

Detection of Breast Cancer Relapse Prognosis by ML Algorithms

G. Shalini¹, Prof. Dr. H A. Girijamma²

¹Computer Science and Engineering, RNS Institute of Technology, Channasandra , Bangalore, India

²Professor, Computer Science and Engineering, RNS Institute of Technology, Channasandra , Bangalore, India

Abstract - According to medical reports, cancers are massive issues within the world society. In this paper we are supposed to predict breast cancer recurrence by building a proposed model with Fully Convolutional Neural Network (FCNN) model and application of transfer learning using VGG16 model. The Fully Convolutional Neural Network (FCNN) is one of the most powerful and successful deep learning approaches. FCNNs have already provided superior performance in different modalities of medical imaging including breast cancer classification, segmentation, and detection. In this paper, the proposed FCNN approach is applied for breast cancer classification on publicly available kaggle Breast Histopathology Images (198,738 IDC(-) image patches; 78,786 IDC(+) image patches) datasets. IDC is the most seen subtype of all breast cancers in women. The experimental results achieved by FCNN model provides superior classification of Invasive Ductal Carcinoma (IDC) Malignant cancer dataset in terms of Confusion matrix, Visualization graphs and global Accuracy.

Keywords: Breast Cancer, Recurrence, IDC, CNN, FCNN.

I. INTRODUCTION

Cancer is one of the leading causes of morbidity and mortality around the world. Approximately fourteen million individuals are suffered by cancer, and it is estimated that this number will be above 28 million by 2030. According to a study by the American Cancer Society (ACS) [1], in the USA the estimated deaths due to breast cancer account for approximately 14% of all cancer deaths (a total of forty one thousand, in 2017) which is in the second-leading cause of cancer death in women after lung and bronchus cancer. A diagnostic test followed by microscopic image analysis is common once diagnosis Carcinoma. A breast tissue diagnostic test permits the medical specialist to histologically access the microscopic level structures and parts of the breast tissue. These histologic pictures enable to the medical specialist to tell apart between the traditional tissue, non-malignant (benign) tissue, and malignant lesions. The ensuing data is then went to perform a prognostic analysis [2]. However, in few cases, breast cancer will relapse after the surgery. It is important to know if the breast cancer will be relapsed or not based on the information that for each patient is provided. If the doctor knows that breast cancer will be relapsed for a specific patient, the methods for treating that patient will be different.

As a result, one of the common pre-processing steps for automatic aggressiveness grading is to delineate the exact regions of IDC inside of a whole mount slide. The original dataset consisted of 162 whole mount slide images of Breast Cancer (BC) specimens scanned at 40x. From that, 277,524 patches of size fifty x fifty (50 x 50) were extracted (198,738 IDC negative and 78,786 IDC positive) [3].

II. PREVIOUS WORK

Significant effort has been place forth for carcinoma (BC) recognition from microscopic anatomy pictures within the last decade, wherever most efforts are created to classify the 2 elementary forms of breast cancer (benign and malignant) using Computer Aided Diagnosis (CAD). For the foremost half, research in this area has been conducted using a very small number of samples from primarily private datasets. Recently a revealed on microscopic anatomy image analysis for carcinoma detection and classification that clearly describes the dualities and limitations of various in public accessible [4]. An effective framework has been projected with color texture options and multiple classifiers utilizing pick technique that according roughly 87.53% average recognition rate for patient level BC classification. In this implementation, the SVM, the Decision Tree (DT), a Nearest Neighbor Classifier (NNC), Discriminant Analysis (DA), and Ensemble classifiers were used. Before 2017, this system achieved the best recognition accuracy of all machine learning based approaches [5].

Furthermore, many works have already been published that discuss breast cancer recognition using DL approaches, where CNN variants are applied for classification. A few of these experiments are conducted with the BreKaHis dataset. In 2016, a magnification freelance carcinoma classification was projected supported a CNN wherever completely different sized convolution kernels (7×7, 5×5, and 3×3) were used. They performed patient level classification of breast cancer with CNN and multi-task CNN models and reported an 83.25% recognition rate [6]. In the same year, another work was published based on a model similar to AlexNet with different fusion techniques (including sum, product, and max) for image and patient level classification of breast

cancer. This paper reports 90% and 85.6% average recognition accuracy with the max fusion method for images and patient level classification respectively [7]. Another deep learning-based method was published in 2017. In this work, a pre-trained CNN was used to extract the feature vectors, and eventually the feature vectors were used because the input to a classifier. This method was called DeCAF and achieved a recognition accuracy of 86.3% and 84.2% at the patient level and image level respectively [8].

The CNN model was used for the classification of H&E stained breast biopsy images from another challenging dataset in 2017 [9]. The images were classified consistent with four completely different classes: traditional tissue, benign lesion, in-situ carcinoma, and invasive carcinoma. Images were conjointly classified in terms of binary categories, carcinoma (which includes normal and benign tissue) and non-carcinoma (which includes the in-situ and invasive carcinoma classes) are considered. Work in [9] provides results for both image-based and patch-based evaluation. The CNN based mostly approach achieved roughly 77.8% recognition accuracy when performing the four-class experiment, and 83.3% recognition accuracy for the binary class experiment when tested with the BC Classification Challenge 2015 dataset. Recently, multi-classification of carcinoma from histopathological pictures was given employing a structured deep learning model referred to as CSDCNN.

The CNN is trained over a large amount of image patches (tissue regions) from WSI to learn a hierarchical part-based representation. The method was evaluated over a WSI dataset from 162 patients diagnosed with IDC [10]. 113 slides were selected for training and 49 slides were held out for independent testing. Ground truth for quantitative evaluation was provided via expert delineation of the region of cancer by an expert pathologist on the digitized slides. The experimental evaluation was designed to measure classifier accuracy in detecting IDC tissue regions in WSI. Our method yielded the best quantitative results for automatic detection of IDC regions in WSI in terms of F-measure and balanced accuracy (71.80%, 84.23%), in comparison with an approach using handcrafted image features (color, texture and edges, nuclear textural and architecture), and a machine learning classifier for invasive Carcinoma classification using a Random Forest (RF). The best performing handcrafted features were fuzzy color histogram (67.53%, 78.74%) and RGB histogram (66.64%, 77.24%). Our results also suggest that at least some of the tissue classification mistakes (false positives and false negatives) were less due to any fundamental problems associated with the approach, than the inherent limitations in obtaining a very highly

granular annotation of the diseased area of interest by an expert pathologist.

III. PROPOSED METHODOLOGY

A. Machine Intelligence Libraries

Google TensorFlow [11] was used to implement the machine learning algorithms in this study, with the aid of other scientific computing libraries: matplotlib[12], numpy[13], and scikit-learn[14]. Keras [15] Applications are deep learning models that are made available alongside pre-trained weights. These models is used for prediction, feature extraction, and fine-tuning.

B. Convolutional Neural Network

A FCNN [16] model is an advanced engineering version of a conventional neural network where the convolution operation is been introduced, which allows the network to extract local features as well as global features from the information, enhancing the decision-making procedure of the network. To absolutely control the workflow of a CNN network, along with a convolutional layer, a few intermediate layers have been introduced. VGG convolutional neural network model for image recognition proposed by the Visual Geometry Group in the University of Oxford, where VGG16 refers to a VGG model with 16 weight layers, and VGG19 refers to a VGG model with 19 weight layers. ResNet [17] architecture is extremely deep networks can be trained using standard SGD (and a reasonable initialization function) through the use of residual modules.

C. Existing CNN Model

In this method, the input image is convolved by first 2 layers are Conv2D layers. These are convolution layers that will deal with our input images, which are seen as 2-dimensional matrices. 64 in the first layer and 32 in the second layer are the number of nodes in each layer. This number can be adjusted to be higher or lower, depending on the size of the dataset. In our case, 64 and 32 work well, Kernel size is the size of the filter matrix for our convolution. So a kernel size of 3 means we will have a 3x3 filter matrix. Refer back to the introduction and the first image for a refresher on this. Activation is the activation function for the layer. The activation function we will be using for our first 2 layers is the ReLU, or Rectified Linear Activation. This activation perform has been verified to figure well in neural networks. In between the Conv2D layers and therefore the dense layer, there is a 'Flatten' layer. Dense could be a commonplace layer kind that's utilized in several cases for neural networks. After Max Pooling layer with 64 layers with an ReLU rectifier. 0.25 of the information has been dropped out in the drop-out layer before sending them through the decision layer

(SVM/Sigmoid) distinguishes the IDC (+) and IDC (-) data.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 24, 24, 32)	896
conv2d_2 (Conv2D)	(None, 22, 22, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 64)	0
dropout_1 (Dropout)	(None, 11, 11, 64)	0
flatten_1 (Flatten)	(None, 7744)	0
dense_1 (Dense)	(None, 128)	991360
dropout_2 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 1)	129

Total params: 1,010,881
 Trainable params: 1,010,881
 Non-trainable params: 0

Figure 1. Existing CNN Model

D. Proposed FCNN Model

In this model we have utilized both the FCNN model and Transfer Learning concept together. At first the input image is convolved by the convolutional layer C-1 with a 3x3 kernel along with a ReLU rectifier. This layer produces feature vectors and the size of each feature vectors is 32 x 32. Consecutively there are another two layers, C-2 and C3, placed one after another. After the layer C-3 one pooling layer named P-1 has been introduced with the kernel size 2 x 2. As the pooling layer uses a 64 x 64 kernel, the output of P-1 produces a 256 x 256 kernel. After the P-1 layer a flat layer has been introduced, followed by a dense layer which produces 512 neurons. After the layer C-4 and C-5 one pooling layer named P-1 has been introduced with the kernel size 512 x 512. The output of this layer has been used as the input layer for the VGG16 model. As this layer contains a one dimensional vector. After the VGG16 layer one flatten d layer of 512 neurons has been placed followed by a dropout of 0.25 of the data. . After the drop-out layer a dense layer has been introduced, followed by 128 neurons. After that a decision layer has been placed which distinguishes the IDC (+) and IDC (-) data.

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, None, None, 3)	0
block1_conv1 (Conv2D)	(None, None, None, 64)	1792
block1_conv2 (Conv2D)	(None, None, None, 64)	36928
block1_pool (MaxPooling2D)	(None, None, None, 64)	0
block2_conv1 (Conv2D)	(None, None, None, 128)	73856
block2_conv2 (Conv2D)	(None, None, None, 128)	147584
block2_pool (MaxPooling2D)	(None, None, None, 128)	0
block3_conv1 (Conv2D)	(None, None, None, 256)	295168
block3_conv2 (Conv2D)	(None, None, None, 256)	590080
block3_conv3 (Conv2D)	(None, None, None, 256)	590080
block3_pool (MaxPooling2D)	(None, None, None, 256)	0
block4_conv1 (Conv2D)	(None, None, None, 512)	1180160
block4_conv2 (Conv2D)	(None, None, None, 512)	2359808
block4_conv3 (Conv2D)	(None, None, None, 512)	2359808
block4_pool (MaxPooling2D)	(None, None, None, 512)	0
block5_conv1 (Conv2D)	(None, None, None, 512)	2359808
block5_conv2 (Conv2D)	(None, None, None, 512)	2359808
block5_conv3 (Conv2D)	(None, None, None, 512)	2359808
block5_pool (MaxPooling2D)	(None, None, None, 512)	0

Total params: 14,714,688
 Trainable params: 14,714,688
 Non-trainable params: 0

Model: "model_1"

Layer (type)	Output Shape	Param #
image_input (InputLayer)	(None, 50, 50, 3)	0
vgg16 (Model)	multiple	14714688
flatten (Flatten)	(None, 512)	0
dropout_3 (Dropout)	(None, 512)	0
fc1 (Dense)	(None, 128)	65664
dropout_4 (Dropout)	(None, 128)	0
predictions (Dense)	(None, 1)	129

Total params: 14,780,481
 Trainable params: 65,793
 Non-trainable params: 14,714,688

Figure 2. Proposed FCNN Model

IV. EXPERIMENTAL RESULTS

To demonstrate the performance of the FCNN models, we have tested them on BC datasets: kaggle Breast Histopathology Images, classification of IDC tumors. For this implementation, the Keras, and Tensor Flow

frameworks were used on a single Digital Ocean Droplet (cloud instances) CPU machine with 16G of RAM and 50GB Memory. We considered different criterion for histopathology image analysis in this implementation. In most cases, the dimensions of the Whole Slide Images (WSI) are larger than typical digital images. In addition, the pathological images are acquired with different magnification factors. However, in this case the images are typically fed to the model as several patches.

The Experiment carried out with three stages of refinement, to obtain efficient accuracy as below:

A. Data Augmentation

In every dataset, we tend to applied totally different information augmentation techniques including: consecutive rotation by forty (40) degrees, dimension shift with issue of 0.2, height shift with issue of 0.2, shear with a factor of 0.2, zooming with a range 0.2, horizontal flipping, and vertical flipping. Examples of images along with different augmented samples for the four different data classes.

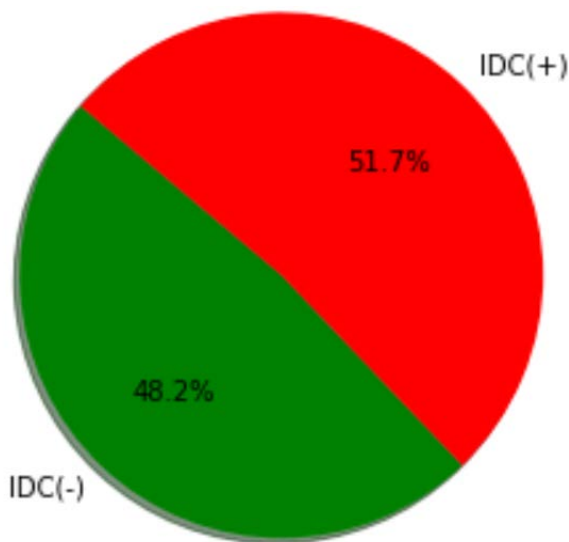


Figure 3. Data Augmentation

B. Transfer Learning

Transfer Learning (TL) by the VGG16 model. By adding FCNN model at the top of the proposed model. Important aspect is to set convolutional layers to not train models. To improve the performance and accuracy of the model.

C. Performance Analysis

A confusion matrix is used as summary of predicting recurrence of IDC(+) and IDC(-) from kaggle dataset. The number of correct and incorrect predictions are summarized with count values and lessened by every category. The confusion matrix results are given in Figure 4 with 2 – dimension representation.

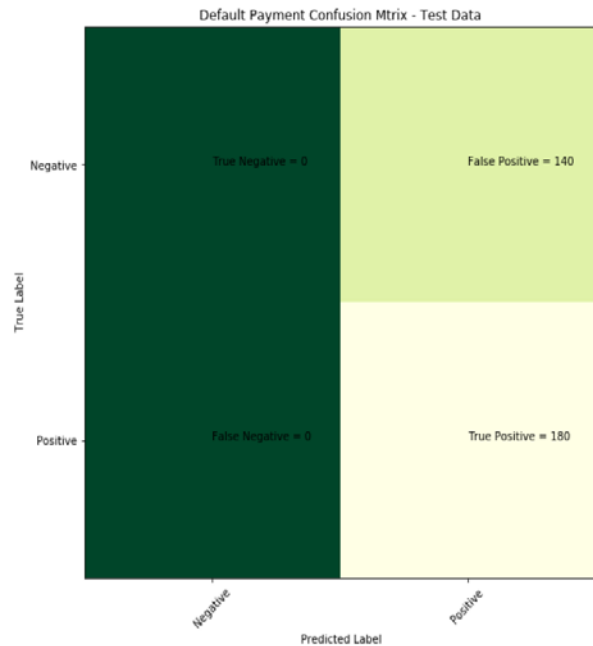


Figure 4. Confusion Matrix

From the Table 1 and Table 2, which compares the accuracy of Proposed FCNN model and CNN model. By considering the parameters of accuracy with compared features like data augmentation and transfer learning.

TABLE 1. RESULTS GAINED BY EXISTING (CNN) MODEL

Accuracy	Epoch	Transfer Learning	Data Augmentation	
			Shift Factor	Rotation (degree)
50.62	100	CNN Model	0.2	40

TABLE 2. RESULTS GAINED BY PROPOSED (FCNN) MODEL

Accuracy	Epoch	Transfer Learning	Data Augmentation	
			Shift Factor	Rotation (degree)
88.12	100	CNN Model	0.2	40

V. CONCLUSION

The main conclusions of the study are provided in a short Conclusion Section. This paper considered to classify the clinical samples that all had the Breast Cancer (BC) based on the fact that whether their cancer will be relapsed or not. To do this, proposed FCCN Model is trained with IDC kaggle dataset. The results expressed proposed neural network with outputs in the hidden layer led to the 88.12% of highest accuracy. Also, generally, FCNN resulted in the 50.62% of lowest accuracy without transfer learning. Application of data augmentation for better visualization.

In this section conclusion of the research work should be explained.

REFERENCES

- [1] Loukas, C., Spiros Kostopoulos, Anna Tanoglidi, Dimitris Glotsos, C. Sfikas, and Dionisis Cavouras. "Breast cancer characterization based on image classification of tissue sections visualized under low magnification." *Computational and mathematical methods in medicine* 2013 (2013).
- [2] Elston, Christopher W., and Ian O. Ellis. "Pathological prognostic factors in breast cancer. I. The value of histological grade in breast cancer: experience from a large study with long-term followup." *Histopathology* 19.5 (1991): 403-410.
- [3] <https://www.kaggle.com/paultimothymooney/predicting-idc-in-breast-cancer-histology-images/>.
- [4] Veta, Mitko, Josien PW Pluim, Paul J. Van Diest, and Max A. Viergever. "Breast cancer histopathology image analysis: A review." *IEEE Transactions on Biomedical Engineering* 61, no. 5 (2014): 1400-1411.
- [5] Gupta, Vibha, and Arnav Bhavsar. "Breast Cancer Histopathological Image Classification: Is Magnification Important?." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1724. 2017.
- [6] Bayramoglu, Neslihan, Juho Kannala, and Janne Heikkilä. "Deep learning for magnification independent breast cancer histopathology image classification." In *Pattern Recognition (ICPR), 2016 23rd International Conference on*, pp. 2440-2445. IEEE, 2016.
- [7] Spanhol, Fabio Alexandre, Luiz S. Oliveira, Caroline Petitjean, and Laurent Heutte. "Breast cancer histopathological image classification using convolutional neural networks." In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pp. 2560-2567. IEEE, 2016.
- [8] Spanhol, Fabio A., Luiz S. Oliveira, Paulo R. Cavalin, Caroline Petitjean, and Laurent Heutte. "Deep features for breast cancer histopathological image classification." In *Systems, Man, and Cybernetics (SMC), 2017 IEEE International Conference on*, pp. 1868-1873. IEEE, 2017.
- [9] Araújo, Teresa, Guilherme Aresta, Eduardo Castro, José Rouco, Paulo Aguiar, Catarina Eloy, António Polónia, and Aurélio Campilho. "Classification of breast cancer histology images using Convolutional Neural Networks." *PloS one* 12, no. 6 (2017): e0177544.
- [10] Angel Cruz-Roa, Ajay Basavanahally, Fabio González, Hannah Gilmore, Michael Feldman, Shridar Ganesan, Natalie Shih, John Tomaszewski, Anant Madabhushi "Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks" *Proc. SPIE 9041, Medical Imaging 2014: Digital Pathology*, 904103 (20 March 2014); doi: 10.1117/12.2043872 .
- [11] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2015. "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems." (2015). <http://tensorflow.org/Softwareavailablefromtensorflow.org> .
- [12] <https://doi.org/10.1109/MCSE.2007.55>.
- [13] Stefanvander Walt, S Chris Colbert, and Gael Varoquaux, 2011. "The NumPy array: a structure for efficient numerical computation." *Computing in Science & Engineering* 13, 2(2011), 22–30.
- [14] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. "Scikit-learn: Machine Learning in Python". *Journal of Machine Learning Research* 12(2011), 2825–2830.
- [15] <https://keras.io/application/>.
- [16] <http://cs231n.github.io/convolutional-networks/#overview>.
- [17] <https://www.pyimagesearch.com/2017/03/20/imagenet-vggnet-resnet-inception-xception-keras/>.