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MAMMOGRAM CLASSIFICATION OF BREAST CANCER BASED ON HYBRID METHOD USING DEEP LEARNING

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Abstract

Deep Learning (DL) is a rising field of research from the last decade by exposing a hybrid analysis procedure including advanced level image processing and many efficient supervised classifiers. Robustness of the DL algorithms to the big data enhances the analysis capabilities of machine learning models by feature learning on heterogeneous image database. In this paper, Convolutional Neural Network (CNN) architecture was proposed on simplified feature learning and fine-tuned classifier model to separate cancer-normal cases on mammograms. Breast Cancer is a prevalent and mortal disease appeared resultant mutating of normal tissue into tumor pathology. Mammograms are the common and effective tools for the diagnosis of breast cancer. DL-based computer-assisted systems have the capability of detailed analysis for even small pathology that may lead the curing progress for a complete assessment. The proposed DLbased model aimed at assessing the applicability of various feature-learning models and enhancing the learning capacity of the DL models for an operative breast cancer diagnosis using CNN. The mammograms were fed into the DL to evaluate the classification performances in accordance with various CNN architectures. The proposed Deep model achieved high classification performance rates of 92.84%, 95.30%, and 96.72% for accuracy, sensitivity, specificity, and precision, respectively.

Keywords: ***Deep Learning, Convolutional Neural Networks, Breast Cancer, Mammogram, DDSM, Transfer Learning***

INTRODUCTION

In semi-supervised learning, we provide the algorithm with a small set of labelled data. Then, we give it a much larger set of unlabeled data and put it to work. This type of algorithm is helpful when we need (or have) to start with a smaller batch of data upfront. It learns from all the data, not just the labelled data, and helps you organize it. A self-supervised learning model combines unsupervised and supervised learning problems, then applies a supervised learning algorithm. You can create the model for the algorithm to follow, and it begins applying that to unlabeled data. This type of learning is commonly used on unlabeled images and defines actions that can be taken on those images like rotating them, identifying color or grayscale, or distinguishing between real and fake photos.

LITERATURE REVIEW

Pardamean et al. Applied transfer learning on ChexNet model for breast cancer. They utilized DenseNet architecture for feature learning stage and iterated on various supervised models using many FCs, dropout factor and other learning parameters. They reached a separation accuracy rate of 90.38% [3]. Swiderski et al. Proposed own CNN architecture using the non-negative matrix factorization method at the feature learning stage. They separated cancer and normal mammograms with an accuracy rate of 85.82%, a sensitivity rate of 82.38%, and a specificity rate of 86.59% [4].

Nasir Khan et al. Utilized VGGNet, GoogleNet, and ResNet architectures on multi-view feature fusion model. They performed binary classifications (cancernormal, mass-calcification, and malignant-benign). They highlighted the best performance on classification of cancernormal mammograms as VGGNet with accuracy rate of 94.45%, sensitivity rate of 98.07%, and specificity rate of 88.13% [7]. Touahri et al. Suggested a cancer lesion detection based CADx system to identify malignant and benign. They experimented on the various batch normalization techniques on CNN. They highlighted the performance of using local binary patterns with CNN as the best performance for tumour identification [12]. Suzuki et al. also applied transfer learning on ImageNet weights. They utilized AlexNet architecture for feature learning and re-trained the model on mammograms. Their highest achievements are accuracy rate of 85.35% and sensitivity rate of 89.90% [13].

METHODOLOGY

The proposed method consists of the following method to classify the Breast Cancer with the help of CNN algorithm. Various steps involved in the proposed method is as follows,

Data Sets

In this Process, we collected the data from various Cancer Affected Patients at various Places. The Datasets are used for following stages to Continue the process of Breast Cancer Classification.

Input Images

The first stage is the image acquisition stage.First Capture the Input Image from source file by using uigetfile and imread function However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable, even with the aid of some form of image enhancement.

PreProcessing

Image Resize: In computer graphics and digital imaging, scaling refers to the resizing of a digital image. In video technology, the magnification of digital material is known as up scaling or resolution enhancement.

When scaling a vector graphic image, the graphic primitives which make up the image can be scaled using geometric transformations, without any loss of image quality. When scaling a raster graphics image, a new image with a higher or lower number of pixels must be generated. In the case of decreasing the pixel number (scaling down) this usually results in a visible quality loss. From the standpoint of digital signal processing, the scaling of raster graphics is a two-dimensional example of sample rate conversion, the conversion of a discrete signal from a sampling rate (in this case the local sampling rate) to another.

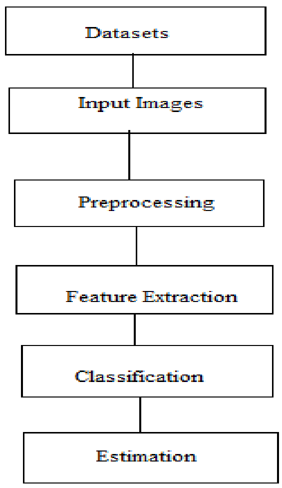

Fig 1 Model Description

Segmentation

We propose an automatic unsupervised breast cancer segmentation method for mammogram images. Firstly, a multidimensional feature vector is constructed with the green channel intensity and the feature extraction by the morphological operation.

Feature extraction

In this paper we extract the features from the mammogram images and train the images with the features and test the images by using the extract images.

Classification

In this cancer classification we use the CNN algorithm for the accurate prediction.The CNN algorithms performs the Three levels of layers to perdict the values.

Input Layer: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data.

Hidden layer: The input from the Input layer is then feed into the hidden layer. There can be many hidden layers depending upon our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. This layer computed by matrix multiplication of output and it makes the network nonlinear.

Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or soft max which converts the output of each class into the probability score of each class.

Estimations

In the process of Estimations, the Sensitivity and specificity are statistical measures of the performance of a binary classification test. Sensitivity measures the proportion of positives that are correctly identified as such the percentage of sick people who are correctly identified as having the condition. Specificity measures the proportion of negatives that are correctly identified as such the percentage of healthy people who are correctly identified as not having the condition.

RESULTS

In this paper the authors proved the best achievements for CNN architectures and performed a complete comparison with the existing literature on DDSM. This experiments were carried out on various CNN architectures using the adaptability of DL algorithms to medical images. The conventional CNN architectures with FCs were trained using 10-fold cross validation.

The average performance of ten testing folds was presented as the evaluation value of CNN architectures. Accuracy, sensitivity, and specificity performance metrics were calculated as independent test characteristics for objective assessment of the CNN architectures. The best classification performances for breast cancer are presented in Table 1.

Table.1 Classification performances for breast cancer using CNN

Methods	DDSM	CNN
Accuracy	85.35%	92.84%
Sensitivity	89.90%	95.30%
Specificity	84.47%	96.72%

DISCUSSION

This Paper aimed at experimenting with CNN architectures with a fixed supervised training to evaluate the impact of CONVs on mammograms for breast cancer.

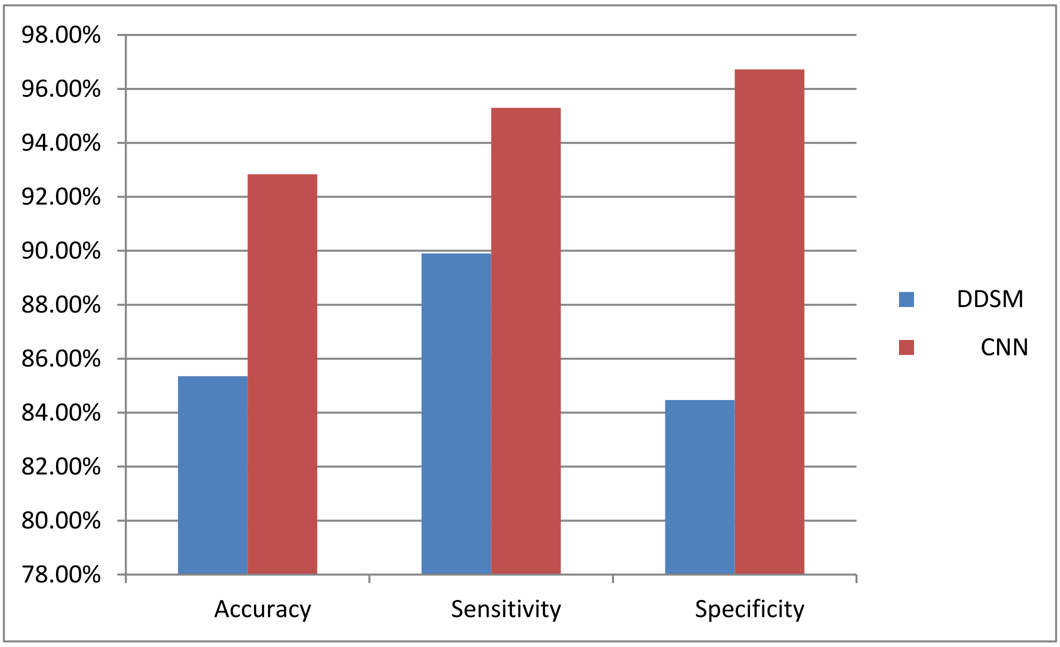

Figure.2 Comparison of proposed Deep Learning architectures considering system performances (%)

A majority of novel researches applied the pre-trained popular CNN architectures to classify mammograms for breast cancer. Especially, The state-of-art of CNN researches for classification of cancer and normal mammograms on DDSM are reached a separation and their highest achievements are accuracy rate of 85.35%,specificity rate of 84.47% and sensitivity rate of 89.90% .

Nasir Khan et al. utilized VGGNet, GoogleNet, and ResNet architectures on multi-view feature fusion model. They highlighted the best performance on classification of cancernormal mammograms as VGGNet with accuracy rate of 94.45%, sensitivity rate of 98.07%, and specificity rate of 88.13%.

Swiderski et al. proposed own CNN architecture using the non-negative matrix factorization method at the feature learning stage. They separated cancer and normal mammograms with an accuracy rate of 85.82%, a sensitivity rate of 82.38%, and a specificity rate of 86.59%. This paper proposed own CNN architecture on mammograms. The proposals aimed at defining the most responsible feature activation map using sequential CONVs. The proposed CNN architecture with the highest classification performance reached the rates of 92.84%, 95.30%, and 96.72% for accuracy, sensitivity, and specificity, respectively.

CONCLUSION

It explores the impact of various feature-learning stages in CNN on CONV and pooling layer variations. The existing literature applied transfer-learning approaches on pre-trained CNN architectures; however, these models have a big number of classification parameters considering the depth of feature learning and supervised stage. The paper contributed on the idea that simple pruned CNN architectures have ability to classify mammograms into cancer and normal cases on mammograms with a detailed feature-learning phase. The proposed CNN architecture provides integrating DeepLearning models into mobile networks and real-time devices for analysis of medical images.

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