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An Analysis of Deep Learning Models to Diagnose COVID-19 using Radiography Images

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***Abstract*—Coronavirus(COVID-19) has created havoc for humanity by causing millions of deaths, adverse effects on physical and mental health and disastrous economic destruction. To aid with fast and efficient detection of the virus which allows for timely treatment of the patients, we have conducted this research work. In this work we have experimented and analyzed all the pre-trained and well known models. The performance of these various models in the detection of COVID-19 from Chest X-Ray images and their comparative study is depicted in this work. The best performing models were InceptionV3 (99.78%), InceptionResNetV2 (99.56%), DenseNet121 (99.34%), DensetNet169 (99.24%), DenseNet201 (99.34%) and Xception (99.12%).**

***Index Terms*—COVID-19, Deep Learning, Transfer Learning, Chest X-Ray images**

I. Introduction

Deep learning is a sub-branch of Machine learning, which is concerned completely with neural networks (inspired by the working and functioning of neurons in our brain)[1]. Deep learning techniques have been on a boost in the past few years due to their ability to learn without help and extremely efficient results like never seen before[2],[3],[7]. Deep learning is being used in various industries and areas of academics.

The variants of the SARS-CoV-2 coronavirus have been responsible for the loss of human life and rise of the pandemic. Since 2020 we have been noticing the cases increase. In November, 2021 we still have thousands of COVID-19 cases coming everyday in India as shown in fig 1. This calls for the need of this work.

In medical imaging especially, a lot of relevant research has been done already in predicting pneumonia using CXR; also in analysing CT scans and MRI images[4],[5],[10]. This makes deep learning the most desired topic of research for detection of Covid-19 in Chest X-Rays[6],[8]. As we know, testing of Covid-19 by X-Rays images does not require any new machinery and is efficient, accurate and feasible.

As of now, the complex patterns of Chest X-Ray images can only be understood and analysed only by specialty radiologistists. These are extremely few in number, especially in under-developed cities, as compared to the need for testing of Coronavirus, which is humungous. This is why we conducted this research: to assist physicians and general radiologists in conducting efficient and accurate prediction of coronavirus with minimum requirements.[9]

In deep learning techniques, Convolutional Neural Networks(CNN) have been extremely efficient for computer vision and are used extensively in medical imaging.[11] This is because the CNN models have proved to be powerful when it comes to the prediction of output by analysing and mapping the images to the correct output[12],[13]. This work aims to efficiently and accurately predict the differences in complex patterns of chest X-Ray images of Covid-19 infected and normal patients, which are indiscernible to the human eye.

Fig. 1. Current Stats of COVID-19 Out Break

II. Related Works

In [15] the author took 6432 chest x-ray scans samples from kaggle repository and compared InceptionV3, Xception and ResNeXt models and reported their accuracy. The author claimed the Xception model gave the highest accuracy of 97.97 %. The author used LeakyReLU instead of relu as an activation function and claimed it as a novel approach. In conclusion, the author stated that the high accuracy observed may be the result of overfitting and in future, larger datasets can be considered so as to validate the proposed model.

In [16] the author proposed Domain Extension Transfer Learning (DETL). The author stated that training a CNN from scratch requires significant expertise for architecture to

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work properly and also requires huge data for training. After performing 5-fold Cross Validation the claimed accuracy were 82.98% for Alexnet, 90.13% for VGGNet and 85.98% for ResNet. The author also implemented the concept of Gradient Class Activation Map (Grad-CAM) to find whether a model paid more attention during classification in an image.

In [17], a model COVID-CheXNet, a hybrid model for detection of coronavirus using X-ray images was proposed for diagnosis of Coronavirus. The dataset used consisted of 400 Covid-19 infected X-Rays and 400 normal X-Rays, curated from different sources. This was then augmented to a total of 24,000 images. Firstly the poor quality of the image was enhanced by the CLAHE method, and noise level was also reduced. Then ResNet34 and HRNet, two deep learning models, were jointly trained on the dataset. The COVID-CheXNet system had diagnosed the COVID-19 patients with an accuracy of 99.99%,specificity 100%, precision 100%, sensitivity 99.98%, and F1-score 99.99%.

In [18], three deep learning CNN approaches were implemented for detecting Covid-19 from Chest X-Rays. They were Transfer learning approaches- Fine-Tuning, Deep feature extraction and end-to-end training of a developed CNN model. For the purpose of deep feature extraction and fine tuning, pretrained CNN models such as VGG16, VGG19, ResNet18, ResNet50 and ResNet101 were used. An SVM classifier with different kernel functions was used for classification of the deep features. A dataset containing 180 COVID-19 infected and 200 normal chest X-ray images was used for this study. The deep features extracted from ResNet50 model showed an accuracy of 94.7% which was the highest of all results. The accuracy of the same model after fine tuning was observed to be 92.6%, whilst end-to-end training of the CNN model developed showed 91.6% accuracy. Various experiments with classifiers for performance comparison showed that deep approaches are more efficient.

III. Materials and Methods

In this section we explain the dataset used and the methodology carried out on various models as well as our custom architecture. We also present the reasoning and deep learning techniques involved in the work.

A. Dataset Collection

The dataset used in the research work is from [14] . The combined dataset of Covid-19 CXR images had been curated by the author from 15 publicly available datasets, which consisted of a total of 4558 COVID-19 X-Rays, 5403 Normal X-Rays, 4497 Viral pneumonia X-Rays, and 5768 bacterial pneumonia X-Rays. As a large number of X-Rays were found to be duplicates, they were removed by the use of Inception V3 architecture and followed by unsupervised learning algorithms based on cosine similarity distances [1].Author has cleaned the dataset and the final curated dataset contains 1281 COVID-19 X-Rays, 3270 Normal X-Rays, 1656 viral-pneumonia X-Rays, and 3001 bacterial-pneumonia X-Rays. For our research work we have used 1281 Covid-19 CXR and 3270 Normal CXR images from this. Link to Dataset : https://data.mendeley.com/datasets/ 9xkhgts2s6/3

B. Dataset Pre-Processing

Due to non uniformity of the dataset and the unevenness in the sizes of X-ray images, we have converted all images into the same size of 256 x 256 pixels. For this, RGB reordering has been applied and the final input to the proposed model is obtained as a 256×256×3 image.

C. Dataset Splitting

The dataset is split into 80% for training, 10% for validation and 10% for final testing/evaluation purposes. Table below shows the distribution of Covid-19 Infected and Normal CXR images for training, validation and testing set:

	Covid-19 Infected	Normal
Training Set	1025	2616
Validation Set	128	327
Testing Se	128	327

D. Dataset Augmentation

In case of most real life problems there is hardly ever an abundance of data, especially for medical imaging. To overcome this shortage we expand the training dataset by data augmentation in such a manner that important information is not lost. In the dataset, we have applied horizontal flip and scaling to best fit the models trained. This dataset is inadequate for training a CNN therefore, we performed data augmentation.

E. Transfer Learning

The process of making use of pretrained CNN models with feature extraction and fine-tuning is known as transfer learning. Rather than training a model right from scratch, we could be benefitted by using the weights from a pre-trained network that would accelerate the learning process. The initial layers of a model can be seen as feature descriptors for the images and the latter ones correspond to particular categories. Thus for most applications, several layers can be reused. Here various pre-trained models like VGG16,VGG19, Inception Family, Resnets Family, Densenets Family are used to perform transfer learning.

IV. Training Methodology

In the proposed method, firstly images are resized to 256*256 size for InceptionV3 and DenseNet169 and rest models; 224*224 for VGG16 & VGG19. This resizing has been done in accordance with the model requirements. Then we flatten the layer and map it with an output layer consisting of two neurons, one for Covid positive and another one for normal CXR images. For both deep feature extraction and fine tuning InceptionV3, DenseNet169 and other pre-trained models has been used.

Training Methodology summarized as in Fig 2:

1) Collecting and Pre-Processing Dataset.
2) Generating more images from existing dataset through data augmentation techniques.

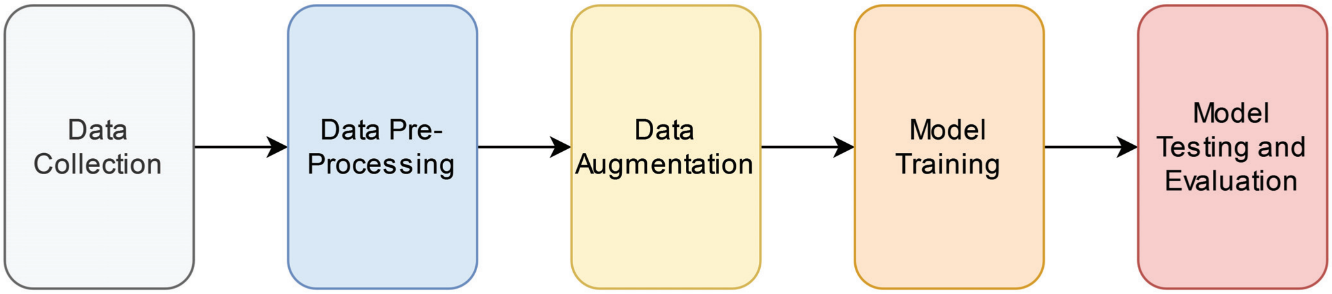

Fig. 2. Proposed Procedure from Data Collection to Model Testing and Evaluation

3) Splitting the dataset into 80% for training the model, 10% for cross Validating and 10% for testing/evaluating the model
4) Setting the Hyperparameters for better performance of the network.
5) Training each network for 100 epochs.
6) Making use of the validation set to evaluate the performance of the network while in training.
7) Using the testing set to report actual performance of the model trained.

A. Loss Function Used : Catagorical Cross Entropy

Loss function is used to help the model measure how far an estimated value is from the true value. This assists in defining what a good prediction is for the model to achieve. Cross entropy loss was the loss function used in the work and it's equation is given below:

$$J(\mathbf{w}) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log\left(\hat{y}_i\right) + \left(1-y_i\right)\log\left(1-\hat{y}_i\right)\right] \quad (1)$$

where,
- $\mathbf{w}$ refer to the model parameters, e.g. weights of the neural network
- y_i is the true label
- $\hat{y}_i$ is the predicted label

B. Classifier Used : Softmax

After training the models, updating weights according to loss function using suitable optimizer we used Softmax function for classification (equation 2).

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (2)$$

$\sigma =$ softmax
$\vec{z} =$ input vector
$e^{z_j} =$ standard exponential function for output
$K =$ number of classes in the multi-class classifier
$e^{z_j} =$ standard exponential function for output vector
$e^{z_j} =$ standard exponential function for output vector

Models were trained for 100 epochs to obtain the best training, validation and testing accuracy.

V. Experimental Setup

All the pre-trained models and our proposed model were implemented with Tensorflow in python. The training is performed for small epochs on personal computer with Intel(R) Core(TM) i7-6500U CPU 2.50GHz, Nvidia 940M GPU with compute capability 5.0 and 16 GB RAM. The complete training part is done on kaggle with GPU Tesla P100-PCIE-16GB compute capability: 6.0 and 16 GB GPU RAM. Each

VI. Results and Discussion

After data preprocessing and analyzing, we started implementation of various pre-trained deep learning models for our dataset and use case. Various optimizers have been experimented on and used for better performance in different models based on their analysis, comparative results are shown below.The first models we implemented were the VGG16 and VGG19 models with different optimizers(Table I) and this showed good accuracy, but with a lot of parameters. We then implemented Inception and InceptionResNet family of models, which are very popularly used; results shown in Table II : Inception Networks. Then the DenseNets and the ResNets(Residual Networks) were implemented with Adam and SGD optimizers, the results of which are shown in Table III and Table IV, respectively. Xception, AlexNet and NASNetLarge were also carried out with most commonly used optimizers; the results of which are shown in Table V. These were experimented on, as they have shown great performance in recognizing medical images before. InceptionV3 and DenseNet169 have performed extremely well.

TABLE I
RESULTS OBTAINED FOR VGGNET FAMILY WITH ADAM AND SGD OPTIMIZERS

No.	Name	Optimizer	Training Accuracy	Cross Validation Accuracy	Testing Accuracy	Parameters
1	VGG16	Adam	99.23	98.46	98.02	14,715,714
2	VGG16	SGD	98.55	98.46	98.46	14,715,714
3	VGG19	Adam	98.89	99.12	98.46	20,025,410
4	VGG19	SGD	98.31	97.8	98.24	20,025,410

TABLE II
RESULTS OBTAINED FOR INCEPTIONV3 AND INCEPTIONRESNETV2 WITH ADAM, SGD AND RMSPROP OPTIMIZERS

No.	Name	Optimizer	Training Accuracy	Cross Validation Accuracy	Testing Accuracy	Parameters
1	InceptionV3	Adam	99.35	98.68	98.9	21,806,882
2	InceptionV3	SGD	98.84	98.68	99.78	21,806,882
3	InceptionResNetV2	Adam	99.51	96.05	95.82	54,339,810
4	InceptionResNetV2	RMSProp	98.8	99.12	98.9	54,339,810
5	InceptionResNetV2	SGD	99.61	99.12	99.56	54,339,810

TABLE III
RESULTS OBTAINED FOR DENSENETS FAMILY WITH ADAM AND SGD OPTIMIZERS

No.	Name	Optimizer	Training Accuracy	Cross Validation Accuracy	Testing Accuracy	Parameters
1	DenseNet121	Adam	99.38	99.34	98.24	7,039,554
2	DenseNet121	SGD	99.81	99.34	99.34	7,039,554
3	DenseNet169	Adam	99.56	99.34	99.56	12,646,210
4	DenseNet169	SGD	99.96	99.12	99.24	12,646,210
5	DenseNet201	Adam	99.72	99.56	99.34	18,325,826
6	DenseNet201	SGD	99.69	99.34	98.9	18,325,826

TABLE IV
RESULTS OBTAINED FOR RESIDUAL NETWORKS WITH ADAM AND SGD OPTIMIZERS

No.	Name	Optimizer	Training Accuracy	Cross Validation Accuracy	Testing Accuracy	Parameters
1	ResNet50	Adam	97.72	97.36	98.46	23,591,810
2	ResNet50	SGD	94.85	95.82	95.16	23,591,810
3	ResNet152	Adam	96.85	96.92	97.58	58,375,042
4	ResNet152	SGD	93.18	97.36	97.14	58,375,042

TABLE V
RESULTS OBTAINED FOR XCEPTION, ALEXNET, NASNETLARGE MODELS WITH ADAM AND SGD OPTIMIZERS

No.	Name	Optimizer	Training Accuracy	Cross Validation Accuracy	Testing Accuracy	Parameters
1	Xception	Adam	99.82	99.12	99.12	20,865,578
2	Xception	SGD	99.57	99.34	98.90	20,865,578
3	AlexNet	Adam	99.03	98.02	97.8	58,295,042
4	AlexNet	SGD_0.001	99.76	98.68	97.14	58,295,042
5	AlexNet	SGD	99.92	98.68	98.9	58,295,042
6	NASNetLarge	SGD	85.87	93.41	92.53	84,924,884

A. InceptionV3

Inception net V3 is a 48 layers deep convolutional neural network and uses inception module. An Inception Module consists of an Input layer, 1x1 3x3 5x5 convolution layer, Max pooling layer and Concatenation layer.

The InceptionV3 model shows an accuracy of 99.78%, sensitivity of 100% and specificity of 99.21% as shown in Table 3. The loss and accuracy curve of the model training is shown in fig 3 & 4 respectively.

B. DenseNet169

It is a type of convolutional neural network that utilises dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other. The DenseNet169 model shows an accuracy of 99.56%, sensitivity of 100% and specificity of 98.43%. Fig 5 & 6 shows the model loss and accuracy as the epochs increase for training and testing sets respectively.

VII. CONCLUSION

This work has explored the utilization of Chest X-Ray images which are a feasible, efficient and cost-effective method of testing for the efficient and accurate detection of COVID-19 in patients. The curated dataset of total CXR images was pre-processed and augmented before the most extensively used models were experimented on with suitable optimizers. Experiments were conducted on this basis and the results were compiled to present a comparative study of all the

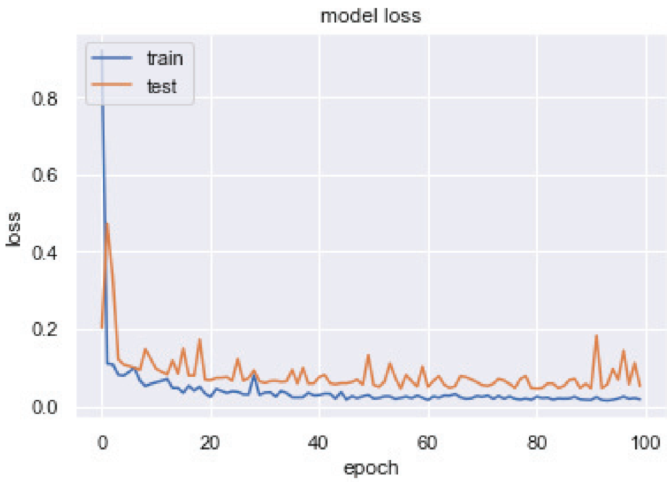

Fig. 3. InceptionV3 loss on Training and Testing on 100 Epochs

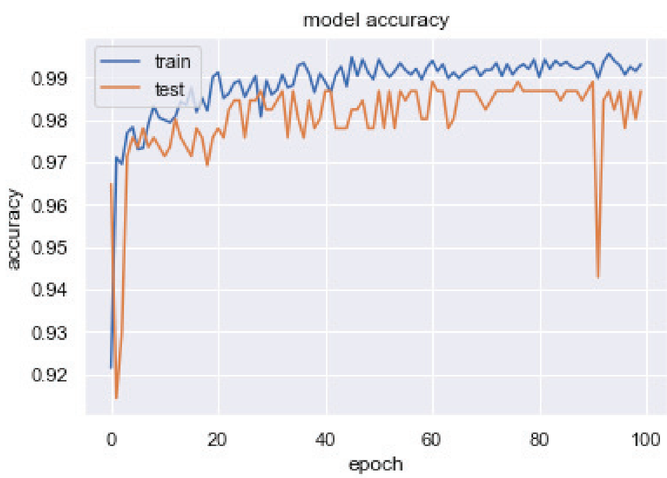

Fig. 4. InceptionV3 accuracy on Training and Testing on 100 Epochs

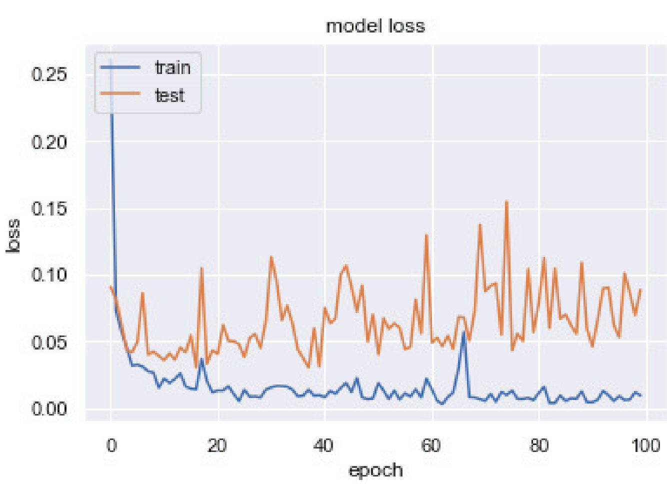

Fig. 5. DenseNet169 loss on Training and Testing on 100 Epochs

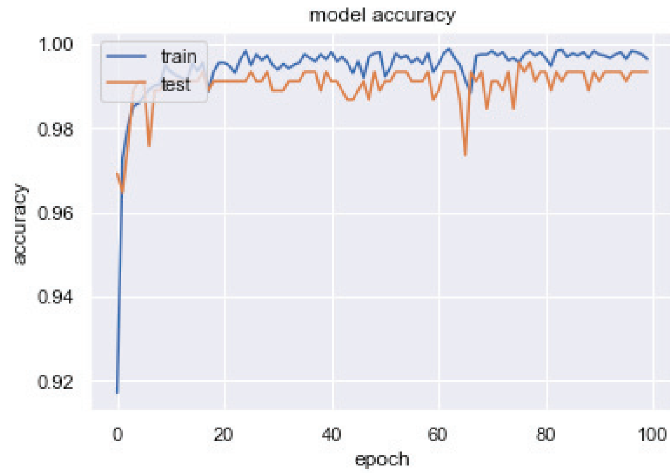

Fig. 6. DenseNet169 accuracy on Training and Testing on 100 Epochs

models and their performance: Accuracy and time taken. The best performing models in terms of accuracy were InceptionV3 (99.78%), InceptionResNetV2 (99.56%), DenseNet121 (99.34%), DensetNet169 (99.24%), DenseNet201 (99.34%) and Xception (99.12%). The models which took the least amount of time for a decent accuracy were These models can be considered for use on more heterogeneous datasets and also for detecting other lung diseases like pneumonia in the future.

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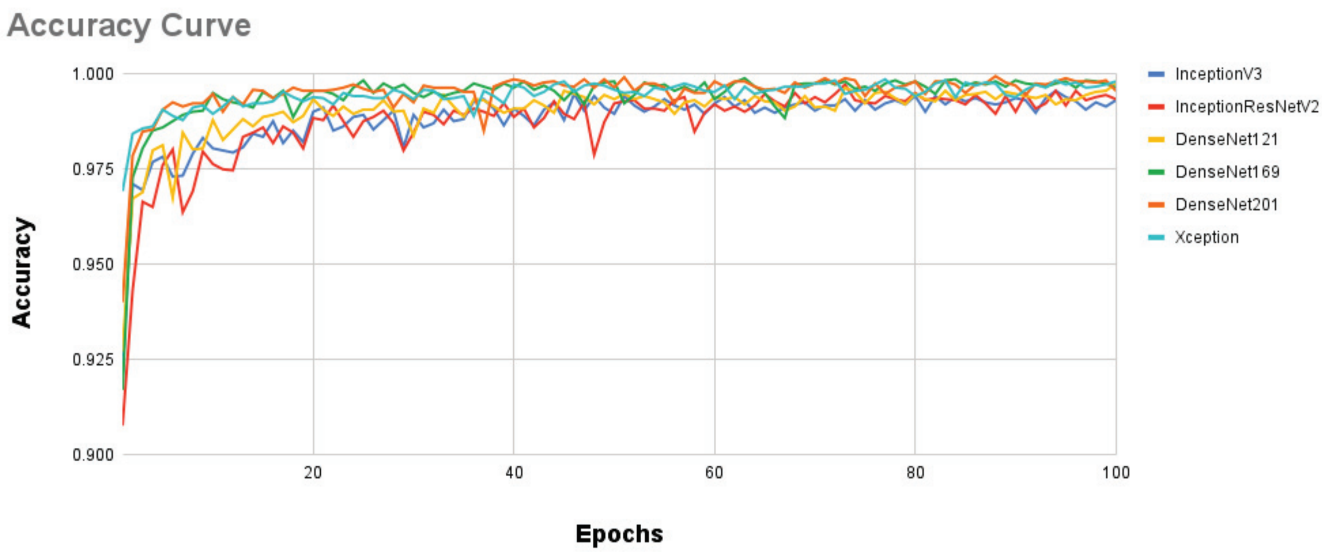

Fig. 7. Accuracy Curve of Top Performing Models (InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169, DenseNet201, Xception)

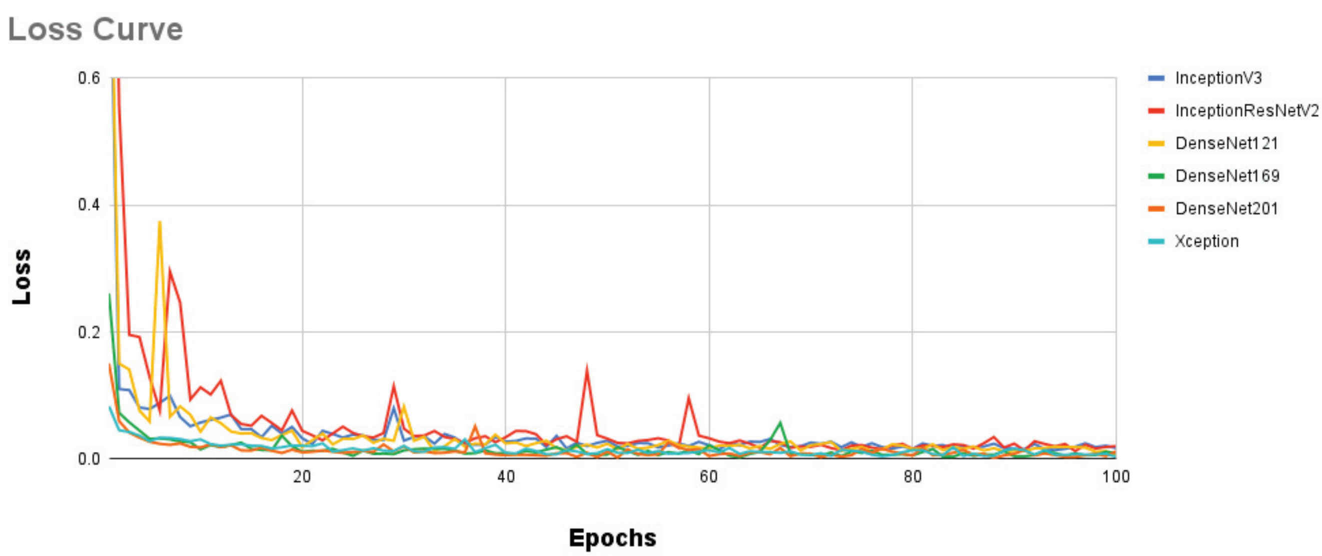

Fig. 8. Loss Curve of Top Performing Models (InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169, DenseNet201, Xception)

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