Classifying Chest X-Ray COVID-19 images via Transfer Learning

Ethics and Explainability for Responsible Data Science (EE-RDS) 2021

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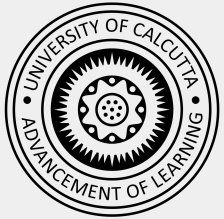

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Introduction

- COVID-19 has changed the way humans interact with the world. It is one of the events in history where humans has thrown almost everything to fight the pandemic with science and technology.
- Medical sectors have a tremendous opportunity in applying Artificial Intelligence and Deep Learning for leveraging the diagnosis process via automation.
- This study deals with the application of Transfer Learning in classifying Chest X-Ray COVID-19 images with high Accuracy, Sensitivity and Specificity.
- We have used standard known Deep Learning architectures as backbone to classify the given dataset.[†]
- The models used here were previously trained on the ImageNet dataset and were fine-tuned to get desired results.

[†]Dataset Retrieved from https://cxr-covid19.grand-challenge.org/Download/

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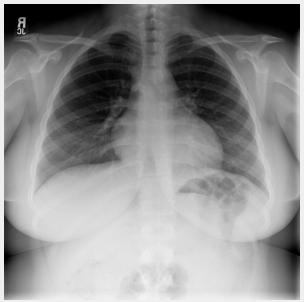
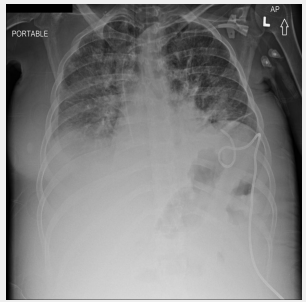
Dataset

- There are **3** classes present in this dataset as shown in the right.
- There are **5273** Pneumonia images, **7966** COVID-19 images, and **8151** Normal images of sizes **512x512** and **1024x1024** (both 3 channel and grayscale).
- There is a minor class imbalance.
- The distribution of Training and Validation dataset is shown in the Figure (on right).
- The images were rescaled to **360x360** size with 3 channels with intensities normalized between 0 and 1 before passing to the model.

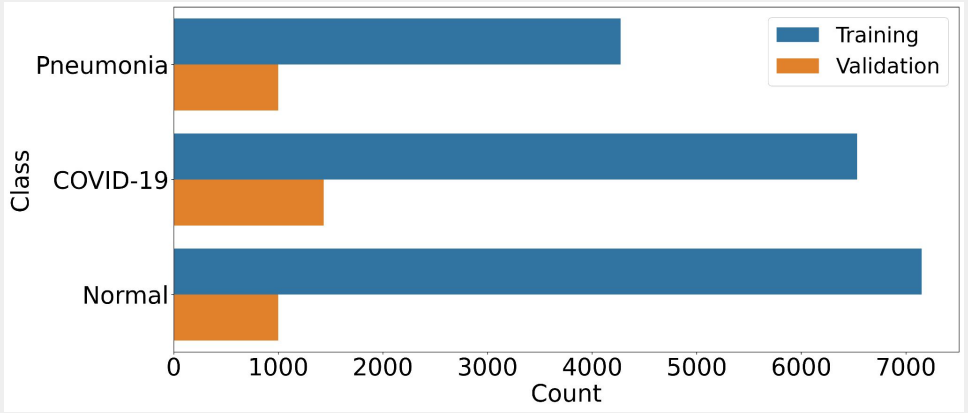


Normal

Covid-19



Pneumonia



Data distribution across different classes

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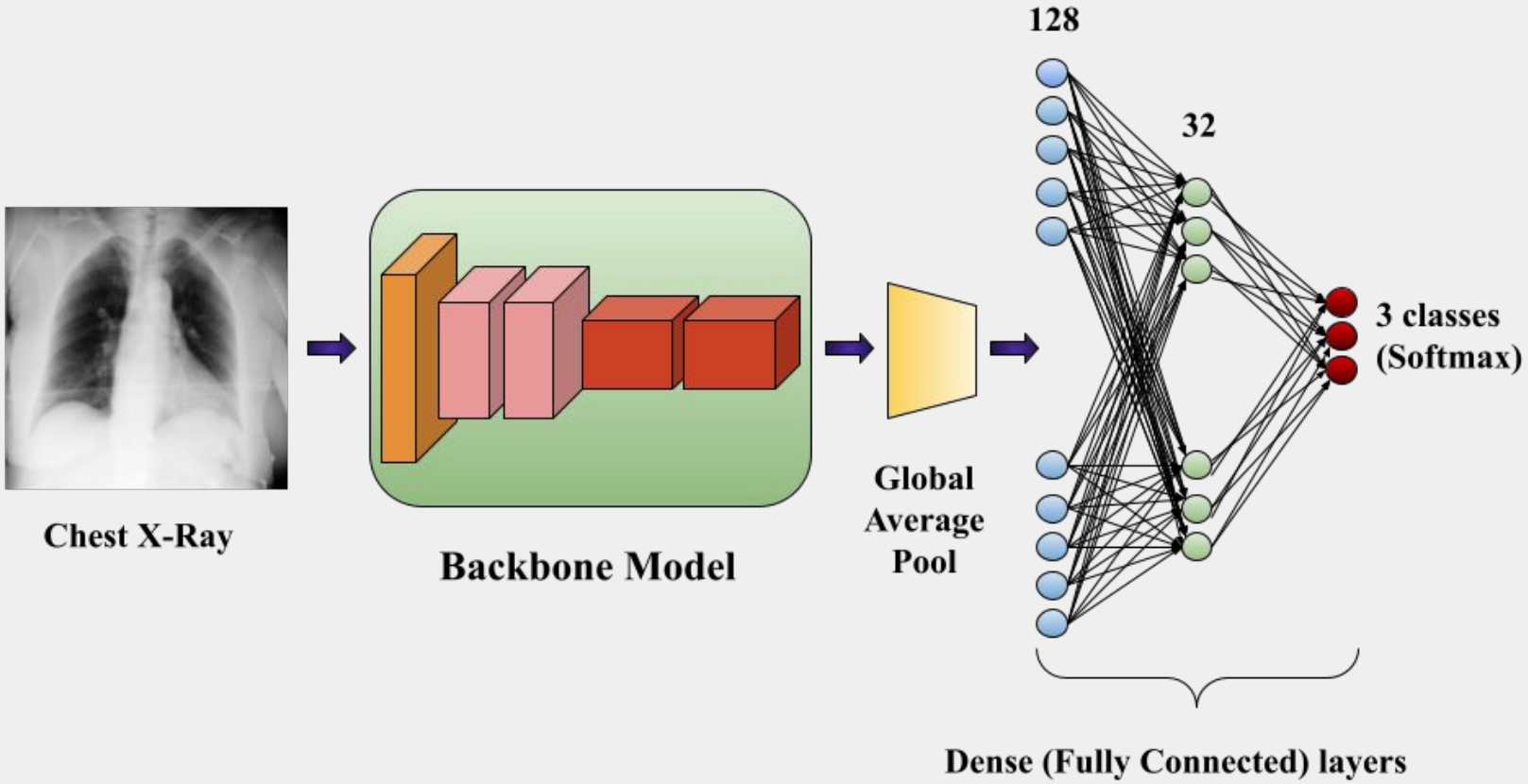
Model Structure

- The architecture of the model which was used to check the performance of validation dataset is shown in the figure (next page).
- We use the backbone model as the convolutional part of all the standard architectures that were taken into consideration for the study.
- After the backbone model, a global average pooling was used before passing it to fully connected (dense) layer comprising of **128-32-3** neurons.
- The output layer has 3 neurons corresponding to the 3 classes with softmax as activation function.

Model Structure



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Metrics

- Categorical Cross-Entropy is used as loss function which can be written as:

$$CE = -\sum_{i}^{C=3} t_i log(s_i)$$

- Here, t_i is the actual class and s_i is the predicted class.
- Accuracy, Sensitivity and Specificity are written as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad Specificity = \frac{TN}{TN+FP}$$

$$Sensitivity = \frac{TP}{TP+FP}$$

- Here, TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative.
- Adam optimizer was used with a learning rate of 1e-04.
- All the models were made using Tensorflow and Keras framework in Python3 language.

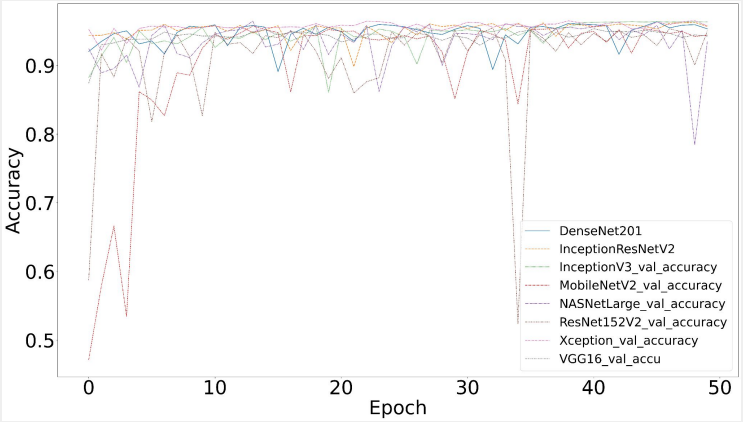
Results on the Validation Datasets

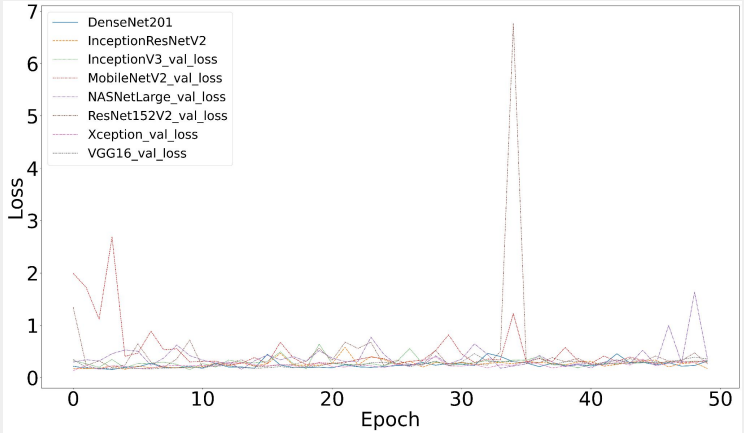
- We have used standard architectures and computed the results on the validation dataset by using the same model as shown in the previous slide.
- The results obtained from training is shown in the Tables (in right).
- Due to the limitations in memory we have selected different batch sizes, and the details of each of them are shown in the Table (in right).
- It is worth noting that Inception V3 performs better than all of the other models in the validation dataset by training on training dataset.
- The graph across 50 epochs are shown in the next slide for training of individual models.

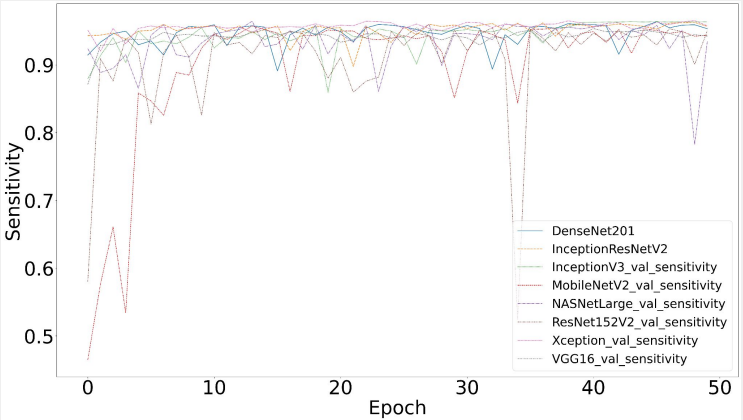
Model Name	Accuracy (in %)	Sensitivity (in %)	Specificity (in %)
MobileNetV2 [14]	96.29	94.09	97.36
VGG16 [9]	96.85	94.75	97.74
DenseNet201 [12]	96.87	94.79	97.75
Xception [13]	97.16	95.34	97.99
InceptionResNetV2 [23]	97.11	95.30	97.94
ResNet152V2 [10]	96.69	94.51	97.61
NASNetLarge [16]	95.69	92.61	96.63
InceptionV3 [11]	**97.57**	**95.98**	**98.27**

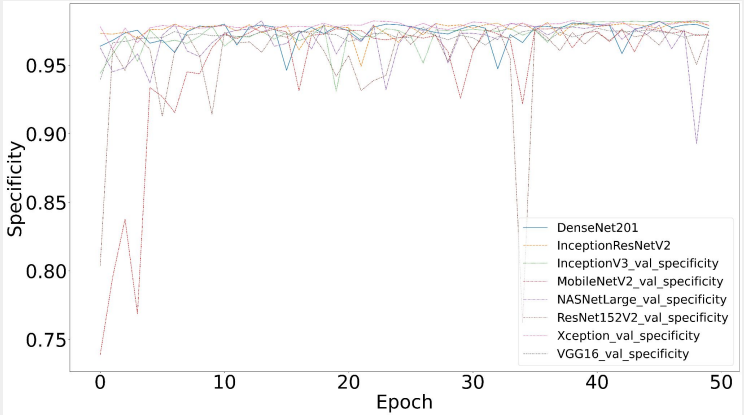
Model Name	Total Parameters (in Million)	Batch Size	Avg Time per epoch (in sec)
MobileNetV2 [14]	2.42	32	224
VGG16 [9]	14.78	32	303
DenseNet201 [12]	18.57	16	366
Xception [13]	21.12	16	489
InceptionResNetV2 [23]	54.53	16	438
ResNet152V2 [10]	58.59	8	590
NASNetLarge [16]	85.43	8	1443
InceptionV3 [11]	92.06	32	218

Results on the Validation Datasets









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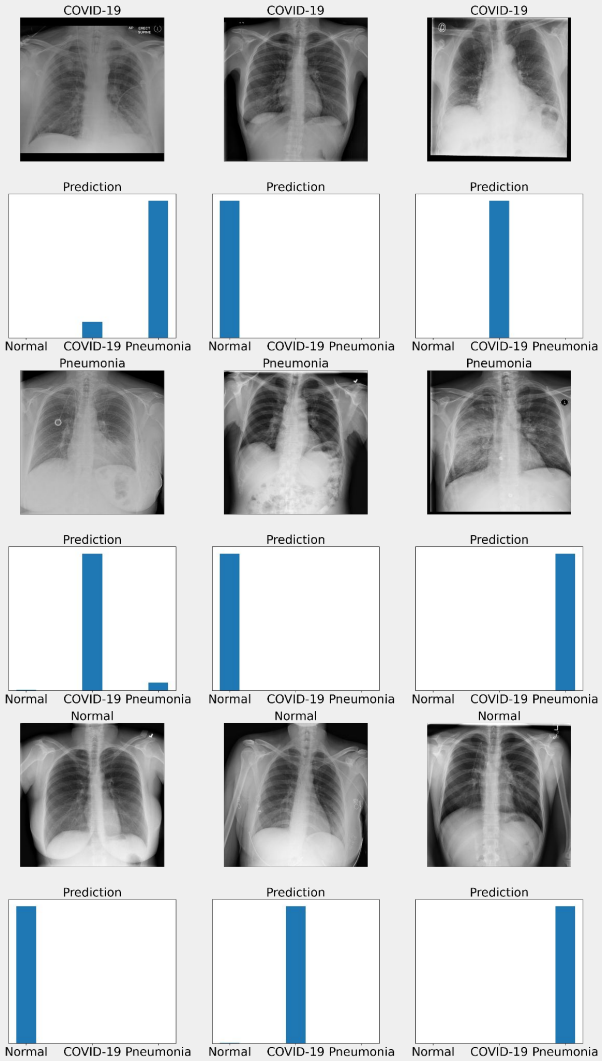
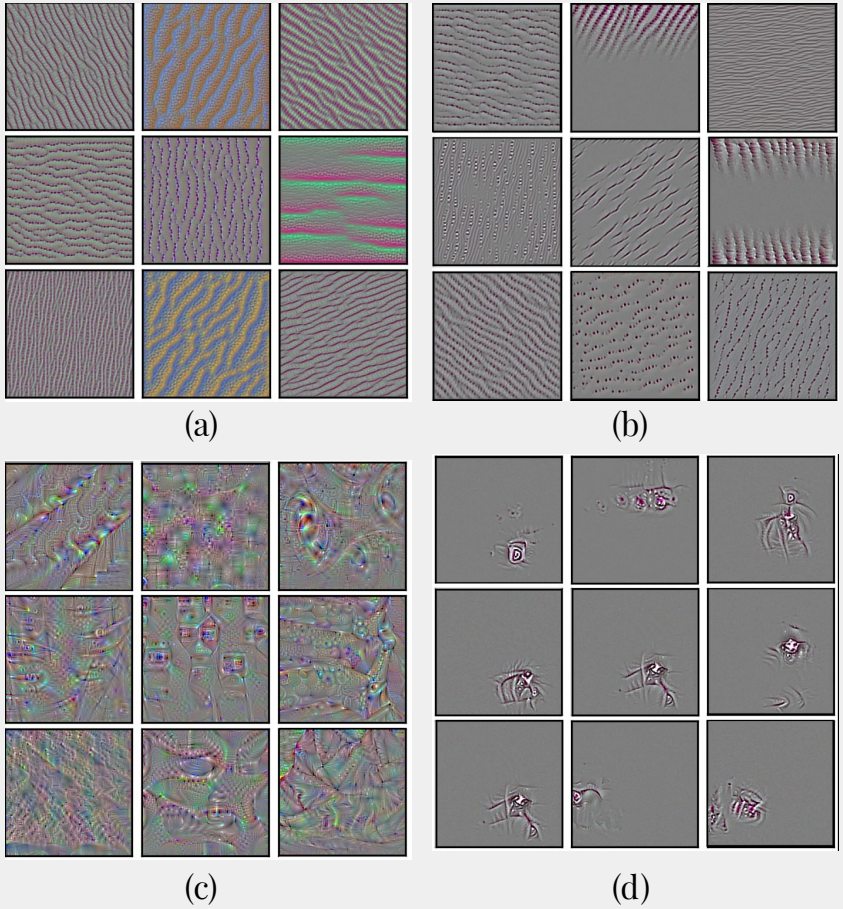
Confidence of Deep Learning Models

- Since VGG-16 model have a relatively good result, we have selected that model to check the confidence by providing different images.
- Each of the samples shows whether a class is classified correctly or is misclassified when provided to the VGG-16 model.
- We can see that whenever the model is making any guess, it confidently guesses it wrong.
- This makes it challenging to see what actually the neural network model learns and what exactly the model is motivated to make a particular decision.
- This will help medical practitioners to check the authenticity of the predictions of Deep Learning architectures.



Visualization of Filters Learnt

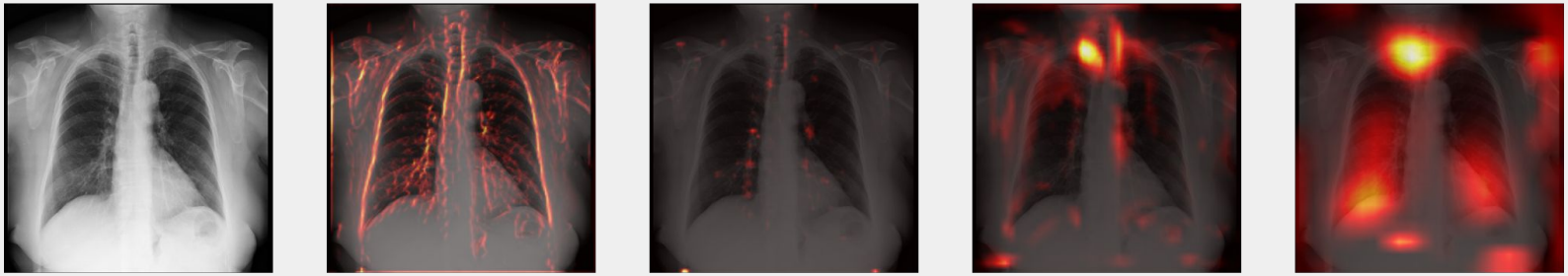
- To visualize the difference between the filters learnt we have used the weights of VGG 16 model before transfer learning (images on left side, i.e., Figure (a) and (c)) and after transfer learning (images on left side, i.e., Figure (b) and (d)).
- The figures shows that the filters changes from recognizing textures and patterns from natural imagery to problem specific images, i.e, Chest X-Ray image features.
- Even the colour changes from natural to grayscale related to X-Ray images.
- The initial layers learns textures and the final layers learns patterns which describe the class as a whole.



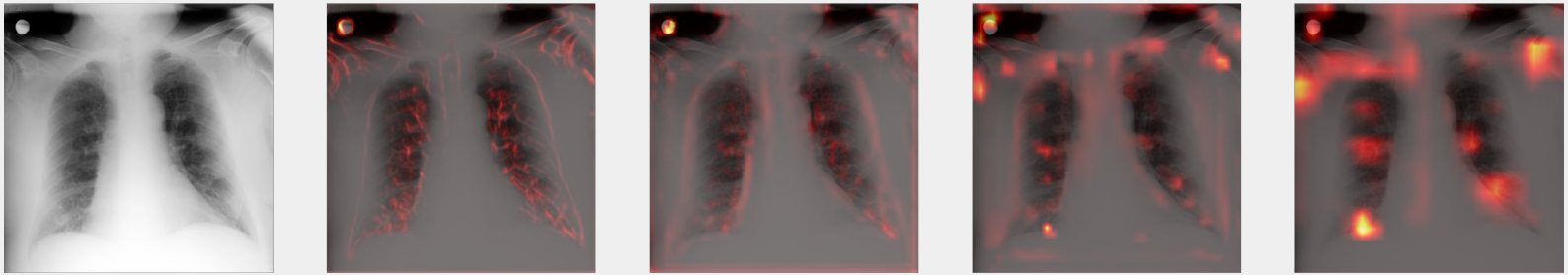
‘Belief’ of Deep Learning Models

- Sometimes the predictions of the Deep Learning models might be very confusing, and there may be very less information why the model selects a particular class for a particular image.
- In the next slide we have made some effort in justifying the confidence or belief of deep learning model via **GRAD-CAM**.
- From the visualizations it looks like that the model is not taking into account the confidence from the final layers only, rather it is taking confidences from the individual layers, right from the beginning to the final layers.
- It may be very confusing for normal people to justify what the Deep neural network architecture actually sees.

What does the model think?

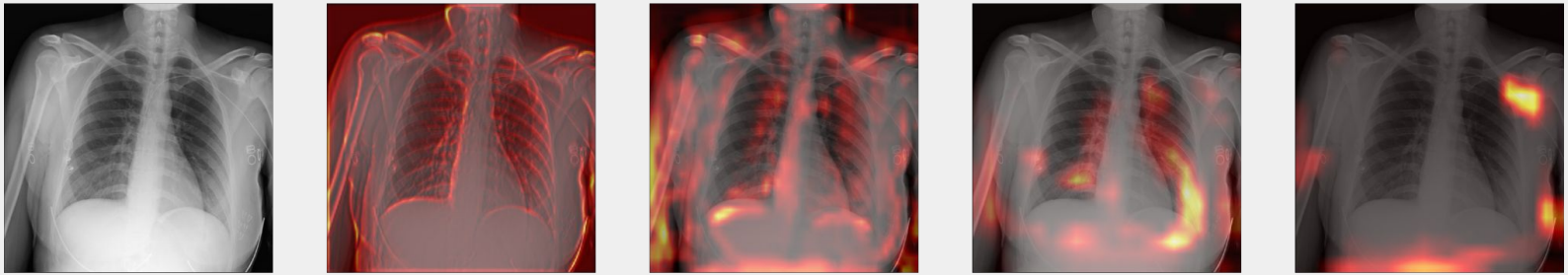


(a) True positive: COVID detected as COVID

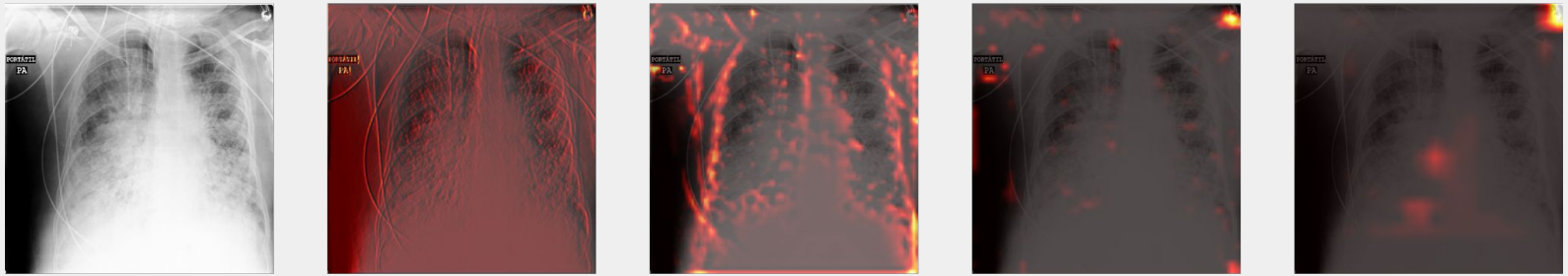


(b) False negative: COVID detected as Normal

What does the model think?



(c) False positive: Normal detected as COVID



(d) COVID detected as Pneumonia

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Ablation Study

- For ablation study, we used input image size of 500x500, fully connected layers of 1024-1024-3 neurons, Dropouts or their combinations, with VGG16 and InceptionV3 models.
- For studies where the above were not used, we used input image size of 360x360 or a fully connected layers of 128-128-3 neurons.
- We noted the performance of the two models for different input for different input features.
- The result showed that it is not necessarily true that the performance of Deep Learning architecture will increase overall when we combine individual sub-structures which gives better result for a particular setting.
- Also, a particular structure might not give better result when the backbone model is changed, i.e., performance of model and structure is dataset dependent.
- The results obtained from Ablation study is shown in the next slide.

Ablation Study (Results on VGG-16 and Inception-V3 models)

Model Name	500x500x3*	1024-1024-3†	Dropouts	Accuracy (%)	Sensitivity (%)	Specificity (%)
VGG 16	✓			96.87	94.83	97.77
		✓		**96.96**	**94.99**	**97.82**
			✓	96.87	94.91	97.77
	✓	✓		95.82	93.15	97.02
		✓	✓	95.82	92.95	97.00
	✓		✓	96.30	93.81	97.37
	✓	✓	✓	**96.96**	94.91	**97.82**
Inception V3	✓			97.51	95.80	98.24
		✓		96.95	94.99	97.83
			✓	97.20	95.31	98.00
	✓	✓		**97.63**	**96.03**	**98.32**
		✓	✓	97.29	95.58	98.08
	✓		✓	97.28	95.50	98.08
	✓	✓	✓	94.42	90.54	96.05

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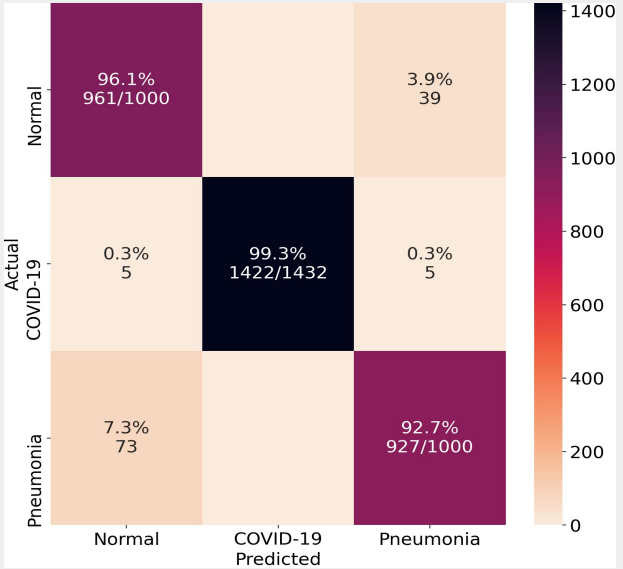
Results on Test Set

- When evaluated on unseen test, the results were a bit lower from the one obtained when trained on the training dataset and tested on validation dataset.
- The model which performed the best on Ablation study, was selected.
- Also, it is worth noting that when we are combining the train and validation dataset for training the model and testing on test dataset, the performance decreases slightly, this might be due to the fact that the distribution of the train and validation dataset combined might be shifted from the train and test dataset, hence decreasing the performance.
- Hence the final model obtained was trained on just the train dataset and tested on unseen test dataset.

Model Name	Accuracy (in %)	Sensitivity (in %)	Specificity) (in %)
InceptionV3 (train)	94.67	94.67	94.78
InceptionV3 (train + val)	94.41	94.41	94.68



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Conclusion and Limitations

- Application of Transfer Learning shows performance of a deep learning architecture can be improved significantly without the use of data augmentation.
- Ablation studies showed that combining different substructures which performs good individually might not result in a better overall structure.
- It may be confusing for the humans to understand what the Deep Learning architecture actually sees, hence we need to find more transparent way of seeing the belief of Deep Learning architectures.
- The model performs best on the distribution of data in which it was trained on, so bringing data from slightly different domain may result in degradation of performance hence this cannot be used as a diagnostic tool.

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Future Work

- Since the model doesn't perform as good when it was trained on training dataset and evaluated on validation dataset, so, combining data from different domains can help to learn domain invariant features, by performing domain adaptation to increase the performance of the existing model.
- Neural Architecture Search can be used to find the best model for the given dataset, but it is computationally very expensive task.
- Attention module and building of different substructures might increase the performance of the existing models.

Contents

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Contents

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Thank You!

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