

CNN을 활용한 흉부 X-ray 이미지 분류

1조 | 김서현 김연성 서문홍 조건우 최지은

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01. Introduction

01 | Introduction



“코로나19”의 위험성 증대

→ 팬데믹 상황 속 비효율적인 대응이 이루어짐



기존의 문제 상황

코로나19 PCR 검사는 **시간과 비용 측면에서 비효율적**이다.

- 의료진들의 공공 인력 낭비, 의료 인력 부족
- 검사 결과를 확인하기 위해 하루라는 시간이 소요
- 약 8만원이라는 높은 검사 비용
- 검사 과정에 고통과 불쾌감 유발 가능
- 검사 장소에 여러 사람이 모이게 되어 또 다른 전파의 위험성 증대
- 일회성 검사도구로 인한 환경 오염

코로나19와 폐렴을 **가시적으로 구분하기 어렵다**.

- 비슷한 증상: 기침, 발열, 오한
- 감염경로의 유사성: 비말감염, 간접전파
- X-ray 상으로 구분 어려움 (데이터 수집 사례가 적음)



목표 설정

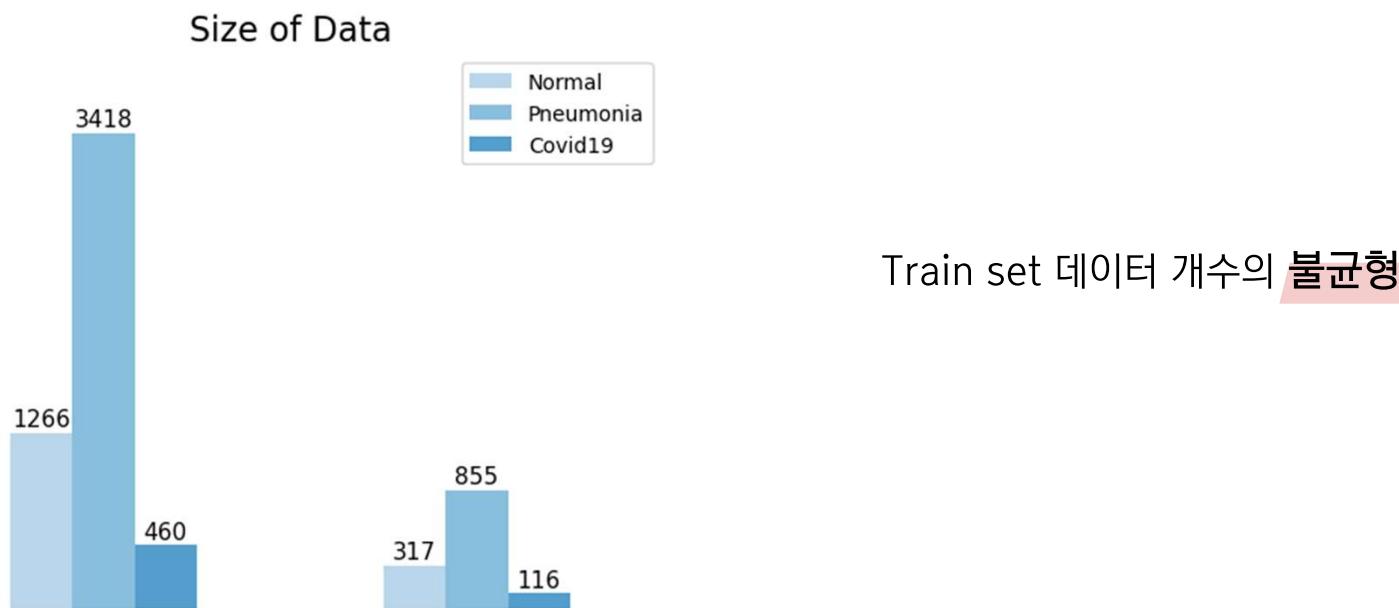
보다 효율적인 새로운 코로나19 판별 검사 필요
X-ray 사진만으로 바로 분류! 사람이 아닌 기계가 바로 분류하는 새로운 코로나19 검사법 제안

또한, 코로나19와 폐렴 데이터가 충분하지 않아서 적은 데이터로도 딥러닝을 할 수 있는 CNN 방식이 필요하다.

02. Data

EDA

- 데이터 세트는 train, test로 구성
- train, test 모두 3개의 하위 폴더(COVID19, PNEUMONIA, NORMAL)를 포함
- 데이터 세트에는 총 6432개의 X-ray 이미지가 포함되어 있으며 테스트 데이터는 전체 데이터의 20%를 차지



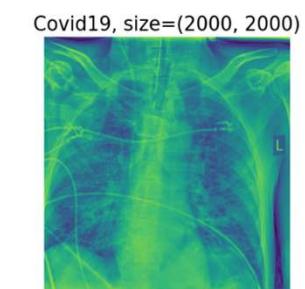
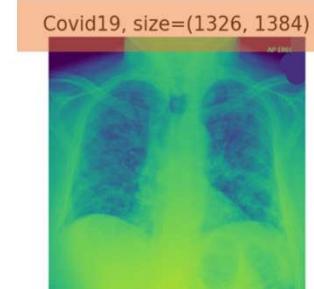
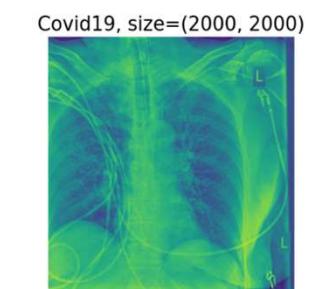
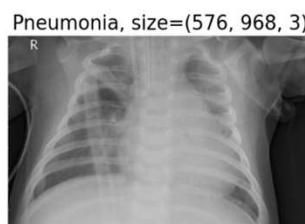
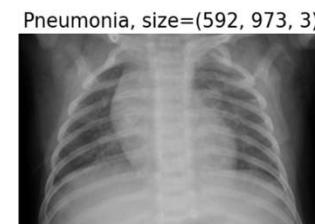
EDA

Data size

데이터 세트 별 X-ray 이미지 확인

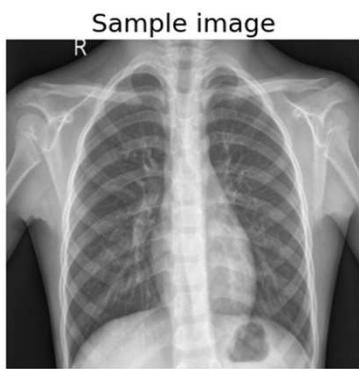


이미지 별 **픽셀 사이즈, 채널 수**
모두 다름

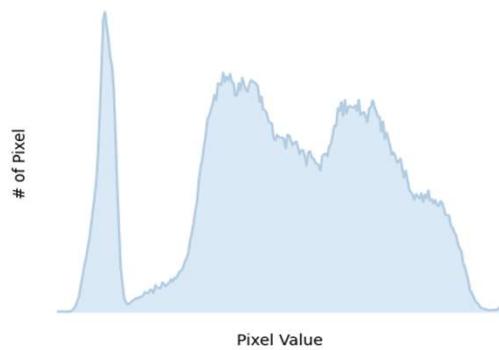


EDA

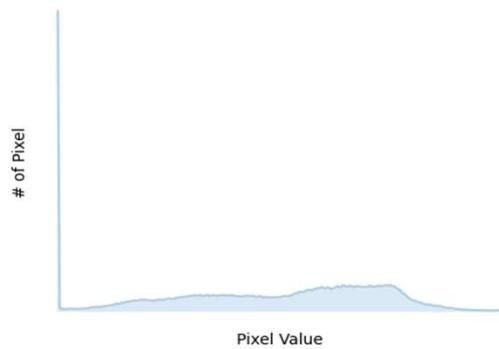
Image Histogram



Histogram for Pixel of Sample image



Histogram for Pixel of Sample image



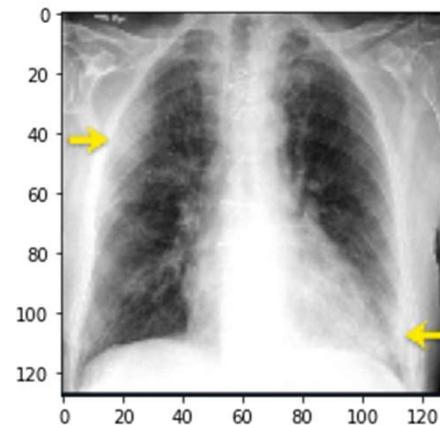
X-ray 이미지 별 Pixel의 분포를 알 수 있는
Image histogram 확인



픽셀 분포가 불균등하여 이미지의 contrast가
떨어짐

Data Preprocessing

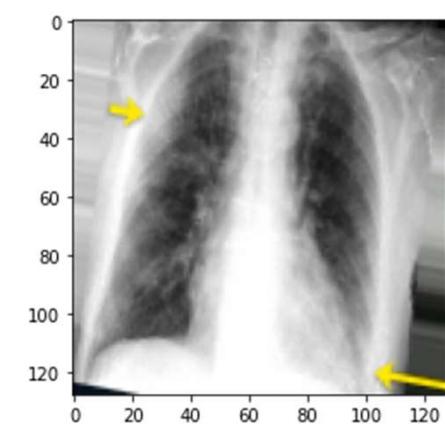
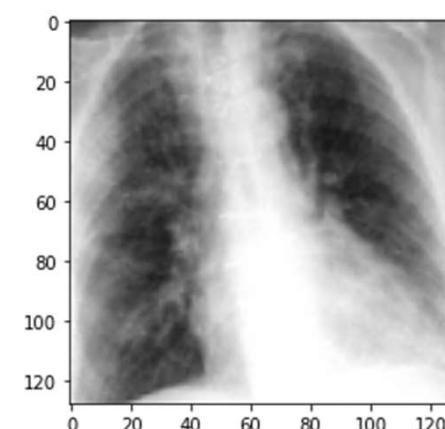
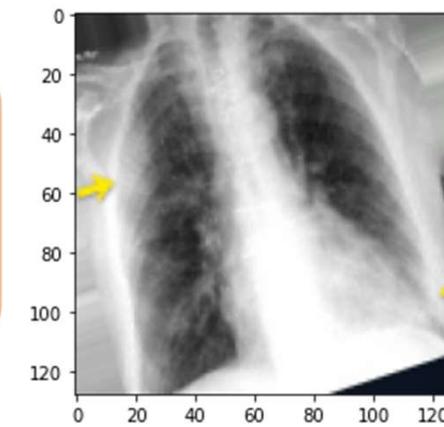
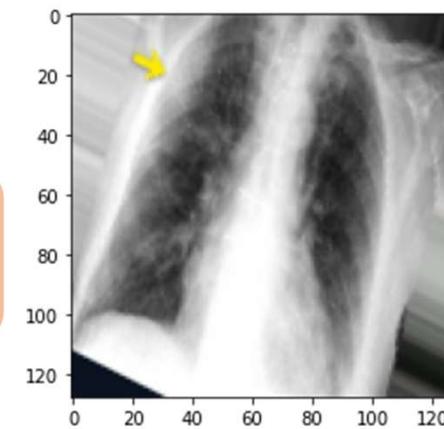
Data Augmentation



Size
(128, 128, 3)

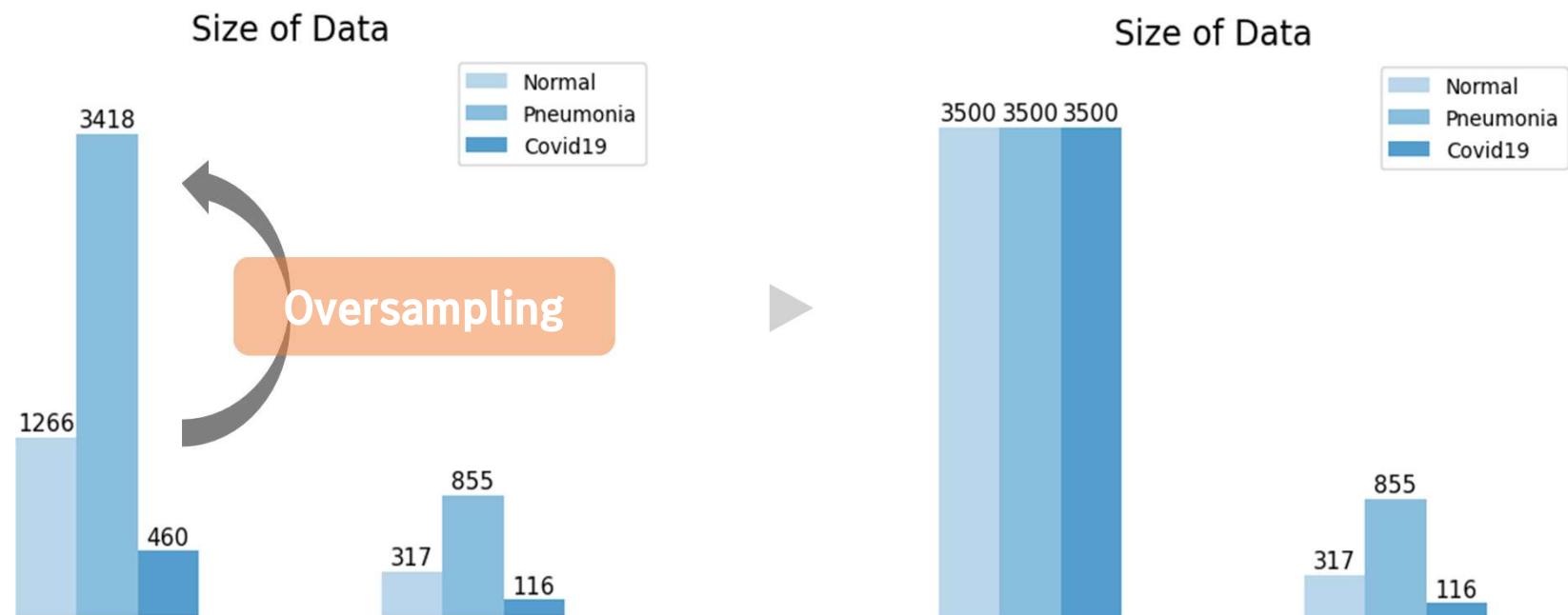


Random
- Rotation
- Shear
- zoom



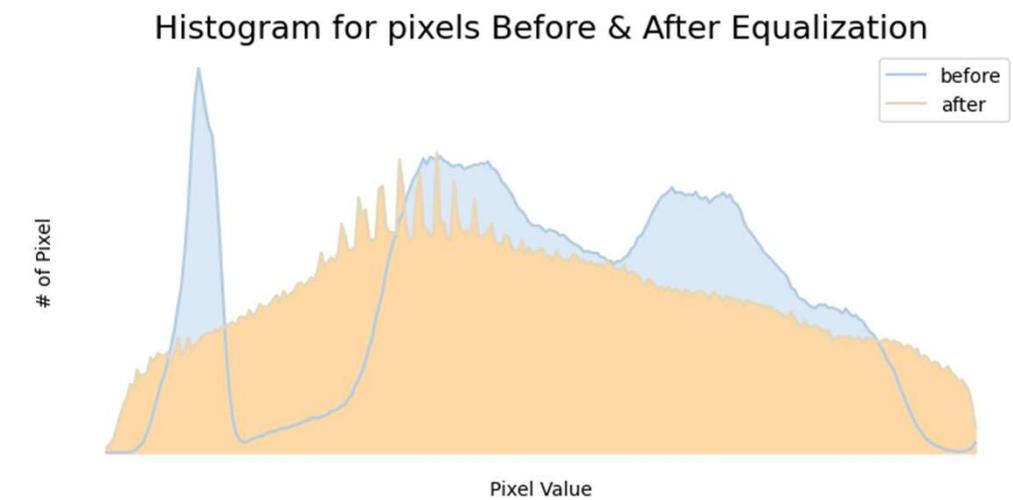
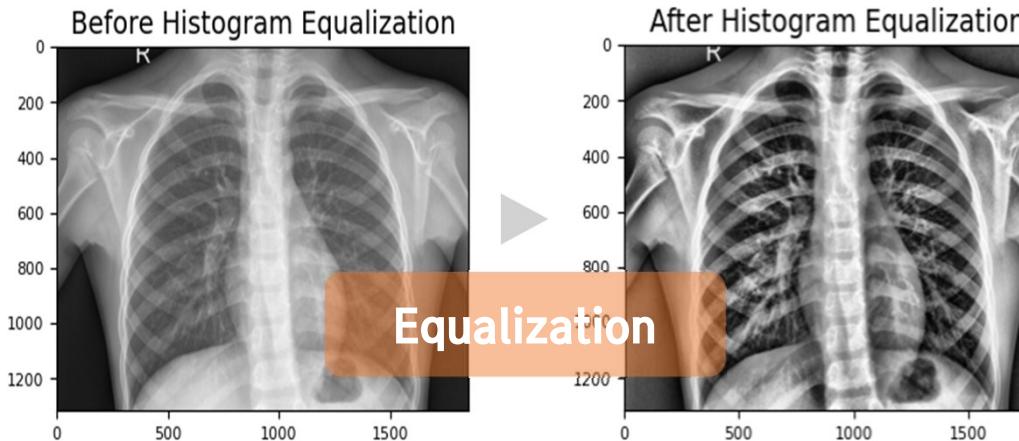
Data Preprocessing

Oversampling



Data Preprocessing

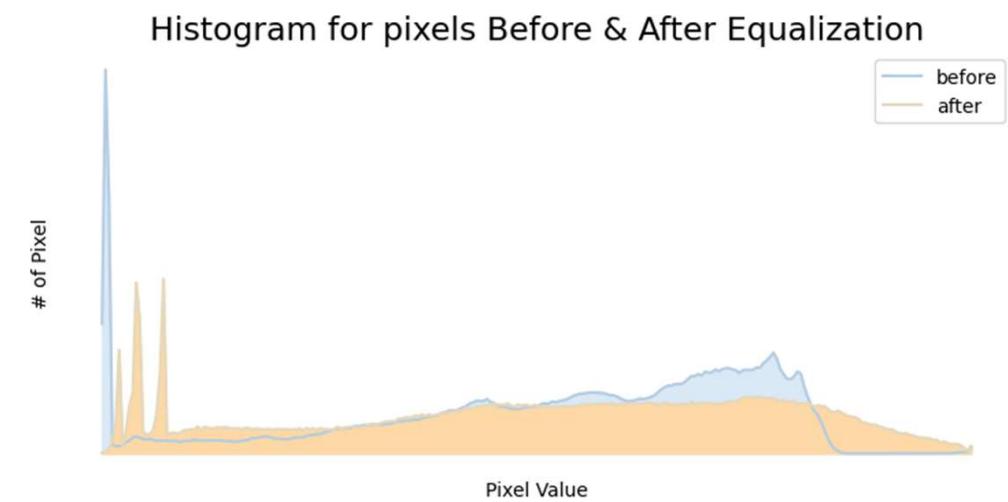
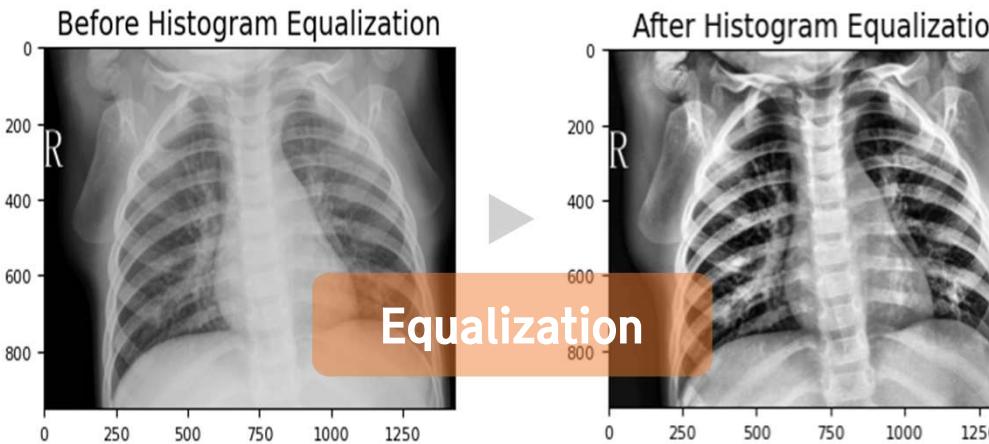
Histogram Equalization



모든 intensity가 동일한 빈도수로 사용되도록 equalization

Data Preprocessing

Histogram Equalization

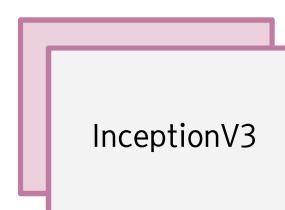
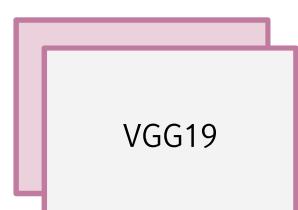
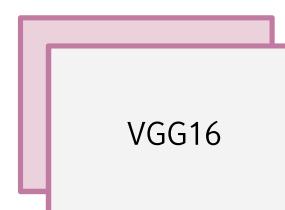


03. Modeling

Deep Learning Models

Models

총 9개의 딥러닝 모델을 사용하여 실험을 진행하였다.

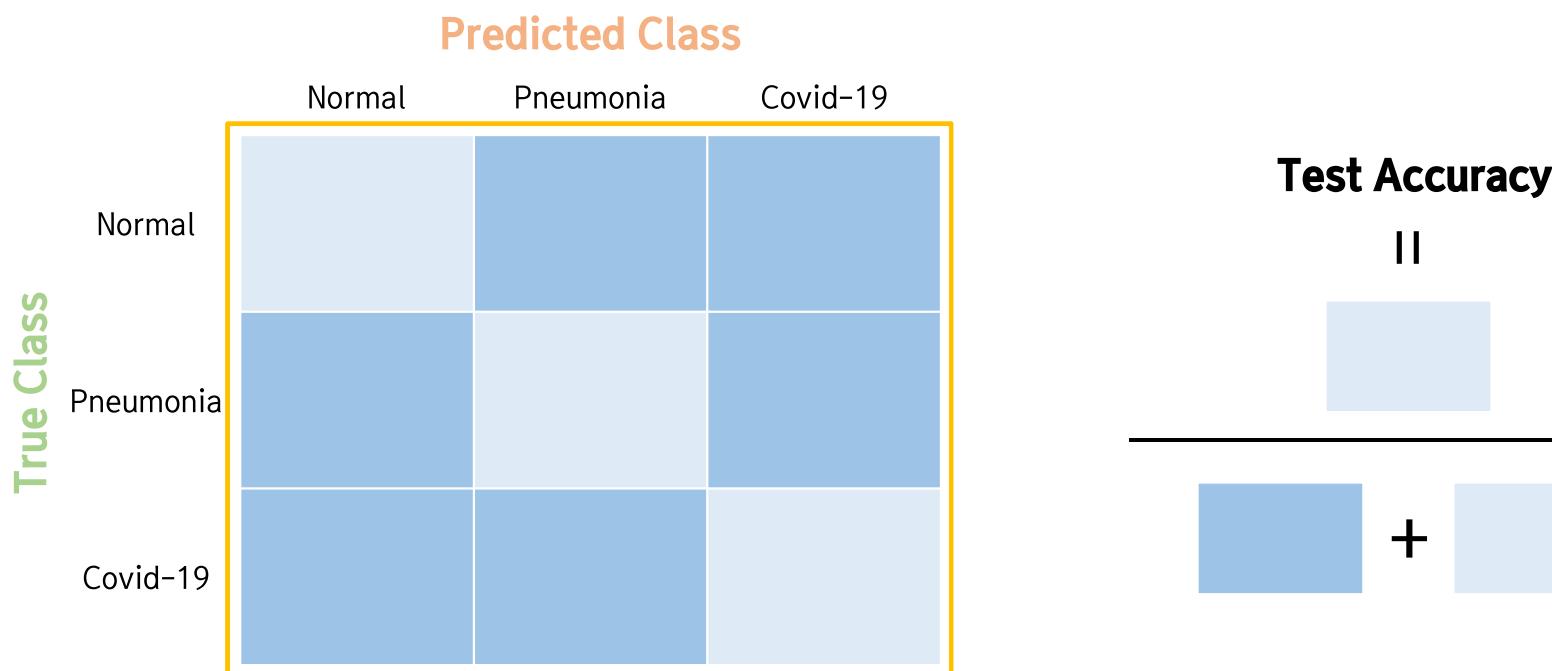


Default Settings

- epochs = 100
- batch size = 32
- optimizer = SGD, RMSprop
(Learning Rate = 0.001)
- Validation Split = 0.2
- Early Stopping
(Validation loss, Patience=10)

Confusion matrix

Confusion Matrix



Confusion matrix

Confusion Matrix

		Predicted Class		
		Normal	Pneumonia	Covid-19
True Class	Normal			
	Pneumonia			
	Covid-19			

Normal Recall(vs Cov.&Pne)

||

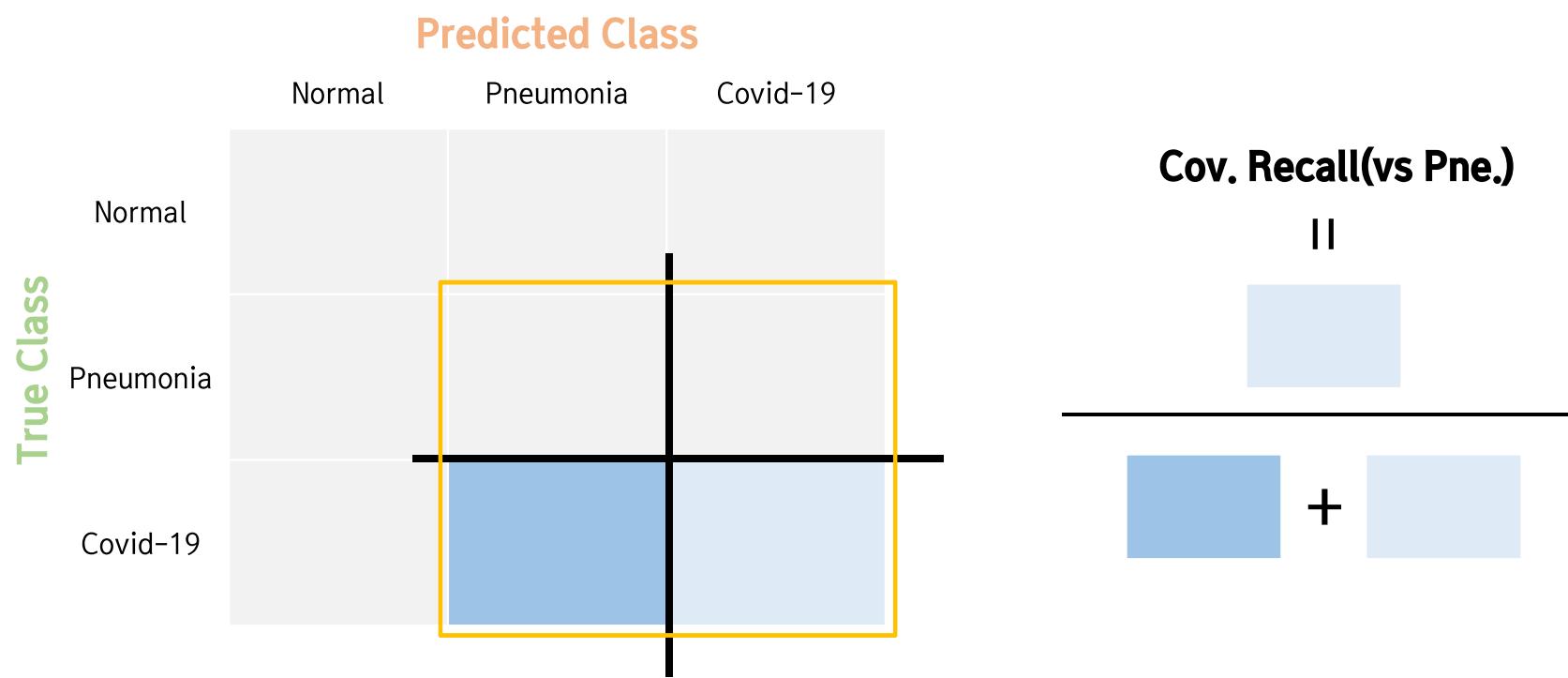


+



Confusion matrix

Confusion Matrix



EX. VGG19

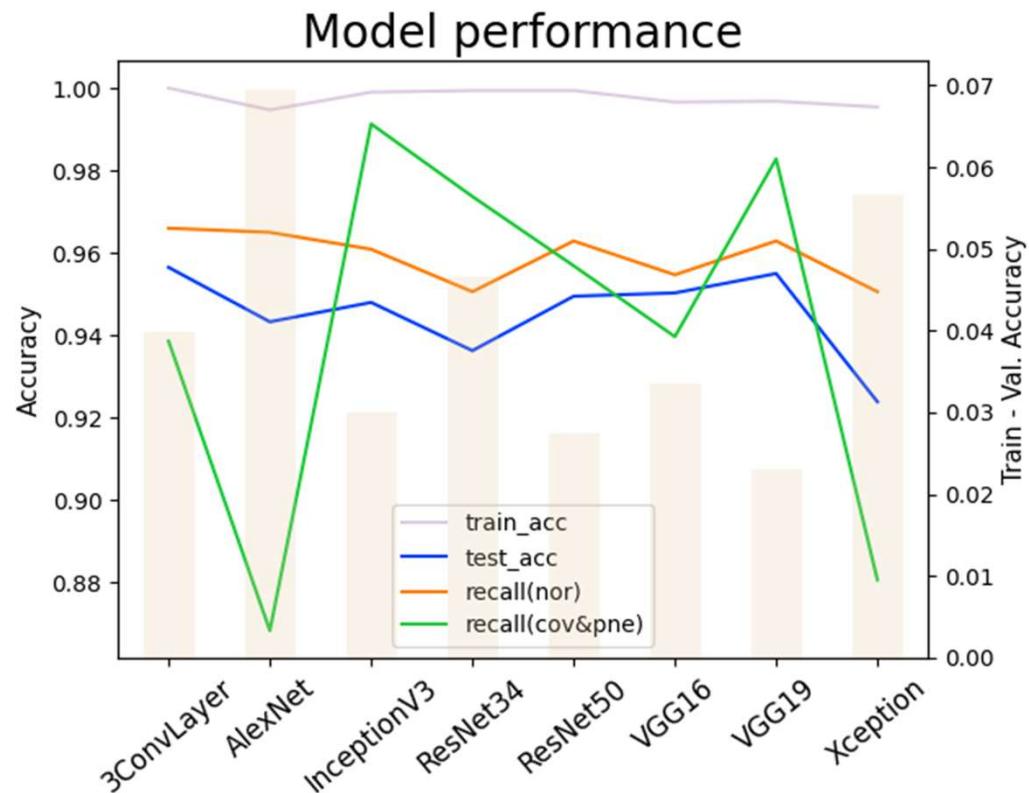


Summary

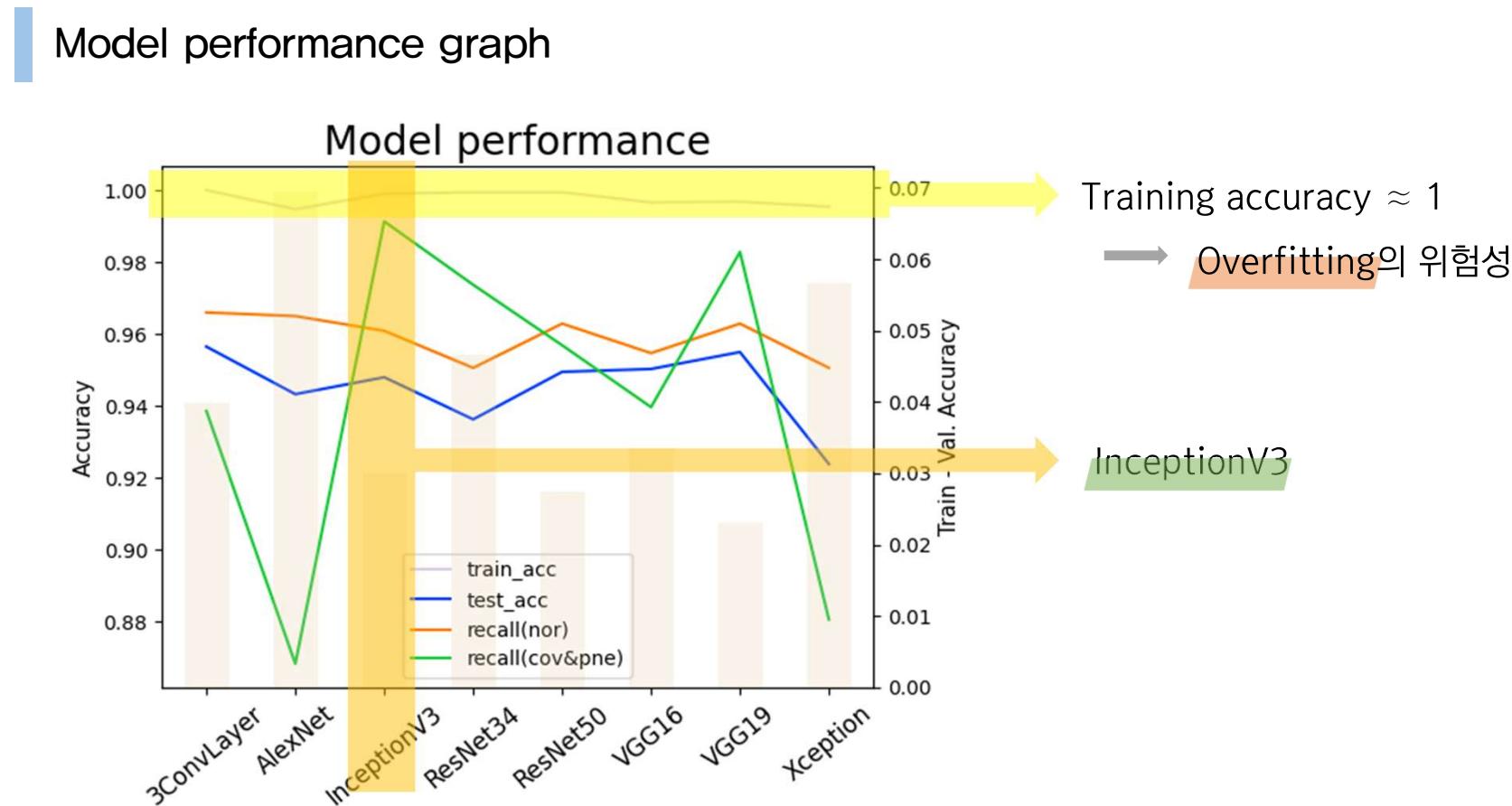
Value	Train Accuracy	Validation Accuracy	Test Accuracy	Recall (Normal)	Recall (COVID19 vs PNEUMONIA)
3 Conv. Layer	0.9980	0.9557	0.9371	0.9485	0.9181
VGG16	0.9964	0.9833	0.9681	0.9711	1.0000
VGG19	0.9966	0.9781	0.9704	0.9763	0.9913
ResNet34	0.9995	0.9757	0.9588	0.9742	0.9824
ResNet50	0.9983	0.9029	0.8812	0.9711	1.0000
AlexNet	0.9984	0.9638	0.9503	0.9629	0.9913
InceptionV3	0.9996	0.9714	0.9456	0.9577	0.9739
Xception	0.9982	0.9724	0.9526	0.9660	0.9652
DenseNet50	0.9982	0.9700	0.9417	0.9423	1.0000

Summary

Model performance graph

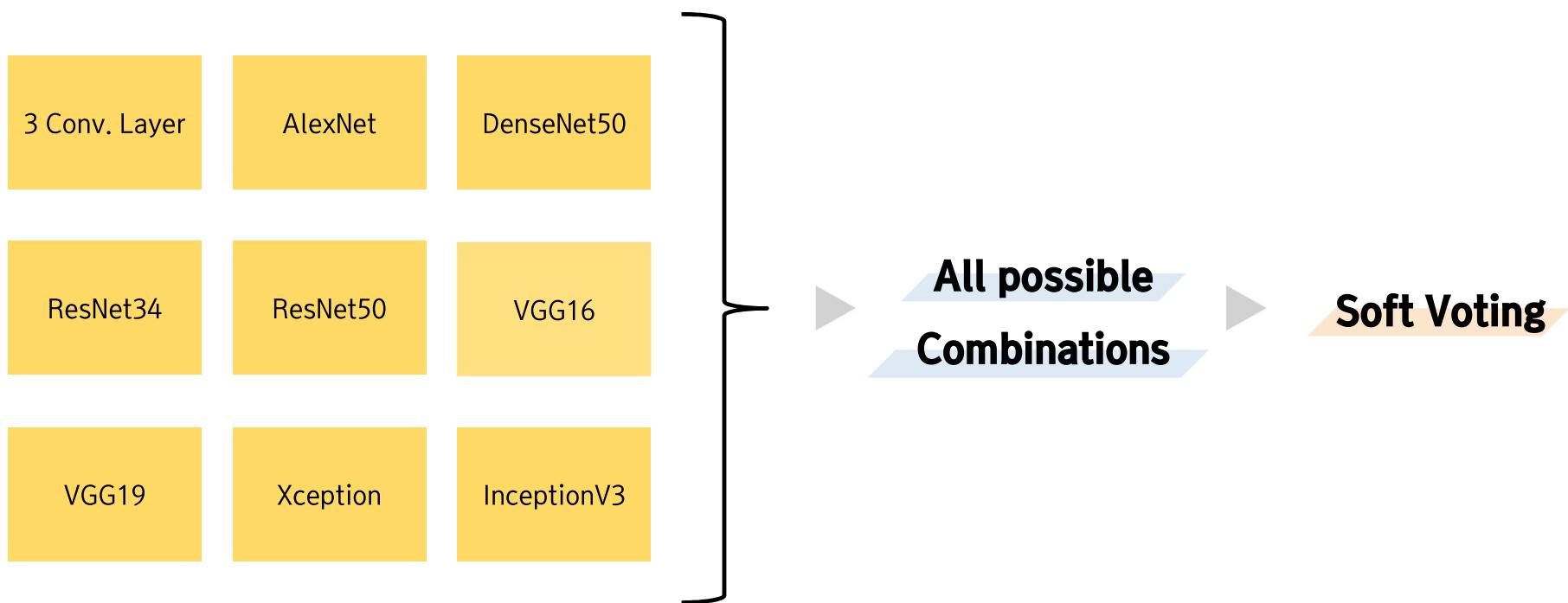


Summary



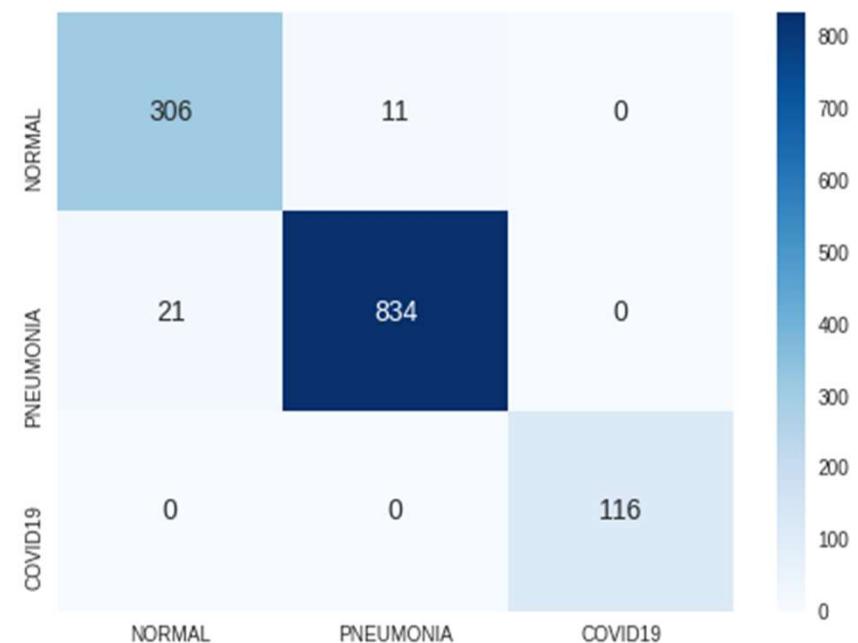
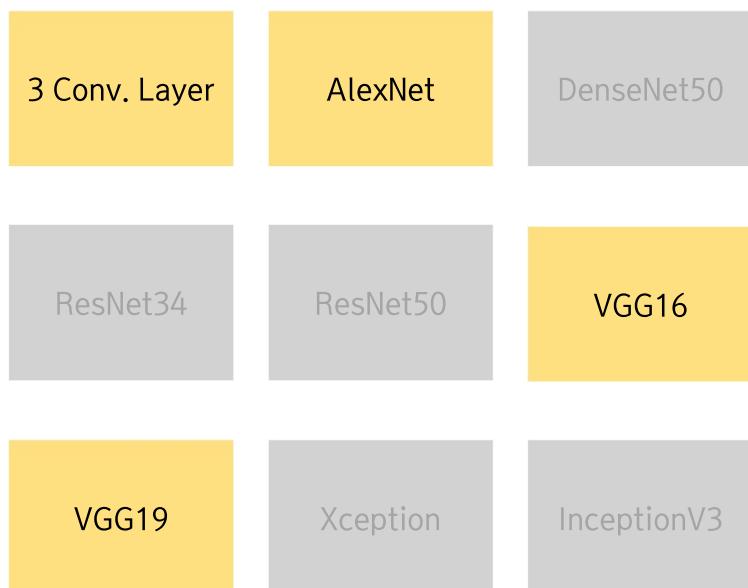
Ensemble

Soft voting



Ensemble

Soft voting



Test accuracy = 0.9756

Normal Recall(vs Cov.&Pne) = 0.9784

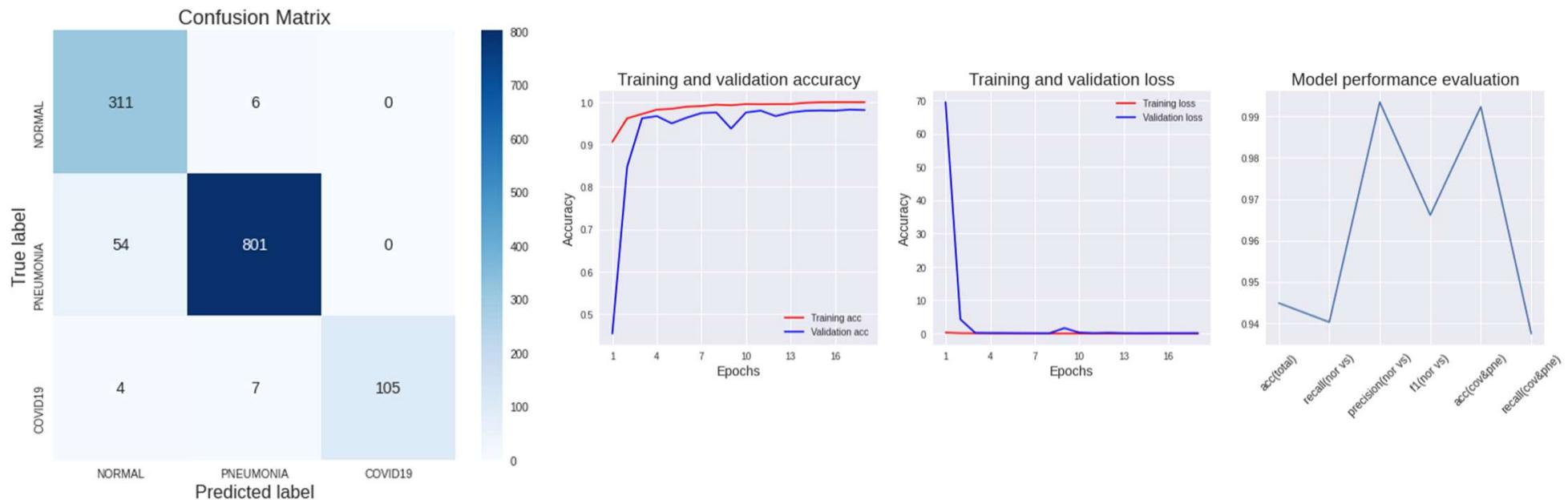
Cov. Recall(vs Pne.) = 1

Fine tuning – InceptionV3

Model (RMSprop)	Freezing pre-trained model layer			Dense layer		Regularizer		
	0%(True)	50%	100%(False)	0	0 + Dropout(0.5)	L1(0.1)	L2(0.1)	L1 + L2(0.1)
①	0	X	X	X	X	X	X	X
②	X	0	X	X	X	X	X	X
③	X	X	0	X	X	X	X	X
④	0	X	X	0	X	X	X	X
⑤	0	X	X	X	0	X	X	X
⑥	0	X	X	0	X	0	X	X
⑦	0	X	X	0	X	X	0	X
⑧	0	X	X	X	X	X	X	0
⑨	X	0	X	X	0	X	X	0

EX. Fine tuning

② Freezing pre-trained model layer: 50%

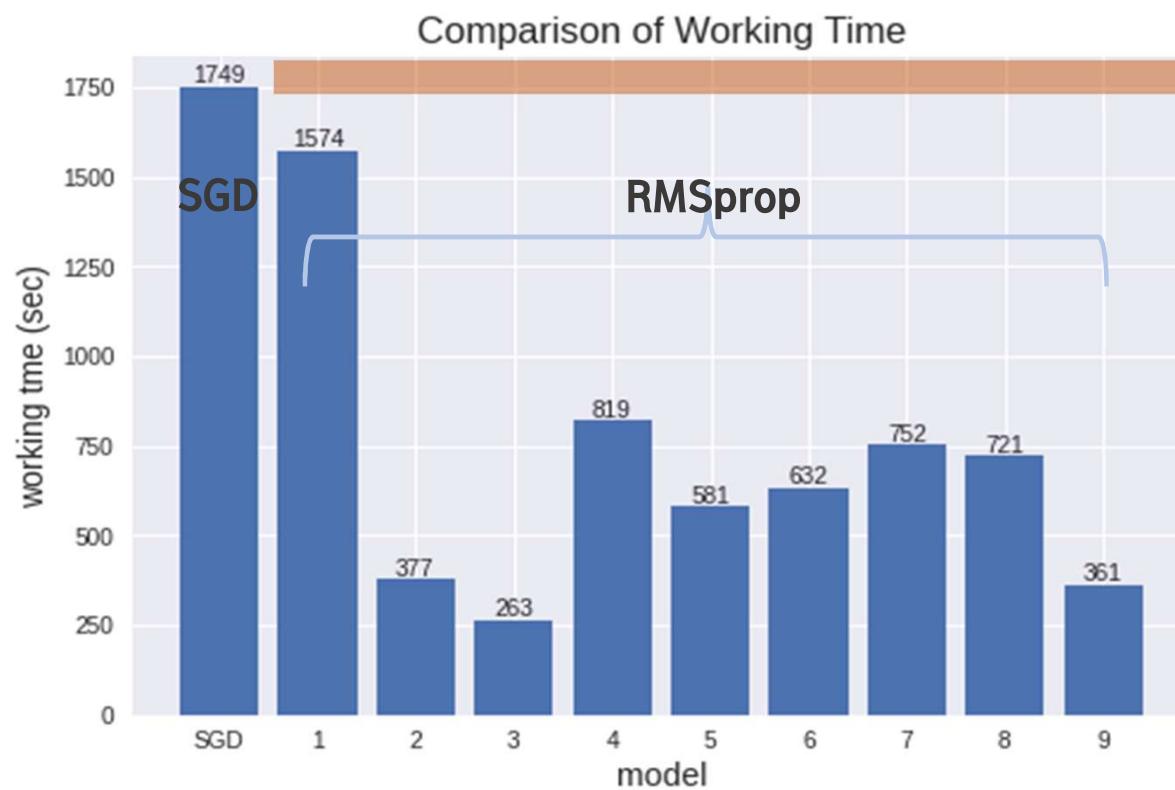


Summary

Model #	Train Accuracy	Validation Accuracy	Test Accuracy	Recall (nor. vs)	recall (cov&pne)	Train - Val Accuracy	time(s)
SGD	0.9990	0.9690	0.9480	0.9609	0.9913	0.0300	1749
①	1.0000	0.9876	0.9658	0.9763	0.9828	0.0124	1575
②	0.9999	0.9814	0.9449	0.9403	0.9375	0.0185	378
③	0.9833	0.9271	0.9177	0.9351	0.9123	0.0562	264
④	0.9989	0.9800	0.9612	0.9722	0.9914	0.0189	820
⑤	0.9998	0.9829	0.9589	0.9670	0.9913	0.0169	581
⑥	1.0000	0.9814	0.9464	0.9609	0.9914	0.0186	632
⑦	1.0000	0.9833	0.9682	0.9856	0.9914	0.0167	753
⑧	1.0000	0.9838	0.9674	0.9701	1.0000	0.0162	722
⑨	0.9371	0.9852	0.9635	0.9743	0.9828	0.0481	361

Summary

Model performance time



SGD vs RMSprop

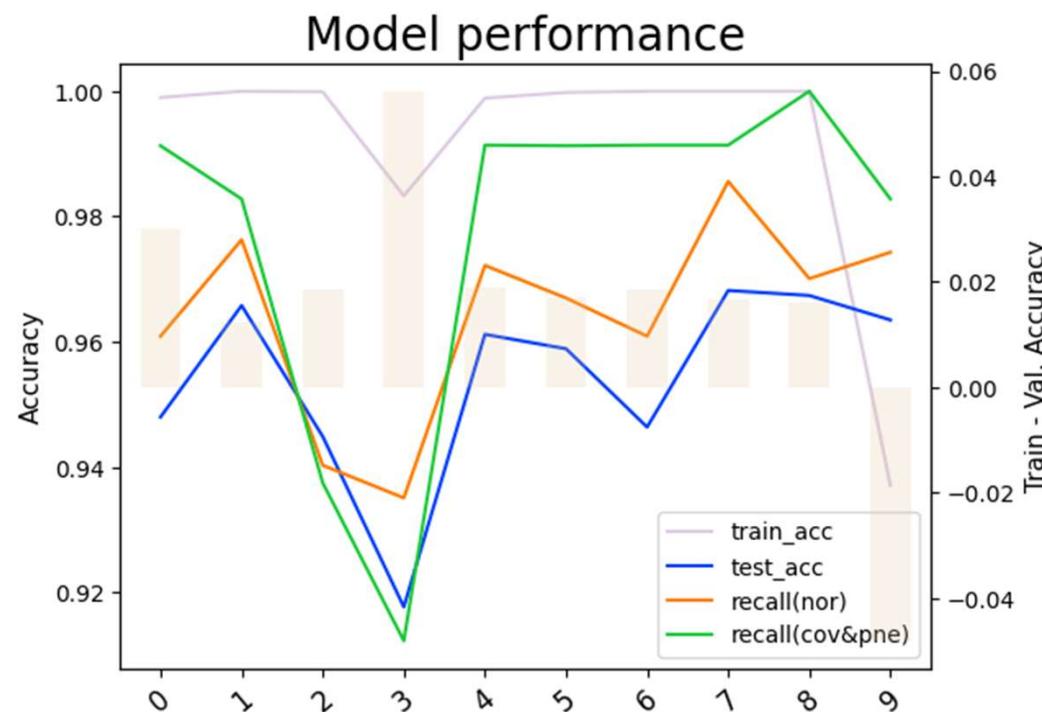
- 고속 Optimizer
- learning rate 자동 조절



Working Time ↓

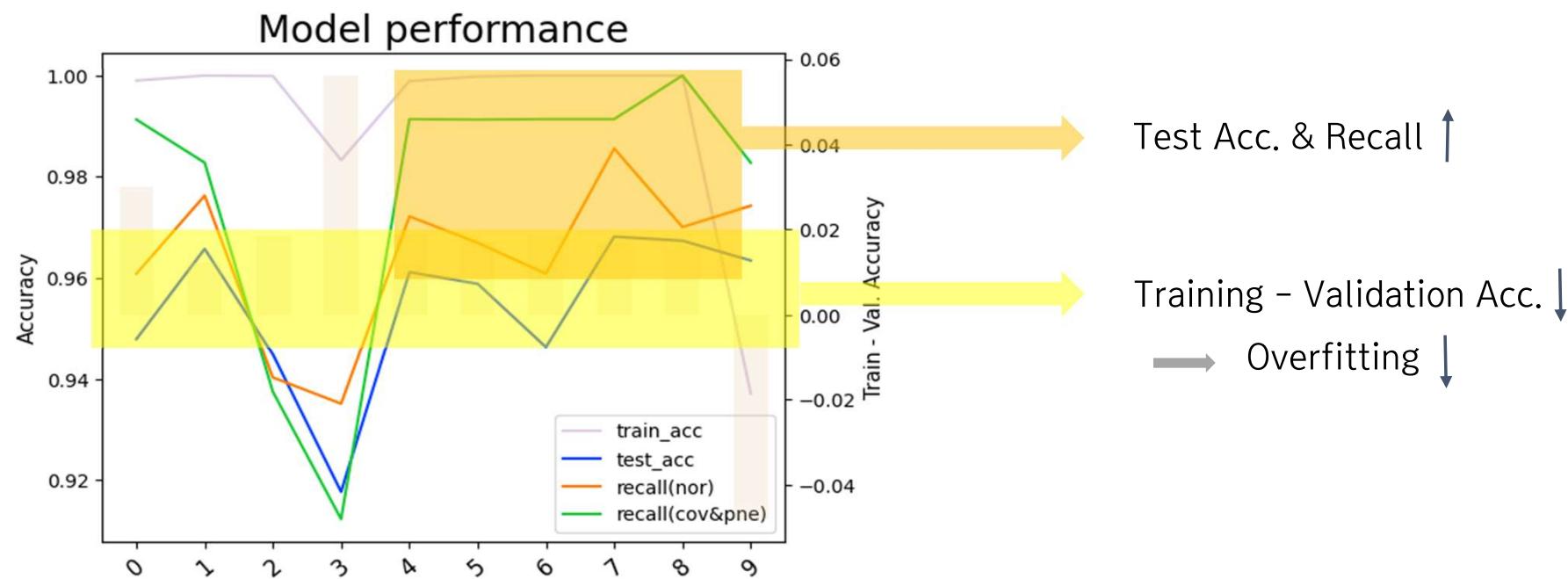
Summary

Model performance graph



Summary

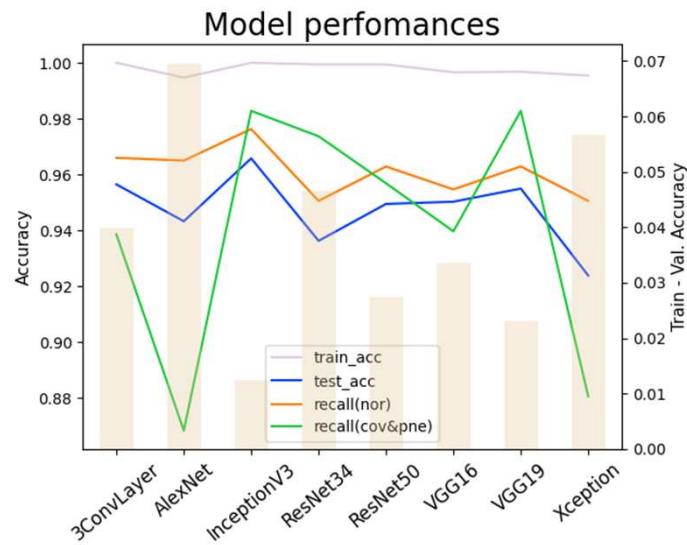
Model performance graph



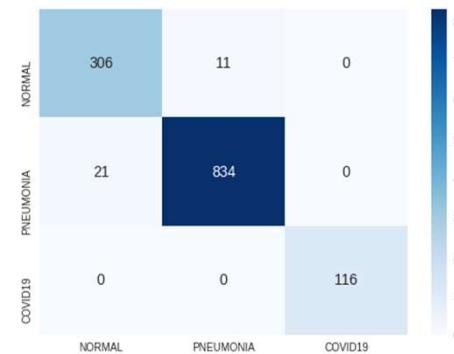
04. Results

Results

Summary



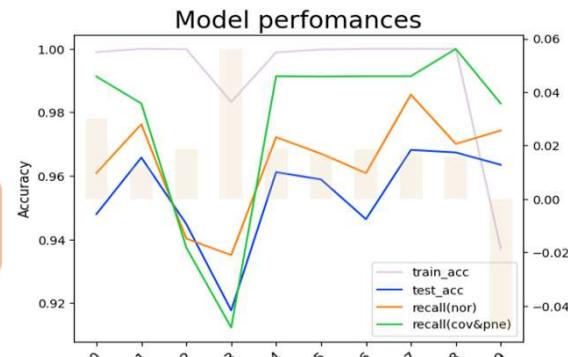
**Ensemble
(Soft voting)**



Test Acc. = 0.9756

Normal Recall(vs Cov.&Pne.) = 0.9784

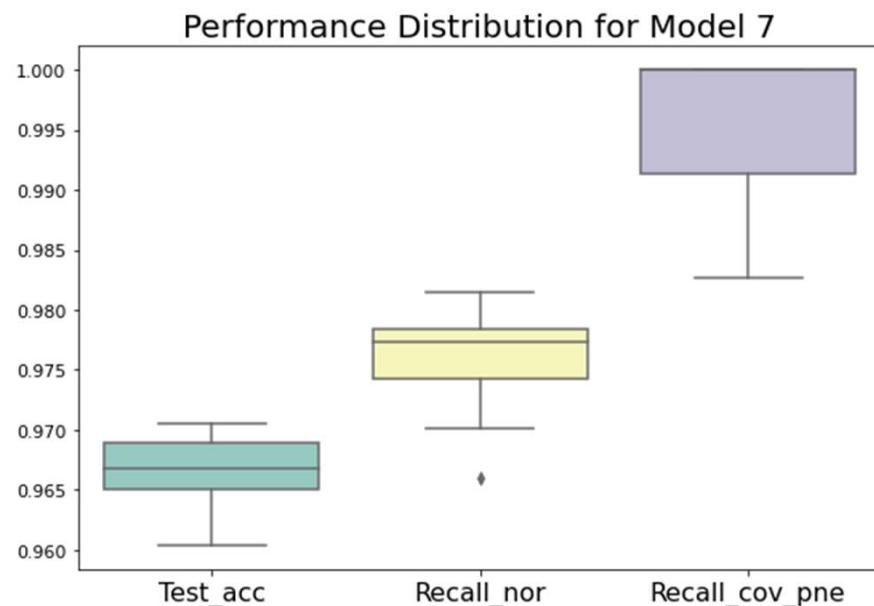
Cov. Recall(vs Pne.) = 1



⑦ InceptionV3 + Regularizer(L2)

Performance Distribution

앞서 선정한 Model ⑦(InceptionV3 + Regularizer(L2))에 대하여 50번의 반복 시행을 통하여 모델의 Performance의 Distribution을 구해보았다.



Mean Value :

Test_acc	0.9668
Recall_nor	0.9764
Recall_cov_pne	0.9955

Test Acc. = 0.9682



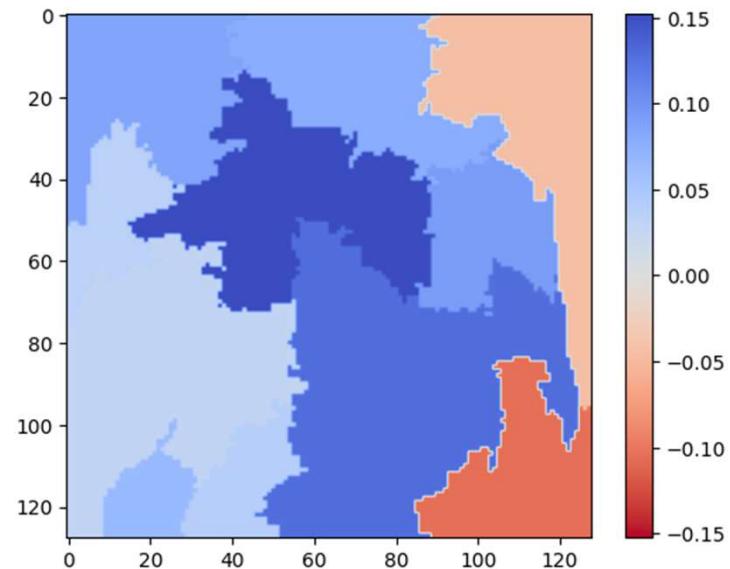
Normal Recall(vs Cov.&Pne.) = 0.9856

Cov. Recall(vs Pne.) = 0.9914

Performance Distribution의 평균값이 앞서
구한 값과 비슷하지만 다소 차이가 존재함

Visualization

Prediction Visualization by LIME



Predicted class의 Local Area에 따른 Prediction rate

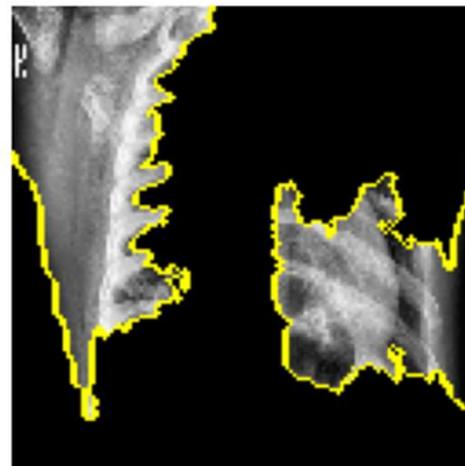
Visualization

Prediction Visualization by LIME

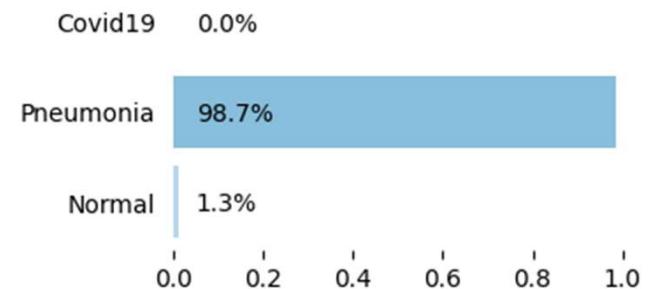
Actual class : Pneumonia



Visualization of detection



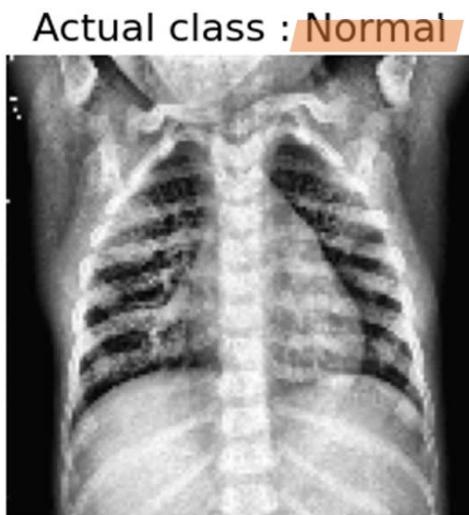
Predicted class : Pneumonia



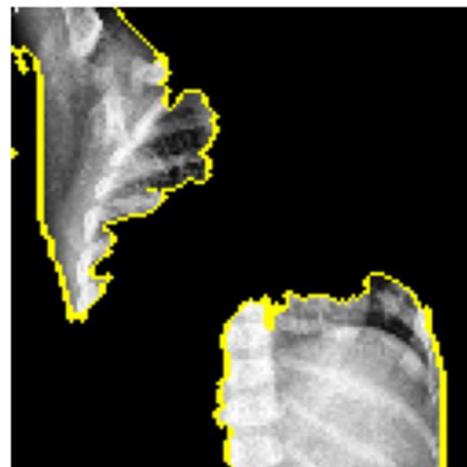
Predicted class의 예측값이 높은 Local area와 각 class에 대한 Prediction rate

Visualization

Prediction Visualization by LIME



Visualization of detection

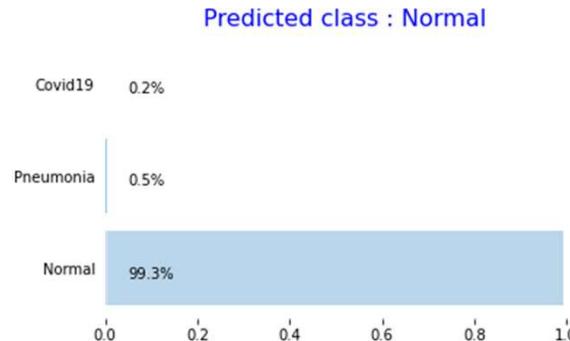
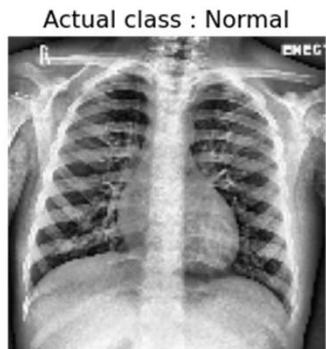
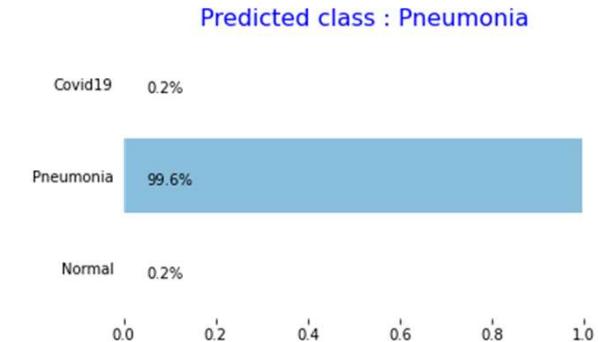
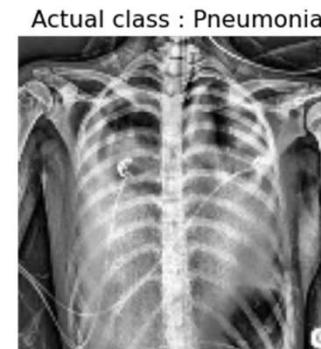
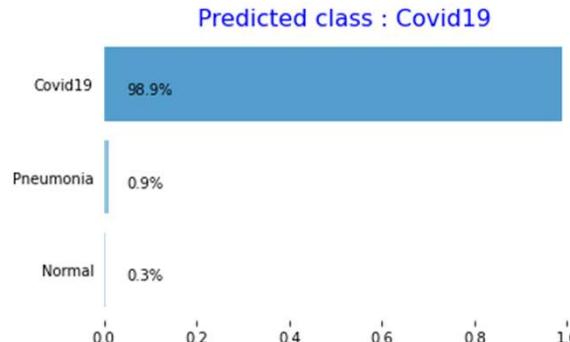
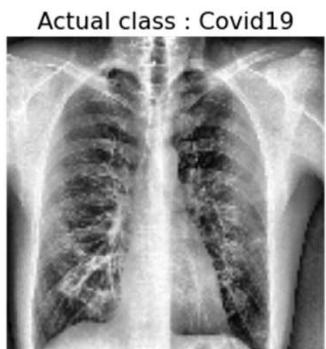


Predicted class : Pneumonia



Model Test

구글에서 Random하게 구한 x-ray 이미지(Normal / Pneumonia / Covid-19) 총 9개에 대하여 분류 성능을 테스트 해보았다.



9개 이미지 중 8개에 대해 예측 성공!!

Limit

Limit

- 한정된 Computing Power

Measure에 대한 보다 정교한 값을 구하기 위해서는 Distribution을 구하는 것이 좋다.

그러나 제한적인 메모리와 GPU로 인해 비교적인 적은 횟수로 딥러닝 모델을 Fitting해야 했다.
이러한 이유로 하이퍼파라미터 튜닝에 어려움이 있었다.

- 충분하지 않은 Dataset

실험을 진행한 Dataset의 Data 숫자는 약 5,000개 였다.

따라서 모델을 Fitting할 때마다 Measure에 대한 편차가 컸다.

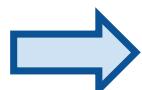
Conclusion

X-ray를 활용한 코로나 진단법의 장점

- 1) 타인과 대면할 필요가 없어 위험이 감소되어 **안전성**이 **증가**한다.
- 2) 검사를 위한 **시간과 비용을 절약**할 수 있다.
- 3) 일회용 사용을 줄여 **환경오염을 줄일** 수 있다.
- 4) **폐렴과 쉽게 구분**된다.
- 5) 한정된 의료 자원을 우선순위가 높은 환자에게 배분 할 수 있다.

CNN을 활용한 이미지 분류 검사법의 의의

- 1) CT, MRI 등 다른 **영상의학적 촬영 장비**에 개발한 모형을 적용하여 의료 혁신을 이룰 수 있다.
- 2) 데이터가 축적될수록 **정확도**가 빠르게 **개선**될 것으로 기대된다.
- 3) 적은 **비용**으로도 일정 수준의 진료를 기대할 수 있다.



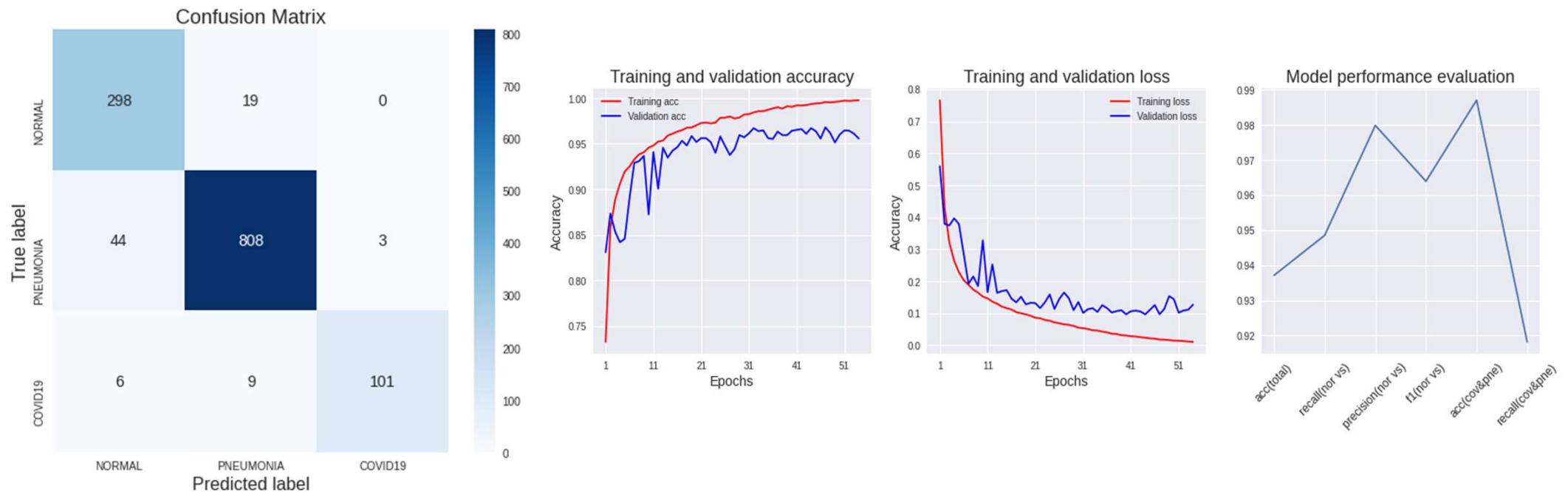
X-ray 이미지 분류 검사법을 사용하면 코로나19 판별의 **효율성이 개선되고 정확도 높은 코로나 판별이 가능하다.** 또한 CNN을 활용한 검사법은 **다양한 질병의 검사 방식으로 확장 가능하다.**

감사합니다 😊

(부록) 예측 성능 도표

모델별 예측 성능 도표

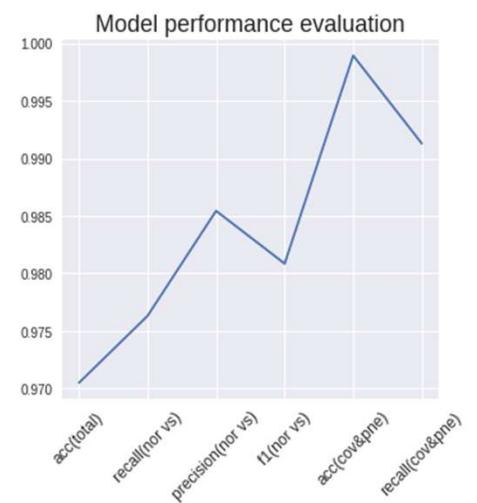
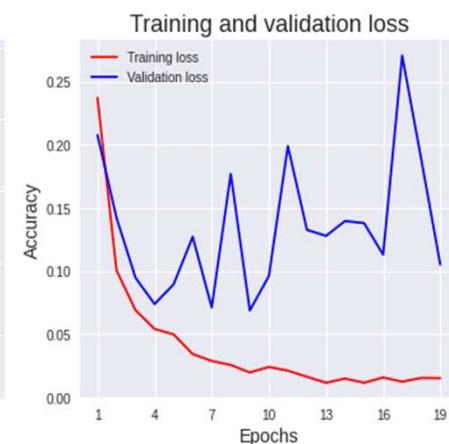
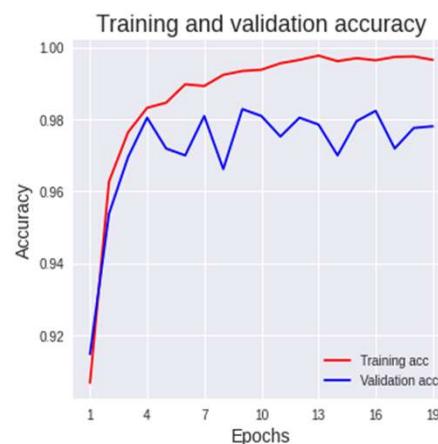
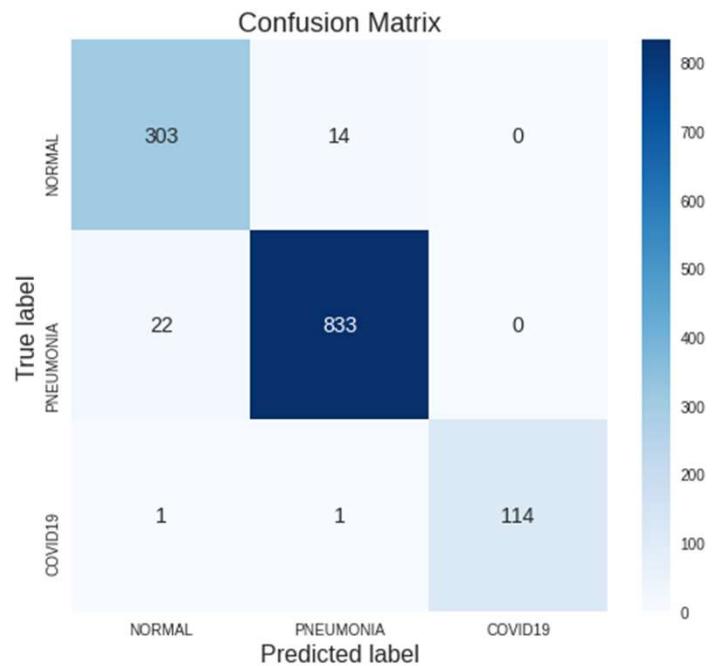
3 Conv. Layer



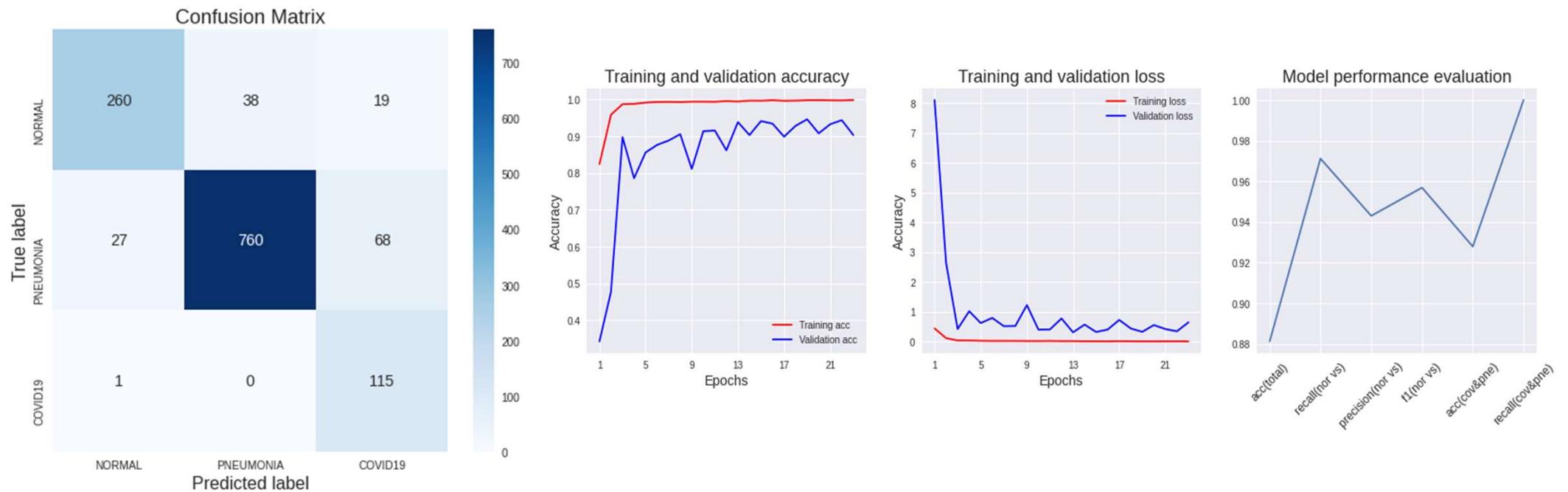
VGG16



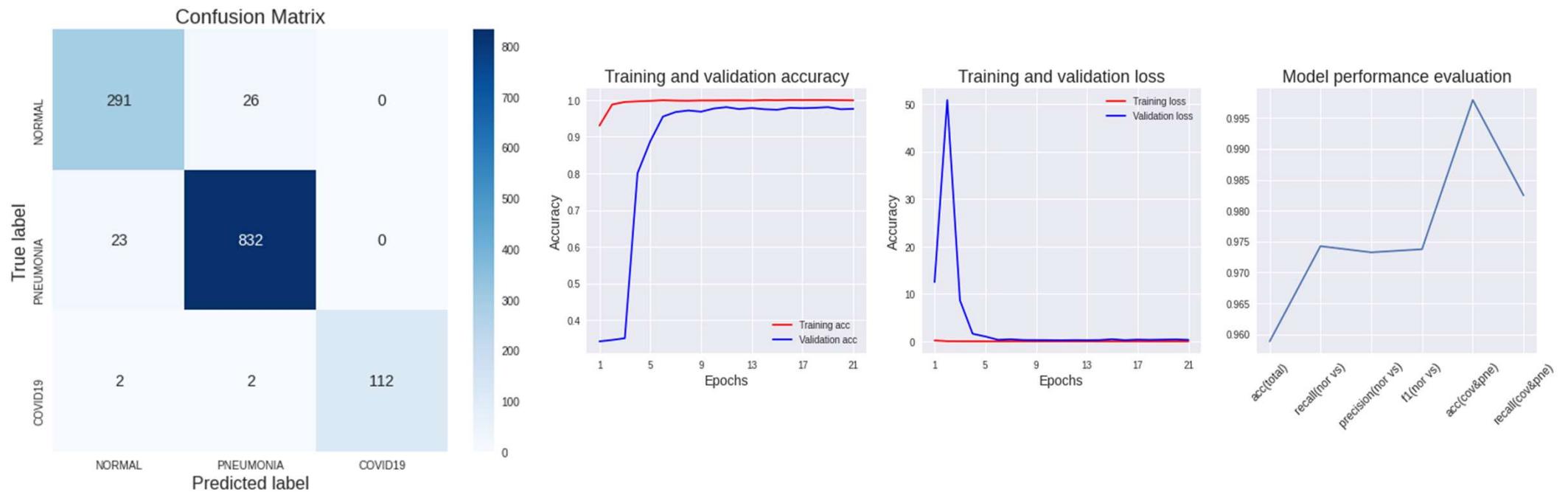
VGG19



ResNet34



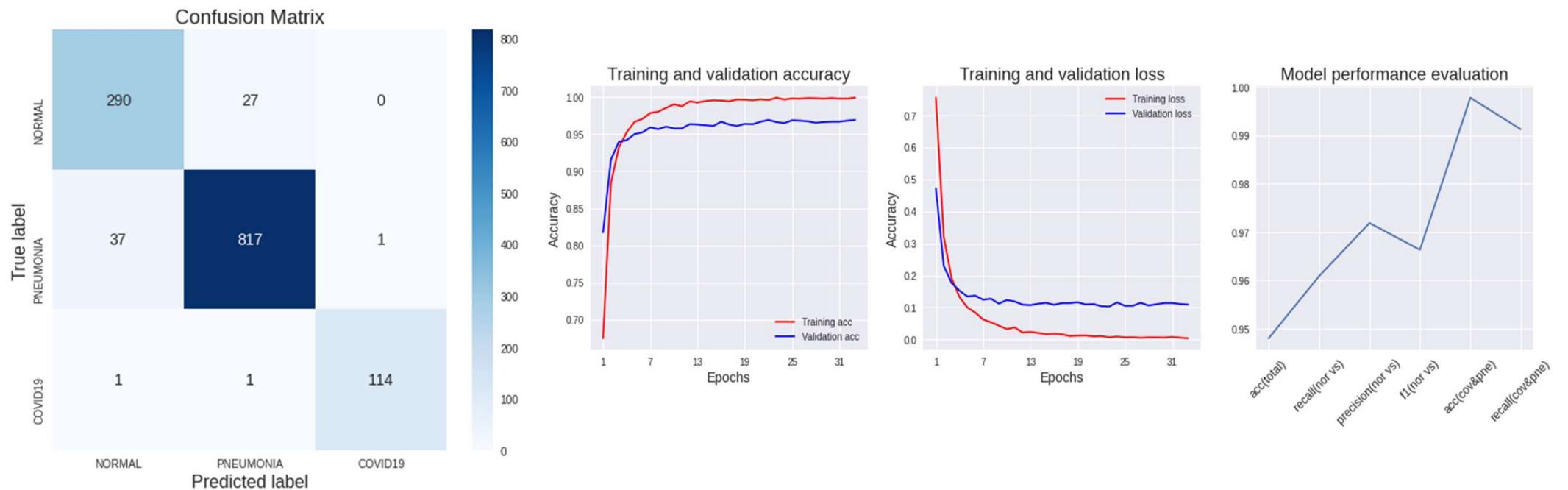
ResNet50



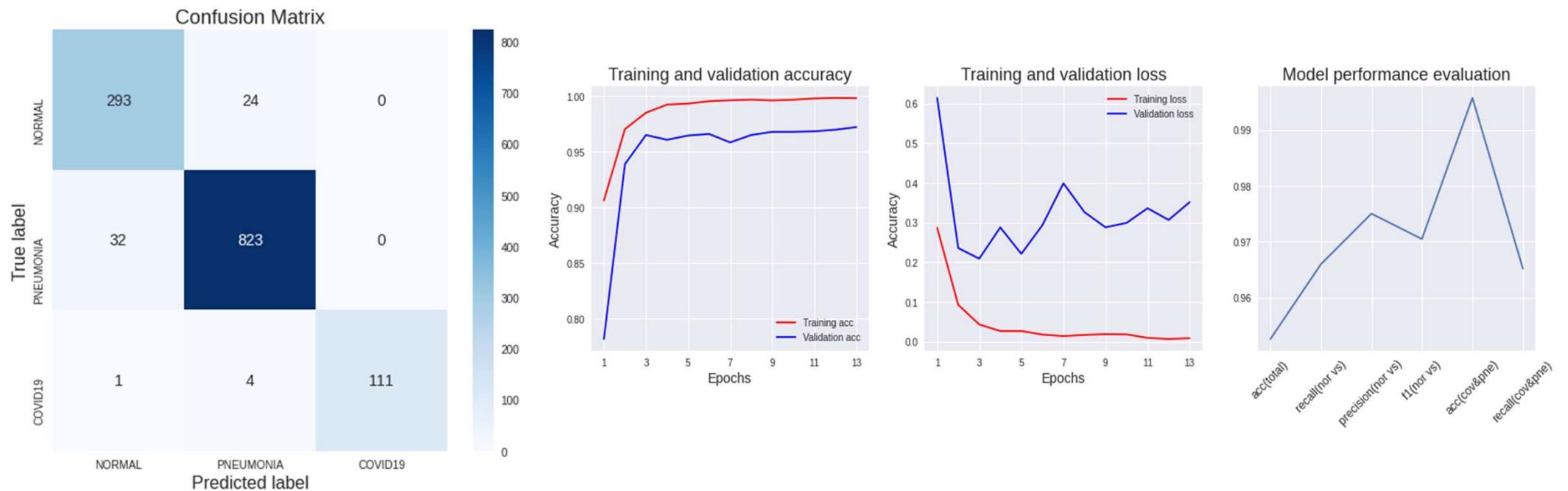
AlexNet



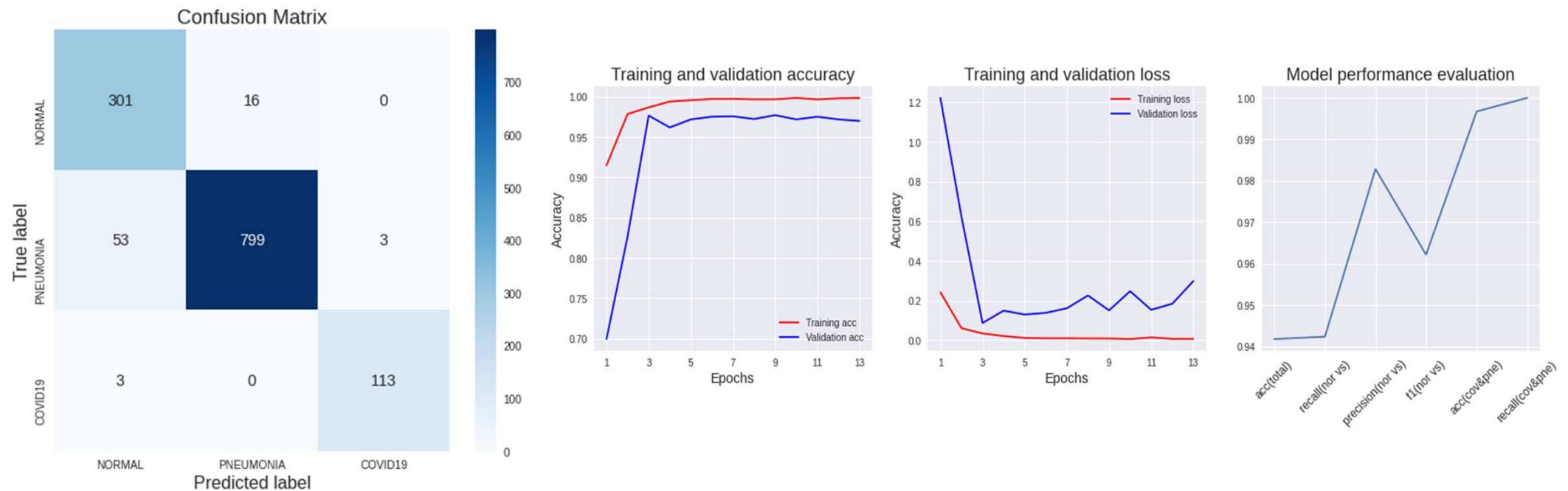
InceptionV3



Xception



DenseNet50



InceptionV3 – Fine tuning 예측 성능 도표

Fine tuning - Inception

① Freezing pre-trained model layer: 0% (True)



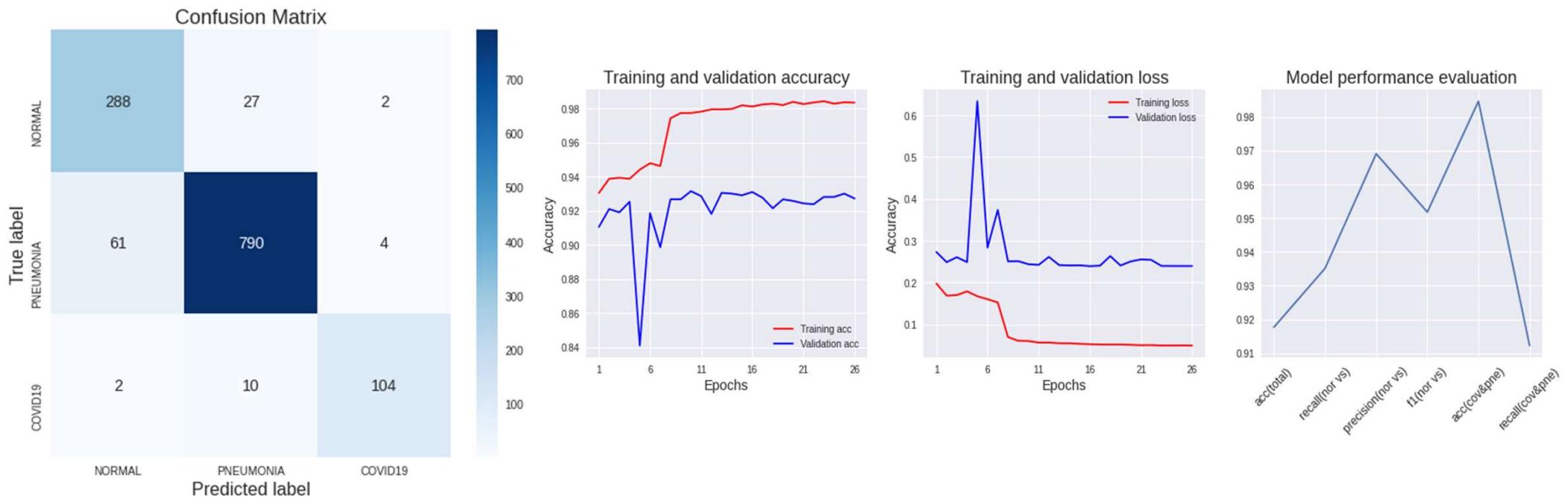
Fine tuning - Inception

② Freezing pre-trained model layer: 50%



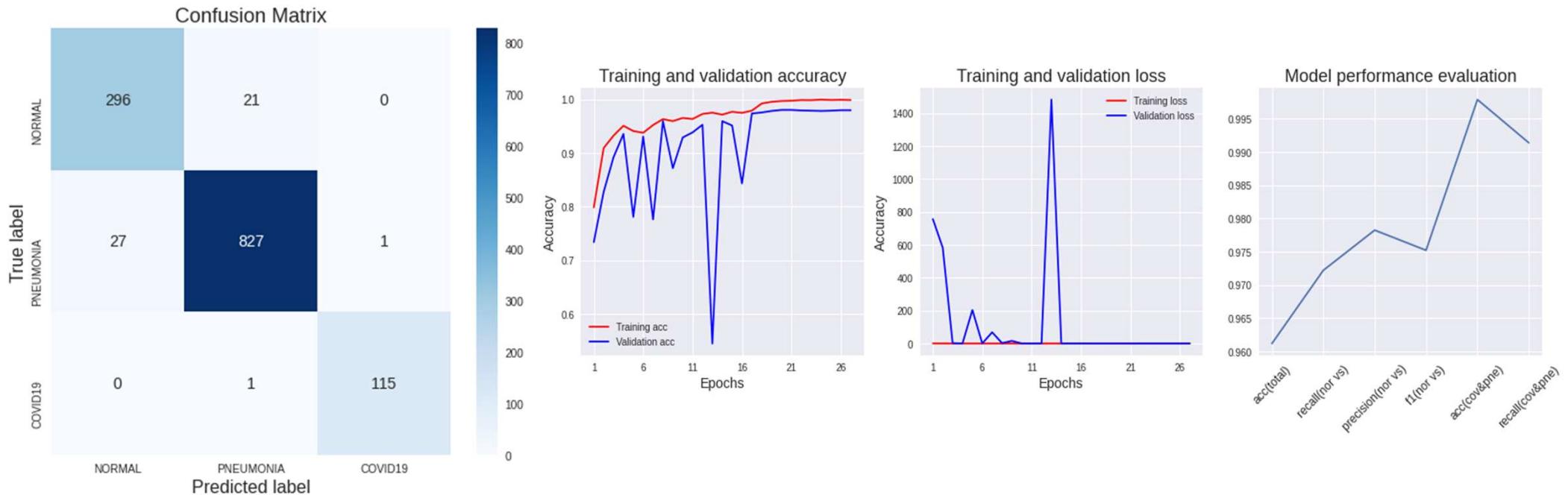
Fine tuning - Inception

③ Freezing pre-trained model layer: 100%(False)



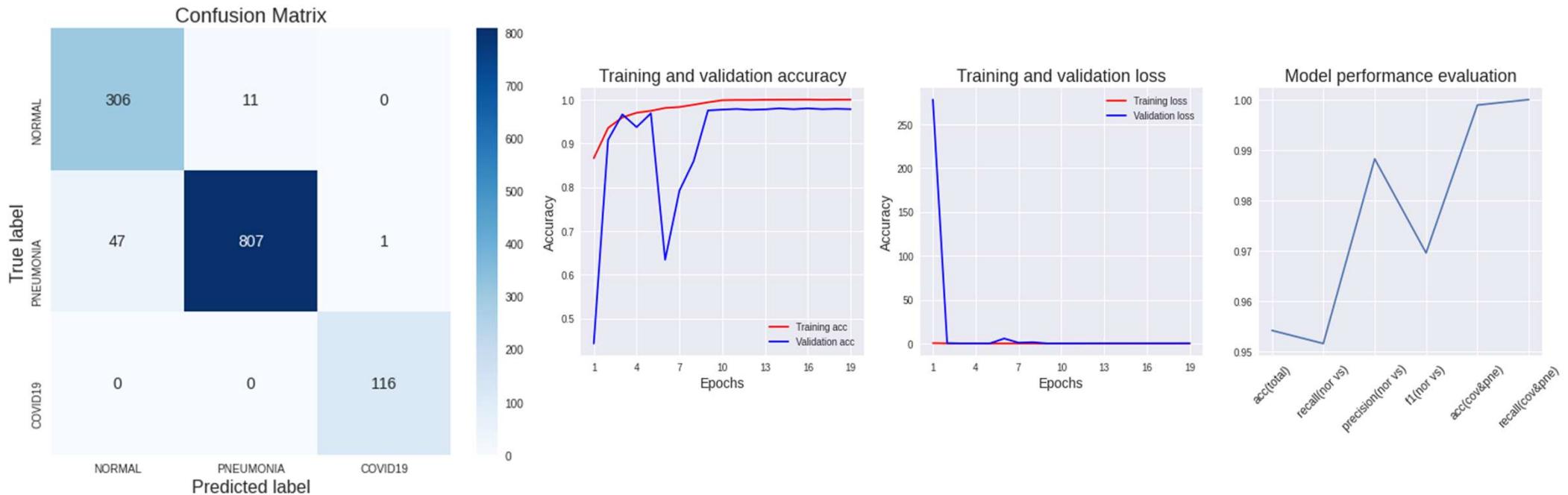
Fine tuning - Inception

④ Dense layer: O



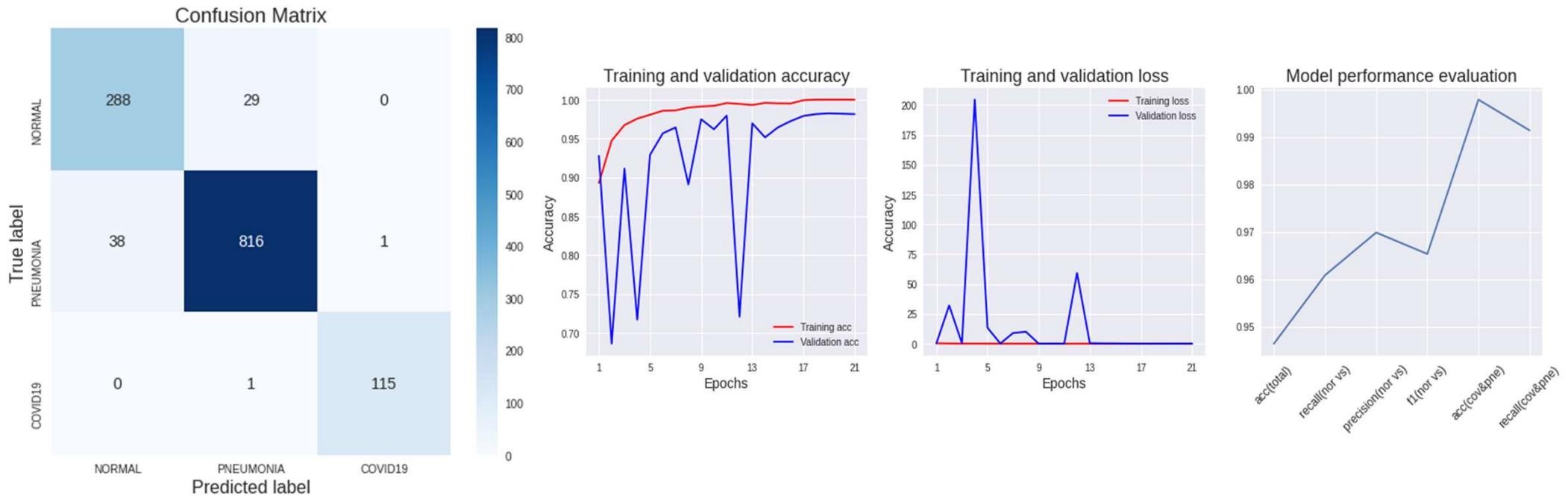
Fine tuning - Inception

⑤ Dense layer: O + Dropout(0.5)



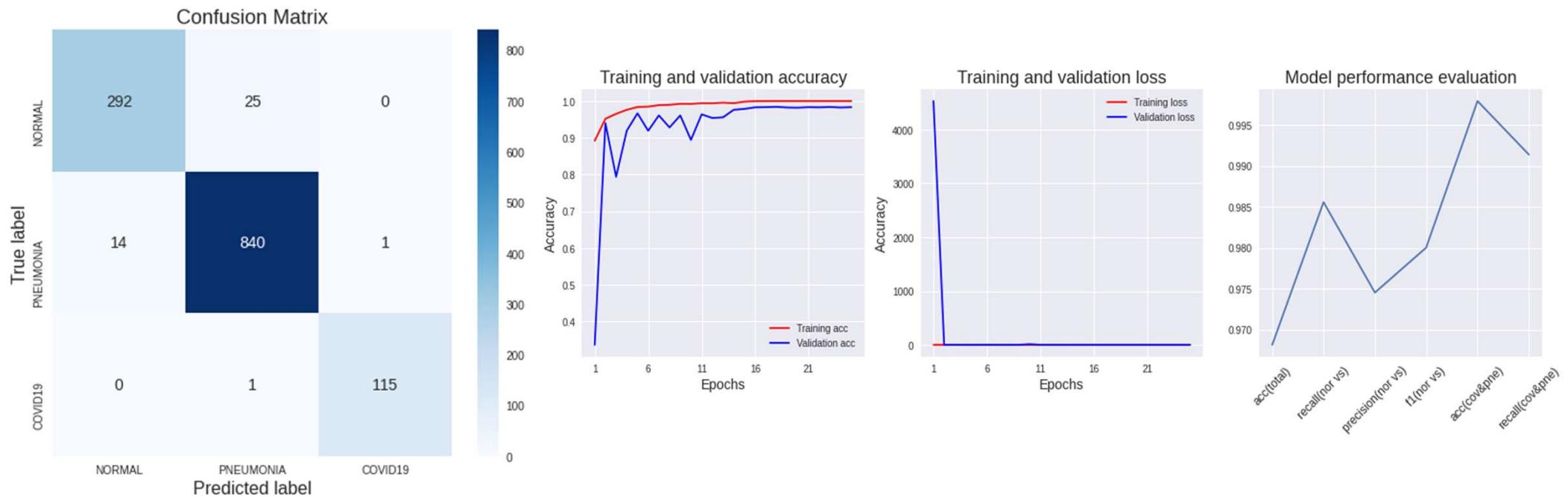
Fine tuning - Inception

⑥ Regularizer: L1



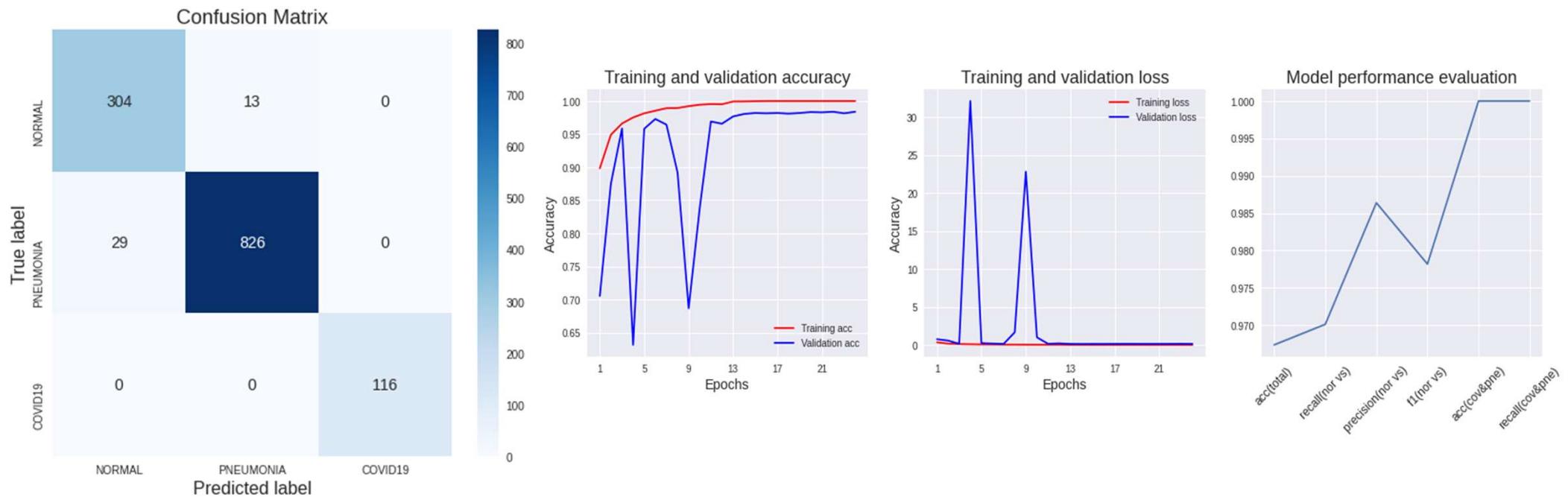
Fine tuning - Inception

⑥ Regularizer: L2



Fine tuning - Inception

⑥ Regularizer: L1 + L2



Fine tuning - Inception

⑨ Freezing pre-trained model layer: 50% / Dense layer : O + Dropout(0.5) / Regularizer: L1 + L2

