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Breast Cancer Detection using Convolutional Neural Network Models

Ms. Ishwari Dawkhar[1], Mr.Aniket Asalkar[2] , Mr.Vaibhav Mankar[3] , Prof. Swati B.Patil[4]
[1,2,3]UG – Information Technology, Vishwakarma Institute of Information Technology, Pune, Maharashtra
[4] Assistant Professor, Information Technology, Vishwakarma Institute of Information Technology, Pune, Maharashtra

ABSTRACT
This research paper discusses eight distinct convolutional neural network models for detection of breast cancer with the help of histopathology images. The eight different models are broadly classified into four main models, namely, VGC 16, DenseNet 201, MobileNet V2, and Inception V3, and use of optimizers for deriving different training and validity accuracies. This research paper compares all the 8 models on the basis of their accuracies and losses to determine a preferable model that can be used for breast cancer detection.
Keywords— convolutional neural networks, image recognition, deep learning, machine learning

1. Introduction

Breast cancer is caused when cells in the breast, lymph, and nodes grow out of control exponentially. Breast cancer is majorly caused in young females and is one of the most common type of cancer to be diagnosed in women. Histopathology images from the primary form of diagnostic for a patient, wherein, cells and tissues from suspicious body parts are tested for malignancy. Since early detection and diagnosis can play a major role in reducing the life-risk of patients, medicinal science and technology are collaborating optimistically to develop better detection methods for people. This research paper is produced on the basis of eight convolutional neural network models. Any convolutional neural network is a type of artificial neural network developed in order to facilitate the process of image recognition, image classification, and image processing. Convolutional neural network within deep learning has shown positive results, especially for medical detection and diagnosis. Any convolutional neural network model architecture is designed to accept input data (most commonly image data) and take up the strategy of 'transfer learning', where a model is built on input which is used to train the machine to achieve high accuracy results from the main data based on the data used to train the system. This research paper describes the use of 4 broad convolutional neural network models which are known as VGG16, DenseNet 201, MobileNetV2, and InceptionV3, and their different optimizers to train the machine model to detect whether a patient is diagnosed with cancer or not, depending on the data used to train the model. Each model has its own list of advantages and disadvantages which are depicted by the accuracy obtained as a result of the models, but the basic advantages of these models are that they can efficiently detect complex and important image features which are crucial for image processing, image classification, and image recognition, without human interference and they help maximize performance, accuracy, and efficiency of huge data ecosystems to achieve targeted results.

2. Experimental Methods or Methodology

This research paper consists of 4 convolutional neural network models namely, VCG16, DenseNet 201, MobileNetV2, and InceptionV3, and their different optimizers whose accuracy is then further compared for the detection of breast cancer.
The four broad convolutional neural network models developed for breast cancer detection are VCG16, DenseNet 201, MobileNetV2, and InceptionV3, along with their optimizers to form eight

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different models to compare the results of all the models developed on the basis of validation accuracy.

A. VGG16:- VGG sixteen is a sixteen-layer deep convolutional neural network. A formerly skilled model that has been skilled on extra than one million photographs from the ImageNet dataset may be loaded through developers. The formerly skilled network is in a position to differentiate among a thousand items of various sorts categorically consequently the community has followed a sizeable variety of picture functions of various items and categories. The dimensions of any picture enter in the version are (224,224,3). The version is designed to method the output of a thousand values. The vector is an illustration of the class opportunity of facts classes. In this case, 'class 0' represents non-cancerous histopathology photographs, and 'class 1' represents cancerous histopathology photographs. The elegance possibilities are introduced to one through the use of the softmax function.

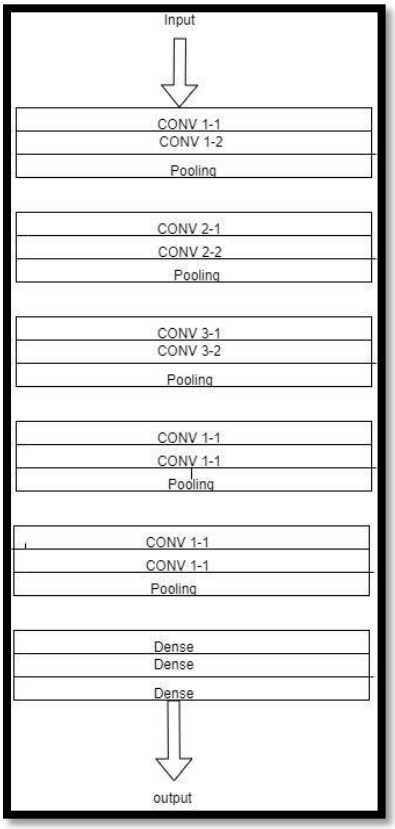

Fig 1: Flow of VGG16 Model

B. DenseNet 201:- It is determined in convolutional neural networks that information vanishes among the long-distance of input layers and output layers ensuing in a vanishing gradient. Therefore, the DenseNet version is evolved to enhance the accuracy via way of means of growing the intensity of the network by lowering the wide variety of layers. For instance, if a network has ‘d’ number of layers in its network, the number of connections among the layers will be ‘d’. Densenet version allows us to have d(d+1)/2 number of connections among the layers and thus, the network density is accelerated compared to that of additive models like ResNet. In the method of accepting input from all of the previous layers, the version is certain to stand a characteristic map explosion as quickly because the layers boom in number. Therefore, a dense block is delivered for a prespecified number of layers to keep away from clustering and the explosion of feature maps. The output from one dense block is driven to a ‘transition layer’ from in which it’s miles driven for ‘max pooling’ for reduction of the dimensions of feature maps. The intensity of DenseNet 201 is 201 layers.

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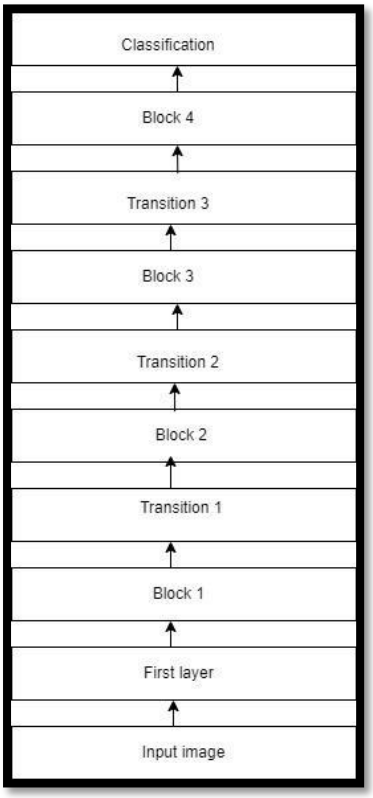

Fig 2: Flow of DenseNet 201 model

C. MobileNet V2:- MobileNet V1 was brought with the intention to lessen the usual version length and computation length of neural networks and lead them to effortlessly well matched with cell gadgets and different gadgets which own low computational power. A MobileNet V2 version includes 2 blocks with three layers of each respectively. The first block is called the 'residual layer' with 1 stride and the second one block with 2 strides is used for downsizing. The first layer in every block is 1X1 along side ReLU6. ReLU6 is thought for its performance with much less particular computation, the second one layer is for acting light-weight filtering through a single filter for a convolutional network for every input channel and the third layer is a 1X1 convolution unbiased of non-linearity.

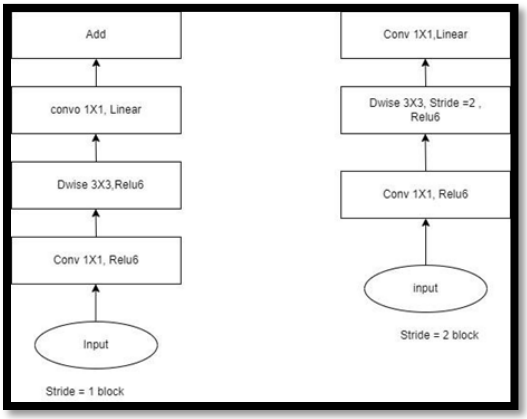

Fig 3: Flow of MobileNet V2 model

D. InceptionV3:- The Inception V1 model was developed to counter the issue of data overfitting due to multiple deep layers of the convolutional network by applying multiple filters of varied sizes on a single layer. The resulting Inception models enable the model to be wider because of parallel layers

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instead of deep layers. Inception V3 is an advanced and modulated version of the preceding models V1 and V2. It is also cost-effective and functions at the same computational speed as V1 and V2. The traditional 5X5 convolutional layer of V1 was replaced by two 3X3 convolutional layers in V3 which reduces the computational cost. Furthermore, asymmetric convolutions involved replacing the two 3X3 convolutions with one 1X3 convolution and the next 3X1 convolution and thus the improved spatial arrangement reduces the computation cost further by around 33% of the previous reduced cost. The grid size, as compared to V1 and V2 is also reduced in V3 by the expansion of the activation dimension of network filters.

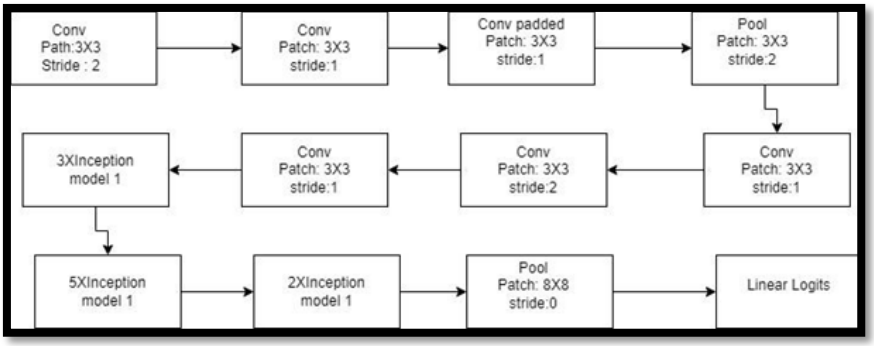

Fig 4: Flow of InceptionV3 model

This paper comprises of eight distinguished models, results of accuracy of which are compared with each other.

A. VGG16:- In this paper, we carried out the conventional VGG16 along with unique optimizers. The number one use of optimizers is to decrease losses through changing the attributes of weights and rates of learning. The first is with Adam as an optimizer and loss function as a 'binary_crossentropy' as it is binary classification. For our VGG16 version, we didn't encompass the top layer and trained with the 'ImageNet' dataset. Till the block5_pool layer, the layers of the model are frozen and we encompass different top layers. We flattened the preceding output and brought the primary dense layer with 128 neurons observed through a dropout of 0.3, on the other hand, dense layer with 64 neurons after which the top layers have best one neuron because it classifies binarily. The activation features utilized in dense layers are 'Relu' and for the top layer 'Sigmoid' is used for the binary classification.

B. DenseNet 201:- In this paper, we carried out the conventional DenseNet 201 along with one of a kind optimizers. For DenseNet201, we used Adam as an optimizer, the loss function is binary_crossentropy and accuracy is metric for the training of our model for classifying photos into malignant or benign. Here additionally we eliminated the top layer of DenseNet201 and all of the above layers are frozen. We delivered a few layers and gave the input because the output of the pre-trained version. First, we delivered a max-pooling layer with the stride of (1,1) then we flattened the output of the max- pooling layer. We have 2 layers with the sixteen neurons and however one dense layer of eight neurons and the 'relu' changed into the activation function we used. Then we've a top layer with a single neuron with a sigmoid as an activation function for our binary classification.

C. Inception V3:- In this paper, we applied the conventional Inception V3 along with distinctive optimizers. The real model includes symmetric and deviated assembling blocks, together with convolutions, common pooling, max pooling, dropouts, concatenations, and absolutely linked layers. Batch normalization is applied extensively throughout the model and applied to activation inputs. Loss is processed utilizing 'Softmax'. We compiled the model with the identical parameters as we trained for DenseNet201, as Adam as an optimizer, loss function as 'binary_crossentropy', and metrics as accuracy. We excluded the top layer of the pre-trained model and iced up all of the layers in order that the ones want now no longer gain knowledge of again. Then we flattened the output of

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the model and surpassed as a input to subsequent Dense layer that we brought which has 32 neurons with 'relu' as an activation function for a few non-linearity after which there's a top layer that has a single neuron and 'sigmoid' as an activation function.

D. MobileNet V2:- In this paper, we implemented the conventional MobileNet V2 model. The convolution layer structure includes 32 channels, trailed through 19 leftover bottleneck layers. Since MobileNet V2 is primarily based totally on an inverted residual structure contrary to mobileNet V1, the residual blocks are skinny bottleneck layers.

3. Results and Discussion

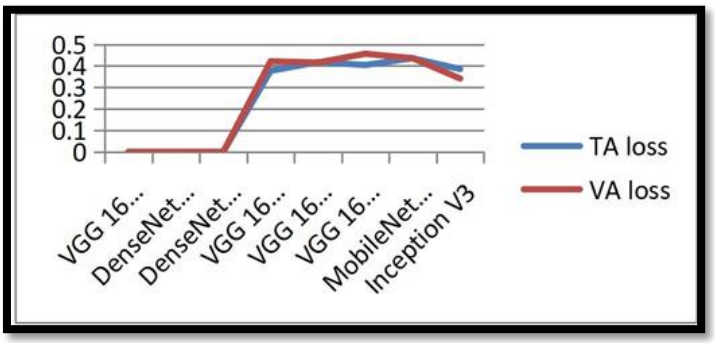

Fig 5: Result analysis of training and validation accuracy of all models

Given above is the comparison of accuracies (training and validation) procured from the models described in the paper earlier. It can be observed that even though Densenet 201 25% trainable batch size 64 has maximum training accuracy, the validation accuracy obtained is less and the difference between both the accuracies is 3.06 which is considerably high. The next highest training accuracy is observed for Densenet 201 0% trainable wherein validation accuracy is also obtained less and the difference between the two accuracies is highest amongst all other models, that is 3.4. Hence, Densenet 201 gives a remarkable training accuracy but the difference between the training and validation accuracy of densetnet201 weakens the performance of the entire model. This happens because the Denset201 model requires comparatively more epochs in the testing phase than in the training phase to successfully reach the convergence stage. The model with promising training and validation accuracies with comparatively less difference between the two is InceptionV3. The reason for high accuracies in both training and validation dataset is because InceptionV3 gives best results when the data is independent of each other, that is, there are no or very less data samples which are common in classes of data. In the dataset that we have used, it is observed that we have two distinct classes of images, class 0 and class 1, which give image data for cancerous and non- cancerous containing cells for patients through histopathology reports. This is why the accuracy obtained in case of InceptionV3 is high and hence it can be considered strongly for detection of breast cancer through histopathalogy reports.

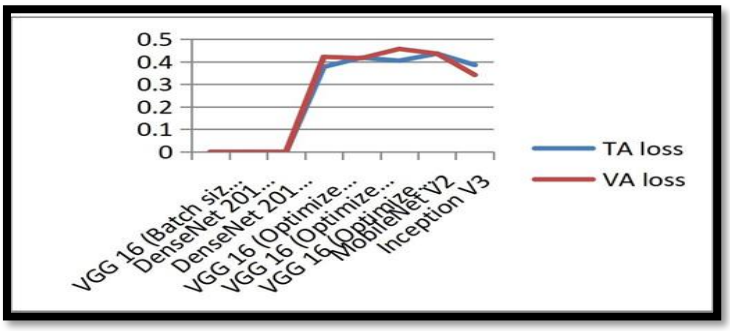

Fig 5: Result analysis of training and validation accuracy losses of all models

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Given above is the comparison between the training loss and the validation loss for all the models. It is clearly seen that VGG 16 batch size 34 and Densenet 201 give out no losses in execution of their model but other models do.In case of VGG 16 as a model, the conventional VGG 16 records no losses but when executed with optimizers such as SGD, RMSprop, and Adagrad records losses, which are highest in the case of adagrad. This can be resolved by implementing the model in an enlarged convolution kernel and to reduce some intertwined and connected layers of the model in order to decrease the overall complexity of the model and the parameters that cause the effect of losses on the model's overall accuracy. Since the accuracy for all VGG 16 models is lower than other models, it is let below in the order of preference of the usage of the model for breast cancer detection. MobileNet V2 model also records some high losses while execution of the model. These losses can be covered through increase in the number of channels allocated in the previous convolutional network so that the overall capacity of the network enhances, leading to fewer losses. MobileNet V2 has upper hand in it's advanatages as compared to VGG 16 and Densenet 201, but since we recorded less accuracies for the model than Inception V3, the model steps down in order of preference. In the case of Inception V3, the model has recorded second least training accuracy loss and least validation accuracy loss. This is because of 'label smoothing' that is implemented in addition to the preceding versions of the model. This component was incorporated in order to regulate over-fitting of data which causes losses to decrease considerably. Hence Inception V3 is a model which not only gives high accuracy but also cuts short of the losses experienced in previous models.
The next step in this model development can be integrating an external feature extraction method to increase the accuracy of the models and get a detailed detection report of cancer cells present or absent in a patient's body through the test of histopathology images. Feature extraction will help majorly in image processing and detecting new variants of cancer that seem to be occurring in patients in the current day and age**.**

3.2 Comparison of Observations

Model	**Observations**		
	parameters	***Training accuracy***	***Validation accuracy***
VGG16 (Batch size - 32) Epoch – 30	Total parameters: 14,846,273 Trainable parameters: 131,585 Non-trainable parameters: 14,714,688	82.96	83.22
DenseNet201 (25% trainable) (Batch size-64) Epoch- 200	Totalparameters: 20,986,433 Trainableparameters: 8,484,289 Non-trainableparameters: 12,502,144	88.56	85.50

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DenseNet201 (0% trainable) Epoch -200	Totalparameters: 20,986,433 Trainableparameters: 2,664,449 Non-trainableparameters: 18,321,984	86.66	83.26
VGG16 (optimizer-SGD) (0% trainable) Epoch-200	Totalparameters: 15,108,929 Trainableparameters: 394,241 Non-trainableparameters: 14,714,688	83.94 (loss-0.3771)	82.84 (loss-0.4215)
Model	**Observations**		
	parameters	***Training accuracy***	***Validation accuracy***
VGG16 (optimizer-RMSprop) (0% trainable) Epoch-200	Totalparameters: 15,108,929 Trainableparameters: 394,241 Non-trainableparameters: 14,714,688	83.74 (loss-0.4045)	80.32 (loss-0.4568)
VGG16(optimizer-Adagrad) (0% trainable) Epoch-200	Totalparameters: 14,977,857 Trainableparameters: 263,169 Non-trainableparameters: 14,714,688	81.74 (loss-0.4178)	83.74 (loss-0.4158)
MobileNetV2 Epoch-200	Totalparameters: 5,011,521 Trainableparameters: 2,753,537 Non-trainableparameters: 2,257,984	80.75 (loss-0.4357)	80.20 (loss-0.4358)
InceptionV3 Epoch-200	Totalparameters: 22,065,185 Trainableparameters: 262,401 Non-trainableparameters: 21,802,784	83.53 (loss-0.3854)	85.10 (loss-0.3414)

Table.1. Comparision of observations recorded

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CONCLUSION

While concluding this research paper, it is proved that the validation accuracy obtained for all models discussed in the paper is in the range 80.20-85.10 and the training accuracy obtained for all models discussed in the paper is in the range 80.75-88.56. It can also be concluded that the highest accuracies recorded with the least difference in training and validation accuracies is in the case for the Inception V3 model. Thus the most adequate and effectively trained model is InceptionV3 which can be used for breast cancer detection through an extensive input of breast histopathology images.

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