

BREAST CANCER DETECTION USING MASK RCNN SEGMENTATION AND ENSEMBLE CLASSIFICATION WITH FEATURE EXTRACTION

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ABSTRACT

Breast cancer continues to be the common cancer which causes more decease among women and about more than two million cases is identified every year and according to the record 523,000 deaths are caused per year due to breast cancer. Mammographic mass identification and segmentation are accomplished usually as sequential and distinct tasks, where in previous studies segmentation was often manually performed only on true positive cases. Machine learning (ML) approaches have been grown from manually provided inputs to systematic initializations. The developments in ML techniques have produced independent and more intelligent computer-aided diagnosis (CAD) systems. Moreover, due to the learning ability, ML techniques have been upgraded constantly. Recently, ML techniques are progressive with deeper and varied representation methods, generally termed as deep learning (DL) techniques, and have produced significant impacts on increasing the ability of diagnosing using CAD systems. So this paper proposes the novel architecture in detecting the breast cancer. Here the input database is mammogram image dataset. Initially this image has been resized by pre-processing process, then this pre-processed image has been segmented using Mask RCNN (Region-based convolution neural networks). Then this segmented image has been sent for extracting the feature using inception V3 and ResNet 152 networks. The ensemble classifier of decision tree and random forest has been used for classification and this classified output is detected based on the color variation and tumor size gives the enhanced accuracy in detecting the cancer.

Keywords: Breast cancer, Mammographic mass, Machine learning (ML), pre-processing, Mask RCNN, inception V3, ResNet 152, decision tree, random forest.

1. INTRODUCTION

One of the most commonly diagnosed cancers by women worldwide is breast cancer. Mammography is considered as the basic method for breast screening, where fatigue and missing detections in human examination can arise from the vast amount of data involved. CAD systems were designed as a 'second pair of eyes' in interpreting mammography in order to support radiologists and improve the detection confidence [1]. The CAD system, at first, typically extracts candidate regions from breast mass and classifies these regions as either normal or abnormal depending on the extracted features. Conventional CAD systems focus primarily on generating unsupervised candidate regions along with hand-crafted features for detecting breast masses [2].

In the recent days, biomedical along with nanotechnology have been used to provide the greatest possible degree of advancement towards human health care. Nano-material shall therefore become one of the goods with the size of 1 to 1000 nm (10⁻⁹ m)[3]. As stated by World Health Organisation (WHO), the most prevalent cancer found in women worldwide is breast cancer. One affected women for every three cases lose their life. Current investigation techniques for breast cancer include various methods like magnetic resonance imaging (MRI), mammography and pathological tests. In these approaches, the standard histopathological images enhance the diagnostic accuracy with patients previously investigated with mammograms. In addition, this assessment provides more accurate and reliable information on the diagnosis of cancer and the evaluation of its effects on the tissues around it [4].

In medical diagnosis, machine learning techniques and expert systems are extensively used. In fact, the most significant factors for diagnosis is the assessment of patient data and the decisions made by the experts. Various

Artificial Intelligence and expert systems can assist diagnosis. Automated diagnostic systems help the medical experts made to avoid the errors and diagnosis data more quickly and deeply. Training sets can also include both abnormal and normal images obtained from the mammography scan, Ultrasound scans, or else in biopsy data. The machine can process only grey scale image and to extract image without noise or artifact we are using different filters to remove the artifact [5].

At this point, numerous procedures exist for detecting cancer in humans such as X-ray mammogram, ultrasound, MRI, biopsy and Positron Emission Tomography, etc. Even though several techniques exist, only experience physicians are involved in diagnosis. When compared to this, involving machine learning approaches can improve the accuracy of detection. Classifiers can help the physicians to diagnose more precisely by minimizing errors. The J48 decision tree is the most common classifier involved whose advantages are

- Can be constructed easily
- More flexible
- Debugging is easier
- Can be applied for numerical and categorical data
- Suitable for regression and classification models

Boosting/Bagging methods exist to ensemble different classifiers for classifying efficiently. Several existing classification methods are expensive and complex. In this proposed method, priority is set for various attributes in the dataset. Therefore, the priority of the attributes is also considered along with the information gain during classification.

Classification is one of the most extensively used decision-making task in machine-based learning algorithms. The major aim of classification is to accurately predict the target class for every data sample. In training phase of classification, every sample data has predefined target class. Whereas while testing, unknown test instances are predicted using the model constructed for training set. Classifying algorithms involve huge volume of data and the classification is based on the training set [7].

The remaining part of the paper is presented as follows. Section 2 reviews the background works. Section 3 elaborates the proposed model. Section 4 discusses the obtained experimental result after diagnosing and predicting breast cancer. Section 5 concludes this research work and outlines the future enhancements to be carried out.

2. RELATED WORKS

Recent advancements of deep learning (DL) techniques solve the issues of detection and classification as these techniques are more robust. These techniques involve convolutional neural networks (CNNs) to directly observe useful features from the training set and remarkable results were observed. Dhungel et al. [8] developed a multi-scale deep belief network and Gaussian mixture model for detecting candidate region which were then classified by the hybrid approach which integrated R-CNN and random forests. Li et al. [9] used an unsupervised region detecting approach which involved morphological analysis and the candidate regions were classified using CNN. But, these CAD systems perform only detection and do not involve segmentation. A separate approach is applied for segmentation. Dhungel et al. [10] extended their work in [8] by introducing a segmentation method based on conditional random field and a level set scheme. This model performed only segmentation on true positive (TP) detections while the false positive (FP) detections have to be manually rejected. Oliveira et al. [11] adopted residual neural network (ResNet) for detecting candidate regions and CNN approach for classifying them. Segmentation refinement strategy was used for generating contour of masses. The authors of [10] and [11] considered mass detection and segmentation as distinct tasks and comprise of multiple deep learning networks which have to be sequentially fine-tuned. Still, there is a demand for more integrated model which can efficiently perform mass detection and segmentation simultaneously.

Song et al. [12] analysed the effectiveness of different decision tree algorithms like CHAID, C4.5, CART, and QUEST by the use of SAS and SPSS. AlSahily et al. [13] studied and analysed the performance of various decision tree algorithms such as Function Tree, J48, Alternating Decision (AD) Tree, Random Forest Tree, Decision stump and Best First. It was observed that Function Tree classifier produced the precision of 97.7% with and Decision stump with a precision of 88%. The former correctly identified more instances while the latter identified only less instances. Yadav et al. [14] performed a comparative analysis of decision tree and Artificial Neural Network (ANN) which involved breast cancer data. It was observed that the overall prediction accuracy produced by decision tree was from 90% to 94%, and for ANN was from 94.5% to 97%. Bhargava et al. [15] investigated the efficiency of Decision Trees against Univariate and Multivariate methods. It was proved that Multivariate Decision Tree produced better results than Univariate approach. Kaure et al. [16] used WEKA, a data mining tool, as an API of MATLAB to construct the modified version of J48 classifier. Extended version produced an accuracy of 99.87% than the existing J-48 classifier.

Pritom et al [17] investigated few classifiers like Naive Bayes (NB), C4.5 Decision Tree and SVM (Support Vector Machine) for predicting the recurrence of breast cancer. The features were ranked and the attributes were reduced based on the ranking to increase the prediction accuracy. It was observed that SVM produced outstanding results than other classifiers. The prediction accuracy was based on the selection of feature. Nalini et al [18] analysed the performance of NB and J48 classifier in diagnosing breast cancer. Consistency Subset Evaluator was used for feature selection. NB classifier was proved to be a better classifier. Khadhim[19] employed ID3 tree classifier algorithm for classifying the risk factors of breast cancer and determined the more effective factor. Moreover, the issues in designing a breast cancer detecting system were focused. Chaet al [20] employed Genetic algorithms for selecting best attributes and to develop precise near-optimum decision trees which were transformed into chromosomes by encoding and decoding a decision tree.

Alickovic et al [21] used Genetic Algorithm on different classifiers which include Decision Trees, Logistic Regression, Bayesian Network, Random Forest, MLP, SVM, RBFN and Rotation Forest for predicting breast cancer based on feature selection. It was found that Rotation Forest with Genetic Algorithm based on 14 features produced an accuracy of 99.48%. Wang et al [22] coined a novel decision tree based Self adaptive NBTree classifier which integrated Naive Bayes and Decision trees. NBTree resolves overgeneralization and overspecialization. Freund et al [23] constructed ADTree which was similar to C5.0 with boosting and when its efficiency was analysed, it was found that error rate was identical for both methods. Venketasan et al [24] made a comparative study on decision tree classifiers namely CART, J48, BFTree and ADTree. J48 obtained a high accuracy of 99%, BFTree with 98%, ADTree with 97% and CART with 96%. Snousy et al [25] used single and ensemble methods and involved chi-square and gain ratio attribute methods for selecting features. Ensemble methods improved the rate of accuracy. For bagging, approaches like C4.5 and REP Trees and for boosting, approaches like AdaBoost, Random Forests and ADTree were involved.

Prasath Alias Surendhar S distinguishes and arranges MR pictures of cerebrum just into typical and irregular. In view of the trial results, CNN is considered to real preferences over customary neural systems, because of the way that CNN gains from the preparation information promptly. This speed of learning gives CNN the capacity of adjusting its learning progressively [26,27,28].

3. Materials and Methods

In this section focuses on the materials and methods of this research work. The INbreast dataset is used for this research work which is borrowed from http://medicalresearch.inescporto.pt/breastresearch/index.php/Get_INbreast_Database. At present, this dataset is the first freely available large scale full-digital mammographic dataset with correctly annotated mammograms. 115 cases of 410 mammograms are included. In total, 116 breast masses occur within the size range of [15mmmm2,3689mmmm2]. The mammograms have a pixel scale of 70 with bit depth as 14-bits. The similar validation data partition is used for assessing INbreast to make a clear comparison, where the dataset is partitioned randomly as 60% for training, 20% for testing and 20% for validation.

These below methods are implemented in this research work.

- VGG-16
- Alex Net
- GoogleNet
- CNN
- SegNet
- R2U-Net
- Proposed_DeepIncepRC

The algorithms are executed using Python 3 with 384 GB DDR4 and an NVIDIA Tesla V100 16GB on a Dell EMC PowerEdge R740 server.

4. Results and Discussions

In this section focuses on the results of this research work. The below table gives the parametric comparison of proposed M-RCNN with ensemble classifier. Mask R-CNN performs features extraction and classifies the affected regions. It simultaneously executes identification and segmentation activities and it is possible to optimize the entire network. In this suggested CAD, the mask R-CNN with ensemble classifier does not require any massive training. Just about 10 minutes of 10 epochs is required for every training round. For testing this Mask R-CNN, just only less than 1s per image is required.

Table-1: Parametric comparison of various network models

S.NO	Techniques	Accuracy' (%)	Precision (%)	Recall (%)	F1-score (%)
1	VGG-16	86.2	83.1	91.6	75.3
2	Alex Net	93.8	86.1	91.2	81.3
3	GoogleNet	95.8	89.1	89.4	89.1
4	CNN	97.1	89.1	94.3	88.8
5	SegNet	96.6	86.6	81.4	84.6
6	R2U-Net	95.5	89.3	77.9	81.7
7	Proposed_DeepIncepRC	97.3	97.37	97.15	97.25

The below diagram represents that the accuracy levels of various classifiers. Such as VGG-16 technique gives 86.2% of accuracy level. Alex Net technique gives 93.8% of accuracy level. GoogleNet technique gives 95.8% of accuracy level. CNN classifier gives the accuracy value is 97.1%, SegNet algorithm gives 96.6% of accuracy level. R2U-Net classifier gives 95.5% and Proposed_DeepIncepRC gives 97.3% of accuracy level.

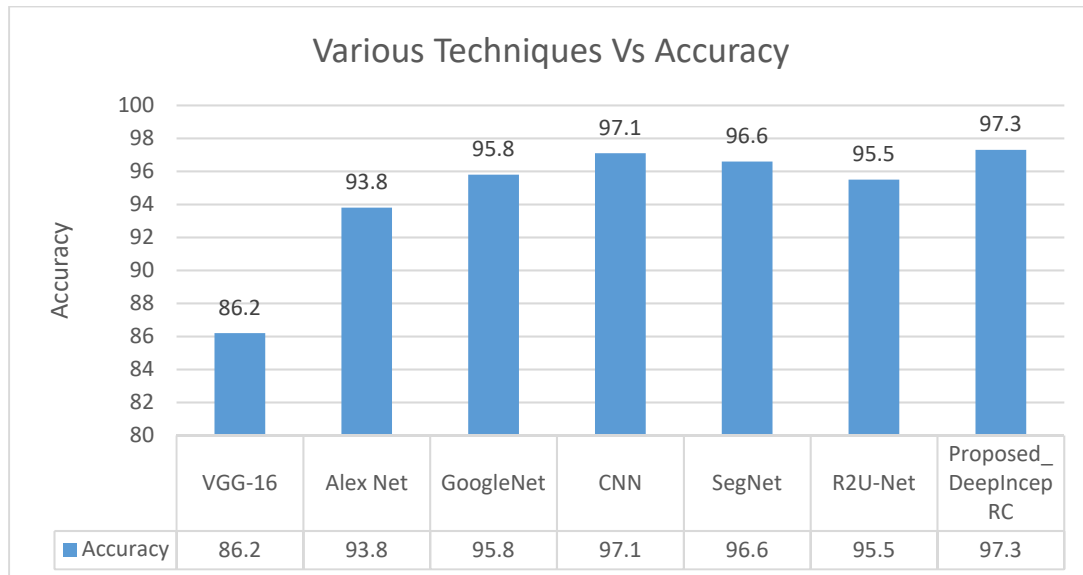


Figure 1: Various Classifiers Vs Accuracy

The above diagram shows that the graphical representation of the various classifiers with their accuracies. GoogleNet, CNN, SegNet, R2U-Net, Proposed_DeepIncepRC are producing above 95% of accuracy level except VGG-16 classifier which is 86.2% of accuracy level. The CNN and Proposed_DeepIncepRC have above 97% of accuracy level.

The below diagram represents that the precision values of various classifiers. like VGG-16 technique gives 83.1% of precision value. Alex Net technique gives 86.1% of precision value. GoogleNet technique gives 89.1% of precision value. CNN classifier gives the precision value is 89.1%, SegNet algorithm gives 86.6% of precision value. R2U-Net classifier gives the precision value is 89.3% and Proposed_DeepIncepRC gives 97.37% of precision value.

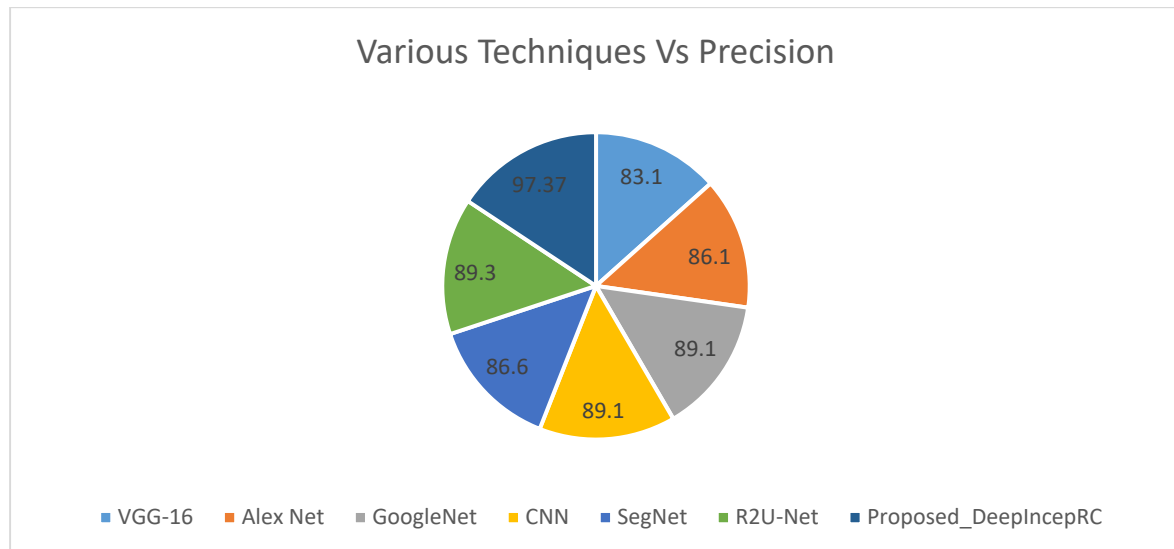


Figure 2: Various Classifiers Vs Precision

The above diagram shows that the precision values of the various classifiers. All the precision values are lies in between 83% to 90% but our proposed method Proposed_DeepIncepRC has highest precision value which is 97.37%

The below diagram represents that the recall values of various classifiers. i.e., VGG-16 technique gives 91.6% of recall value. Alex Net technique gives 91.2% of recal value. GoogleNet technique gives 89.4% of recall value. CNN classifier gives the recall value is 94.3%, SegNet algorithm gives 81.4% of recall value. R2U-Net classifier gives the recall value is 77.9% and Proposed_DeepIncepRC gives 97.15% of recall value.

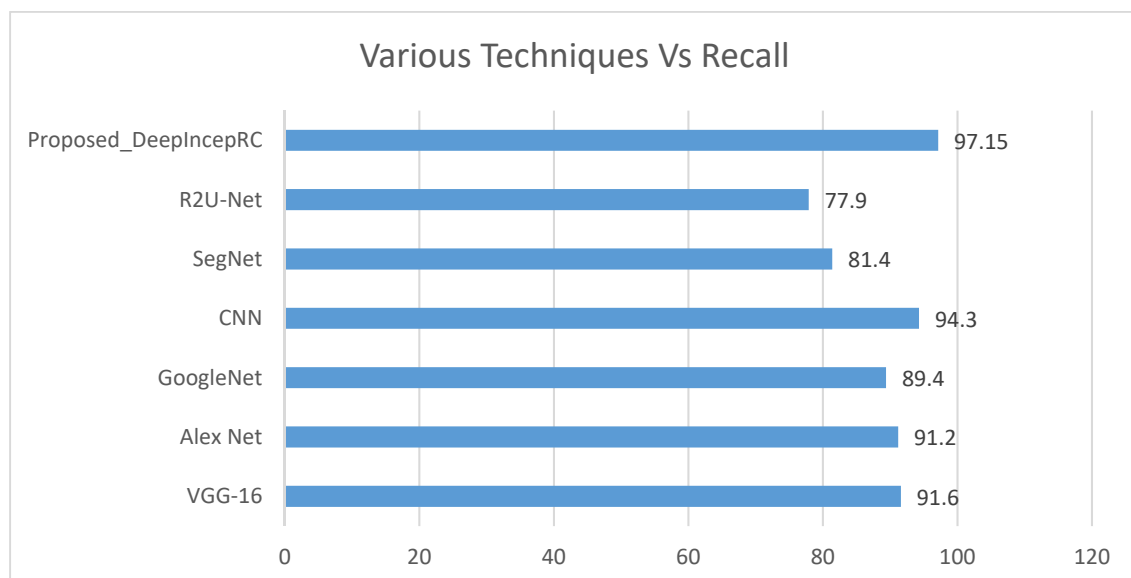


Figure 3: Various Classifiers Vs Recall

The above diagram shows that the graphical representation of the various classifiers and their recall values. R2U-Net classifier has 77.9%. This is one and only classifier has below 80% of recall value. Others are above 80% of recall value. SegNet and GoogleNet classifiers have 81.4% and 89.4%. Rest of the classifiers have above 90%. Our proposed model has highest recall value which is 97.15%

The below diagram represents that the F1 score values of various classifiers. i.e., VGG-16 technique gives 75.3% of F1 Score value. Alex Net technique gives 81.3% of F1 Score. GoogleNet technique gives 89.1% of F1 Score value. CNN classifier gives the F1 Score value is 88.8%, SegNet algorithm gives 84.6% of F1 Score value. R2U-Net classifier gives the F1 Score value is 81.7% and Proposed_DeepIncepRC gives 97.25% of F1 Score value.

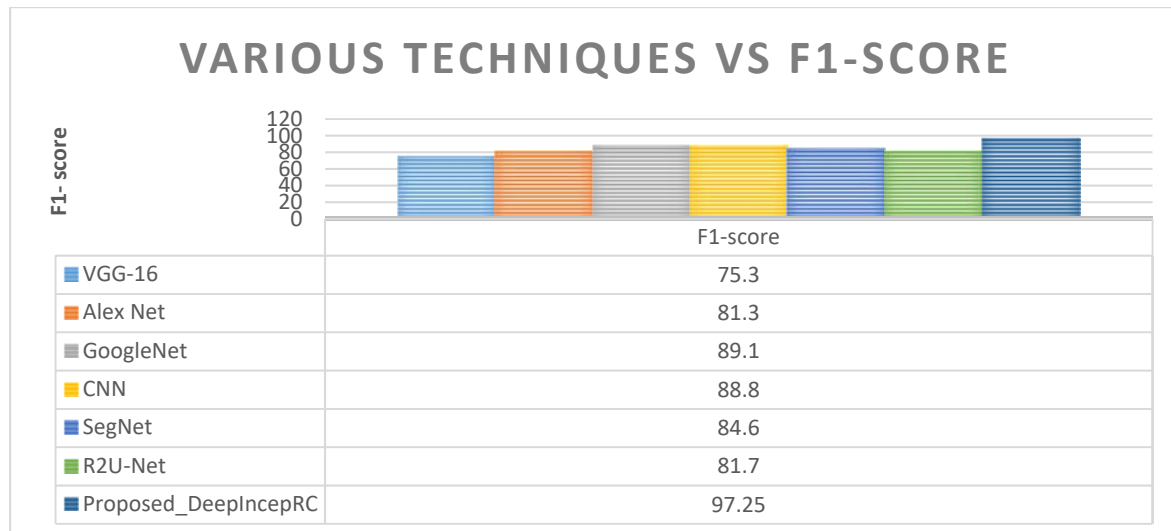


Figure 4: Various classifiers Vs F1- Score

The below diagram represents that the F1 score values of various classifiers. i.e., VGG-16 technique gives 75.3% of F1 Score value. Alex Net technique gives 81.3% of F1 Score. GoogleNet technique gives 89.1% of F1 Score value. CNN classifier gives the F1 Score value is 88.8%, SegNet algorithm gives 84.6% of F1 Score value. R2U-Net classifier gives the F1 Score value is 81.7% and Proposed_DeepIncepRC gives 97.25% of F1 Score value.

5. Conclusion

In this research clearly focuses the optimal solutions of accuracy, precision, recall and F1 score value provided by proposed system Proposed_DOOPIncepRC. Which is producing the 97.3% of accuracy level, 97.37% of precision level, 97.15% of recall value and 97.25% of F1 score value. These results are comparatively high with other models.

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