Comparitive analysis of CNN models to diagnose Breast Cancer

Ketulkumar Govindbhai Chaudhari,
Department of Information Technology, University of The Potomac, USA

***Abstract*— Artificial Intelligence based medical diagnosis is a new approach in medical field, wherein pathologists are no need to work with glass, but they are using pixels to identify the disease (medical imaging). The scanned images can be sent to any place of the world for testing. Using Artificial intelligence approach, we are using machine learning algorithms to diagnose the disease by comparing the existed dataset in the software. Breast cancer is brain cell's disorder that leads to cell to degenerate and inactive. This will be a reason of dementia. The symptoms of dementia are decreasing of thinking capability, behavioral, communication skills that affects people's ability to act independently. In this paper we compare different machine learning approaches, like Support Vector Machine (SVM), Fast RCNN, Faster RCNN, which are used to diagnose Breast cancer . We analyzed training time and testing time of different object detection algorithms.**

Keywords*— *Faster RCNN, RCNN, Breast cancer, Machine learning Introduction

I. INTRODUCTION

Diagnosis is a major task in medical treatment of any health problems. Artificial Intelligence in medical field can play an important role for lab technicians by accurately identifying the diseased part in the blood stool and urine, as well as skin tissues. If there is any suspected or abnormality in blood, urine or tissues, our machine learning model[1] can detect automatically. This is the main advantage of Artificial intelligence.

Breast cancer is the second most common cancer in women and men worldwide. In 2012, it represented about 12 percent of all new cancer cases and 25 percent of all cancers in women.

Breast cancer starts when cells in the breast begin to grow out of control. These cells usually form a tumor that can often be seen on an x-ray or felt as a lump. The tumor is malignant (cancer) if the cells can grow into (invade) surrounding tissues or spread (metastasize) to distant areas of the body.

In the same way our model will suggest appropriate suggestions for treatment based on the training. Breast cancer is brain cell's disorder that leads to cell to degenerate and inactive. This will be a reason of dementia. The symptoms of dementia are decreasing of thinking capability, behavioral, communication skills that affects people's ability to act independently. The symptoms [2] of Alzheimer's disease are forgetting issues. In early stage patient will forget recent events. Slowly he will forget complete issues as the disease increases. We have to diagnose the disease at early stage only.

For this disease, there is no medical solution. In advanced stage of Breast cancer, patient will suffer from severe loss of brain functionalities like dehydration, malnutrition or infection, finally it leads to death.

Due to severity, we have to identify this disease as soon as possible, accurately. To minimize human effort and increase accuracy, we are using machine learning approaches [4] to diagnose this disease.

II. BENCHMARK DATASET

In this work, we used Breast cancer Dataset (4 classes). Breast Cancer Histopathological Database (BreakHis) The Breast Cancer Histopathological Image Classification (BreakHis) is composed of 9,109 microscopic images of breast tumor tissue collected from 82 patients using different magnifying factors (40X, 100X, 200X, and 400X) as shown in figure 1. To date, it contains 2,480 benign and 5,429 malignant samples (700X460 pixels, 3-channel RGB, 8-bit depth in each channel, PNG format). This database has been built in collaboration with the P&D Laboratory – Pathological Anatomy and Cytopathology, Parana, Brazil (http://www.prevencaoediagnose.com.br)[9]. We believe that researchers will find this database a useful tool since it makes future benchmarking and evaluation possible.

The dataset BreaKHis is divided into two main groups: benign tumors and malignant tumors. Histologically benign is a term referring to a lesion that does not match any criteria of malignancy – e.g., marked cellular atypia, mitosis, disruption of basement membranes, metastasize, etc. Normally, benign tumors are relatively "innocents", presents slow growing and remains localized. Malignant tumor is a synonym for cancer: lesion can invade and destroy adjacent structures (locally invasive) and spread to distant sites (metastasize) to cause death[10].

In current version, samples present in dataset were collected by SOB method, also named partial mastectomy or excisional biopsy. This type of procedure, compared to any methods of needle biopsy, removes the larger size of tissue sample and is done in a hospital with general anesthetic.

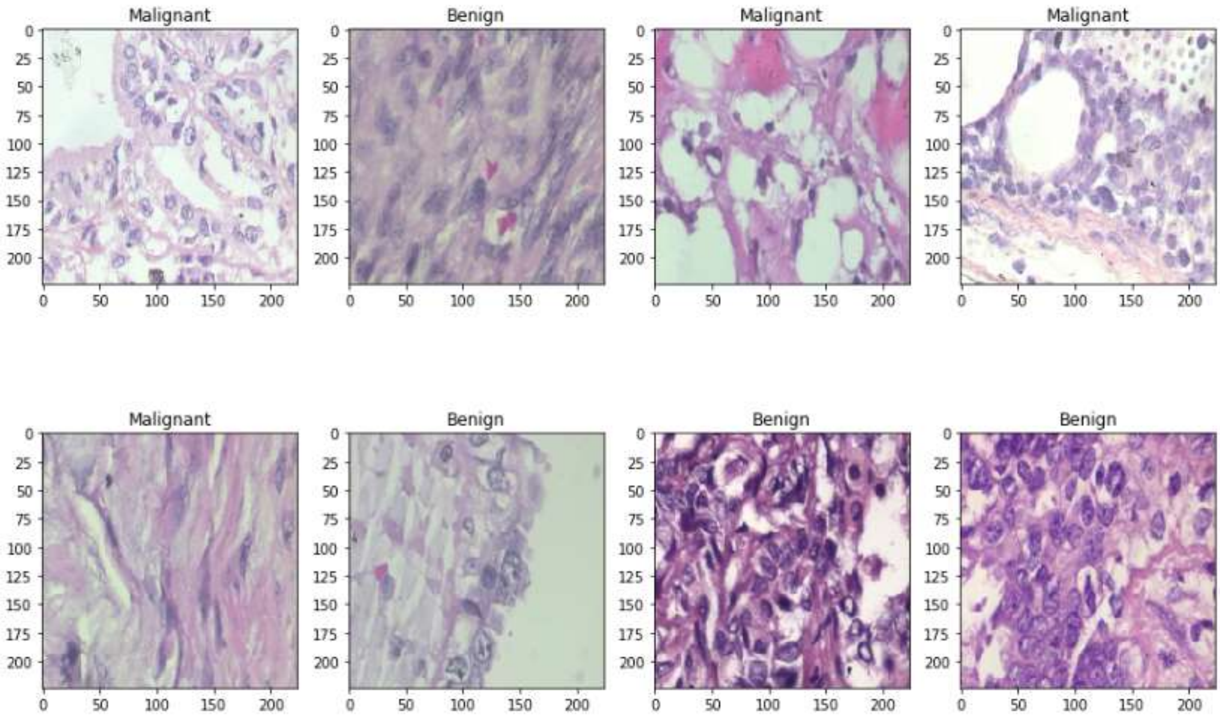


Figure 1. Breast Cancer Histopathological Image dataset

Data exploration

We categorized data into 4 classes. In the data exploration, we explore the hidden patterns. We created three files.

Train: In this folder, we used these images for training purpose. Along with classes, the actual bounding boxes for each class.

Test: we use these images for prediction after training the model.

Train.csv: This file holds the name of the image, class and coordinates of the bounding box. One image can contains more than one object. So there may be more number of rows for a single image.

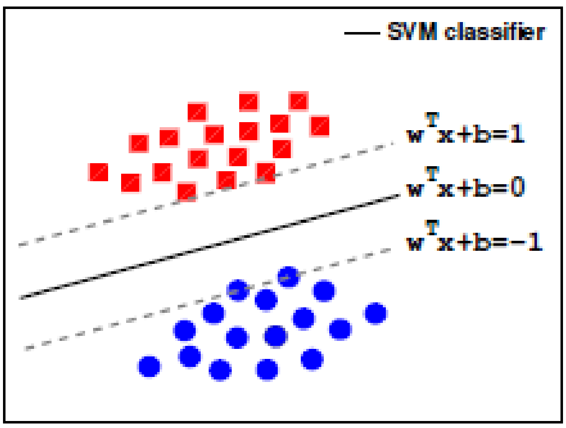
A. SUPPORT VECTOR MACHINE (SVM)

For the classification and regression problems [6], generally we use Support vector machine (SVM), By including the structural risk minimization principle (SRM), SVM gives good generalization performance. SVM uses the maximum margin principle to classify the data points as shown in figure 2 (a). After solving a convex optimization problem, the decision function of SVM is written as,

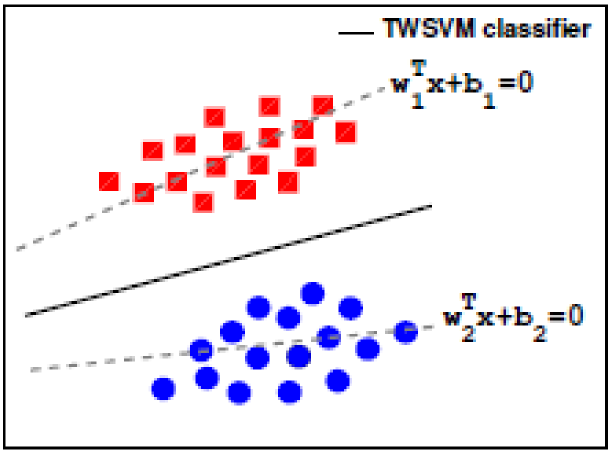
$f(x) = \text{sign}(w^T x + b)$, (1)

where w ---- vector weight

b ---- bias.



(a)



(b)

Fig 2: Plot showing (a) SVM, and (b) TWSVM classifiers.

To classify non-linearly separable data, kernel functions [3] have been used to transform the data to higher dimensions. Moreover, various variants of SVM have been proposed to increase its performance w.r.t. generalization ability and training time [7]. Some computationally efficient variants of SVM are twin support vector machine (TWSVM) [8] shown in figure 2 (b), and least squares based twin support vector machine (LSTSVM) algorithms [8].
To reduce the number of regions selection, Rohs marshick et al. improved a method. In this method, image can be created into 1700 regions using selective approach, these regions are called region proposals. So, there is no need to classify higher number of regions, instead of that we can classify these 1700 region proposals accurately. Approach of selective search is given below.
Selective Search:
1. Using the process of sub-segmentation, we can generate regions proposals.
2. We can merge similar regions into larger region, using greedy algorithm.
3. By using these generated regions based on previous steps, i.e. 1700 region proposals are made into square boxes and make into a convolutional neural network.
The convolutional neural network works for feature extraction. We will get output from CNN output layer, it extracts features from given image. Those characteristics are given to SVM, to identify the abnormal area in the MRI image. This model not only predicts the abnormal region in the image, it will also predict the name of the disease. In addition to predicting the disease within the region proposals. In the below figure 5, the convolution neural network block diagram is given.

III. REGIONAL CONVOLUTIONAL NEURAL NETWORKS

Regional Convolutional Neural Networks extracts one medical image into so many numbers of regional proposals, using selective search. We used these images for training purpose. Along with classes, the actual bounding boxes for each class. It will check by the model. Finally, these characteristics are then used to identify defected part in the scanned image. Comparatively, Regional Convolutional Neural Networks becomes a little bit slow due to more number of steps involved in the algorithms.

Fast Regional Convolutional Neural Networks (Fast R-CNN), sends the given medical scanned image i.e. MRI image to ConvNet which creates ROI (regions of interest). Previously it passes extracted regions from the given medical image. In case of RCNN we use three different models, but in case of this model we use single model that extracts characteristics from given image and classified into regional proposals and classes along with bounding boxes.

Due to all these steps, it execute faster as compared to R-CNN. For higher dataset Fast RCNN will not work effectively. Compare to RCNN model, training and testing time is low. But for higher datasets, we need to use faster RCNN model is good. Architecture of RCNN is as shown in figure 3.

Problems with R-CNN

- Training time is more, comparing to all other predefined models. In this model, it will take more time for training to identify 1700 region proposals per one MRI image.

• It is not used for real time application purpose, due to higher testing time. In this selective search algorithm, there is no learning happened. It will take 47 seconds of time to test one image [12].It will lead to create Error candidate region proposals. `

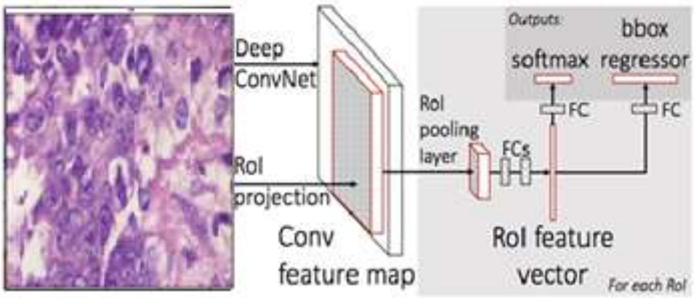


Fig 3: RCNN architecture

Fast R-CNN

Sandeep Chaplet, LM Patnaik is proposed some algorithms to solve the problems of R-CNN to make a faster algorithm for object detection, i.e. Fast Regional Convolutional Neural Networks This algorithm is similar to the Regional Convolutional Neural Networks. Generally we are giving region proposals as input to the convolution neural network to generate feature map of the CNN.

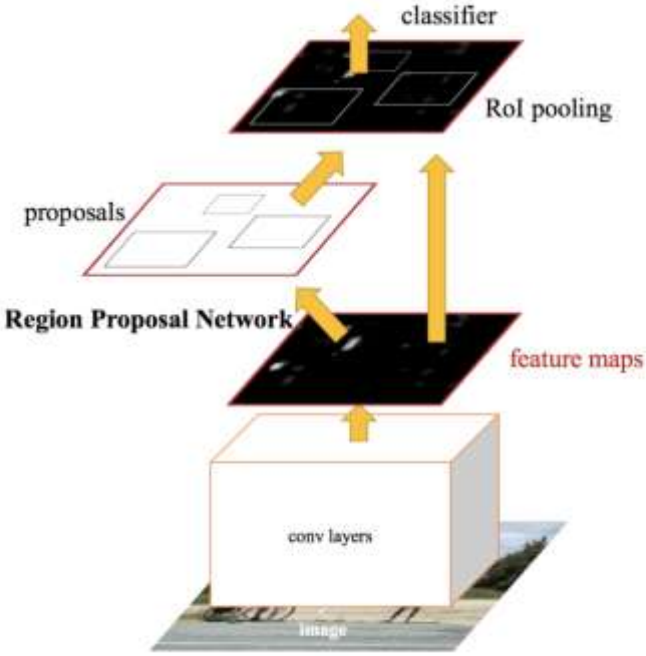


Fig 4: Fast RCNN block diagram

But in this algorithm we are giving input image to the convolution neural network. We recognize region of proposals and wrap them to bounding boxes using a RoI pooling layer, finally we convert into fixed size, and then it is connected to fully connected layer [11]. Through the Region of Interest feature vector, we are predicting the class of objective image by using softmax layer. In this prediction we use offset values for the bounding box. Comparing Regional Convolutional Neural Networks (RCNN), Fast Regional Convolutional Neural Networks (Fast RCNN) is fast. In Regional Convolutional Neural Networks (RCNN), all the region proposals nearly 1700, send to CNN as input. In case of Regional Convolutional Neural Networks, Total Image will be send to CNN as input. In the figure 4, the Architecture of Faster RCNN is explained.

IV. DISCUSSION

Comparing all object detection predefined models, Fast RCNN is good. Training time for different models is given in graph, shown in figure 8. In this graph, we compare training and testing times of various machine learning modes. In this work we explained how

Fast RCNN is better than RCNN. We consider the performance parameters like, Training time and testing time. Spatial Pyramid Pooling in DCNN is used for visual recognition. This SPP-net will generate, fixed length representation with irrespective of medical image. The accuracy and performance of SPP-net model is demonstrated in the figure 8. SPP-net model can compute the feature map from a single image, and pool those features in sub images or arbitrary images to measure fixed length representations, to train the model. Using this method, we can avoid repeated computing of convolutional features.
In the figure 5 and figure 6, we compared the performance parameters, like training time and testing time. Fast RCNN is far better compare to all object detection algorithms. Previously Both Regional Convolutional Neural Networks (RCNN) and Fast Regional Convolutional Neural Networks (Fast RCNN) uses selective search to calculate regional proposals. This is a time taking process and slow, it will affect the performance of the model. So we are using regional proposals instead of selective search. Summary of parameters are given for each layer of convolution neural network to diagnose breast cancer in figure7.

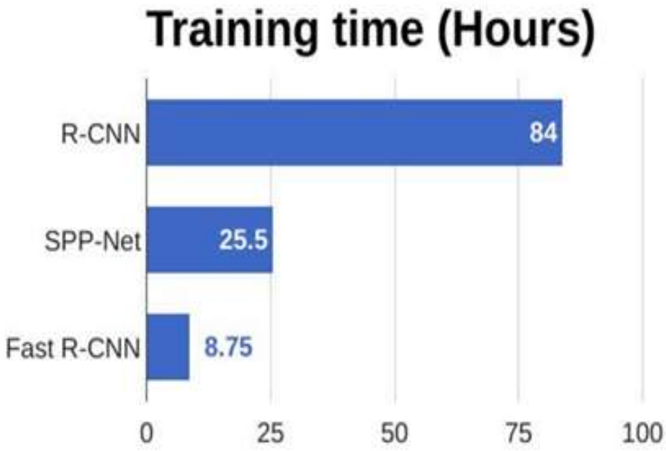


Fig 5: Training time comparison

The predicted region proposals are then reshaped using a RoI pooling layer which is then used to classify the image within the proposed region and predict the offset values for the bounding boxes.

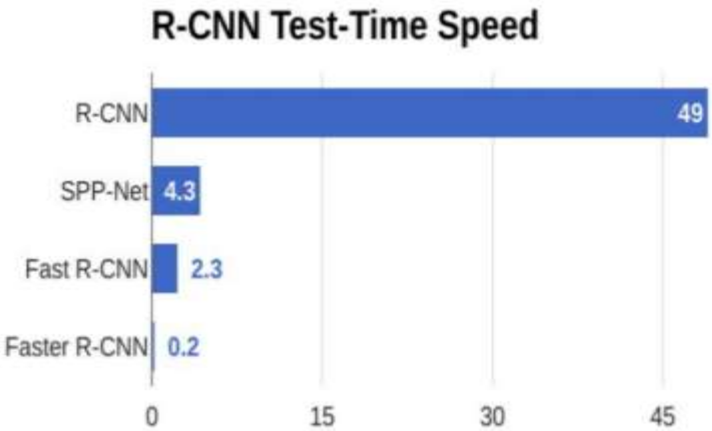


Fig 6: Comparison of test-time speed of object detection algorithms

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
densenet201 (Model)          (None, 7, 7, 1920)        18321984
_________________________________________________________________
global_average_pooling2d_1 ( (None, 1920)              0
_________________________________________________________________
dropout_1 (Dropout)          (None, 1920)              0
_________________________________________________________________
batch_normalization_1 (Batch (None, 1920)              7680
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 3842
=================================================================
Total params: 18,333,506
Trainable params: 18,100,610
Non-trainable params: 232,896
_________________________________________________________________
```

Fig 7: summary of parameters in each layer to diagnose breast cancer

V. CONCLUSION

Among all the object detection algorithms, Faster RCNN algorithm will train and test the model very quickly compare to RCNN, and Fast RCNN. For Breast cancer diagnosis, this type of machine learning algorithm is more efficient than others. We can improve the accuracy of this model by giving more data.

References:

.

[1] J. Carner, A. Mestres, E. Alarcón and A. Cabellos, "Machine learning-based network modeling: An artificial neural network model vs a theoretical inspired model," 2017 Ninth International Conference on Ubiquitou H. Zhang, L. Zhang and Y. Jiang, "Overfitting and Underfitting Analysis for Deep Learning Based End-to-end Communication Systems," 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP), Xi'an, China, 2019, pp. 1-6.

[2] Vishal Dineshkumar Soni. (2018). Prediction of Geniunity of News using advanced Machine Learning and Natural Language processing Algorithms. International Journal of Innovative Research in Science Engineering and Technology, 7(5), 6349-6354. doi:10.15680/IJIRSET.2018.0705232.

[3] D. Dai, M. Hahner and L. V. Gool, "Texture Underfitting for Domain Adaptation," 2019 IEEE Intelligent Transportation Systems Conference (ITSC), Auckland, New Zealand, 2019, pp. 547-552.

[4] Ankit Narendrakumar Soni (2018). Feature Extraction Methods for Time Series Functions using Machine Learning. International Journal of Innovative Research in Science, Engineering and Technology, 7(8), 8661-8665. doi:10.15680/IJIRSET.2018.0708062J. Nagle, "Congestion control in IP/TCP internetworks," IETF, RFC 896, Jan. 1984. [Online]. Available: https://rfc-editor.org/rfc/rfc896.txt

[5] I. Bilbao and J. Bilbao, "Overfitting problem and the over-training in the era of data: Particularly for Artificial Neural Networks," 2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS), Cairo, 2017, pp. 173-177.

[6] Vishal Dineshkumar Soni. (2018). Internet of Things based Smart Parking System using ESP8266. International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering, 7(4), 1839-1843. DOI: 10.15662/IJAREEIE.2018.0704056.

[7] Ankit Narendrakumar Soni (2018). Data Center Monitoring using an Improved Faster Regional Convolutional Neural Network. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 7(4), 1849-1853. doi:10.15662/IJAREEIE.2018.0704058

[8] A. Khan and M. Usman, "Early diagnosis of Alzheimer's disease using machine learning techniques: A review paper," 2015 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K), Lisbon, 2015, pp. 380-387

[9] M. Molinier and J. Kilpi, "Avoiding Overfitting When Applying Spectral-Spatial Deep Learning Methods on Hyperspectral Images with Limited Labels," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 5049-5052.

[10] Karunakar pothuganti (2016) A Comparative Study of Real Time Operating Systems for Embedded Systems , International Journal of Innovative Research in Computer and Communication Engineering, 4(6):12008.

[11] R. Murugadoss and M. Ramakrishnan, "Universal approximation using probabilistic neural networks with sigmoid activation functions," 2014 International Conference on Advances in Engineering & Technology Research (ICAETR - 2014), Unnao, 2014, pp. 1-4.

[12] B. Ding, H. Qian and J. Zhou, "Activation functions and their characteristics in deep neural networks," 2018 Chinese Control And Decision Conference (CCDC), Shenyang, 2018, pp. 1836-1841.