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PERFORMANCE COMPARISON OF THE RESNET50 AND INCEPTIONV3 DEEP TRANSFER LEARNING MODELS OVER THE BREAST CANCER THERMOS GRAM DATASET

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ABSTRACT

This paper simply illustrates a performance comparison of two generally used and efficient deep transfer learning architectures like Resnet50 and InceptionV3. The Resnet50 and IncetionV3 deep transfer learning models are trained and evaluated on the Infrared thermo gram breast cancer dataset. In this study, both these models are trained as well as fine-tuned for the correct classification of breast cancer from the breast thermo gram images. The Resnet50 model simply outperforms the InceptionV3 model by achieving an accuracy of more than 85 %.

Keywords: Breast cancer, Thermogram, Normal, Abnormal, Resnet50, InceptionV3 etc.

I. INTRODUCTION

In present times, cancer of breast is the most frequently detected and diagnosed cancer types in both the genders. However females are mostly diagnosed with this type of cancer [1]. Numerous unknown reasons are accountable for the cancer of breast development in human body but one of the establishedreasons is the irregular development of cells. In human organs, there are some genes which are wholesale responsible multiplication and division of cells but sometimes these genes are unable to detect any anomalies which in future results in sort of accumulation of dead cells in the form of a tumor or cyst. These cyst or tumors can be classified as non-cancerous and cancerous. These cancerous breast tumors may spread or affect other body organs as they transfer via blood. If breast cancer gets diagnosed in its early stage then the chances of patient's health revival as well as survival is maximum [2]. As in its advanced stage, breast cancer is almost incurable. There are number of clinical techniques used for the early detection as well as classification of breast cancer such as time to time screening, use of medical imaging like Thermography, X Ray Mammograms, mris, CT scans etc. Out of these, Infrared thermography (IRT) is one of the effective and economical early screening techniques employed for the Breast cancer detection. This IRT techniques is very popular among patients as well as physicians as it is completely free from any radiation as well as not involve any painful invasive procedures. The IRT is totally based on the concept of quantifying the thermal infrared radiation discharged by surface of any human organ in order to capture its thermal signatures which are used to detect the breast cancer [3]. Even some of the studies has proved that the IRT or Thermography screening technique is far better and accurate for younger women in terms of detecting breast cancer as compare to the conventional mammography screening technique [4]. Deep learning is an evolving field of artificial intelligence and it is being widely used in self-driven cars, industries, object detection, facial recognition etc. So the deep transfer learning models like Resnet 50 and

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Inception V3 can also be used for automatingthe task of cancer of breast detection using the breast thermo grams or IRT images.

A decent amount of research is already being done in the domain of breast cancer detection based on machine learning and deep learning. Arena et al. [5] and Schaefer et al. [6] proposed an algorithm for the breast cancer detection based on machine learning and proposed feature extraction methods. Whereas Partridge and Wrobel [7] based their research over the breast tumor characteristics and genetic algorithms utilizing thermo grams. Then Kennedy et al. [8] come up with a study in which a brief comparison is carried out in between ultrasound, thermography and mammography. Most of the machines learning based approaches are based on new and improved feature extraction methods along with Support vector machine (SVM).These methods deliver an accuracy of 85 to 90 %. Then a new trend is started utilizing Convolutional Neural Network (CNN) models for the breast cancer detection based on thermo gram images. These deep learning based models have completely automate the task of breast lesion or cyst segmentation then feature extraction employing various texture, shape and intensity based feature extraction methods and finally classification using a conventional machine learning classifier. Chougrad et al. [9] and Al-masni et al.[10] developed a CNN centered model for complete cancer of breast screening. Then Flores et al. [11]suggesteda Resnet18 based approach for the classification of cancer of breast and achieves an accuracy of 85%. Then Yadav et al. [12] perform the comparison in between the VGG16 and Inception V3 models for the detection of breast cancer. In this comparison Inception V3 outperforms VGG 16.

II. Proposed Methodology

In this study initially Breast thermal images are preprocessed and augmented. Then this augmented breast thermogram dataset is used for the training of resnet50 and inceptionv3 deep transfer learning models. The complete illustration is represented by figure 1 below:

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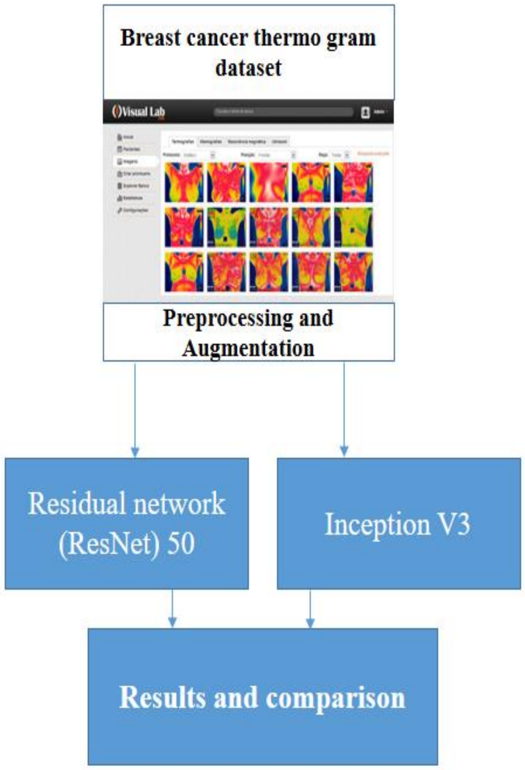

Figure 1: The overall proposed approach

A. Dataset used

In this study, Database for Mastology Research with Infrared Image (DMR-IR) is employed as this database is being +used and referred by the majority of research papers as it is a standard global dataset. This database consist of around 37 cases of breast cancer thermo arm Images and 19 cases of healthy breast thermo gram Images. All these Infrared images are recorded utilizing the FLIR SC620 thermal camera. Each breast thermal images is having a dimension of 640*480 pixels (http://visual.ic.uff.br/dmi).

B. Augmentation

Dataset augmentation is done utilizing data generation of 4 types like rotation range, shear range, rescaling and zoom range. These four types of image augmentation tends to augment the breast thermal images in order to create a sufficient size dataset for the training of Resnet50 and Inception V3 models.

C. Resnet50

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In this paper, we have transfer the resnet50 model trained on the ImageNet to our breast cancer dataset. The initial 49 layers of this model are retained and a fully connected along with dense layer are added to our resnet50 model in order to perform the binary classification [13]. The breast thermal image of size 224*224 is feeded into this model and this resnet50 model tends to converge at 200 epochs with a batch size of 16. With total parameters of 29,861,378 out of which 14,176,258 are trainable and 15,685,120 are non-trainable parameters.

D. Inception V3

The Inception V3 model belongs to the Google's Inception Convolutional Neural Network family. This model is transfer from the Imagenet to the breast cancer dataset by modifying the last layer of this model in order to perform the binary classification [14]. In Inception V3 model, breast thermal image of size 299*299 is given as input and this model also tends to converge at 200 epochs with a batch size of 16. With total number of 22,064,930 parameters out of which 262,146 are trainable and 21,802,784 are non-trainable parameters. The detailed configuration of both the resnet50 and inceptionv3 DTL models used in this study are presented with the help of table 1 below.

Table 1: The configuration parameters of inceptionv3 and resnet50

DTL models parameters	Inceptionv3	Resnet50
Input image size	299*299	224*224
Number of layers	48	50
Learning rate	0.00001	0.00001
Batch size	16	16
Number of Epochs to converge	200	200
Momentum	0.9	0.9
Optimizer	Adam	Adam

II. Result and simulation

The Google Colaboratory (colab) platform powered by the nvidiaTesla T4 GPU is used for the experimentation and simulation in this study. The Python 3.6 is used as an implementation

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programming language.The augmented dataset is used in the proportion of 70:30 i.e. 70 % for training and 30% for validation.

For testing purpose total forty out of which twenty abnormal and rest normal thermal breast images (Breast cancer) are used.The validation and testing performance of both the resnet50 and Inception V3 deep transfer learning models are illustrated using the various classification rates given in the table 2and 3below.

Table 2: Validation performance of resnet50 and Inception V3 model over the thermal images breast cancer dataset

Classification rates	**Their formulas**	**Resnet50**	**Inception V3**
Accuracy	(TP + TN) / (TP +TN+FP+ FN)	78.57	60.71
Sensitivity	TP / (TP + FN)	73.91	60
Specificity	TN / (FP + TN)	81.82	60.78
Precision	TP / (TP + FP)	73.9	13.04
Negative Predictive Value	TN / (TN + FN)	81.82	93.94
False Positive Rate	FP / (FP + TN)	0.1818	0.3922
False Discovery Rate	FP / (FP + TP)	0.2609	0.8696
False Negative Rate	FN / (FN + TP)	0.2609	0.40
F1 Score	2TP / (2TP + FP + FN)	73.91	21.43
Where TP = True positive, TN = True Negative, FP = False Positive, FN = False Negative			

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Table 3: Testing performance of resnet50 and Inception V3 model over the thermal images breast cancer dataset

Classification rates	Resnet50	Inception V3
Accuracy	95	82.5
Sensitivity	95	100
Specificity	95	74.07
Precision	95	65
Negative Predictive Value	95	100
False Positive Rate	0.05	0.2593
False Discovery Rate	0.05	0.35
False Negative Rate	0.05	0.00
F1 Score	95	78.78

The training loss and training & validation graph of resnet50 and Inception V3 model for breast cancer detection are illustrated with the figure 2 and 3. Whereas the ROC curve of resnet50 and Inception V3 model is presented below using the figure 4 and 5.

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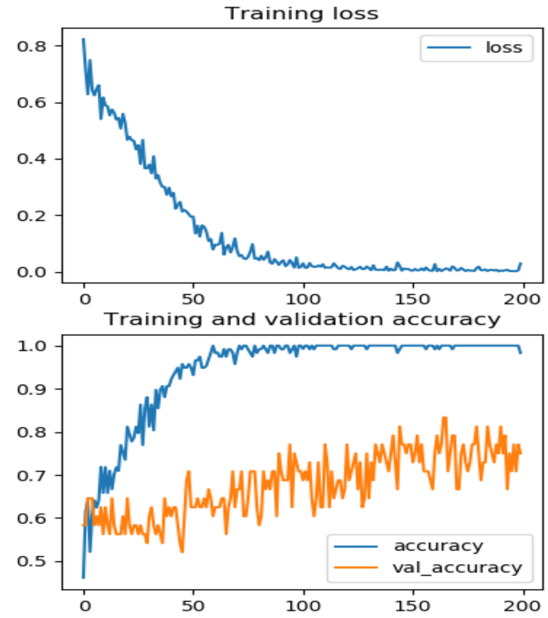

Figure 2: resnet50 model training &validation accuracy and training loss graphs

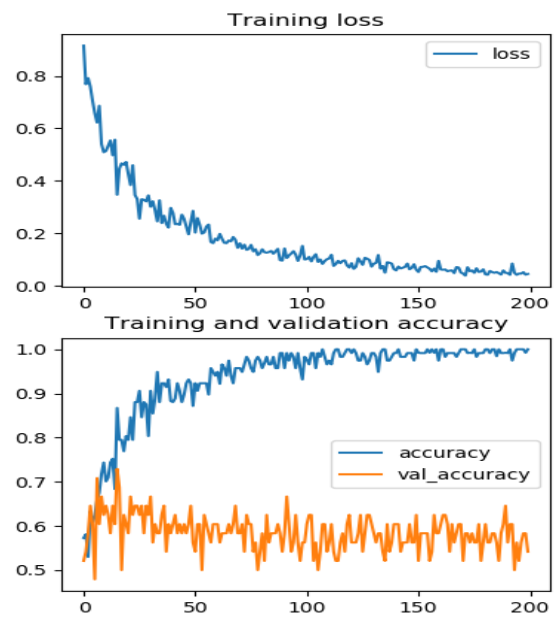

Figure 3: inceptionv3 training & validation accuracy and training loss graphs.

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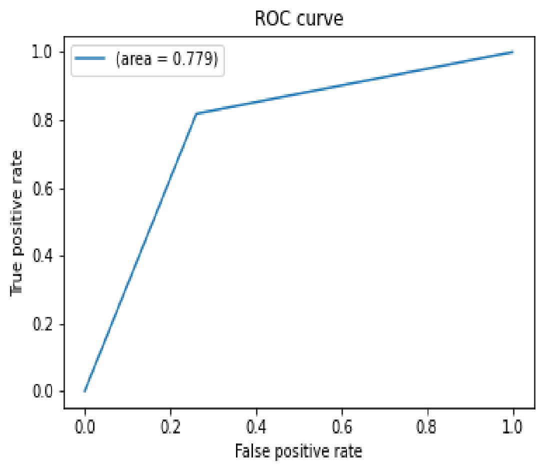

Figure 4: resnet50 model ROC curve

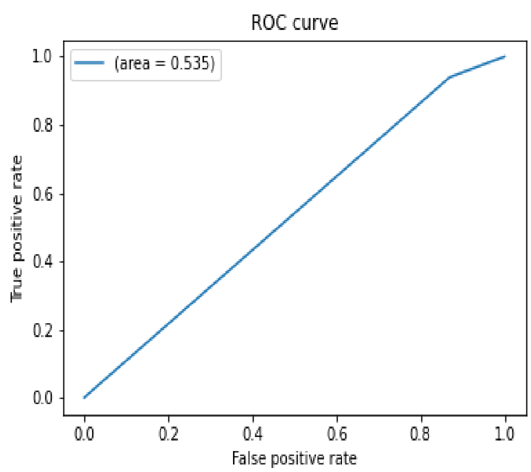

Figure 5: Inception V3 model ROC curve

IV. CONCLUSION

The result section simply proves that the performance of the resnet50 model over the Breast thermal image dataset developed using the DMR-IR database is far better as compare to the Inception V3 model. The validation and testing accuracies of 78 and 95 is delivered by the resnet50 deep transfer learning model. The ROC curve, training loss and training & validation graphs depicted in the result section proves above stated fact. The resnet50 model tends to diagnose the breast cancer with high accuracy. The other deep transfer learning models can also be used in future to train over this breast cancer thermal images dataset and can deliver 100% accuracy.

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