Lung Disease Clasification - Applied AI Final Report

Group-Q

Abstract

Chest X-rays scans are among the most accessible ways to diagnose lung diseases. This study tries to compare the detection of lung diseases using these scans from three different datasets using deep neural networks. Three different backbone architectures, ResNet34, MobileNet V3 Large and EfficientNet B1 were used along with a set of models trained using transfer learning. It is observed that MobileNet takes the least amount of time to train while ResNet converges the fastest. Also, EfficientNet performs the best most of the times on Chest X-ray scans. An F1 score of 0.8 for the pneumonia dataset was obtained, 0.98 for the COVID-19 dataset and 0.46 for the multilabel chest X-ray 8 dataset. Finally, models are visualized using t-SNE and gradCAM to understand the features learned by the models and correlate them with the actual effect of the diseases on the lungs.

1. Introduction

Early diagnosis of respiratory diseases like pneumonia and COVID-19 leads to decreased mortality rate [8] and is a powerful way to manage a pandemic [46]. These diseases can be diagnosed using a variety of tests like pulse oximetry, chest x-ray, CT scan [38], PCR [2] however chest X-rays are by far the most accessible [12] to low and middle income countries. Furthermore, the scan is available in minutes making it one of the fastest ways of diagnosis [39]. However, the bottleneck with this method is the need for an expert radiologists to evaluate the scan [30]. Many researchers have tried to solve this problem by creating a deep learning based lung disease classification system [43] but haven't been able to come up with models that can replace radiologists. Small [15] and highly imbalanced data [43], along with varying specifications of X-ray scanners leading to low inter-hospital accuracy [36] are the biggest problems that researchers have faced. Another issue with using deep neural networks in medical settings is its black-box nature, doctors and patients will not trust a model that cannot explain its results [31].

This project is an attempt to compare three CNN backbone architectures namely, ResNet-34, MobileNet V3 Large and EfficientNet B1 along with three lung disease datasets to identify the type of architecture that works best for lung disease classification. Two of the datasets used presented a multiclass classification problem with 3 classes while the third dataset presented a multiclass, multilabel classification problem. A total of 12 models were trained in this study, four for each of the three datasets. The first three models for each dataset was trained from scratch and the fourth model was trained using transfer learning. Transfer learning was performed by deep-tuning ImageNet weights and the performance was evaluated to check improvement over the models trained from scratch. The small dataset problem and the issue of different radiographic contrast [32] is mitigated using data augmentation. Imbalanced data problem is handled by undersampling the majority class. The hyperparameters were fixed across models and the F1 scores and cross entropy loss have been used to compare models and select the best overall model. All the models were optimized using the Adam optimizer [23] with default parameters and the cosine annealing [29] learning rate scheduler was used to decrease the learning rate as training progressed. Further, an ablation study was performed to find the best learning rate for the selected model. Finally, GradCAM [14] and T-SNE were used to visualize the trained models and understand model predictions better. This would help shed light on the black box nature of the models and allow subject matter experts to trust the predictions better. An F1 score of 0.8 and 0.98 was achieved for the two multiclass datasets, whereas the maximum F1 for the multilabel dataset with 7 classes was 0.46.

Related Works: Li *et al.* [26] were among the first to use CNNs in a medical setting. They used a single convolutional layer to classify interstitial lung diseases using CT scans, achieving better performance than existing state of the art approaches. Since then there has been a dramtic increase in application of CNNs in the healthcare setting, deep neural networks have been used to perform various tasks like segmenting regions of interest in MRI scans [9, 21], classifying X-Ray [35], MRI [11], and CT [3] scans. Further, GANs have been used to generate high quality scans [28] when there is a lack of available data due to either privacy reasons or availability of subjects. GANs have also been used to generate high quality CT scans from MRI scans [27]. Apart from radiographic scans, deep CNNs have also been used to detect malarial parasite in blood smear

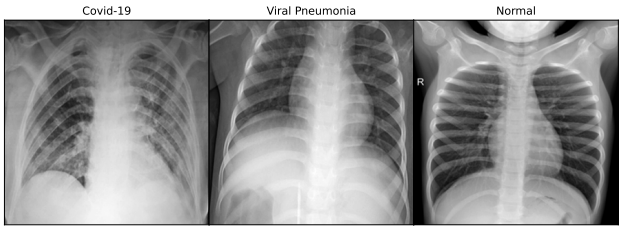
Dataset	No. of Images	Classes	Size
COVID [6, 7, 34]	3.6k:3.6k:1.3k	3	299^2
Pneumonia [22, 41]	3k:1.5k:1.5k	3	224^2
Chest X-Ray8 [44, 45]	7.2k:7k:7k:4.1k :3.9k:3.5k:2.9k	7	1024^2

Table 1. Shortlisted Datasets.

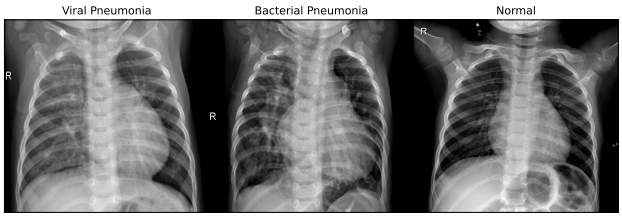
images [42] with an accuracy of 99.96%. Another interesting application is the use of 1-D convolutions to detect heart anomalies using ECG data [24] collected using smartwatches. These models can be trained once for a patient and used to give radiologist level prediction on the go. Researchers have also used architectures like the Inception V3 to perform dermatologist level skin-cancer detection using skin lesion images [10] using transfer learning.

In the recent years, many researchers have tried to predict lung diseases using deep CNNs, Wang *et al.* [44] used state of the art backbone architectures to train a lung disease classifier for multilabel data by training only the prediction and transition layers from scratch and leaving pre-trained ImageNet weights freezed while training. They achieved a high AUC of over 0.6 for most of the classes in the dataset with this technique. Rajpurkar *et al.* [35] created a 121 layer deep CNN - CheXNet to detect pneumonia using chest X-rays with radiologist level accuracy. Labhane *et al.* [25] used transfer learning with state of the art backbone architectures like VGG16, VGG19 and InceptionV3 to predict pneumonia in pediatric patients and achieved an F1 score of 0.97. Islam *et al.* combined CNN and LSTM to create a COVID-19 detector [19]. The CNN extracted complex features from scans and the LSTM was used as a classifier. This method resulted in an improvement over a vanilla CNN network and an F1 score of 98.9% was achieved. Abbas *et al.* [1] created the DeTraC network to detect COVID in chest X-rays that improved performance of existing backbone models significantly with the highest accuracy of 98.23% using the VGG19 architecture. Guefrechi *et al.* [15] on the other hand used data augmentation techniques like random rotation, flipping and noise with transfer learning on backbone architectures like ResNet50, InceptionV3 and VGG16 to achieve a high accuracy of 98.3%.

In the following sections methodology of the approach and the results will be discussed.



(a) COVID Dataset



(b) Pneumonia Dataset

(c) Chest X-Ray 8 Dataset

Figure 1. Sample Chest X-rays from the datasets used.

2. Methodology

Datasets: (Tab. 1) with varying disease types were chosen to ensure model robustness and to get results across a set of different diseases. Other criteria included the *number of images per class* and *image quality* as noisy scans can lead to mis-diagnosis [37].

The **COVID** dataset was created by a team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh along with collaborators from Pakistan and Malaysia in collaboration with medical doctors from the Italian Society of Medical and Interventional Radiology database using 43 different publications [6, 7, 34]. It is a multiclass data with three classes, COVID, viral pneumonia and normal. X-rays with widespread, hazy, and irregular ground glass opacities are of the COVID-19 class [20]. Whereas, the ones with haziness only in the lower regions [47] are viral pneumonia cases as shown in Fig. 1. Chest X-rays of normal lungs provide a clear view of the lungs. The normal class was undersampled to use only 3.6k scans and reduce the data imbalance.

The **Pneumonia**, dataset contains scans from pediatric patients of one to five year olds collected as part of patients' routine clinical care at the Guangzhou Women and Children's Medical Center, Guangzhou, China. [22, 41] This dataset is multiclass with three classes, viral pneumonia, bacterial pneumonia and normal. Scans with one white condensed area affect-

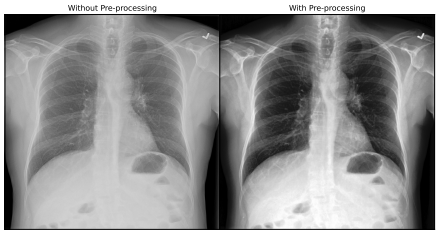


Figure 2. Effect of pre-processing on Chest X-ray images.

Arch.	Params (Mil.)	Layers	FLOPS (Bil.)	Imagenet Acc.
MobileNet	5.5	18	8.7	92.6
EfficientNet	7.8	25	25.8	94.9
Resnet	21.8	34	153.9	91.4

Table 2. Shortlisted Backbone Architectures.

ing only one side of the lungs are tagged as bacterial pneumonia [4] as bacteria tends to aggressively attack one part of the lungs causing inflammation to replace the cells that were otherwise filled with air. On the other hand, X-rays which show bilateral patchy areas of consolidation are classified as viral pneumonia [16] as viruses attack both sides of the lungs producing a homogeneous inflammatory reaction causing mucus and cellular debris. Normal scans here as well produce a clear view of the lungs.

NIH released over 100k anonymized chest X-ray images along with their radiological reports from over 30k patients. Wang *et al.* [44] used this data to create the **Chest X-ray 8** dataset by generating disease labels through NLP from the radiological reports. [45] The dataset contains 15 classes but only 7 Fig. 1 were chosen for this study. This dataset is significantly different from the other two as it is a multilabel dataset, thus the same image can be labelled as two different classes. Classes were iteratively removed, ensuring that they are not highly imbalanced to finally reach the 7 classes. With over 29,000 images of size 1024 x 1024, this dataset was the biggest and thus had to be resized down to 384 x 384 to reduce training and processing times. Furthermore, normal class images were undersampled by first choosing one scan per patient and then selecting 7,000 scans out of this subset randomly. The data consists of multiple scans from the same subject which could lead to data leakage between the train, val and test sets if a random train-test-val split was performed. This was prevented with the use of GroupShuffleSplit from the scikit library to keep scans from the same patient in the same split.

Before training, all the images were pre-processed using histogram equalization and Gaussian blur with a 5x5 filter as Giełczyk *et al.* [13] showed that this improved the F1 score by about 4% for the chest X-ray classification task. Visually, the contrast of the scan improved and allowed irregularities to stand out as shown in Fig. 2. Next, the scans were divided into train, validation and test with the 70:15:15 split. During training, the scans were augmented using RandomAdjustSharpness and RandomAutocontrast in Pytorch to increase the number of images the model gets to learn from and ensure that the model is robust to scans from different machines. RandomHorizontalFlip was also used to make the models invarient to the direction of the scan as some scans were anterior-posterior while others were posterior-anterior [5].

Backbone Architectures: (Tab. 2) of various configuration and blocks were chosen to ensure that different ideas are tested in this study. Other selection criteria were the *number of trainable parameters*, important to keep track of the total training time, *FLOPS* as models that could easily be deployed on to embedded devices were required and the *top 5 classification accuracy* on the ImageNet 1K benchmark dataset.

ResNet 34 residual learning network with 34 layers that are made possible by skip connections. The 34 layer variant was chosen to decrease training time while not compromising on the accuracy much. This architecture had the highest trainable parameters and FLOPS while the lowest Imagenet accuracy. [17]

MobileNet V3 Large uses depthwise separable convolution from MobileNet V2 along with squeeze-excitation blocks in residual layers from MnasNet. This makes it really quick to train while still performing at par with other architectures. This architecture had the lowest trainable parameters and FLOPS among the three selected. Howard *et al.* [18] also used network architecture search to find the most effective model. The large configuration was chosen to not compromise on the prediction accuracy.

EfficientNet B1 uses compound scaling to scale the model by depth, width and resolution. The B1 version was chosen to have faster training without compromising on the accuracy. [40] This architecture performs the best among the selected on the Imagenet benchmark dataset while having a third of the trainable parameters of Resnet34.

Optimization Algorithm: The Adam optimizer [23] is an adaptive learning rate algorithm which was chosen as the algorithm of choice as it converges faster by integrating benefits of RMSProp and momentum. It is also robust to hyperparameters but, requires tweak-

ing of the learning rate depending on the task at hand. For this study, a learning rate of 0.01 and the author recommend settings for $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$ were used for the first and second order moment estimate as defined in Eq. (1) and Eq. (2) where β_1 and β_2 control the decay rates.

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \tag{1}$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2 \tag{2}$$

Further, Cosine annealing [29] learning rate scheduler was used to reduce the learning rate as the training progressed down to a low of 0.001.

3. Results

Experiment Setup:

First undersampling was performed as described in Sec. 2 on the datasets. Then, the scans were preprocessed using histogram equalization and Gaussian blur before resizing them and storing them in separate directories to make it easier for PyTorch dataloaders. Two datasets in this study presented the multiclass classification problem while the third, chest X-ray 8 dataset presented the multiclass, multilabel classification problem. Thus, the training methodology was separated for these two problems. For the multilabel problem, a softmax layer had to be added before the loss function to get 0 or 1 prediction for all the classes of the data. For this, the BCEWITHLOGITSLOSS function of PyTorch was used as it combines the Sigmoid layer and the BCELoss function in one single class. This makes theses operations more numerically stable than their separate counterparts [33]. The backbone architectures were obtained directly from the torchvision library and the final classification layer was modified for the selected datasets. For the models which had to be trained from scratch, the weights were randomly initialized and the entire model was trained for a total of 100 epochs each. For the transfer learning models, the weights were initialized with the IMAGENET1K_V2 weights but the entire model was fine-tuned. The rationale behind performing deep-tuning was that the Imagenet data is very different from chest X-ray scans thus the model would need to learn features from X-ray scans.

The batch size was fixed to 32 for all the models. While training the best model by validation loss was saved to prevent the usage of overfit models for test set analysis. The actual and predicted results from each epoch was also stored to calculate the F1 score at each step of training. While calculating the F1 score, macro averaging was used to get an average score

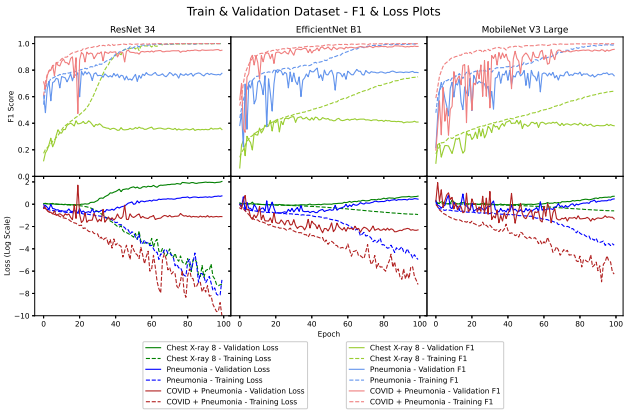


Figure 3. Train & Val, F1 & Loss plots for the 9 models.

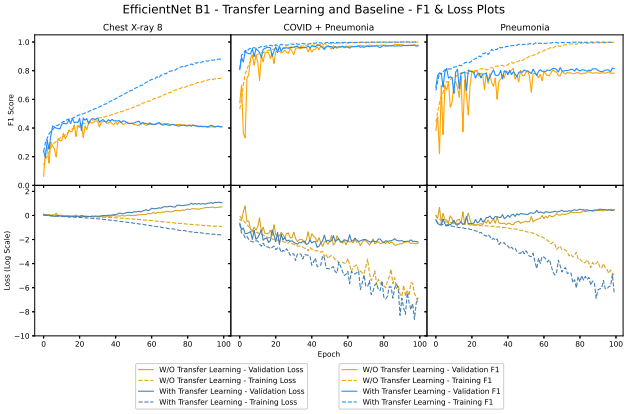


Figure 4. Train & Val, F1 & Loss plots for EfficientNet trained from scratch and with ImageNet weights.

across classes. All images were normalized before getting trained with the mean and standard deviation of the training set of each of the selected datasets.

Initial training runs of the multilabel data produced a zero F1 score due to its highly imbalanced nature. To mitigate this, class wise weights were calculated and used with the loss function. This improved the F1 score considerably.

Finally, the best models from each run by validation loss were used to get the test set metrics that are displayed in Tab. 3. Training and validation F1 score and loss are also provided in Fig. 3 and Fig. 4.

Main Results:

From Fig. 3 it is clear that going from a smaller architecture to a bigger architecture, makes the model start to overfit earlier. The MobileNet model was the most unstable among the three and also took more epochs to reach the minima. The EfficientNet algorithm performs best for the COVID and Chest X-ray 8 dataset and all three architectures performed simi-

Model	ResNet			MobileNet			EfficientNet			EN - Transfer Learning		
Dataset	*F1*	*Time*	*Epoch*	*F1*	*Time*	*Epoch*	*F1*	*Time*	*Epoch*	*F1*	*Time*	*Epoch*
Pneumonia	0.784	82	**22**	**0.804**	**75**	42	0.768	110	44	0.782	114	70
COVID	0.959	50	**21**	0.967	**37**	44	**0.979**	56	46	0.978	56	43
X-Ray 8	0.411	11,502	**19**	0.406	**7,275**	42	0.445	13,820	31	**0.457**	13,813	29

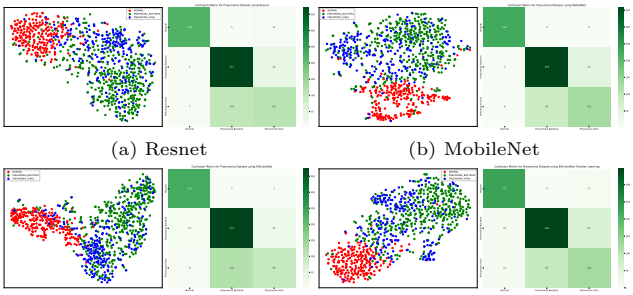
Table 3. F1 (higher is better), time per epoch in seconds (lower is better), and number of epochs to reach the best validation loss (lower is better) for the 12 models that were trained.

lar for the pneumonia dataset. This shows that the compound scaline of EfficientNet gives good results for chest X-ray data. The X-ray 8 dataset performed the worst among the three datasets which could be due to the high number of classes, class imbalance and the multilabel nature of the problem. Surprisingly, the pneumonia dataset performed worse than the COVID + pneumonia dataset which indicates that COVID cases are easier to distinguish from pneumonia cases.

In Fig. 4 it can be seen that the transfer learning model had a much better start than the randomly initialized model. It also converged much quicker than the model trained from scratch. For the Pneumonia dataset, the model trained from scratch was highly unstable at the start and could not catch up to the transfer learning model even after 100 epochs in terms of the F1 score.

Finally, looking at Tab. 3 it can be seen that the MobileNet architecture was the fastest to train per epoch. It consistantly took less time per epoch but, if number of epochs required to converge is considered, it does not train the fastest all the time. It is also evident that ResNet converged the fastest at half the number of epochs compared with other models. EfficientNet models perform the best in terms of the overall F1 score on the test set with the exception of the Pneumonia dataset where surprisingly MobileNet performed the best. The transfer learning models converged quicker than the other models with the exception of the Pneumonia dataset. Another surprising observation is that the EfficientNet model takes the longest to train per epoch even though the number of trainable parameters is nowhere close to ResNet. Also, MobileNet isn't as fast to train as expected when compared to ResNet even though it has 4 times the learnable paramenters. This could be due to two reasons, depthwise convolutions are not optimized in the version of PyTorch and CUDA used and training is getting CPU bound due to the data augmentation before each training run which would take the same amount of time for all the models.

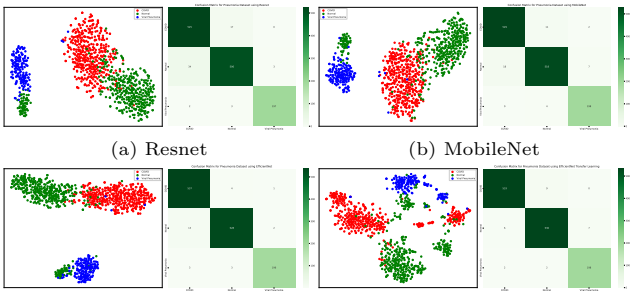
Fig. 5 shows that the models are able to differentiate well between the normal and pneumonia classes but struggle with the viral pneumonia vs bacterial pneumonia classification. MobileNet performs better but



(a) Resnet (b) MobileNet

(c) EfficientNet (d) EN - Transfer Learning

Figure 5. T-SNE and Confusion matrices for the test set of the Pneumonia dataset.



(a) Resnet (b) MobileNet

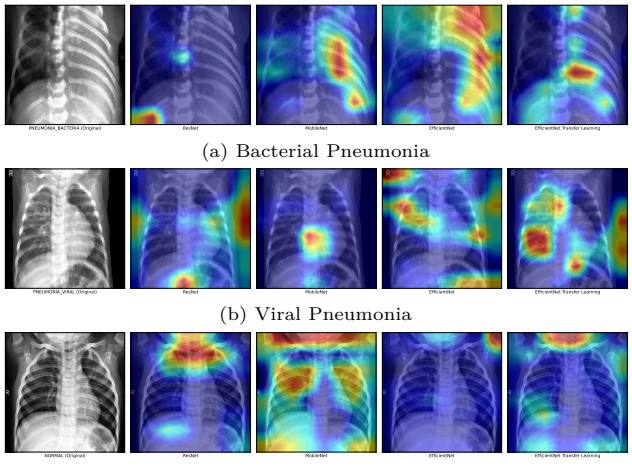
(c) EfficientNet (d) EN - Transfer Learning

Figure 6. T-SNE and Confusion matrices for the test set of the COVID dataset.

the EfficientNet transfer learning model creates better separation of classes. Thus, even though MobileNet performs better in this case, the EfficientNet transfer learning model would generalize well on new unseen data. This is correlated in the confusion matrix where the transfer learning and MobileNet models perform the best.

Fig. 6 shows that all models do a good job of separating classes to create distinct clusters but, the transfer learning model creates better clusters with separate smaller clusters. These smaller clusters could indicate other factors of the disease, for example the severity and amount of lung damage caused by the disease. This performance of the transfer learning model can be confirmed by looking at the confusion matrix as well.

Fig. 7 shows the gradCAM visualization of the last

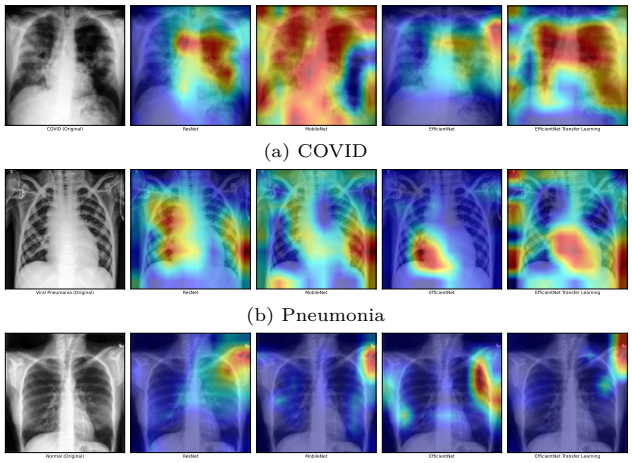


(a) Bacterial Pneumonia

(b) Viral Pneumonia

(c) Normal

Figure 7. GradCAM visualization for the Pneumonia dataset.



(a) COVID

(b) Pneumonia

(c) Normal

Figure 8. GradCAM visualization for the COVID dataset.

layer of the convolutional network. Here it can be seen that the ResNet is learning completely different features as compared to the other models. This could be the reason for its low performance. In case of bacterial pneumonia, the network identifies affected area on the right side of the scan. On the other hand, in case of viral pneumonia, models look at both sides of the lungs. This correlates with the actual progrssion of these diseases as given in Sec. 2.

Fig. 8 shows that MobileNet activates the entire image incase of COVID, this be the reason for its low performance. In case of pneumonia, the EfficientNet models identifies affected areas on the bootom of the lungs. On the other hand, in case of COVID, the models look at a bigger region of the lungs. This correlates

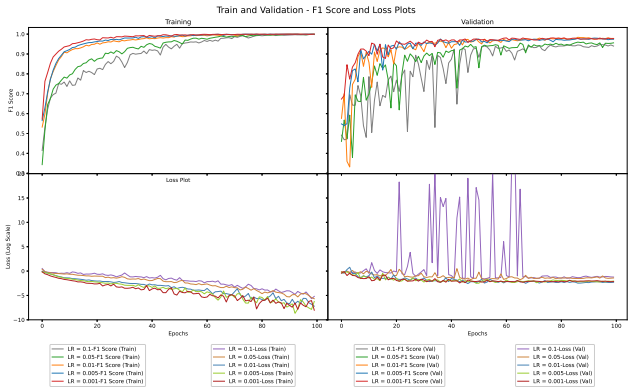


Figure 9. Train & Val, F1 & Loss plots for ablative study models.

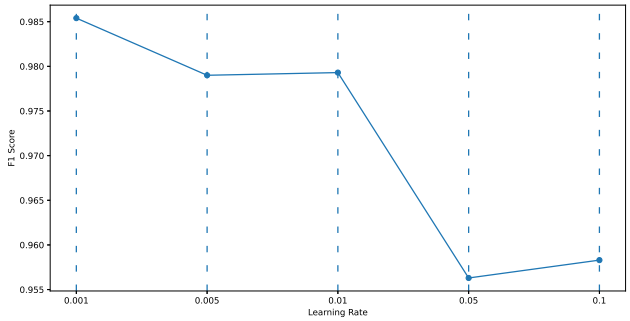


Figure 10. Ablative Study F1 scores (Higher is better).

with how these diseases impact the lungs as given in Sec. 2.

Ablative Study: For the ablative study, the COVID dataset was chosen along with the EfficientNet B1 architecture trained from scratch. The learning rates chosen for the study are 0.001, 0.005, 0.01, 0.05, and 0.1. From the training and validation F1 score and loss plots given in Fig. 9 it is seen that a very high learning rate of 0.1 is highly unstable and prevents the model from reaching close to global minima. Similarly, learning rate of 0.05 also prevented the model from converging on the validation set even after 100 epochs. The other three learning rates all converged on the validation set but, the learning rate of 0.001 was the most stable and reached the highest F1 score earliest. On the other hand, learning rate of 0.01 performed marginally better on the loss plot. From Fig. 10 it can be seen that the best performing learning rate is 0.001 on the F1 score of the test set with 0.005, 0.01 close second and 0.05, 0.1 performing the worst. This matches the results of the validation set on Fig. 9. Thus, a learning rate of 0.001 performs the best on the COVID dataset with the transfer learning EfficientNet model.

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