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# Breast Cancer Classifications Using Capsule Network with Preprocessed Histology Image

Rajasekhar Yadav.A<sup>1</sup>, Sreekanth.K<sup>2</sup>, Rachitha.P<sup>3</sup>, Shalini.V<sup>4</sup>, Spandana.M<sup>5</sup>

Associate Professor, Department of Electronics and Communication Engineering, Siddharth Institute of Engineering and Technology, Chittoor, India<sup>1</sup>

UG Students.Department of Electronics and Communication Engineering, Siddharth Institute of Engineering and Technology, Chittoor, India<sup>2345</sup>

**ABSTRACT:** The main objective of this paper is to classify the different types (4types) of breast cancer using histology images. The mainly 4types of breast cancer are Benign, In situ, Invasive, Normal. Theclassification of histology images can be effectively done by using Convolutional Neural Network (CNN). By using different types of layers.

**KEYWORDS:** Breast Cancer, Capsule Network, Preprocessing, Histology images and CNN.

## I. INTRODUCTION

Cancer is one of the most common diseases found in both men and women. Since the treatments are in the advancedstage, the death rate for cancer has been considerably reduced in past few years [1]. Even though advanced treatments are being found for cancer, one of the main challenges in this field is the early detection of disease. There are different types of cancer based on the body part affected. Among this, breast cancer is one of the deadliest forms of cancer in women and it is the most common cause of death in women aged between20 and 59

The detection of breast cancer is done by the analysis of either mammography or ultrasound imaging and regular checkups. Pathologists check the microscopic elements and tissue structure for detailed analysis. The histology images help to distinguish between normal, benign, in situ and invasive tissues. Benign lesions represent changes in normal structures of breast parenchyma that are not directly related with progression to malignancy. In situ or invasive is the main classification for carcinomas. In invasive carcinoma, the cells spread beyond the structure whereas in in situ carcinoma, the cells are restrained inside the mammary ductal-lobular system

In this paper, the breast cancer classification using histology images is done using deep learning architectures. Among the current methods, Convolutional Neural Networks (CNN) are the backbone for image classification applications. Deepika applied convolutional neural network to aerial images and other datasets and getting good results for classification, which shows the significance of convolutional neural networks. In last few years, several architectures of convolutional neural networks are used for better results for different applications. But, there are few drawbacks such as it fails to capture the orientation and spatial relationship.

Introduced a new architecture called capsule network for image classification application, which overcame the drawbacks of conventional convolutional neural networks. In the present work, we implemented the breast cancer classification model using the capsule networks and to obtain better performance, the histology images are subjected to pre- processing techniques. For the breast cancer classification, the cancer types considered in the present work are Benign, In situ, Invasive and Normal. The dataset for the experiment is collected from BACH 2018 grand challenge. The main motive of this work is to obtain better result for histology image classification using only half of the original data.

## II. MOTIVATION

Breast cancer is a disease in which cells in the breast grow out of control.there are different kinds of breast cancer. The kind of breast cancer depends on which cells in the breast turn into cancer breast cancer can spread outside the breast



through blood vessels and lymph vessels when breast cancer spreads to other parts of our body it is said to have metastasized. There are different type of breast cancers. Here, the proposed method classifies the types of breast cancers using histology images. Due to lot of drawbacks in CNN architecture used for this study is capsule networks.

### III. LITERATURE SURVEY

There are several works exist for breast cancer classification. Also, there are works using the dataset from BACH 2018 grand challenge, but most of the works are using large number of data for their experiments. But, in the present work, we are using only half of the dataset to reduce the computation.

Tomas [3] applied capsule net architecture in breast cancer classification problem and obtained accuracy around 87%. But, they used a total of 400 images for four class classification problem. The next work is done by Carlos [4] using pre-trained Inception Resnet V2 and achieved accuracy of 76%.

In [5], CNN is used for feature extraction and support vector machines for classification. They obtained accuracy around 77.8%. Rakhlin [6] used deep neural network and gradient boosted trees classifier for breast cancer classification and achieved accuracy of 87.2%. In [8], breast cancer is classification as benign and malignant based on computer aided methods applied on the cytological images of fineneedle biopsies. Alexander Brook [9] automated the breast cancer diagnosis from microscopic biopsy images. They obtained high recognition rates by applying multi-class support vector machines on generic features, which are obtained from level set statistics of the images

In [10], skin cancer is diagnosed using deep convolutional neural networks. For diabetes diagnosis using ECG signals, Swapna [11] introduced a machine learning model using convolutional neural network and hybrid network called, CNN-LSTM.

### IV. PROPOSED METHOD

The basic architecture of Convolutional Neural Network (CNN) consists of some steps which may appear many times in an orderly way in a particular network. The main three layers of a CNN are convolution layer, pooling layer and fully connected layer. A particular arrangement of these layers starts with input layer and ends with output layer. These layers are described briefly in the following sections.

#### A. Input Layer

This is the first layer in every CNN. Here, typically input is the pixel values obtained from any image. Sometimes raw pixel values are feed to the network, but also some form of pre-processing can be done for better results. For gray scale images the shape of the input would be (height of the image) x (width of the image) x (Number of Channels = 1). In the case of RGB or true color image the input shape will be (height of the image) x (width of the image) x (Number of Channels =3). However, CNN can also take 1D data or 3D data volume and process these with little modification.

#### B. Convolutional Layer

This layer is the core part of D-CNN. Convolution operation is the building block of this layer... For convolution operation we need to have some filters or kernels that can find specific structures From a given image data. Another terminology used in D-CNN is stride which refers to number of cells to be shifted. The way filters work is that, the filter is placed at the top most corner of the input image then an element wise production is performed between the values of the filter and corresponding values of the image pixels after that, the produced results are summed to get a value. The sum gained is then placed at one cell of the output. After that, the filter is moved to the right one stride and same calculations are repeated. Many filters can be used on the same layer.

#### C. Pooling Layer

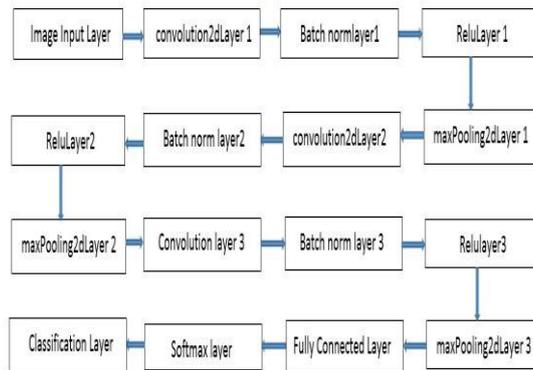
Pooling layer extracts principle features from the input and reduces the height and width of the input. This layer is typically used after one or more convolution layers. By reducing the dimension this layer increases computational performance also by reducing number of parameters this layers Decreases the chance of over fitting. Pooling can be done using several methods, namely, max pooling (where the maximum value is taken from a particular shape of filter), and average pooling (The average value from a certain shape of filter) depict a max pooling operation.



D. Fully Connected Layers

After passing the input data through some convolution and Pooling layers, the output from the last layer is flattened (i.e., reshaped into a linear array) and given as input to the nodes of a fully connected layer. After bringing the outputs of all previous layers into a single linear array a matrix Multiplication with the weights is done followed by an addition with a bias value. E. Output Layer. After fully connected layer, there is output layer. These last two layers can be compared with last layers of typical neural networks. However, a softmax output unit is generally used to get the output.

**BLOCKDIAGRAM**



**ALGORITHM EXPLANATION**

- ✓ Create two image folders like testdata and dataset. Where test data contains testing images and dataset contains images which are downloaded from browser.
- ✓ First read any image from test data, and create a matlabroot to store dataset through (imageDatastore).
- ✓ Create layers such as., Image input layer, Convolution layer, Batch normalization layer, Pooling layer, RELU activation layer (in between), fully connected layer, softmax layer and classification layer.
- ✓ Training options are Plots-Training progress, MaxEpochs-40 and initial learning rate-0.001
- ✓ Using stored dataset (imds), layers and options network is trained.
- ✓ And classification is performed to predict the output

**V. RESULT**

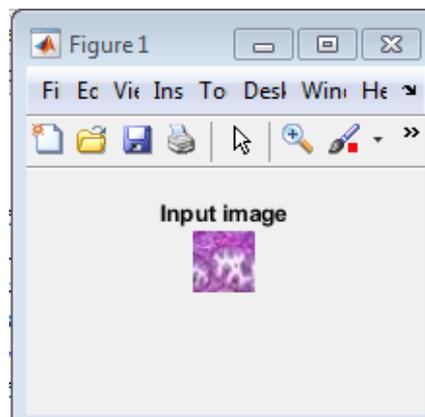


Fig:input image

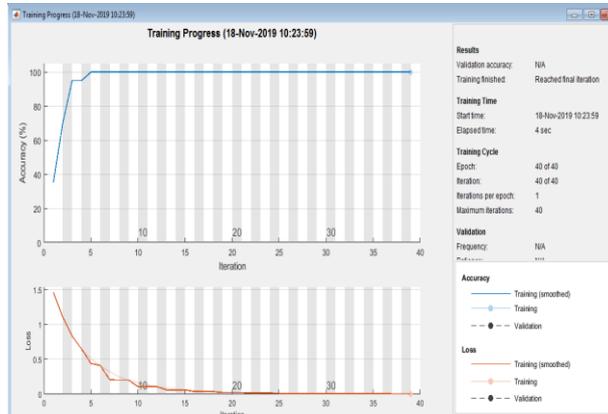


Fig:training progress

Training on single CPU.

Initializing image normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:00	35.00%	1.4624	0.0010
40	40	00:00:04	100.00%	0.0059	0.0010

Fig: Details of the Training Progress

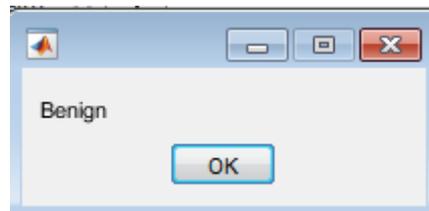


Fig: Classified output

## VI. CONCLUSION

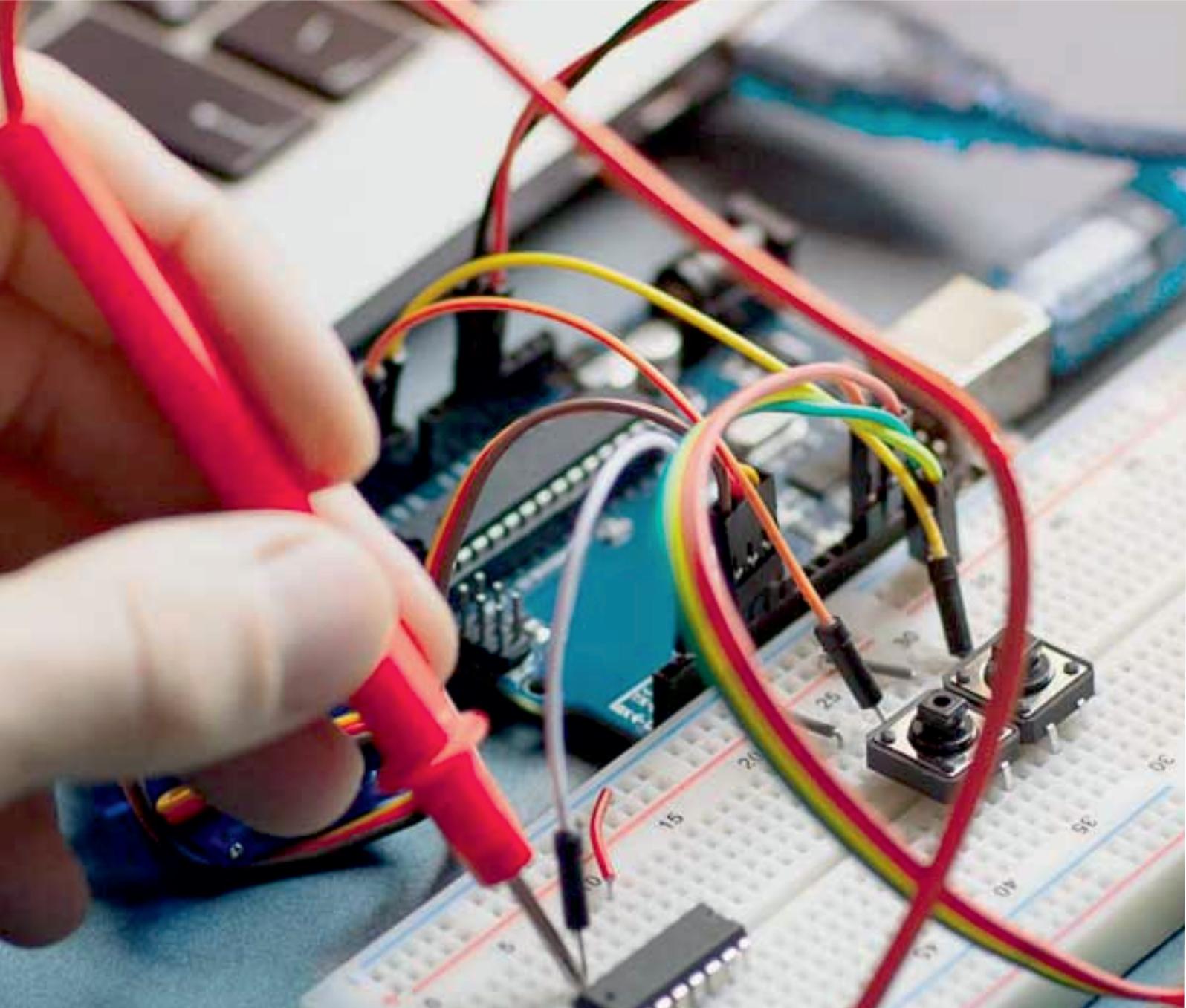
The present work is based on the classification of breast cancer using capsule net architecture. From this work, it is clear that the performance of the conventional architectures can be improved by data pre-processing and parameter tuning. The results show that this method can be used as an automated tool to assist doctors in disease diagnosis, which may lead to higher concentration in the treatment at early stages rather than diagnosis and can increase the cancer survival rate.

## REFERENCES

- [1] Siegel R. L., Miller K. D., Jemal A., “Cancer statistics”, CA Cancer J Clin. 68:7- 30. W.-K. Chen, *Linear Networks and Systems*, Belmont,
- [2] Sabour Sara, Frosst Nicholas, E. Hinton Geoffrey, “Dynamic Routing Between Capsules”, 31st Conference on Neural Information Processing Systems NIPS, 2017.
- [3] Iesmantas T., Alzbutas R., “Convolutional Capsule Network for Classification of Breast Cancer Histology Images”, In: Campilho A., Karray F., ter Haar Romeny B. (eds), *Image Analysis and Recognition, Lecture Notes in Computer Science*, vol 10882. Springer, Cham, ICIAR 2018.
- [4] Ferreira C. A. et al. Classification of Breast Cancer Histology Images Through Transfer Learning Using a Pre-trained Inception Resnet V2. In: Campilho A., Karray F., ter Haar Romeny B. (eds), *Lecture Notes in Computer*



- Science, vol 10882. Springer, Cham., Image Analysis and Recognition, ICIAR2018.
- [5] Teresa Arajo, Guilherme Aresta, Eduardo Castro, Jos Rouco, Paulo Aguiar, Catarina Eloy, Antnio Polnia, Aurlio Campilho, “Classification of breast cancer histology images using Convolutional Neural Networks”, vol. 12, 2017.
  - [6] Rakhlin A., Shvets A., Iglovikov V., Kalinin A. A., “Deep Convolutional Neural Networks for Breast Cancer Histology Image Analysis”, In: Campilho A., Karray F., ter Haar Romeny B. (eds), Lecture Notes in Computer Science, vol. 10882. Springer, Cham, Image Analysis and Recognition, ICIAR2018.
  - [7] Reinhard E., Ashikigmin M., Gooch B., Shirley P., “Color Transfer between Images”, IEEE Computer Graphics and Applications, pp.34-40, 2001.
  - [8] Filipczuk P., Fevens T., Krzyzak A., Monczak R., “Computer-aided breast cancer diagnosis based on the analysis of cytological images of fine needle biopsies”, IEEE Transactions on Medical Imaging. pp.2169–2178,2013.
  - [9] Brook A., El-Yaniv R., Issler E., Kimmel R., Meir R., Peleg D., “Breast Cancer Diagnosis From Biopsy Images Using Generic Features and SVMs.”, pp. 1–16,2007.
  - [10] Esteva A., Kuprel B., Novoa R. A., Ko J., Swetter S. M., Blau H. M., Thrun S. “Dermatologist-level classification of skin cancer with deep neural networks”, Nature, vol.542, pp.115–118,2017.
  - [11] Swapna G, Soman, K. P., and Vinayakumar R., “Automated detection of diabetes using CNN and CNN-LSTM network and heart rate signals”, Procedia Computer Science, vol. 132, pp. 1253-1262, Sreekanth.k,rachitha.p,Shalini.v,spandana.m,2021



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