., & Zhang, F. (2020). Breast cancer histopathological image classification using a hybrid deep neural network. *Methods*, *173*(February), 52–60. https://doi.org/10.1016/j.ymeth.2019.06.014
28. Zhu, C., Song, F., Wang, Y., Dong, H., Guo, Y., & Liu, J. (2019). Breast cancer histopathology image classification through assembling multiple compact CNNs. *BMC Medical Informatics and Decision Making*, *19*(1), 1–17. https://doi.org/10.1186/s12911-019-0913-x

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