Performance analysis of Rheumatoid Arthritis using Convolutional Neural Networks

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Rheumatoid Arthritis (RA) is a kind of an autoimmune and chronic disease. RA generally observed with inflammation, swollen, stiffness, joint pain and loss of functionality in the joints. Inflammation starts at smaller joints of the body, in later stages inflammation spread to heart and other organs of the body. Initial symptom are shown to be less effective but in later stage it causes major difference in the functionality of the joints. Therefore, an accurate RA detection in its early stage is very much essential. Various modalities are being used for the purpose of RA diagnosis notably radiography, ultrasound and Magnetic Resonance Imaging (MRI). Even though various modalities used in the assessment of joint damage and position changes, plain radiography is the best and effective method. Different scoring methods used in the RA assessment but all scoring methods involved the joint evaluation of finger, hands, feet and wrist. The traditional scoring methods and manual diagnosis process require more human intervention and time. The development of CNN architecture for automated RA detection avoids manual method of preprocessing, handcrafted segmentation and classification. CNN architecture plays vital role in the RA disease diagnosis and automation. The work includes the development of four different CNN architectures for RA detection namely ResNet50, VGG16, DenseNet121 and InceptionV3. All the models have trained with augmented and non-augmented dataset. At the end of 50th epoch, InceptionV3 accuracy reached 98.91% with error of 1.85%. DenseNet121 model reached 97.27% with minimum error of 7.73%. InceptionV3 validation accuracy reached 98.8% on validation set that indicates that InceptionV3 has low variance compared to other models. Even inceptionV3 perform well on F1 score, precision, recall and specificity plots of other models.

Keywords: Convolutional Neural Network (CNN), Inceptionv3, Rheumatoid Arthritis (RA), ResNet50, Vgg16, X-ray

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I. INTRODUCTION

RA generally observed with inflammation, swollen, stiffness, joint pain and loss of functionality in the joints. Connective tissues, tendons, ligaments, cartilages and muscles also get affected by RA [1 2 3]. However, early detection of the disease may save the life and increase life span of the people with proper medication and treatment plan. Along with primary check-up and blood test, the rheumatologists suggest for imaging of the affected part for proper disease evaluation. Radiography considered as the best and effective tool in the assessment of RA because experimentation is relatively cheap and service available at almost all the hospital and clinic [4 5 6]. There is no cure and permanent solution for RA disease. Early beginning of the medication can avoid disease progression and future disability problems. Few medications used for RA disease such as disease-modifying

antirheumatic drugs (DMARDs), AntiTNF drugs, B-cell therapies and T-cell therapies [7 8]. Different modalities are being used for the purpose of RA diagnosis problems namely X-ray, MRI, ultrasound, bone scintigraphy and CT. X-ray is the best and effective tool in the assessment of joint damage and position changes in RA patients [9 10 11]. Recent method of RA evolution is modified total sharp (mTS) score method but mTS methods requires more time and rheumatologists intervention for disease diagnosis. Implementation of mTS score method used support vector machine and which include 45 dataset [12]. The manual methods are time consuming and need physician intervention for RA disease diagnosis. An automatic detection can be possible with machine learning methods. A convolutional neural network (CNN) is a subset of machine learning method used for automatic RA detection. CNN used in many other applications like natural language processing, audio processing, image analysis and medical applications. CNN is particularly reduces the burden in feature extraction and classification stages [13 14]. Different CNN architectures shows their vital role in the field of classification, localization and object detection in computer vision application [15 16]. Apart from the computer vision problems, CNN pulled is attention in the medical field. CNN architecture based medical application used in image classification and object detection problems [17]. CNN based medical application include an automatic osteoarthritis severity predication [18], early detection and different stages in the management of gout arthritis and Poststreptococcal reactive arthritis in children [19 20] etc. The complete deep learning applications in the medical image analysis discussed [21 22]. DenseNet is a 121 layer CNN [23]. CheXNet [24] network trained with ten thousand X-ray images with 14 different diseases. The Xception model [25] and Vgg16 based model used for image classification. The work includes the performance analysis of different CNN architectures like ResNet50, DenseNet121, VGG16 and InceptionV3 for the RA classification purpose.

II. Literature review

In RA diagnosis, doctors suggest any one of the modality test along with blood test based on problem severity. Radiography consider as the best and effective tool in the assessment of joint damage and position changes, but radiograph gives only two-dimensional (2D) visualization whereas MRI and ultrasonography gives three-dimensional(3D) visualization of RA affected joints. Kumara et al [26] used a series of image processing operation like contrast enhancing followed by adaptive histogram equalization. Gaussian filter used for the removal of random noise. Finally, edge detection used to find edges. Bhisikar et al [27] presented automatic RA analysis based on statistical feature. Analysis process involves preprocessing and segmentation. Gabor filter used for local texture feature. Subramoniam et al [28] used image segmentation algorithms for arthritis detection. Median filter used to remove noise from the input image. Histogram calculated from the filter image, and then a region-growing algorithm used for grouping purpose. Once the grouping operation is completed, edge detector used to find out edges. Mitta et al [29] presented an arthritis detection method based on a morphology operation. Dilation and erosion are the morphology operations used for image enhancement. Vinoth et al [30] introduced an arthritis detection method. The detection process involves operations like de-noising, histogram smoothing, and edge detection segmentation. The GLCM used to extracting features such as energy, entropy, correlation, homogeneity and contrast. Helwan et al [31] introduced new system for RA identification. System involved preprocessing, segmentation and neural classifier for RA identification. Murakami et al [32] implemented a system for RA diagnosis based on bone erosion. CNN architecture along with segmentation algorithms used to RA disease diagnosis. Segmentation algorithm used for phalangeal area extraction whereas CNN architecture used for detection of pathology information. The experimentation contains 129 hand radiology images that include both normal and RA images. Oyedotun et al [33] proposed RA classification based on neural network. CNN architecture has input layers, hidden layers and output layer. The input images presented at input layer and classification result obtained at output layer. The hidden layer learns all the needed features, which are essential for image classification. Murakami et al [34] implemented automatic bone erosion detection using crude segmentation and Multiscale

Gradient Vector Flow (MSGVF) snake method. The traditional manual methods use handcrafted features for medical image classification. Advancements of computer vision and machine learning algorithms many of the medical image analysis applications using for object detection as well classification. Deployment of machine learning, especially in the field of lupus arthritis, brain tumor, osteoarthritis etc., plays vital role [35, 36, 37]. CNN architectures having capable of extracting feature which are essentially required for further processing [38]. Few CNN large-scale online dataset like MNIST, CIFAR-10 and ImageNet are available. Keras produces few CNN's that have pre-trained models with ImageNet dataset are VGG16, VGG19 [39], ResNet50, Inception V3 and Xception [40] and other available CNN networks are AlexNet [41], ResNet [42] and DenseNet [43]. Moreover, CNN used for image classification application need high-rich extracted feature. CNN extract features stage by stage at convolution layers [44]. The work includes the evaluation of different performance matrices with different CNN architectures, which are helpful in the classification of the normal and RA images. The main contributions of this work include as follows (i) accuracy based comparative study of CNN models (ii) variation of categorical cross entropy loss with different networks (c) evaluation of different performance measures like precision, recall, specificity and F1 score.

III. Materials and Methods

CNN architecture has input layers, hidden layers and output layer. Input images presented at input layer, associated features are leant at hidden layers and the result is obtained at output layer. CNN architecture has multiple convolution layers, pooling layer and activation layer. The convolution layers of the CNN plays vital role in feature extraction. The convolution filters used to find different feature at different layers by applying multiple filters of different kernel sizes on input images. Pooling layers help to reduce the network parameters, reduction in the parameters reduce processing complexity at the next layers. Pooling layer implemented with some nonlinear function such as average pooling and max pooling. A ReLU it maps all the negative values to zero and retains all the positive values.

a. Image dataset

The X-ray dataset collected from ChanRe Rheumatology and Immunology Center, Bangalore, Karnataka, India. Dataset include both normal and RA affected images. A dataset consisting of 398 radiographs images, which includes 201 normal images and 197 RA images. The total dataset divided into training and validation dataset. Training dataset includes 358 images (90% of the total dataset) and 40 images used for validation (10% of the total dataset). Image dimension is restricted to 256 * 256 sizes. Few x-ray samples of normal and RA image is shown in fig 1.

Fig 1: shows RA images and Normal images.

b. Data augmentation

Deep learning needs a large amount of dataset for correct production on testing image but it is very difficult to get required amount of dataset in various fields like medical. Data augmentation is a necessary step to increase overall performance of the network and also it avoids overftting, irrelevant pattern reorganization, and memorizing condition occurred during network training phase. All the algorithms are trained with non-augmented as well as augmented dataset. Initially images are resized to 256*256 sizes. Data augmentation operations include width shift and height shift by 0.1 pixels, shear transformations by 0.01 pixels, zoom range by 0.15 and rotation by 5 degree. All the images are normalized to 256 * 256 sizes. Table 1 describes about data augmentation operations used in the RA detection.

Table 1: Describe about data augmentation operations

Data augmentation operations	Values
Width shift range	0.1
Height shift range	0.1
Shear range	0.01
Zoom range	0.15
Horizontal flip	True
Fill mode	Reflect
Rotation range	5

c. CNN architectures

The work includes CNN architectures such as ResNet50, VGG16, DenseNet121 and InceptionV3. Tensor Flow machine learning platform used to create different CNN architectures. All algorithms are trained with non-augmented as well as augmented dataset. Images are resized to 256*256 sizes. The models are trained in Tesla-K80 GPU, which can do up to 8.73 Teraflops single-precision and up to 2.91 Teraflops double-precision performance with NVIDIA GPU Boost.

Binary cross entropy is given by,

$$CE = -\sum_{i=1}^{C'=2} t_i log\left(f(s_i)\right)$$
$$= -t_1 log\big(f(s_1)\big) - (1 - t_1) log\big(1 - f(s_1)\big) \quad (1)$$

Where $f(s_i)$ represents sigmoid function given by

$$f(s_i) = \frac{1}{1 + e^{-s_i}}$$

IV. Results and discussion

CNN architectures like ResNet50, VGG16, DenseNet121 and InceptionV3 trained with normal and RA x-ray images. Every model is trained for about 50 epochs. Training phase performed with non-augmented as well as augmented dataset. The images are resized 256*256 sizes.

a. Evaluation metrics

The CNN architectures like ResNet50, VGG16, DenseNet121 and InceptionV3 are trained with augmented as well as non-augmented dataset. The performance of the each model is evaluated by using different parameters such as accuracy, loss, sensitivity, specificity, recall, precision and f1 score. Table 2 describes different performance analysis parameters and its formulas used in the RA detection.

Table 2: Describes about performance analysis formulas.

Performance parameters	Formulas
Accuracy	(TP+TN)/(TP+FN+TN+FP)
Loss	(FP+FN)/ (TP+FN+TN+FP)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)
F1 score	2 * (Precision * Recall) / (Precision + Recall)

Where TP, TN, FN and FP represents the total number of true positive, true negative, false negative, false positive respectively.

Table 2: Performance analysis of ResNet50, VGG16, DenseNet121 and InceptionV3

Architecture	ResNet	VGG16	VGG16	DenseNet 121	DenseNet 121	Inception	Inception
Augmentation	NO	YES	NO	YES	NO	YES	NO
Loss	0.1177	0.3989	0.2664	0.0773	0.0727	0.0466	0.0185
Accuracy	0.9454	0.8306	0.9126	0.9672	0.9727	0.9836	0.9891
F1	0.9488	0.7904	0.9102	0.9679	0.9702	0.9797	0.991
Precision	0.9667	0.9585	0.8712	0.9804	0.9907	0.9815	1
Recall	0.9338	0.6889	0.9592	0.9589	0.9514	0.9798	0.9825
Specificity	0.9705	0.9596	0.8758	0.9785	0.9881	0.9889	1
Val_loss	0.6661	2.5056	25.4669	0.8945	9.1439	0.5947	0.0244
Val_accuracy	0.6842	0.4211	0.5263	0.6316	0.5263	0.9474	1
Val_F1	0.75	0.3529	0	0.4615	0	0.9474	1
Val_precision	0.6	0.375	0	0.75	0	0.9	1
Val_recall	1	0.3333	0	0.3333	0	1	1
Val_specificity	0.4	0.5	1	0.9	1	0.9	1
ResNet	NO	YES	NO	YES	NO	YES	YES
0.2022	0.1177	0.3989	0.2664	0.0773	0.0727	0.0466	0.0185
0.9344	0.9454	0.8306	0.9126	0.9672	0.9727	0.9836	0.9891
0.9335	0.9488	0.7904	0.9102	0.9679	0.9702	0.9797	0.991
0.944	0.9667	0.9585	0.8712	0.9804	0.9907	0.9815	1
0.9254	0.9338	0.6889	0.9592	0.9589	0.9514	0.9798	0.9825
0.9391	0.9705	0.9596	0.8758	0.9785	0.9881	0.9889	1
34.6733	0.6661	2.5056	25.4669	0.8945	9.1439	0.5947	0.0244
0.5263	0.6842	0.4211	0.5263	0.6316	0.5263	0.9474	1
0	0.75	0.3529	0	0.4615	0	0.9474	1
0	0.6	0.375	0	0.75	0	0.9	1
0	1	0.3333	0	0.3333	0	1	1
1	0.4	0.5	1	0.9	1	0.9	1

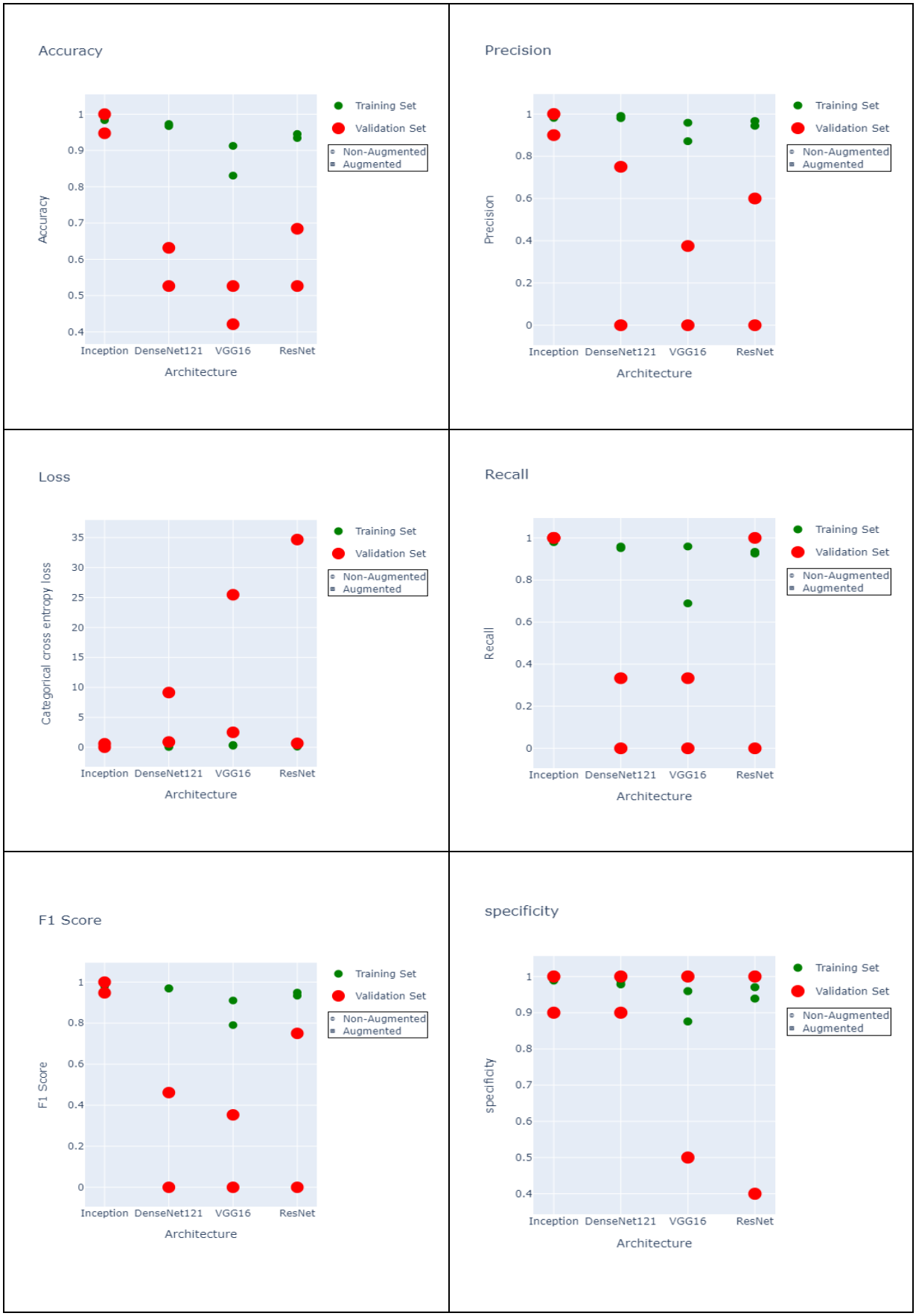

Fig 2: Performance analysis of ResNet50, VGG16, DenseNet121 and InceptionV3

Fig 2 shows ResNet50, VGG16, DenseNet121 and InceptionV3 performance analysis parameters and its values. InceptionV3 accuracy reached 98.91% for non-augmented dataset with error of 1.85% whereas DenseNet121 model accuracy reached 97.27% with error of 7.73%. InceptionV3 model validation accuracy reached 94.7% on validation set indicating that InceptionV3 has low variance compared to other models. From aaccuracy plot, inceptionV3 performs well on both training and validation dataset compared with other models. On the other hand loss plot shows the variation of categorical cross entropy loss of different networks. InceptionV3 results minimum categorical cross entropy loss of 1.85% and 4.6% for non-augmented and augmented dataset respectively compared with other models. Similar conclusion can be observed in F1 score, precision, recall and specificity plots of inceptionV3. InceptionV3 perform well compared to other models. At the end of 50th epoch, the accuracy of inceptionV3 and DensNet121 are reached 95% and above. InceptionV3 perform well on both training and validation set. InceptionV3 model validation accuracy is more compared to all other models. Network with good validation accuracy specify that network has low variance. Also, it is observed that there is a wide gap between training and validation set in F1 score, accuracy, precision, specificity and recall of VGG16 and ResNet50 (VGG16 even being more). Networks with more gaps indicate that, those networks are not as generalizable as InceptionV3 and DenseNet121. From recall plot, inceptionV3 recall value is 0.9825 on training set in case of non-augmented and even performs well on validation set. InceptionV3 recall value indicates that network is slightly better robustness towards prediction of disease compared to other networks. From specificity plot shows that, specificity of inceptionV3 and DenseNet performs well on validation set. Validation specificity values of both inceptionV3 and DenseNet network are 0.9 for non-augmented and 1 augmented dataset respectively. Validation specificity value indicates that predication of non-disease cases. InceptionV3 and DenseNet both networks good in predication of non-disease cases. It is observed that the size of inceptionV3 is higher compared to VGG16 and ResNet50. In ResNet, Inception a layer to receive outputs from the previous second or third layer but it's not the case of DenseNet hence more memory is needed than the shown in case of DenseNet for prediction described in Fig 3.

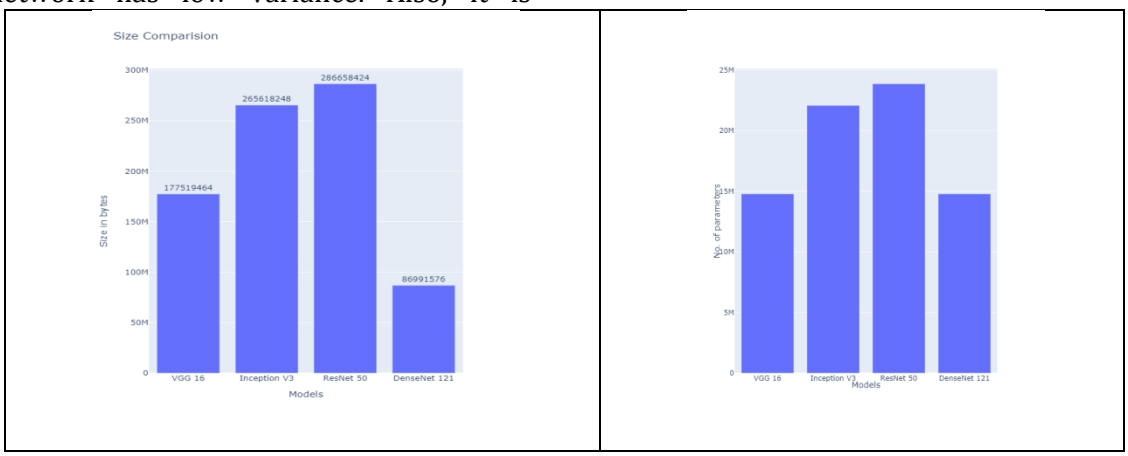

Fig 3: Comparison of ResNet50, VGG16, DenseNet121 and InceptionV3 parameters and size

V. Conclusion

The work includes comparative study of ResNet50, VGG16, DenseNet121 and InceptionV3 architectures for RA disease diagnosis. All the networks trained with augmented as well as non-augmented dataset. At the end of 50th epoch, InceptionV3 accuracy reached 98.91% for non-augmented dataset with minimum error of 1.85% whereas DenseNet121 model accuracy reached 97.27% with error of 7.73%. InceptionV3 model validation accuracy reached 94.7% on validation set indicating that InceptionV3 has low variance compared to other models. From aaccuracy plot, inceptionV3 performs well on both training and validation

dataset compared with other models. On the other hand loss plot shows the variation of categorical cross entropy loss of different networks. InceptionV3 results minimum categorical cross entropy loss of 1.85% and 4.6% for non-augmented and augmented dataset respectively compared with other models. Similar conclusion can be observed in the InceptionV3 plots of F1 score, precision, recall and specificity. InceptionV3 perform well on both augmented and non-augmented compared to other models.

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