Predictive and Perspective Modeling for Early Detection of Malignancy in Human Breasts using Non-Invasive Imaging Modality: Deep Learning from Scratch

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Abstract*: In recent years, cancer has been one of the controversial causes and censurable reasons of the high number of deaths and could become one of the compelled causes of most deaths in the coming decades. Early detection with practical accuracy and correct diagnosis of the disease can increase the survival rate of patients suffering from cancer profoundly. Masses and micro calcification clusters are important early signs of breast cancer. Objective of this work is to deliver predictive and perspective classification model for an early detection of breast cancer using image processing and advances of soft computing techniques to provide an integration of prescription with prediction. To provide a system that can be used to classify breast tissues as benign or malignant and if malignant then can further classify which type- invasive or non-invasive type of malignancy. To provide a perspective model that can also prescribe treatment for predicted malignant class with details like time taken, degree of seriousness, probability of curing by opted treatment because treatment of a breast cancer depends on type and stage of malignancy. To achieve higher or clinical usage accuracy by deploying advances of soft computing and image analysis like deep learning and deep neural network to decrease breast cancer mortality rate. To provide the computer aided system with interface of classification and prescription for predicted type of malignancy with practical results scrapped from source of dynamic data or forum native to cancer diseases.

Index Terms: Benign, Imaging modality, Invasive, Malignant, Mammograms, Non-invasive.

I. INTRODUCTION

Breast cancer is the fitful growth of cells that originate in the breast tissue. Breast cancer is any form of malignancy which develops from breast cells. Cancer is a diseases in which malignancy cells in the body grow, change and multiply out of control. It is the most common cancer disease in women worldwide, especially those who are in the age group of 40 to 55 years [1] and one of the leading causes of death from cancer in women. Breast cancer is reported as the second most prevalent cause of the cancerous death in the report of World Health Organization [2].

Most of the invasive cancer starts from non-invasive type because 60% to 90% breast cancer starts from duct or lobules part of the breast [3]. If uncontrolled or abnormal growth of breast cells occurs in ducts only then it is a type of non-invasive malignancy else invaded in other tissues that is beyond ducts is an invasive malignancy. Non-invasive is also called ductal carcinoma in situ (DCIS) or "pre-invasive" or "pre-cancerous". DCIS is also called intra-ductal (within the milk ducts) carcinoma. Although DCIS is non-invasive, without treatment, it can develop into invasive breast cancer. Cancerous cells can spread in any other part of the body by lymphatic or blood flow system during any stage of a breast cancer. Most vulnerable part to breast cancer invasion is underarm lymph nodes [4].

The recent statistics of a study by American Cancer Society gives an alarming message that about 3,30,080 and 2,550 new patients among women and men of breast cancer to be detected in the U.S in 2018 respectively. In India, there are around 2.5 million diagnosed with cancer and will lead to 5,56,600 deaths per year. By 2020, India is reported to have over 17.5 lakhs diagnosed patients with breast cancer and near 8.8 lakhs deaths caused by this disease [5]. As reported in literature, most prevailing cancer in India is breast cancer and its explanation is a 27% count in all types of cancer in women [6].

Although there are no effective ways to meet this tragic challenge of breast cancer, early detection is observed and considered as an effective way for the prevention of breast cancer and thus reduction of mortality native to this cancer. It is reported that an early detection of the cancer disease can help strongly to boost the compliance of survival [7]. The world health organization (WHO) has also advised that mortality rate associated with breast cancer can be curtailed enormously in its amount by its detection at an early stage [8]. The enactment of a computer-aided detection (CAD) system can revamp the early cancer detection rate and could also share the experts' workload[9]. Many Computer Aided Diagnosis (CAD) Systems prospected to assist radiologists to curtail the diagnostic errors effectively by using mammogram and MRI imaging modality of breast mass or calcification[10][11]. Computer aided detection systems (CAD) substantiated a probably compelling tool for detecting the masses or micro calcifications in recent considerations [12].

II. RELATED WORK

Evaluation and advancements in soft computing techniques adoption in expert medical diagnosis is a pivotal force that drives the implementation role of classification systems in the diagnosis process of medical field and

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flourishing capitally for early detection and thus prevention. These intelligent classification algorithms and systems help doctor's with minimized error. This degree of minimized error increases if we consider a scene of inexperienced practitioners [13]. Several models in literature proposed and implied to detect substantial deformity in the detection of breast cancer.

Ryua [14] developed a classification model using a technique named as an isotonic separation. The experiment results were compared in contrast to decision tree, learning vector quantization, induction support vector machines and some other methods. They modeled their work by utilizing two different data sets of breast cancer. The experimental results exhibited that isotonic separation is effective and practical for classification in this field.

In diagnosing breast cancer, Sahan [15] practiced hybrid machine learning method. The fuzzy artificial immune system with k-nearest neighbor algorithm was incorporated to test on Wisconsin Breast Cancer Dataset (WBCD). Experimental results demonstrated that incorporated method exhibited improved accuracy in reference to literature.

Ubeyli [16] contributed all-inclusive perspective on automation. This work is a recommendation of automatic detection of breast cancer. He analyzed and tabulated the efficiencies in contrast to combined neural network (CNN), support vector machine (SVM) and other variant of neural network. Plentiful solutions and incorporated systems used neural networks as a composing element, including this work; the newly devised and mixed approaches still deteriorated the drawbacks of implied soft computing algorithms like drawbacks of perceptron network. The aim of that works was to impart a counselor in literature who wants to evolve this kind of systems.

Yuanjiao also proposed a technique to segment or cluster micro-calcifications. In this work they extracted clusters with improved and detailed edge considerations to fetch more and more concealed information. This work was to detect concealed information in mammograms that is rare to be detected without these proposed image processing techniques or naked eyes to assist radiologist for early detection of breast cancer [17].

Heng-Da[18] proposed a computerized micro calcification detection model. They implemented the work using fuzzy logic. The experiment results were compared in contrary to literature in reference to accept or publish with acceptable accuracy.

Performance of Vibro-Acoustography was analyzed by Azra Alizad[19] in detecting micro calcifications in excised human breast tissue. They experimented and analyzed the result on mammograms of 74 samples of breast tissues for breast cancer diagnosis. This work was refined using probabilistic neural network with practical accuracy.

Anna N. Karahaliou[20] analyzed texture of tissues. They appropriated image feature extraction to analyzing texture of tissue surrounding micro calcifications for the detection of breast cancer. They experimented retrospective analysis and shielding on mammograms captured in advance for the detection of malignancy in masses.

Al Mutaz M et al [21] proposed analysis of statistical based texture features for detection of breast cancer. They implemented ANN, SVM, PCA and other functions like NDA, LDA. Performances were compared in contrast to these methods and SVM was reported to be the highest in consistent accuracy. The aim of this work was an early detection of breast cancer to improve survival rate. This work of classification was based on statistical textural features.

Buller [22] was one of the first who did classification for detection of breast cancer using ultrasound imaging modality. He did his work by training artificial neural network for benign and malignant images. He also deployed a naïve approach named "spider web" to represents two parameters one for local and other for global effect in surroundings of the arrangement. These variables or vectors make this approach practical to be used to achieve enhanced results. This can be further matured by considering more and more variables like texture and shape to represent classification of an image as benign or malignant.

Ruggierol [23] implemented his work by training artificial neural network of standard architecture with one hidden layer using run length and transition probability tensor on texture and shape parameters. They utilized a standard practice of supervised machine learning as training process followed by testing phase on unseen data and experimented practical output in solid and liquid lesion as well.

Hassanien [24] developed a classification system with merging advantages or options from more than one soft computing technique on magnetic resonance imaging (MRI) images as an input dataset for an early detection of breast cancer. He experimented and validated his results delivered by SVM and ANN.

Research Gaps

Though sophisticated outcomes have been proclaimed in literature, the best possible experimented results achieved are near 90%, which is less practical for pursuit in clinical usages [25]. This is also noted that these results gleaned on peculiar type of datasets and still not summarized in substantial practice or a blueprint of some reference rules between diagnosis result and type of dataset[26][27]. This happens owing to the evidence that traditional techniques are attuned to perform on datasets of a peculiar type while others are implemented in consideration of mammographic datasets and can be well accepted to an immense pool of mammographic data[28][29][30]. In most of the literature, black box effect of the classifier is not concerned.

Most of the work does not state about the sensitivity of different imaging modalities for different densities of breast tissues. No one has considered taking advantage of an additional type of imaging like MRI that provides more detail by screening the same tissues in different frequencies and variables. Magnetic Resonance Imaging delivers unmatched feature of visualization and characterization of tissues to meet early detection in whom one type of imaging modality for example mammography is less sensitive, for example, women of the age group less than 40 years.

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Most of the works classify breast images as benign or malignant and if malignant then do not further classify which type of malignancy that is non-invasive or invasive cancer. Perspective modeling is not considered that can also prescribe treatment for predicted malignant class with details like time taken, degree of seriousness, probability of curing by opted treatment because treatment of a breast cancer depends on type and stage of malignancy for both male and female.

A preeminent gist for hybrid of different fields for use of many advanced key techniques like deep learning, Deep Neural Networks etc to improve or mature performance in contrary to the existing models. A computer aided system with interfaces that can be used on mobile or desktop or web will result in anywhere, anytime and anyone access. Other gaps are computational cost, computational complexity and absolute knowledge of every variable that is impractical. In this era, preeminent gist for any field is hybrid and devise of many advanced key techniques to improve or mature performance.

III. IMPLEMENTATION STRATEGY

Quantitative approach can be subjected to rigorous quantitative analysis to infer characteristics or relationships parameters with greater control over the research environment. Qualitative approach to research is concerned with subjective assessment of attitudes, opinions and behavior. This work of developing a predictive and perspective model as a research product adopts quantitative approach for some of the parameters like features extracted, features selected, weights assigned to classifier etc and qualitative approach for others like acceptable prediction of a model for classification of an image with true label, perspective output for early detection of malignancy etc. These steps of hybrid approach are shown diagrammatically in next figure “Fig. 1”.

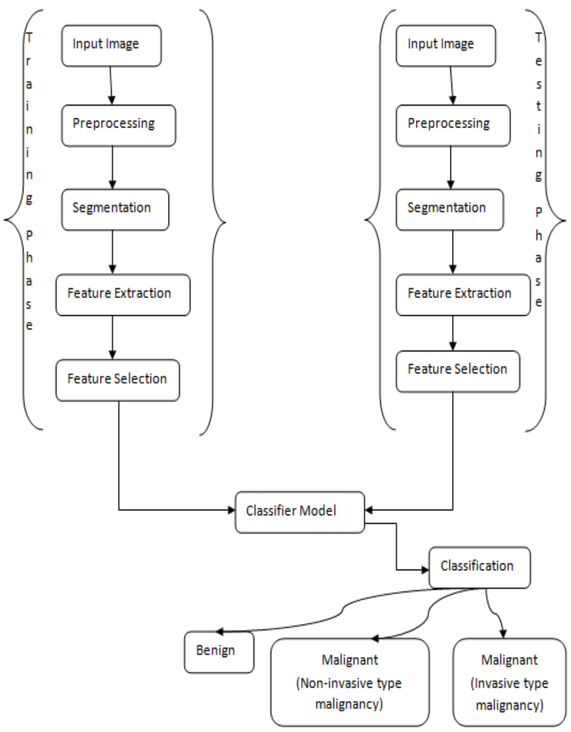

Fig. 1: Architecture of prospected model.

Soft computing with advancements like deep learning and in a hybrid fashion as well to achieve a maximum accuracy for clinical usages can be used. We prospected supervised classification with deep learning methods like Convolution Neural Network (CNN) instead of shallow learning.

Deep learning for supervised image classification can be used either as a transfer learning or from a scratch. Pre-trained deep neural networks like AlexNet, GoogleNet, VGG etc are trained on non-medical images [31-36] are available to fine tune for your work. In our proposed work of medical field we are talking about training of deep neural network on medical images means also considering defining and training a new network that is also called deep learning from scratch. We will compare and validate our experiments with both of these approaches of deep learning application to meet higher practical accuracy with applied on-line or off-line augmentation on input set of mammograms to meet a challenge of ample amount of data for training of deep neural network. Deep neural network and algorithms provide automation for feature selection and extraction. But in order to achieve minimized tolerance threshold we performed different some on-line and off-line augmentations like preprocessing, segmentation, scaling, flipping etc.

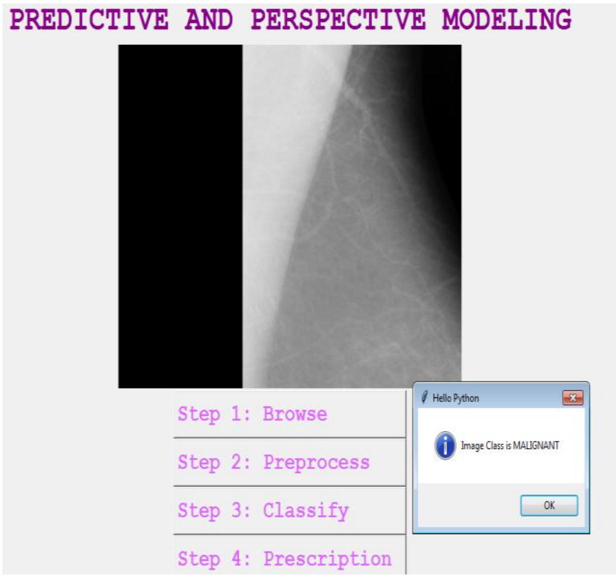

Fig. 2: Functioning of proposed model.

IV. EVALUATION & RESULT

Most commonly used performance evaluation matrix on the basis of various parameters for classification models are confusion matrix, classification report and ROC. Confusion matrix shows all true labels against all predicted labels to calculate TP, FP, TN and FN. Classification report is a matrix that displays precision, recall(sensitivity) and f-score. ROC curve plots True Positive Rate (TPR) and False Positive Rate (FPR). Precision means "How many selected items are relevant?" and calculated as TP/(TP+FP). Higher precision means low value of false positive. Recall means "How many relevant items are selected?" and calculated as

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TP/ (TP+FN). Higher recall means low value of false negative. F-Score (F_1-score or F-measure) represents perfect value of precision and recall. This is calculated as (2*(precision*recall))/ (precision + recall). F-score is best at value 1(worst at 0) where precision and recall are perfect.

True Positive Rate (TPR) is calculated as TP/(TP+FN) and False Positive Rate (FPR) is calculated as FP/(FP+TN). Area under the ROC Curve (AUC) measures the entire two-dimensional area underneath the entire ROC curve from (0,0) to (1,1). Higher value of AUC means higher value of accuracy for prediction of a model. Further micro-average and macro-average ROC can be plotted for multiclass classification[37][38].

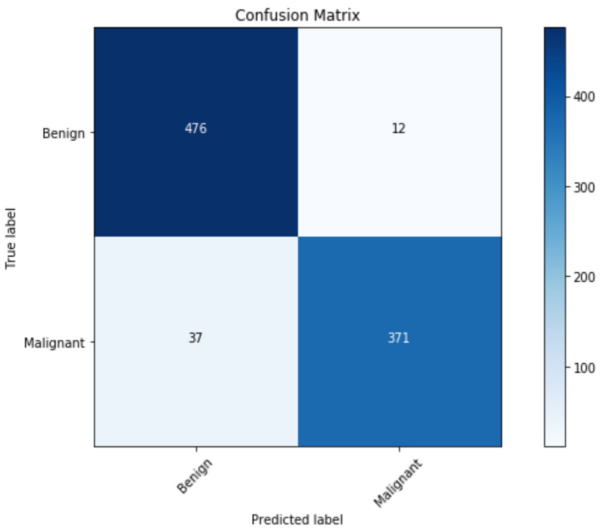

Fig. 3: Confusion matrix

Classification Report

	precision	recall	f1-score	support
Benign	0.93	0.98	0.95	488
Malignant	0.97	0.91	0.94	408
avg / total	0.95	0.95	0.95	896

Fig. 4: Classification report

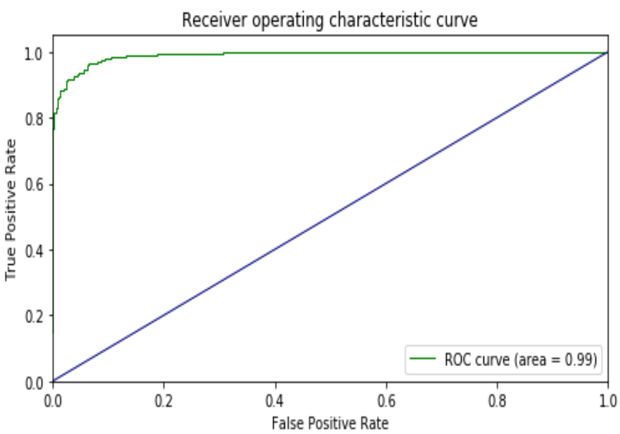

Fig. 5: ROC with AUC.

For experimental setup we are running Python 3.6.5(Anaconda environment and Jupyter Notebook) with packages keras, openCV, matplotlib and tKinter on 6th generation i7 processor with 16 GB RAM and 2TB SSD hard disk . In this work we are using a standard research dataset, mini MIAS (Mammographic Image Analysis Society), an organization of UK research groups [39].

V. CONCLUSION AND FUTURE WORK

There are some significant tasks to be imperative to execute in near time for diagnosis systems in medical science. First, it is mandatory to enhance the existing models with technological advancements in entire domain. Second, the requirement of hybrid of different technologies or techniques to deliver more practical and substantial results that can further classify on subtypes of malignancy will be appealing. Third, to devise elegant tool for diagnosis with accuracy of clinical usage or higher that can be used by radiologist and end user as well. Fourth, the development of these models or systems with interfaces that can be used on mobile or desktop or web will result in anywhere, anytime and anyone access. Fifth, work can be done by extracting features in the frequency domain representation of digital mammograms and MRI images instead of spatial domain as well. Sixth, devising and deploying intelligent diagnosis systems that can learn and prescribe from newly available data in any form (Big Data) is required.

In this study we prospect to develop and\or deploy advance technique(s) to automatically detect and classify breast cancer using advancements in soft computing to assist diagnosis process or decision making process of classifying a breast tissue is Malignant or Benign and if malignant then which type of malignancy with prescription. This proposed system will be comprehensively delivered using Python 3.6.5. Effectiveness of the system in an early detection of the breast cancer using mammograms and MRI by this model will be shown by the validated experimental results. To conclude, the proposed work under is an aim to implement innovative software architecture and advancements of technologies like deep neural network, deep learning and data science to fight against breast cancer.

Perspective modeling result may be calculated from big data and also input images from cloud using parallel GPUs, cross validation of work with available research on path lab primary data of patients in literature and devising performance matrix or criteria for perspective modeling aspect to evaluate or compare this type of work are tangible points of future scope.

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