Advances and Applications in Mathematical Sciences
Volume 20, Issue 7, May 2021, Pages 1187-1196

MAMMOGRAPHY IMAGE BREAST CANCER DETECTION USING DEEP TRANSFER LEARNING

TIMMANA HARI KRISHNA and C. RAJABHUSHANAM

Department of Computer Science and Engineering
Bharath Institute of Higher Education and Research
Chennai, India-600073

Abstract

All over the world, the bosom disease is analysed in about 12% of women during their lifetime and is the driving motive after the death of women. Since early findings can improve treatment outcomes and have time for patients with prolonged endurance disease, it is noteworthy to construct bosom malignant growth detection procedures. The Conversational Neural Network (CNN) can naturally remove highlights from images and order them later. Massive marked images may be required to train CNN without any preparation, which is possible for certain types of clinical picture information, A promising mechanism is to implement transfer learning on CNN. In this article, we applied the MIAS dataset on three training strategies: CNN to highlight previously prepared VGG-16 models with input mammograms, and to create a Neural Network classifier. Used these highlights for and refreshed the load. By back-spreading (tweaking) to identify abnormal areas in pre-prepared VGG-16 model layers. Compare proposed models and parameters related to performance metrics.

1. Introduction

All Over the world, bosom malignant growth is analysed by about 12% of American women during their lifetime (Siegel et al., [10]), which has heavy clarification behind the demise of women. Preliminary mammographic search dependent on computer-aided strategies can improve treatment outcomes for bosom disease and prolonged endurance times for patients. Traditional CAD evaluations depend on anatomically distinct highlights; However, they have an assortment of disadvantages; Hand-made highlights, for example, will be apparent in general, and the process of highlight configuration can be

2010 Mathematics Subject Classification: 68T05, 68T07.
Keywords: breast cancer classification; transfer learning.
Received September 7, 2020; Accepted February 18, 2021

monotonous, troublesome, and non-normal (Yi et al., [14]). An alternative technique to include extraction is to validly highlight entire images through a composite neural network (CNN) (Jamieson et al., [6]). CNN has performed well in several picture order erodes (Provost and Fawcett, 2001).

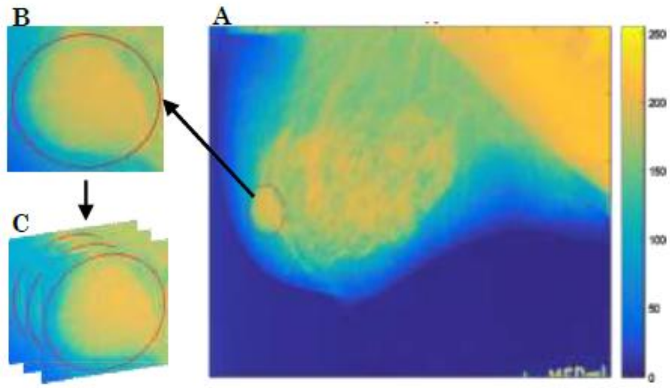

Figure 1. (A) A virtual *r* mammographic image from MIAS (B) Cropped image from abnormal region(C) Created RGB image from a greyscale image.

Alex Net was created using 1.2 million named images. Such prerequisites are routinely for certain types of clinical picture information, for example, mammographic tumor images because they are difficult to obtain, are rare in true positive datasets, and master marking is expensive (Shin et al., [13]). A promising mechanism is to reuse as element extractors a pre-fabricated CNN model that has been prepared with large image datasets from different regions or retrained such models as e.g. Using a predetermined number of clinical pictures (Tajbakhsh et al., [13]). This method, similarly called gait realization, has been effectively applied to various PC vision questions (Penatti et al., [8]). Truth be told, some of the results of move learning are clear: previous examinations for aspiration embolism and melanocytic injury identification (Tajbakhsh et al., [13]) suggest that highlights from common images can be transferred to clinical Huh. Pictures, even if objective drawings, differ significantly from pre-prepared source images.

2. Literature Survey

In the past, various machine learning methods to classify bosom malignancy (Ganesan et al., [2]) using mammogram images. MIAS is the most common open digital database used for mammography screening (Heath et al., n.d.). Some researchers used usually programmed highlight extraction (not manual extraction) procedures, for example, Gabor channels, fragmentation Fourier transforms and grey level co-occurrence matrices (GLCMs), to obtain highlights and to be applied later. The nervous system has been similarly classified (Dhungel et al., [1]). In addition, some examinations applied CNN to create highlights from mammographic images (Jiao et al., [7]). Part of these investigations involved the use of previously prepared CNN as transfer learning with hardly any prior investigation, results obtained using CNN only for component age were introduced and the mammogram arranged for the fatal status of Bosom. In our examination, CNN front layers are responsible for the stage involved, and the fully fused (FC) layers are classifiers that classify the data.

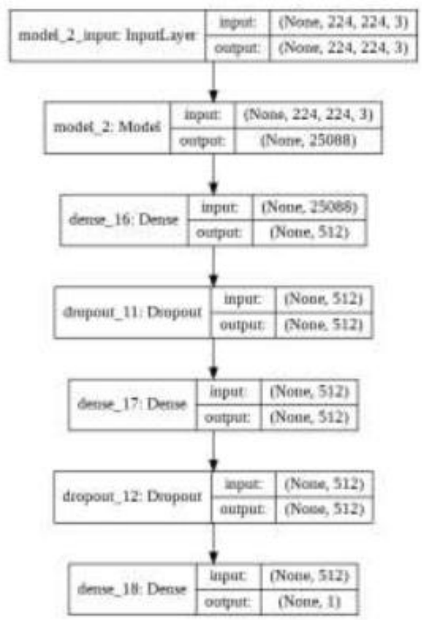

Figure 2. Model Snapshot used for experiments.

Mammographic pictures of the MIAS dataset are used for the researches. We tried three formulation strategies on MIAS: 1) Base VGG16 Model without augmentation, 2) VGG16 model with augmentation (Simonyan and Zisserman, [11]) to extract the highlights from the input pictures and using these highlights Created a neural network (NN)-classifier, 3) Fine-tune the final layer of VGG-16 model to identify irregular locations. We measured the models with 10 cross-validation methods of scikit-learn API Approval precision merges, and there was no inevitable overfitting. The proposed system accuracy is about 0.905 discrepancy versus simple arrangement and AUC is 0.96. Our proposed model can arrive at 0.950 accuracies for all cases

3. Materials and Methods

In Mammography, low-vitality X-ray images are used to envisage human life for determination and screening. Medial oblique and craniocaudal are had two major considerations in X-Ray. The purpose of mammography is that the initial gratitude of bosom malignant growth usually from framed *X*-beam images through the location of the public or strange districts. Generally, such strange areas are seen by specialists or master radiologists. In this paper, we used mammographic images from the Mammographic Image Analysis Society (MIAS) database (Suckling et al., [12]). MIAS is a UK survey group inspired by the empathetic of mammograms and has formed the digital mammogram database. The MIAS database contains 322 images with 102 inconsistent and 220 simple examples. Each image is of greyscale with size 421 × 421-pixels. Areas and boundaries of districts with these discrepancies are given. Each case consists of four pictures speaking on one side and tilted to the right in views of bilateral craniocaudal and mediolateral oblique. In this experiment, we used the pre-trained VGG16 model that was much profounder and more widespread than former neural designs. The VGG-16 model has five convocation blocks, 13 narrow layers and 3 FC layers. Each layer process 3x3 pixel convolutions. This pre-designed VGG-16 model was intended with around 1430 thousands of images from the IMAGNET database and it improved the human-level performance on IMAGNET (Ren et al., [9])

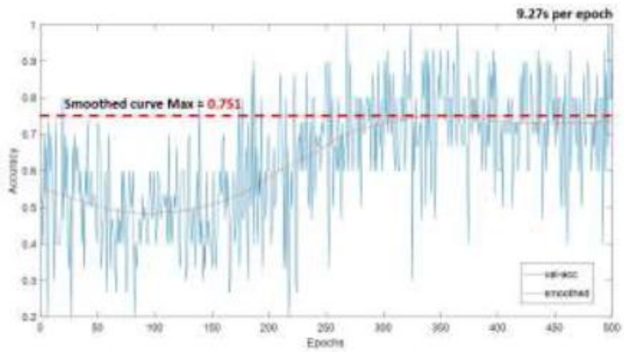

Figure 3. Base Model Training accuracy.

4. Experiments and Results

These implementations are developed on google Colaboratory Notebook using TensorFlow and Keras APIs and executed on Tensor Processing Unit (TPU) Cluster. The Google TPU cluster is of 32 GB RAM and 80 GB storage space. In this paper, we used mammographic images from the MIAS dataset experimented with different parameters of CNN Models: base model, the base model with augmentation and fine-tuned model.

The mammographic images are downloaded from MIAS official site. These images are of PGM Type and processed using MATLAB Functions. We used ROI instead of exhaustive images to design the nervous system. These ROIs are edited in square shape and acquired by (a) For abnormal ROIs from images that differ from the standard, they are the base square shape region that encompasses the entire given ground truth range. (b) Irregular ROI. The image size of ordinary ROIs is 505 × 505 pixels. We amended one ROI from the entire typical Bosom image for this experiment. Measures of odd ROI change with variation from standard limits. Since all information images for CNN require RGB color images with a clear shape, But MIAS images are grey scaled. As shown in Figure 1, we restructured ROIs and replaced them with replicating RGB.

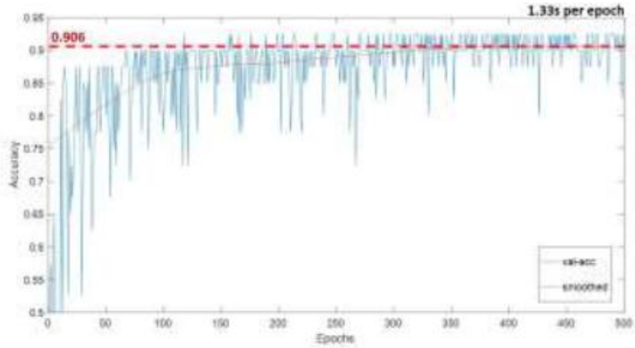

Figure 4. Training Accuracy of Base model with Augmentation.

The pre-trained VGG16 model with Image Net weights is used for our experiments. We replace the final layer with a dropout layer of 1 that is used for binary classification 0 or 1. The dropout layer (Srivastava et al., [5]) sets a part speed of information units to 0 for each of the following layers during preparation; This may enable CNN to overcome over fitting. The yield layer uses a sigmoid potential, which maps the incentive to the yield to the scope of [0, 1]. The pre-trained VGG16 model consists of 13 Convolution layers and 3 Fully Connected (Simonyan and Zisserman, [11]). The weights of all layers will be imported from the pre-trained VGG Model. The weights of the layers except Fully connected layers will not be changed while training the Model The main variance in the fine-tuning model is that we did not consider complete weights of pre-trained CNN. The first four convolutional blocks of layers will be frozen and the final convolutional layer weights are updated during the training. The Fully connected layer weights are imported from former feature extraction instead of arbitrary initialization.

5. Discussion

These implementations are developed on google Colaboratory Notebook using Tensor Flow and Keras APIs and executed on Tensor Processing Unit (TPU) Cluster. The Google TPU cluster is of 32 GB RAM and 80 GB storage space.

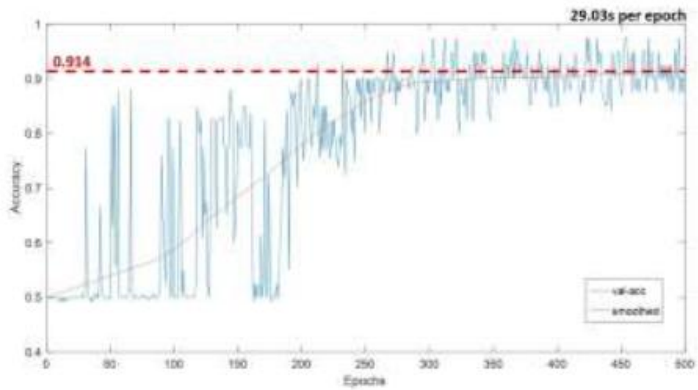

Figure 5. Training Accuracy of Tuned-model.

Initially, we started experimenting with the dataset on the base model. Then feature-model followed by tuned-model. We have chosen 95 ROI images and split them into train and test data set in the ratio of 15: 4. For our experiment, we resized the greyscale images into 421×421-pixels. We assigned the labels 0 and 1 for normal and cancer classes respectively. As the image classes are two, we are considering it as binary classification. we used binary cross-entropy as loss function and Softmax as the activation function. The default parameters of the RMSprop (Hinton et al., n.d.) from Keras is used as the optimizer for our experiments.

The training accuracy of the base model is as shown in Figure 3. Training precision after each epoch is represented in blue color and the red line shows the normalized value. These results show that the maximum accuracy of the base model is 0.751 which is low and is not stable. We identified ourselves with the depth of some late examinations.

The training accuracy of the base model with augmentation and fine tuned model is as shown in Figure 4 and Figure 5. These results show that the maximum accuracy of the base model is 0.906 and the accuracy is 14% tuned compared to the base model. Fine-tuned VGG16 model achieved 91.4% of model accuracy and improved around 0.88 percent compared to other models. The training accuracies of three experimented models are shown in Figure 6 yellow, red, and blue lines represent the base model, base model with augmentation and fine tuned model. By correlation, preparing the classifier by the highlighted classifier is the precise method for the study because its precision is exceptionally close to adjustment and the cost of time is about 5% of the calibration. It may be appropriate to adjust correspondingly, for real applications, because it may have enough opportunity to produce a generally excellent model for use *b*.

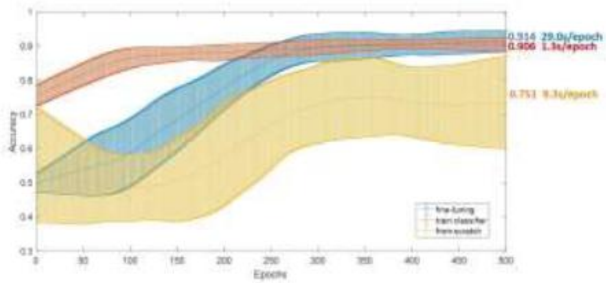

Figure 6. Comparing the three CNN classification models.

These investigations in Table 1, implemented exchange learning in CNN to identify mammogram-dependent bosom lethal anomaly. By testing with these probes, we used CNN classifiers and much more mammographic images for the preparation and testing of an infallible pre-prepared model. The theory is about the opposite class. Our one-FC layer is easy engineering in the NN-classifier and can be coordinated with the previously prepared fixture layers as a complete CNN. The proposed fine-tune model has an accuracy of 0.952 and AUC of 0.96 (Guan and Loew, [3]).

Table I. Comparison of state-of-art models.

Model	Accuracy	AUC Score
Finetuned CNN	0.967	–
CNN+HC features + RF	0.93	0.76
AlexNet + MIL	0.92	0.85
Fine Tuned VGG16	0.952	0.96

6. Conclusion

In this paper, we used the MIAS mammogram dataset for designing the automated feature extraction and classification. We experimented with the Deep Convolutional network model VGG16 with mammogram images. We fine-tuned the model and applied the image augmentation techniques to achieve improved performance. We utilized the power of transfer learning techniques to reduce the training time with improved accuracy.

References

[1] N. Dhungel, G. Carneiro and A. P. Bradley, The automated learning of deep features for breast mass classification from mammograms. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9901 LNCS, 106-114. https://doi.org/10.1007/978-3-319-46723-8_13 (2016).

[2] K. Ganesan, U. R. Acharya, C. K. Chua, L. C. Min, K. T. Abraham and K. H. Ng, Computer-aided breast cancer detection using mammograms: A review. In IEEE Reviews in Biomedical Engineering 6 (2013), 77-98. Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/RBME.2012.2232289

[3] S. Guan and M. Loew, Breast cancer detection using transfer learning in convolutional neural networks, Proceedings-Applied Imagery Pattern Recognition Workshop, 2017-October. https://doi.org/10.1109/AIPR.2017.8457948

[4] M. Heath, K. Bowyer, D. Kopans, R. Moore and P. Kegelmeyer, (n.d.). The Digital Database For Screening Mammography.

[5] G. Hinton, N. Srivastava and K. Swersky, Neural Networks for Machine Learning Lecture 6a Overview of mini-batch gradient descent,

[6] A. R. Jamieson, K. Drukker and M. L. Giger, Breast image feature learning with adaptive deconvolutional networks, In B. van Ginneken and C. L. Novak (Eds.), Medical Imaging 2012: Computer-Aided Diagnosis 8315 (2012), 831506. SPIE. https://doi.org/10.1117/12.910710

[7] Z. Jiao, X. Gao, Y. Wang and J. Li, A deep feature based framework for breast masses classification. Neurocomputing 197 (2016), 221-231. https://doi.org/10.1016/j.neucom.2016.02.060

[8] O. A. B. Penatti, K. Nogueira and J. A. Dos Santos, Do deep features generalize from everyday objects to remote sensing and aerial scenes domains? IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (2015), 44-51. https://doi.org/10.1109/CVPRW.2015.7301382

[9] S. Ren, K. He, R. Girshick and J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6) (2017), 1137-1149. https://doi.org/10.1109/TPAMI.2016.2577031

[10] R. L. Siegel, K. D. Miller and A. Jemal, Cancer statistics, (2015), CA: A Cancer Journal for Clinicians 65(1), 5-29. https://doi.org/10.3322/caac.21254

[11] K. Simonyan and A. Zisserman, Very deep convolutional networks for Large-scale image recognition http://www.robots.ox.ac.uk/ (2015).

[12] J. Suckling, J. Parker, S. Astley, I. W. Hutt, C. Boggis, I. W. Ricketts, E. Stamatakis, N. Cerneaz, S. Kok, P. Taylor, D. Betal and J. Savage, The mammographic image analysis society digital mammogram database, Undefined (1994).

[13] N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway and J. Liang, Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? IEEE Transactions on Medical Imaging, 35(5) (2016), 1299-1312. https://doi.org/10.1109/TMI.2016.2535302

[14] D. Yi, R. L. Sawyer, D. Cohn, J. Dunnmon, C. Lam, X. Xiao and D. Rubin, Optimizing and Visualizing Deep Learning for Benign/Malignant Classification in Breast Tumors (2017). http://arxiv.org/abs/1705.06362.