Comparison of two Deep Learning Methods for Classification of Dataset of Breast Ultrasound Images

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ABSTRACT

Breast cancer is the prominent cancer types which account to high mortality. Early detection could serve to improve clinical outcomes. Ultrasonography is a digital imaging technique which is used for differentiating benign and malignant tumors. Recently a dataset of breast ultrasound image has been released which gives opportunity to apply machine learning methods over it and enable one to automatically classify them in the respective tumor class. In the present study, I compared the performance of two deep learning methods: AlexNet, and MobileNet for the classification of breast ultrasound images using an augmented data set of 12000 images (6000 each of benign, and malignant) and received an F1-score of 0.914 and 0.974 respectively so herewith concluded that the later deep learning approach performs better then the former in classifying the ultrasound images of breast tissues in benign and malignant cancer types.

Key Words: Breast cancer, AlexNet, MobileNet, Machine Learning

1. INTRODUCTION

Breast cancer is a prominent cancer type which account to almost twenty five percent of all cases [1]. In past year, over 2 million new breast cancer cases have been reported and almost 6.25 lakh cases met to mortality [2]. Its prevalence in developed countries is more common then in developing one [3]. Early detection can help in reducing the number of early deaths.

Though mammography is considered the best imaging method for its detection but it may issue false signal in cases with women having anatomically dense breast tissues. So Breast ultrasonography is generally used in conjugation with mammography to arrive at final clinical decision. Ultrasound is a imaging techniques that uses high frequency sound waves to create real time images of inside the body for matters related to breast health. It can be used to find or assess a breast lump, guide a breast biopsy needle or marker for breast surgery, assist fluid-filled cyst draining, assess breast implant, helps characterize the stage of any breast cancer present and screened for breast cancer. Though this last function is somewhat controversial and is not widely used.
Ultrasound can detect abnormalities too small to be felt, can add to information already obtained by a mammogram, can cover areas of the breast, a mammogram machine can not reach, and can show abnormalities in the dense areas of the breast, a mammogram may have difficulty seeing. Ultrasound can also detect non-cancerous fluid-filled cysts with 100% accuracy, allowing a doctor to rule out cancer immediately. Ultrasound is an invaluable imaging tool as it allows us to examine the breast from nearly any orientation. It can result in early detection of cancer and helps patients avoid further examination or biopsy.

Ultrasound equipment includes a scanner, a display screen, and a transducer – a small handheld device that is used to scan the body. Most ultrasound examinations are painless, fast and easy. Often an ultrasound can give the doctor enough information about a breast abnormality to confirm. It is benign, in some cases however, it is not possible to tell from diagnostic imaging alone whether an abnormality is benign or cancerous and to make a distinction, a biopsy is required. A breast biopsy is the removal of a sample of breast tissue or fluid by needle or surgery to be examined for sign of cancer. Even if an abnormality is already appear to be cancerous, a biopsy confirms the diagnosis – speeding up the process of treatment planning. As with any medical procedure, an ultrasound is not perfect, it can miss, overestimate, or underestimate a breast abnormality and it may not detect breast calcifications, mineral deposits which may signify cancer as well as mammogram can. nevertheless an ultrasound is very useful tool to help locate, diagnose and biopsy other abnormalities.

A breast ultrasound result is categorized into three classes: normal, benign, and malignant. Benign tumour is free from cancerous cells so does not require any medical intervention. They can be removed for comfort. Malignant tumour, on the other hand contain cancerous cells and must be operated surgically or subjected to chemo- or/and radiotherapy.

Ultrasound images of breast cancers can be used for classification, detection, and segmentation of cancers using machine learning methods and such digital pathology would help clinicians in recommending medical decisions with confidence.

Machine learning is a recent development in the field of computer science which deals with development of computer programs with intrinsic capability of learning from large datasets. These program produce output which are not exact but tend to show resistance to input biases and errors. Deep learning models are graphical structure which has nodes and interconnections between these nodes and these are used for feature extraction and transformation. These methods are routinely used in biological image analysis [4-5].
AlexNet is a deep learning network defined for the ImageNet LSVRC-2010 challenge of classifying 1.2 million images into 1000 unique categories [6]. It was implemented through Keras which is a neural network API written in Python and integrated with TensorFlow.

MobileNets are a class of small, low-latency, low-power models that can be used for classification, detection, and other common tasks convolutional neural networks are good for [7]. Because of their small size, these are considered great deep learning models to be used on mobile devices. This method was used on breast cancer image datasets using a web-based tool-Teachable Machine that can create machine learning models very fast.

Recently a dataset of ultrasound images of breast has been released by Dhabyani et al. (2020) [8] which enable us to apply different machine learning methods over these images and could help in automatically classifying them in tumor classes. This classification would improve the early detection as well as subsequent clinical outcomes.

2. MATERIAL AND METHODS

I took 437 images of benign tumour and 210 images of malignant tumours. These images were then augmented using an image generator from Keras library which adjusted the height, width, horizontal, and vertical flip, and zoom. In this way size of dataset was increased to 12000 images with each class contains equal number of images. Over 80% of images were used to train each model and remaining 20% were used as test data. Image dataset was resized to 224 X 224 and 3e^-3 was set as initial learning rate and model was trained for 50 epoch.

The MobileNet model was used online from https://teachablemachine.withgoogle.com/ and the architecture of AlexNet was implemented in python. Input layers constituted a total of 224X224X3 nodes and layer second to seventh were the hidden layers. Number of nodes in each layers were: second – 256, third – 384, fourth – 384, fifth – 256, sixth – 9216, seventh – 4096, and eight – 4096.

To access the performance of both machine learning methods, a confusion matrix was plotted. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class [9]. After learning has been over, precession, and recall were calculated from confusion matrix using following equations.

\[
\text{Precession} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}
\]

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}
\]
To combine the precision and recall, an F-measure was estimated using the following equation for both the models which is the harmonic mean of precision and recall [10].

$$F = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

Both learning algorithms worked through the training dataset by a fixed number of times – termed epochs which is a hyperparameter which was set a value to 50 for both the methods. Two line plots showing epochs along the x-axis as time and the error or skill of the model on the y-axis were also created by these methods to assess the learning of models.

3. RESULTS

Confusion matrices obtained for MobileNet and AlexNet are presented in Figure 1. These were used to estimate precision, and recall for both deep learning methods. F1-score were then evaluated from these values. MobileNet generated a precision of 97% and a recall of 98% which gave a F1 score of 0.974. AlexNet generated a precision of 91% and a recall of 92% which gave a F1 score of 0.914.

![Confusion Matrices obtained for MobileNet, and AlexNet respectively](image)

It has been identified that MobileNet shown less difference between training accuracy and validation or test accuracy them AlexNet (Figure 2).
In line with the line plots of training vs test accuracy, the training loss for AlexNet was more prominent than MobileNet (Figure 3).

4. CONCLUSION

The results of this short study therefore indicated MobileNet to be a better deep learning model in classifying ultrasound images of breast tissues in benign and malignant types. However, our limitation was that the number of ultrasound images were less to train the models and to conclusively state the classification performance of either model. Furthermore, for clinical setting, more accuracy is demanded for taking medical decision. Different variants of deep learning models can be tested in future to get a more confident classification system.

5. REFERENCES

1) Anon 2014 World Cancer Report 2014 (International Agency for Research on Cancer)
2) Bray F., Ferlay J., Soerjomataram I., Siegel R.L., Torre L.A., Jemal A. November 2018. CA Cancer J Clin. 68.6.

3) World Cancer Report 2014. World Health Organization. 2014. pp. Chapter 5.2. ISBN 978-92-832-0429-9.

4) Yadav DP, Jalal AS, Garlapati D, Hossain K, Goyal A, Pant G. 2020. Deep learning-based ResNeXt model in phycological studies for future. Algal Research. 1;50:102018.

5) Pant G, Yadav DP, Gaur A. 2020, ResNeXt convolution neural network topology-based deep learning model for identification and classification of Pediastrum. Algal Research. 48:101932.

6) Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M, Adam H., 2017, Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

7) Krizhevsky A, Sutskever I, Hinton GE., 2017. Imagenet classification with deep convolutional neural networks. Communications of the ACM, 60(6):84-90.

8) Al-Dhabyani W, Gomaa M, Khaled H, Fahmy A., 2020. Dataset of breast ultrasound images. Data in brief, 1;28:104863.

9) T.U.H. Baumeister, M. Vallet, F. Kaftan, L. Guillou, A. Svatoš, G. Pohnert, 2020, Identification to species level of live single microalgal cells from plankton samples with matrix-free laser/desorption ionization mass spectrometry, Metabolomics, 16: 1–10.

10) A. Tharwat, 2018, Classification assessment methods, Applied Computing and Informatics, https://doi.org/10.1016/j.aci.2018.08.003 In Press.
Appendix

I have addressed the concerned raised by reviewers:

1. Briefly conclusion section has been added with limitations and future direction.
2. More relevant references have been added.
3. Architecture of AlexNet is also defined briefly.

Thanks