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Improved Mask R-CNN Segmentation and Bayesian Interactive Adaboost CNN Classification for Breast Cancer Detection on Bach Dataset

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ABSTRACT- Breast cancer is considered as the predominant type of cancer that affects more than ten percentage of the worldwide female population. Though microscopic evaluation remains to be a significant method for diagnosing, time and cost complexity seeks alternative and effective computer aided design for rapid and more accurate detection of the disease. As DL (Deep Learning) possess a significant contribution in accomplishing machine automation, this study intends to resolve existing problems with regard to lack of accuracy by proposing DL based algorithms. The study proposes Improved-Mask R CNN (I-MRCNN) method for segmentation. In this process, RPN (Region Proposal Network), predicts the objectless scores and object bound at every position. Here, (RoI Align) Region of interest Align is used for feature extraction as it is capable of resolving the conventional RoI pooling issues by attaining high accuracy for small objects and also eliminates quantization issues. Further, classification is performed using the proposed Bayesian Interactive Adaboost CNN classifier (B-IAB- CNN) that integrates the advantages of CNN, Bayesian and Adaboost classifier. The advantages of the three classifier enable optimum classification of the input Bach dataset that is confirmed through the results of performance analysis of the proposed system. Outcomes reveal that, average accuracy for segmentation is 96.32%, while, the classification accuracy is exposed to be 96%. As Timely prediction is significant, high prediction rate of the proposed system will assist the medical practitioners to detect breast cancer quickly which is the important practical implication from this study for diagnosing breast cancer.

Keywords: Deep Learning, Breast Cancer, Otsu threshold, Adaboost, Mask RCNN.

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1. INTRODUCTION

Globally, Breast cancer remains to be a major reason for the cancer associated death in women. Evidentially early and prompt diagnosis could significantly increase the success of the Breast cancer treatment[1]. The signs and symptoms of BC are different and accurate diagnosis needs physical examination, biopsy, ultrasound testing and mammography. Generally biopsy is performed after the identification of certain abnormality with the employment of ultrasound and mammography[2]. Despite biopsy results are accurate, the tissue sample that was removed surgically involved painful procedure and microscopic imaging of such sample were complex due to its huge size[3]. Hence pathologists rely on computer aided design for reducing the workload and invasive diagnosis. Considering this, existing researches have endeavored to perform breast cancer classification and segmentation using different approaches.

Accordingly, the study presented a flexible, simple and generalized segmentation of the dataset with the improved mask RCNN process. This approach effectively identifies the objects I the dataset while consequently generating high quality mask for every instance. Mask RCNN is an extension of Faster R CNN by including a branch for object mask prediction parallel with the prevailing branch for the recognition of bounding box[4]. Further the process is improved with RoI align. Region of interest (RoI) is utilized for the purpose of feature extraction from the appropriated convolution layers shared and the extracted features are passed to fully convolution layer for classifying the abnormal regions[5]. ROI uses nearest neighbour interpolation, a quantization process when the optimal features are derived from the convolutional layers[6]. The adopted quantization operation the RoI features are transferred to a fixed dimension. Meanwhile after RoI pooling, the RoI of resulted feature maps mismatches the input RoI image. Hence, it is clear that, the existing RoI pooling might lead to mismatches of feature maps.

Hence, this study utilizes RoI align which is different from RoI pooling that consider bilinear interpolation for calculating the

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position pixel value and eliminating quantization. This process generally process the region proposals and categorize every region proposal to $K \times K$ units that left the each unit boundaries to be unquantified. The coordinate values are estimated in every unit and the position pixel value are estimated by bilinear interpolation followed by the max pooling. This operation obtain high accuracy for small objects thereby eliminating quantization operation. Accordingly Mask RCNN adds only smaller overhead to Faster RCNN that runs at 5 fps. The ground truth has been generated by using Otsu threshold method. The Otsu method is used widely in the existing studies to perform image segmentation since it needs very less computation time when compared with other methods. Since Otsu thresholding adopts simpler mathematical expressions during the determination of best threshold value it is utilized in this study for generating ground truth[7]. On contrary, the existing studies have been deficient with regard to accuracy rate. Hence, to enhance the accuracy rate, the study utilizes Adaboost classifier to increase the accuracy and effectiveness of the prevailing classifier with its characteristic features like less susceptibility to overfitting[8]. Likewise Bayesian classifier on integration with Adaboost and CNN could able to handle the discrete and continuous features present in the dataset[9]. Therefore the input images are classified with proposed Bayesian Interactive Adaboost CNN classifier that integrates the advantages of every individual classifier. Hence, through these processes, this research proposes Improved-Mask R CNN (I-MRCNN) method for segmentation and Bayesian Interactive Adaboost CNN (B-IAB-CNN) for classification which is considered to be the novelty of this study. From extensive analysis, it is found that, regardless of the attempts by the existing works for breast cancer classification, most of the conventional researches lacked accuracy and most of them have not concentrated on segmentation for which the present research aims to accomplish classification as well as segmentation of the images from the Bach dataset.

Objectives

- To improve the reliability of breast cancer diagnosis with the proposed Improved Mask RCNN segmentation and Bayesian Interactive Adaboost CNN classifier.
- To perform effective segmentation with RoI align based Improved Mask RCNN (IMRCNN) segmentation and to compare the segmentation results with the ground truth generated by OTSU threshold.
- To classify the breast cancer images by using Bayesian Interactive Adaboost CNN classifier (B-IAB- CNN) effectively.
- To perform performance analysis of the classification results with the state of art methods.

The paper organisation is as follows: *Section 1* provides the introduction of the breast cancer diagnosis, importance of mask R CNN segmentation and ensemble classification approaches. *Section 2* provides the information about the existing works in accordance to the proposed system. *Section 3* describes the proposed methodology briefly followed by the description of results obtained in *section 4*. Finally *section 5* concludes the work in detail.

2. REVIEW OF LITERATURE

The following are the review of literature in accordance to the proposed system. Breast had been a most common and invasive cancer in women. It affects approximately 10% or more than of women in worldwide. One of the most important biopsy was microscopic analysis and it had been used for diagnosing types of breast cancer. It needs a specified analysis by pathologists for performing task (*i*) high time and less costs consuming and (*ii*) it leaded only non-consensual results. By goal for achieving this, BACH (Breast Cancer Histology images) had been sued. It aimed for localization and classification of clinical related histopathological classes in microscopic images and it inserted as dataset. [10] This study collected large datasets and registered classes in microscopy and efficiently entered into the competition. This algorithms improves automated classifiers for diagnosing breast cancer through microscopic images with 87% of accuracy. This CNN are most successful method in BACH challenge. [11] This study emphasized for choosing splitting for validations and training and it had not been suitable for clinical determination. Additionally, a trained database set needs to be more precise and also with similar annotations. The computer assists diagnosing methods would be useful for excluding these cases. Similarly,[12] this proposed study of using extra region level supervision for classifying of histopathology images for breast cancer through CNN, where the ROI (Region of Interest) are local and used for guiding classification network through attention simultaneously. The proposed SAM (Supervised Attention Mechanism) specially enables neurons in diagnostically related regions when it suppressed actions of not related and noisy areas. This class activates maps are generated by proposed technique which correlates with expected pathologist outcome. However, the proposed system surpasses the BACH microscopic testing dataset with important margin.

2.1 Existing approaches on Mask R CNN segmentation

The computer aided techniques had been sued for diagnosing breast cancer by MRI (magnetic resonance imaging). Initially step was to find abnormal areas. This [13] An R-CNN (Deep learning Mask Regional Convolutional Neural Network) had been executed for searching complete set of detected and suspicious images of lesions. Two DCE-MRI datasets had been used for 241 patients and it spotted 98 patients with large types of tumours. The tumour had been separated and segmented through Fuzzy C means algorithms for serving for truth. The output of results are obtained 9.5% of lesions and 100%lesions in trained datasets.

Here, [14] added a frame work to RCNN as 3D- Mask RCNN (3D- mask region based convolutional neural network) with CAD (computer aided diagnosis) system for developing for mass segmentation and detection with comparative analysis for performing on patient groups with various clinical pathologic character. For eliminating this, 364 sampling data are taken from database and trained dataset with n-201 and testing dataset with n=163. Hence, the results shows about the 3D-mask RCNN framework had been compared to 2D-mask RCNN and other faster methods of RCNN. The sensible 3D-mask RCNN detected 90% with 0.8 FP (false positives) for lesion based mass

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detection as well as sensible 2D-mask RCNN and other faster RCNN detected 90% with 2.37 FP for lesion of mass detection using CAD respectively. The CAD of prostate ultra-sounded images had been used for treating and detecting prostate cancer. Moreover, this had been disturbed by speckle noise, poor detected accuracy and low SNR. For overcoming this, [15] proposed an S-mask RCNN (deep learning model with S mask and RCNN) and inception–V3 in UIAD (ultrasound image aided diagnosis) diagnosing prostate cancer.

This proposed technique has high accuracy that manual detection and diagnosis of doctor. This effective and simple technique had been served as a baseline for helping to work may research in this method and ease for future research in CAD for diagnosing prostate cancer. Also, [16] used mask RCNN for automated detection of nucleus on high quality histopathological images for diagnosing breast cancer. This mask RCNN implements ResNet for combining modules like FPN (feature pyramid networks), FCN (fully convolutional network) and ROI align. The result shows about uses and implementation of this prosed algorithms and its performance had been measured using recall, accuracy and F- measure. In order to achieve better performance in feature extraction and detects targets using deep learning methods. [17] This paper established a model of Mask R-CNN for segmentation and ResNet (Residual Network) and DenseNet (Densely convolutional networks) for extracting features. The feature maps are inputted to RPN (Region Proposal Network) for training ROI and FCN. Results shows that this method attained high accuracy with precision rate of 97.31% and recall rate of 95.70%. Also, [18] paper implemented same Mask RCNN with advantages as multi-scale feature extraction with RPN, precision improvement with multi-organ segmentation and attained effective results with less false detection.

2.2 Existing approaches on Ensemble Classifier

The following This research [19] developed a two layered nested ensemble classifiers. This study suggested WDBC (Wisconsin Diagnostic Breast Cancer) and K-fold CV (Cross Validation Technique) for evaluation. Hence, the result explains about two layered Nesting ensemble performers as a single classifiers. The SV-BayesNet-3-MC (Meta classifiers) and SV-NB-3-MC attained 98.07% of accuracy with k=10. Thus, SV-NB-3-MC are more accuracy for building a model. Towards with CNN [20] this paper implemented a new machine learning design AdaBoost for dealing with large imbalanced datasets along with highest accuracy. This proposed Adaboost-CNN had been designed for reducing computational cost for dealing with large number of sets of trained data. The experimental results of AdaBoost-CNN shows the accuracy about 16.98% with high efficiency when compared to the classical AdaBoost technique with imbalance dataset. In addition to, AdaBoost-CNN reached a high efficiency of accurate values with 94.08% on testing 10,000 samples of synthesised misbalancing dataset and it also higher than CNN of 92.05%. Using this CNN techniques, [21] this paper implemented a classification approach as DLA-EABA (Deep Learning assisted Efficient AdaBoost Algorithm) for detecting breast cancer with advanced CAD technique. The classification are actively gone through CNN approached. This results shows high accurate level values with 97.2%, specificity 96.5% and sensitivity 98.3% where it compared to other existed systems. Along with this accuracy [22] this paper introduced an extension of Bayesian classifiers to Bayesian optimizations for permitting an efficient machine learning parameter for procedural animation based applications. This applications also assisting animators for taking risk of challenging tasks for developing curl based velocity fields with less domain knowledge when compared to other identified simulation which had been said to be “looks right”.

2.3 Research Gap

Existing articles have various limitation as follows. Mask RCNN works on only still images and hence could not explore the desired object temporal information like dynamic hand gestures[23]. Additionally mask CNN fails in the detection of object suffering from motion blurs at considerably low resolution[14]. Similarly in RoI pooling of the existing works, the quantization blocks the boundary point values which are generally integers. Coming to classification limitation of the existing system, Adaboost requires a high quality dataset and outliers and noisy data must be prohibited[21]. Likewise Bayesian algorithm face zero frequency problem that assign zero probability to variable in the testing data in training dataset. In CNN huge training data is needed. In addition, conventional researches have revealed different prediction rates. Accordingly, the study [22] has used SVM-hybrid features showing 92.2% accuracy, the research [13] has exposed 91.3% accuracy while using CNN-RDNN. Though satisfactory results have been attained, prediction rate has to be improvised. On contrary, most of the researches have only considered classification, while, other studies have failed to regard segmentation process [11, 13, 14, 18]. Nevertheless, few studies have considered segmentation but failed to expose high accuracy. For example, the paper [29] has considered to use dual DL based model and has shown 94% as segmentation rate, while, the study [30] has regarded 91.67%. Hence, it is important to procure high accuracy by considering classification and segmentation process for breast cancer diagnosis. Such existing limitations are attempted to be overcome by the proposed system.

3. PROPOSED SYSTEM

This section briefly describes the proposed system that comprise segmentation of the Bach dataset with improved mask RCNN and classification of the input dataset with the proposed ensemble Bayesian- interactive Adaboost– CNN classifier.

The framework has been deliberated in figure 1. The breast input images are passed to improved mask R-CNN segmentation process in which RPN (Region Proposal Network), a fully connected network predicts simultaneously the objectness scores and object bound at every position. Further RPN has been trained end to end for generating high quality proposals. The output images from RPN are further splitted to Binary class and Mask region delta followed by intensity enhanced ROI align. ROI has been utilized for feature extraction from the convolutional layers and these features were fed as input to fully connected layer for Faster R CNN

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classification. This process generally process the region proposals and categorize every region proposal to K × K units that left the each unit boundaries to be unquantified. The ground truth was generated by the Otsu threshold method and the comparative analysis proves the effectiveness of the proposed system.

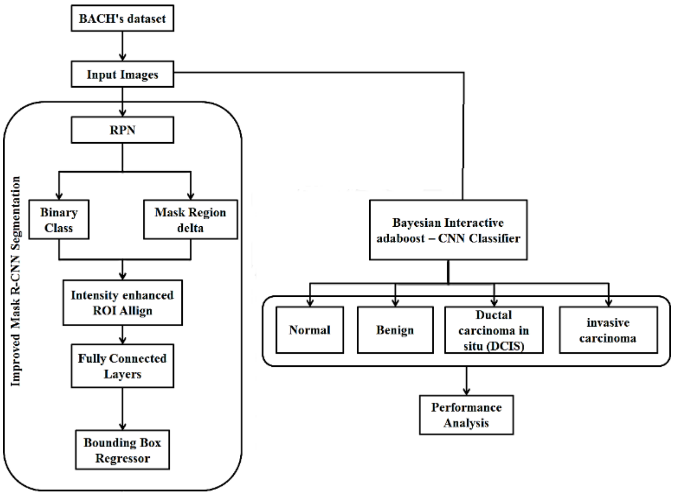

Figure 1. Framework for the proposed segmentation and classification on Bach dataset

Other sector of the proposed method deals with the classification of the input breast images by pre-processing through resizing and classification of the processed image by ensemble classification that involves Bayesian – interactive adaboost and CNN classifier. The advantages of the three classifier enable optimum classification of the input Bach dataset to normal, benign, invasive carcinoma and DCIS (Ductal carcinoma insitu). The performance of the classifier has been compared with the state of art methods.

3.1 Improved-mask R-CNN ((I-MRCNN)) segmentation

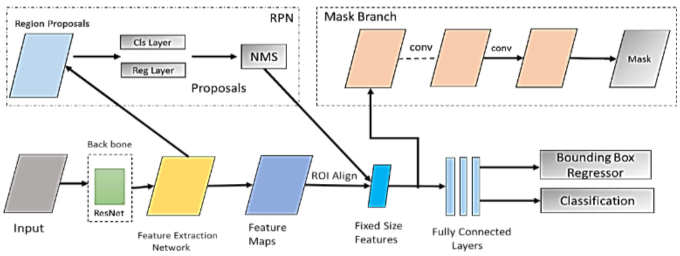

Figure 2. Architecture diagram for proposed IM-R-CNN (Improved Mask R-CNN) segmentation

The Mask R-CNN is the improved model for R CNN and by including mask branch, corresponding masks could be developed for covering the objects in accordance with the class and location of the identified objects. As depicted in the dual stage architecture in *figure 2*, the RPN in the first stage has been utilized for the generation of object region proposal and for the determination of background and foreground of the input images. In the next stage the CNN extract features from the candidate proposal followed by classification and generation of the bounding box and masks. This method increase the model accuracy and subsequently involved in the network optimization, reduction of calculation parameters and increasing the detection speed.

The input images are transferred to the proposed IM-R-CNN (Improved Mask R-CNN) segmentation process to perform effective segmentation of the breast images. Here RPN considers the breast cancer images from the dataset as the input and delivers a rectangular object sets with corresponding score and detects the role of anchor as foreground or background. It also corrects the initial coordinate for the foreground anchors. Accordingly an anchor is centred at sliding window and observed to be correlated with aspect and scale ratio. In Mask R CNN, the region that has been feed to the RoI Align (Region of Interest) is huge that ranges from 100 to 300.Here there exists large segmentation maps to be learned that makes it complex for feature extraction in mask branch. For resolving the issue, the non-maximum threshold suppression in RPN has been increased to 0.7 from 0.5 and consequently the IoUat 0.7

3.1.2. Loss function

A third loss function for mask generation has been included based on Fast RCNN thereby the total loss function of the proposed segmentation process is

$$L = L_{cls} + L_{box} + L_{Mask} \quad (1)$$

Accordingly the regression and classification losses are described as

$$L_{box} = \sum_{i=1}^{4} W_{L1}(t_i^u - v_i) \; (2)$$

$$L_{cls} = -\log A_{u'} \; (3)$$

$$W_{G1}(X) = \begin{cases} 0.5x^2, & |r| < 1, \\ |r| - 0.5, & otherwise. \end{cases}$$

A is (k + 1) dimensional vector signifying the pixel probability of K-class. For each ROI

$$A = (A_0, A_1, \cdots, A_k)$$

And t_u denotes the probability of class u and stated as

$$t_u = (t_r^u, t_y^u, t_w^u, t_h^u)$$

The above equation signifies the predicted translation scale factor of class u.

Further t_r^u, t_y^u denotes similar scale translation as like object and t_w^u, t_h^u represents the width and height of logarithmic area in accordance to object proposal. Accordingly t_1, t_2, t_3, and t_4 in the equation 2 signify t_r, t_y, t_w and t_h respectively. Furthermore, V_i denotes the ground truth bounding box parameter.

It should be noticed that smooth L1 loss has been used in the *equation 2* because of the following reasons. When compared with the extensively employed L2 loss, the smooth L1 loss is excellent for outlying points. Existing methods utilize smooth L1-loss. This study uses similar bounding loss function that could enable better comparison of the algorithms. Further it is also observed that other box regression loss functions like

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GIoU, CIoU and DIoU were also companionable with the presented system[18].

In *equation 1*, L mask represents the mask loss of the newly included background segmentation branch and in the improved framework, RoI output dimension is defined as $K * m * m$ for the additionally included mask-branch in which K refers the categories and $m * m$ defines the mask size. Accordingly generation of K binary masks was also performed. When obtaining the identified mask, the sigmoid function has been estimated for each mask pixel and the results obtained was considered as one of the input of L mask. Further only positive sample ROI is used for the calculation of L mask, where 0.5 is stated as the positive sample. L mask is observed to be same like L_{cls} except that L mask is estimated based on pixels and L_{cls} estimation is based on the images. Further mask comprising multiple pixels and so L mask is described as the average of cross entropy of every pixel.

3.1.3. Intensity enhanced RoI align

For a convolution neural network comprising of L layers, consider input image x_0. This network employed a non-linear transformation $H_i(\cdot)$ in which i refers the i^{th} layer. Here i layer obtain feature maps of r_0, r_1, ….r_{i-1} of all the existing layer as input as

$$r_i = H_i([r_0, r_1, \cdots\cdots, r_{i-1}]) \quad (4)$$

Further $[r_0, r_1, \ldots r_{i-1}]$ denotes the feature map cascade. $H_i(\cdot)$ is stated as the integrated function of $3 * 3$ convolution and ReLU function. The number of feature maps has been represented as G_0 and the input/output of b^{th} unit is defined as Fb-1 and Fb. Output of c^{th} layer could be referred as

$$F_{b,c} = H\{[F_{b-1}, F_{b,1}, \cdots\cdots, F_{b,c-1}]\} \quad (5)$$

Feature map compression at the unit end is necessary due to the vital use of connection mode in between the convolution layer and the input of unit. Hence the corresponding feature maps regulated with 1×1 convolution layer could be defined as

$$F_{b,GF} = H_{GEF}^{b}\{[F_{b-1}, F_{b,1}, \cdots\cdots, F_{b,c}]\} \quad (6)$$

Here denotes 1 × 1 convolution and the finalized output of the system has been defined as

$$F_b = F_{b-1} + F_{G,LF} \quad (7)$$

For ensuring flow of maximization information between every layer all the network layer were directly connected. For maintaining the characteristics of feed forward character, input of every layer is the summation of mapping output layer of the existing layers. Further the result of own feature mapping has been utilized as the subsequent layer input.

The overall loss of the proposed approach comprise loss due to two aspects which are classification loss and regression operation loss by RPN (L_{RPN}) as well as the training loss observed in multi-branch predictive network (L_{mbr}) that are described below

$$L_{final} = L_{RPN} + L_{mbr} \quad (8)$$

L_{RPN} – RPN classification and regression loss has been estimated by

$$L_{RPN} = \frac{1}{Q_{cls1}}\sum_i L_{cls}(A_i, A_i^*) + \lambda_1 \frac{1}{Q_{reg1}}\sum_i A_i^* L_{reg}(t_i, t_i^*) \quad (9)$$

L_{mbr} is defined as the summation of mask loss and training loss in multi branch predictive network.

$$L_{mbr} = \lambda_2 \frac{1}{Q_{reg2}}\sum A_i^* L_{reg}(t_i, t_i^*) + \gamma_2 \frac{1}{Q_{reg2}}\sum L_{mask}(s_i, s_i^*) \quad (10)$$

Algorithm 1: The pseudo code of Improved mask R CNN Segmentation

Input: X : dataset of Input images;
Output: A : Segmented X;
Initialize: Q: the RPN of X;
while i = 1 to Q do
Extract $A = (A_0, A_1, \cdots, A_k)$ from X_i
Extract $t_u = (t_r^u, t_y^u, t_w^u, t_h^u)$ of X_i ;
while i = 1 to Q **do**
while L = 1 to Li **do**
$index = t_u$;
Converting to Enhanced ROI Align
while F = 1 to F_b **do**
while H = 1 to F_{index} **do**
Calculate L between t_i^u and A_{index}^m;
if L ≤ mask **then**
if $A_{i,j}^M = A_{index}^m$ **then**
Merge t_u and t_{index}^u
Draw the Bounding Box Regressor using Improved R CNN Segmentation;
Update A ;

By considering that the whole abnormal areas were cropped to more images during database construction, the paper integrated the perceived abnormal regions for constant evaluation. Initially the paper integrate all the detected image with spelling by using location details stored previously during the collection of images. Consequently, predicted images are described as X= $\{X_1 \ldots X_N\}$.$A_k i$ denotes the number of identified abnormal regions in i^{th} image. F_b denotes the number of identified defect region in b^{th} image. Finally the paper calculated d (the minimum distance) in between the adjacent abnormal and normal region. Further bounding box regression drawing using enhanced R CNN segmentation was processed followed by updating A.

3.2 Classification of breast cancer Bach dataset using Bayesian Interactive Adaboost-CNN classifier (B-IA-CNN)

For classification of breast cancer as Normal, Benign, Ductal Carcinoma in situ and Invasive carcinoma using BACH dataset, the proposed study established a newly approach namely Bayesian Interactive Adaboost- CNN classifier (B-IA-CNN).

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Several classifiers are integrated with Adaboost method for developing an ensemble strong classifier. In accordance to that weak classifiers are trained sequentially in this method. The errors of the every employed classifiers are carefully trained followed by weight allocation to all the training sample. If the samples were not trained properly, then the weight of the sample were minimized in an exponential rate. All the new classifier has been trained with more number of sample weights. If the training dataset is $(x1, c1), \ldots\ldots (xn, cn)$, here xn is the p-dimensional input vector and cn is the output with respect to $xi, ci = \{1,2..K\}$in which k is the total number of classes. The trained classifier $C(x)$ is utilized to identify the unseen testing data's class label. For every sample, the weights are considered in training data, there exists a data weight vector refer as $D = \{di\}, i = \{1,2, \ldots. N\}$, no. of training sample is N.

With the use of $di = 1/n$ initialization of data weights are performed. CNN are trained sequentially for k networks. For the first iteration of sequential learning concept, CNN initial weight are initialized randomly and for it is trained for one or more epochs for learning task difficulty.

Initial CNN $d^{a=1}(x)$, no. of estimators (a)has been trained on similar weight of every training samples. After training the CNN output is measured for training samples. The output of proposed B-IA-CNN is K-dimensional output vector. For K no of classes the predicted values are obtained in vectors. For Xi (input sample) $P(xi) = [pk\ (xi)], k = 1\ to\ k$, and displays the applied input probability to $K\ classes$. The input is allocated to highest probability class during input testing. First CNN output $d^{a=1}(x) = d_k^{a=1}(x)$ utilized for data weights updating, D = {di} using *eq.(1)*

$$d_i^{a+1} = d_i^a exp((-\alpha \frac{M-1}{m} Y_i^t log\left(p^a(x_i)\right), i = 1, \ldots., n \quad (11)$$

d_i^a is i^{th} training sample weight utilized by a^{th}-CNN, learning rate is α, label vector is Y_i^t with respect to i^{th} training sample. For few of the samples trained, the weights have only sensible values. Related with more CNN learning parameters number the no. of untrained samples is small and based on traditional adaboost, the present CNN concentrated on smaller set of untrained samples. Transfer learning is considered as important CNN characteristics and assists CNN to assure the previous knowledge attained in process of learning. The transferred CNN attains better knowledge about whole data, it doesn't requires learning epochs in greater number. Computational cost is further minimized by the current learning parameters transfer to present CNN.

The proposed B-IA-CNN architecture is shown in following *fig. 3*, developed based on increasing depth and width without increasing its computational cost. For gradient propagation, the network is benefitted and through several paths the errors are back-propagated. At every step different features level are combined. A 70-layer architecture is approved and it comprised with 21 convolutional layers with 3x3 filters sizes applied in two-branch network. Every convolutional layer is followed by ReLU and Batch normalization. The feature map size minimized for pooling part and max pooling maintains the most. It leads to loss of lesser significant data from feature map. The average pooling resulted in various information from feature map. Lesser and more important data are combined. Average pooling layer applied for maintaining all features reached at network end. Three fully connected layers are established and among every two layers there exist a dropout layer to address the over fitting issue. There exist SOFTMAX function at each model to finalize the output. Hence the following *fig. 3* presents the proposed B-IA-CNN, the training process completed when the resulted accuracy is stable with 80 epochs.

CNN utilized no. of shared weights refer as kernel w, to map an input to feature map. If there exists no. of feature maps in lth layer then *eq. (12)* is used for measure the feature map activity,

$$y_i^t = \sum_j f(w_{i,f}^t * y_j^{t-1} + b_i^t \quad (12)$$

$w_{i,f}^t$ is convolutional kernel mapping the j^{th} feature map to i^{th} feature map, bias is b_i^t. * is convolutional operator, f(.) is convolutional layer, after every convolutional layer max pooling layer is used and passes greater value in local window. By reducing no. of features, computational cost minimized by pooling layer.

The pseudo code of the proposed B-IA-CNN is,

1. Initialize the i^th data sample weight with d_i=1/(n) where *i*=1,2,······,n, and n is the total number of training initialize A, *i.e.* the total number of CNNs.
2. For m =1 to A:
3. If a ==1
   a. Train the first CNN, *i.e.* C^(a=1) (x),on the training data using the initial sample weights_(a=1)={d_i=1/n}.
   b. Else
4. Transfer the learning parameters of the previous CNN, C^(a-1) (x),to the a^th CNN, *i.e.* C^a (x).
5. Train the a^th CNN, *i.e.* C^a (x), on the training data for one epoch using the sample weight vectorD_a={d_i }.
6. Obtain the output of the a^th CNN,i.e.Class probability estimates, for all the M classes:
7. 〖p〗 _k^((a)) (x) Where k=1,2,…….,m.
8. Update the data sample weight D_(m) based on p_k^((a)) (x) using (1).
9. Re-normalize the updated data sample weights, D_a.
10. Save the a^(th) CNN, *i.e.* C^a (x)

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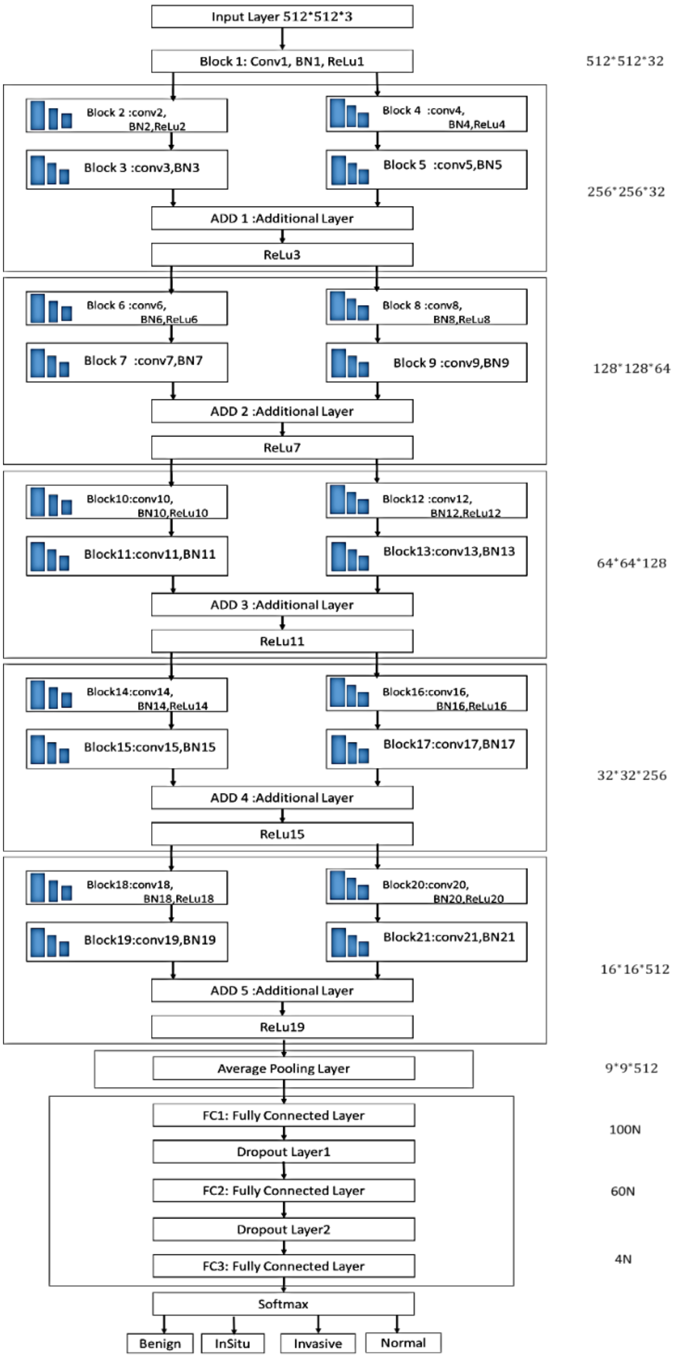

Figure 3. Proposed B-IA-CNN Architecture

From the conv. layer the features extracted are being transformed to fully connected layer.

$$F^l = f(W^t(F^{t-1})^{t+b^t} \quad (3)$$

The regression model output converted using SOFTMAX function to classes' probability distribution,

$$Z = softmax(W^o(F^L) + b^o) \quad (4)$$

An input's output class is,

$$(x) = argmax_m \sum_{a=1}^{A} h_m^a(x) \quad (5)$$

$h_m^a(x)$ is measured by

$$h_m^a(x) = (\mathrm{M}-1)((\log\left(\mathrm{p}_\mathrm{m}^a(x)\right) - \frac{1}{K}\sum_{m=1}^{m}\log(p_m^a(x))) \quad (6)$$

4. PERFORMANCE ANALYSIS

4.1 Description of the Bach Dataset

The BACH (Breast cancer histology) dataset comprise 400 high-resolution Hematoxylin& Eosin stained microscopic images of breast histology labelled as benign, normal, invasive carcinoma and in situ carcinoma. One hundred images from every category were presented in the dataset. These patch images are derived from whole slide and interpreted by two medical experts. The contrasting interpreted images from the pathologists were discarded the following figure 4 highlight the sample image variability. This dataset has been found to be available at https://iciar2018-challenge.grand-challenge.org/dataset/.

Benign	Insitu	Invasive	Normal

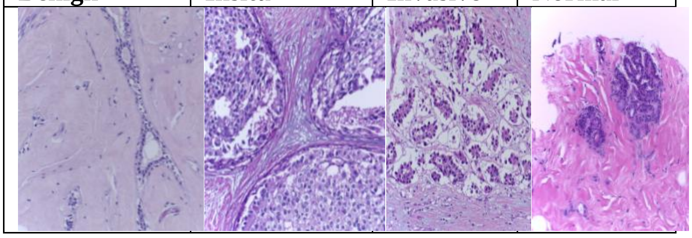

Figure 4. Samples of Benign, Insitu, Invasive and Normal

4.2 Results and discussion

The following *figure 5* represents the confusion matrix results of the proposed system. Here the diagonally represented true positive and true negative images proves the effectiveness of the classifier. Our proposed system detects 96 accurate benign cases, 93 Insitu images, 93 invasive images and 98 normal images accurately that is deliberated in *figure 5*. In addition, *figure 6* represented the OTSU threshold image and the normal image in dataset.

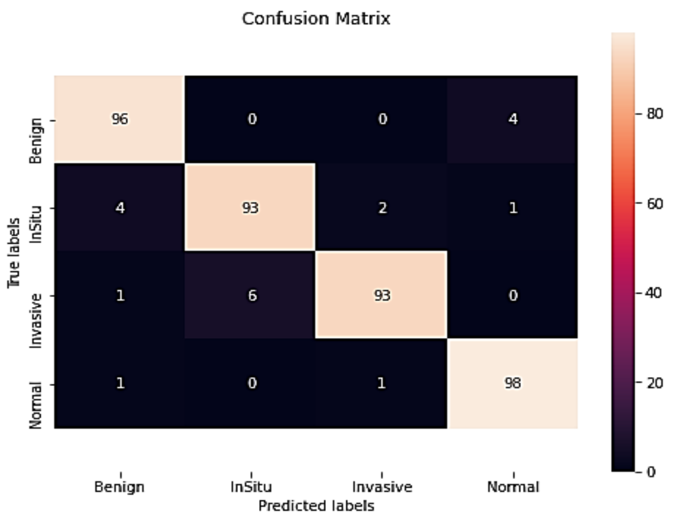

Figure 5. Confusion matrix for the proposed classifier in predicting TN, TP, FP and FN samples

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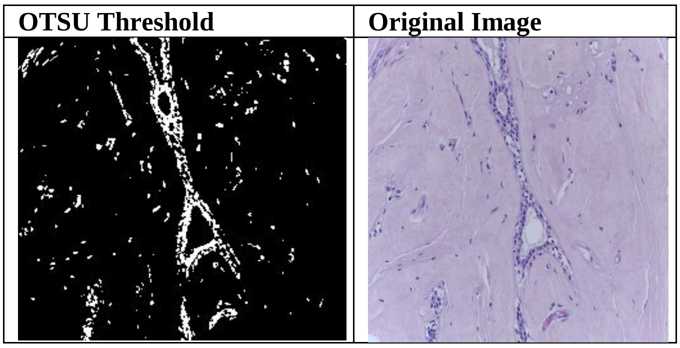

Figure 6. Original image and ground truth generated by Otsu threshold

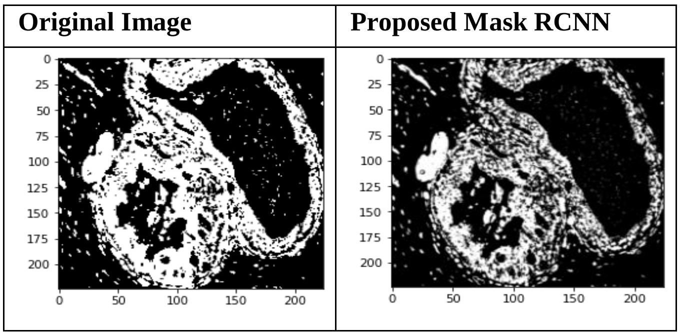

Figure 7. Original image and segmented image of Proposed Mask RCNN

This *figure 7* represented the ground truth generated by Otsu threshold method in which the segmentation is more obvious in the proposed segmentation.

4.2.1 Segmentation results

Table 1. Performance metrics of the proposed segmentation

Performance metrics	Values
TPR (True Positive Rate)	0.6627
TNR (True Negative Rate)	0.9977
PPV (Positive Predictive Value)	0.9941
NPV (Negative Predictive Value)	0.8397
FPR (False Positive Rate)	0.0022
FNR (False Negative Rate)	0.3372
FDR (False Detection Rate)	0.0058
ACC (Accuracy)	0.8768

This *table 2* represents the performance metric values of the IMRCNN segmentation that showed that the proposed model attains low FPR of 0.22% and high accuracy of 87.68% and Further True positive and true negative rate were high as 66.27% and 99.77 % accordingly.

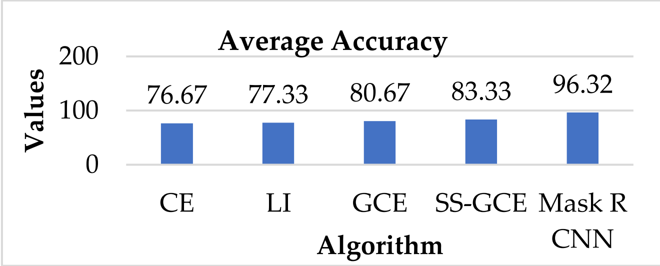

Figure 8. Accuracy of the proposed IMRCNN segmentation model[24]

The average accuracy of the segmented results with the existing algorithms like CE, LI, SS- GCE and GCE and the proposed model were presented in the *figure 8*. The proposed system obtains 96.32% accuracy which is greater than the state of art models. Due to effective RoI Align and loss function integrated with the improved mask RCNN segmentation high accuracy has been attained.

4.2.2 Classification results

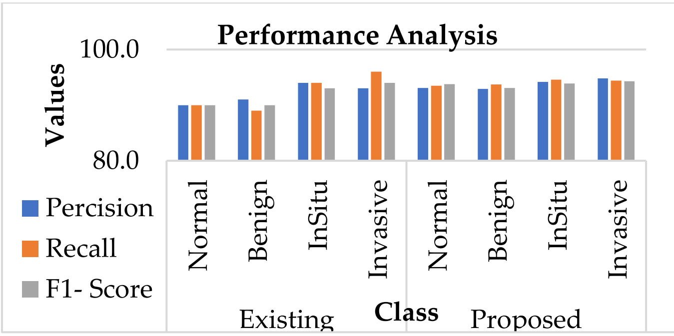

Figure 9. Classification results of the proposed classifier[25]

This *figure 9* represented that the classification results of the dataset based on sub types like normal, benign, insitu and invasive of the proposed and exisitng system. The comparision was performed in terms of precision, Recall and F1 score and showed that the propsed classification results outperfroms the existing interms of the stated perfromance meterics.

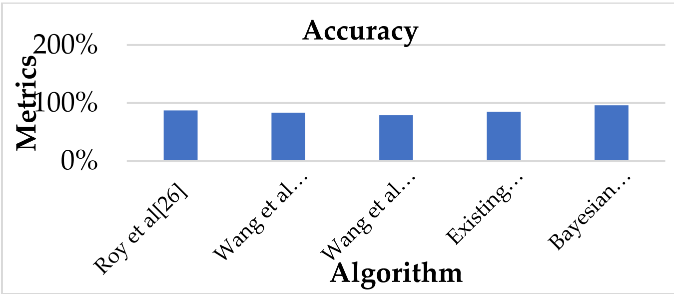

Figure 10. Classification accuracy of the proposed and existing classifiers

This *figure 10* represents the classification accuracy of the proposed and existing system. The classification methods used in the existing systems are compared with the proposed ensemble classifier. Our B-IAB-CNN classifier achieves 96%

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accuracy which is greater than existing approaches like Roy et al [26], Wang et al [27], Wang et al[28], and existing multiple magnification[29]. Prevailing limitation of Bayesian tree, adaboost and CNN were successfully overcome by the proposed ensemble classifier to obtain better results.

5. CONCLUSION

Breast cancer diagnosis and prompt treatment is considered as an urgent research to be greatly focussed nowadays due to its rapidly increasing prevailing rate. Hence suitable segmentation and classification algorithms were meritoriously adopted in this study for obtaining effective results. The proposed segmentation method, IM-RCNN, which is based on Region of interest align and RPN simultaneously predicted the boundary region and objectness scores in an effective manner. Satisfactory segmentation performance values for small objects were achieved thereby preventing quantization operation. Otsu threshold method was generated by Otsu threshold and compared with the segmentation results. The breast cancer images were classified by using Bayesian Interactive Adaboost CNN classifier (B-IAB- CNN). The advantages of the three classifier enable optimum classification of the input Bach dataset to normal, benign, invasive carcinoma and DCIS (Ductal carcinoma insitu) that was proven from the results. The performance of the proposed system was assessed and from the comparative results, segmentation and classification rate were exposed to be high than conventional researches with 96.32% as segmentation rate and 96% as classification rate. The high accuracy attained by the proposed system makes it suitable for applying it in clinics for assisting medical practitioners for fast breast cancer diagnosis. However, there is a scope for enhancing the accuracy rate by attempting to use different DL based algorithms.

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