

To provide an alternative testing methods for prediction of COVID-19 and other Lung Diseases using lung ultrasound imagery with Deep-learning - Machine Learning based detection models.

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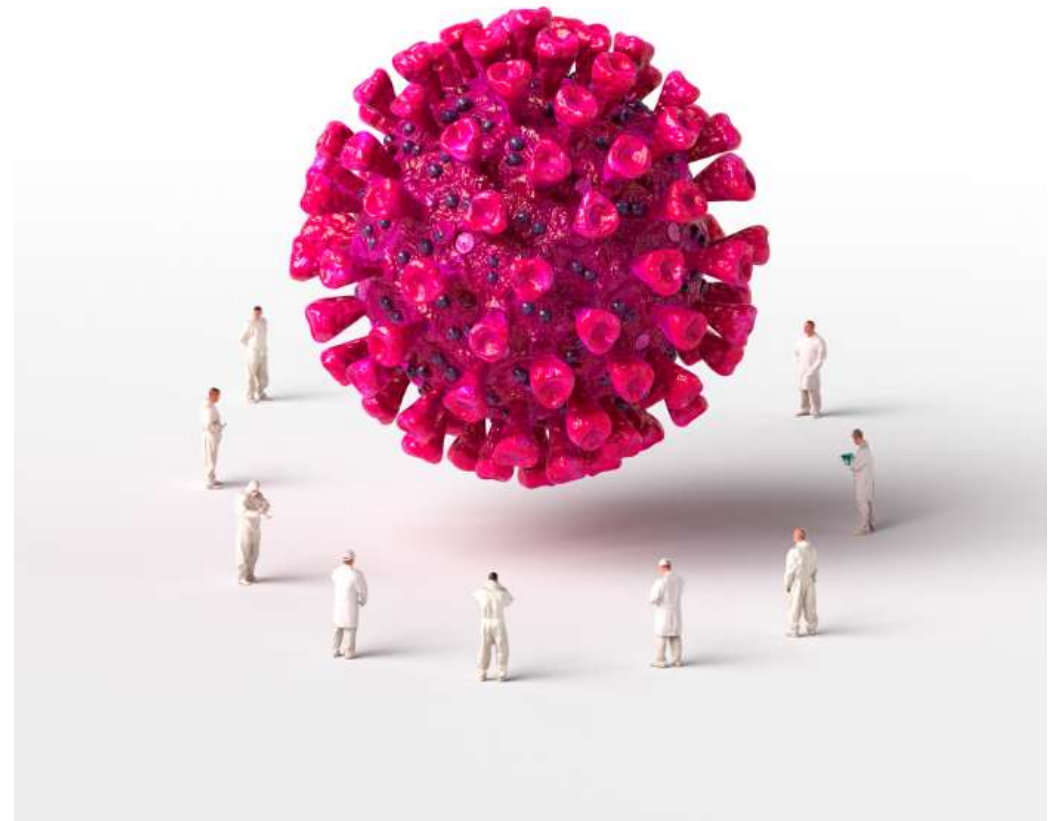


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INTRODUCTION



- The Covid-19 has infected more than 90 million and killed more than 1.9 million people globally
- Despite their apparent similarities, COVID-19 and other respiratory disorders are very different from one another.



INTRODUCTION

- The Lung CT images of COVID-19 pneumonia are significantly different from influenza pneumonia and the substantial overlaps are found among COVID-19, influenza and Organizing Pneumonia.
- The main objective of this project is to assist doctors and help distinguish the Lung Ultrasound (LUS) between the known Lung diseases and Covid.

HOW COVID-19 COMPARES TO OTHER COMMON CONDITIONS

SYMPTOMS	CORONAVIRUS* COVID-19 <small>Symptoms range from mild to severe</small>	COLD <small>Gradual onset of symptoms</small>	FLU <small>Abrupt onset of symptoms</small>	SEASONAL ALLERGIES <small>Abrupt onset of symptoms</small>
 Length of Symptoms	7 - 25 DAYS	LESS THAN 14 DAYS	7 - 14 DAYS	SEVERAL WEEKS
 Cough	COMMON (USUALLY DRY)	COMMON (MILD)	COMMON (USUALLY DRY)	RARE (USUALLY DRY UNLESS IT TRIGGERS ASTHMA)
 Shortness of Breath	SOMETIMES	NO**	NO**	NO**
 Sneezing	NO	COMMON	NO	COMMON
 Runny or Stuffy Nose	RARE	COMMON	SOMETIMES	COMMON
 Sore Throat	SOMETIMES	COMMON	SOMETIMES	SOMETIMES (USUALLY DRY)
 Fever	COMMON	SHORT FEVER PERIOD	COMMON	NO
 Feeling Tired	SOMETIMES	SOMETIMES	COMMON	SOMETIMES
 Headaches	SOMETIMES	RARE	COMMON	SOMETIMES (RELATED TO SINUS PAIN)
 Body Aches and Pains	SOMETIMES	COMMON	COMMON	NO

INTRODUCTION



There are limited ways to determine the covid-19 from other diseases with similar symptoms.



Reverse Transcription-Polymerase Chain Reaction (RT-PCR) is the gold standard laboratory test for COVID-19, usually takes a day to return results.



Rapid test kits as COVID-19 antigen rapid tests return results in minutes. However, these tests tend to have higher false negative, false positive results compared to laboratory-based PCR.



MOTIVATION

- Previous studies compared X-Ray and CT findings of COVID-19 pneumonia with those of other infections however, to our knowledge, no studies to date have included non-infectious organizing pneumonia (OP) for comparison with lung Ultrasound.
- There is an urgent need for accurate, fast, and reliable techniques to classify and differentiate known lung diseases from Covid.
- RT-PCR tests do not provide additional information that supports clinical decision-making with respect to the triage of infected patients.



X-Ray



CT Scan



Ultrasound



RESEARCH OBJECTIVE

- To evaluate and compare the performance of deep-learning techniques vs Supervised Learning Methods for detecting COVID-19, pneumonia, Other fungal infections from lung ultrasound imagery.
- Which machine learning classifier can identify COVID-19 and other categories accurately using lung ultrasound images with the highest accuracy, F1-score, and Confusion Matrix?

DATA DESCRIPTION

- The Source for Dataset is available in GitHub <https://github.com/nrc-cnrc/COVID-US>.
- The dataset consists of 18628 Images which were extracted from videos.
- The current COVIDx-US dataset is constructed from the following datasets:

Data sources



DATA DESCRIPTION

Covid



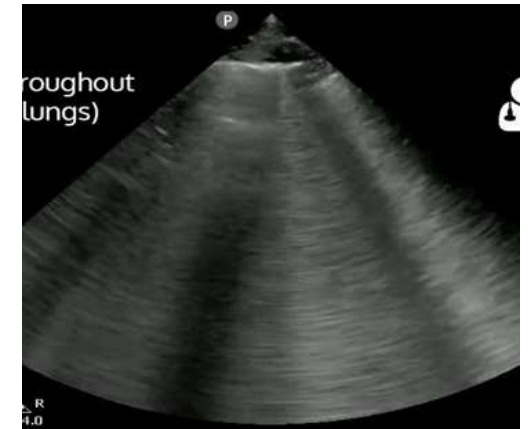
Pneumonia



Other



Normal



- Based on the Image Labels we categorized the images into 5 variables.

1. File_no
2. Source
3. Category
4. Probe Type
5. Frame Number

DATA PRE-PROCESSING

Original Image



Dimensions – 816 x 540

Cropped Image




Dimensions – 408 x 408

METHOD OF ANALYSIS

Data loading - loaded the data into image arrays.



Data Processing - Converting labels to ordinal - Initially data labels are in categorical datatypes, while training the model for better performance labels are converted to ordinal.



Data Normalization - When taking the raw data, there can be lot of bias and variance. So, images are normalized.



Data Partition - Splitting the data into train and test sets with 80% and 20% respectively. As we have imbalanced dataset while splitting the data, we have used stratify method for best performance.



METHOD OF ANALYSIS

Low number of training images per class, hence we have stratified the data to avoid the bias.

Low training epochs for vgg-16 model.

Limited hyper parameter search space for all the models as the processing time is high and we have low resources.

Model Training - Training the model with processed images and respective labels to classify the class labels appropriately.

Model Testing - After training the model, observing the performance of each model with accuracy, f1-score and confusion matrix. And we have checked if the models are overfitting.

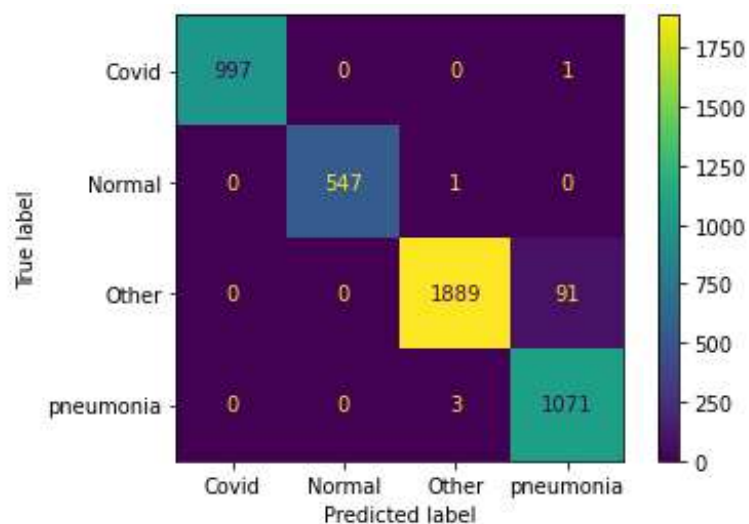
RESULTS

Method	Model	Training Accuracy	Test Accuracy
CNN	VGG-16	98	98
Supervised ML	Random Forest	98	97
	KNN	98	97
	Naïve Bayes	60	59

VGG16

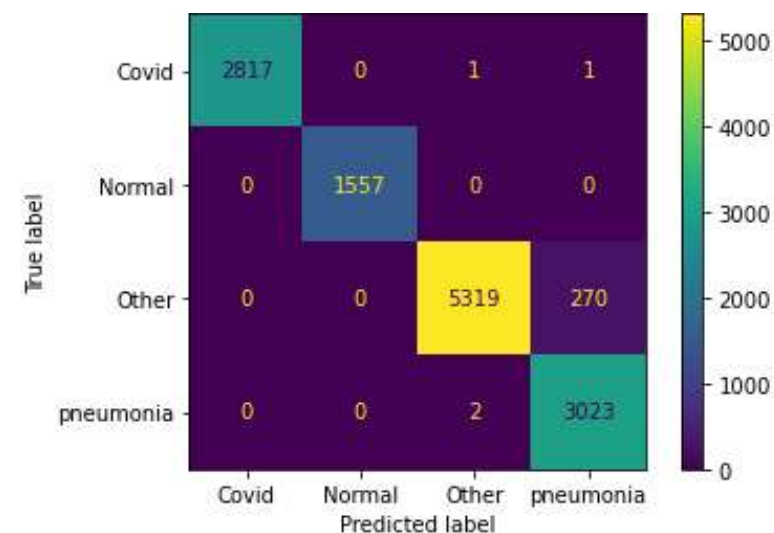
Training

	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	2819
Normal	1.00	1.00	1.00	1557
Other	1.00	0.95	0.97	5589
pneumonia	0.92	1.00	0.96	3025
accuracy			0.98	12990
macro avg	0.98	0.99	0.98	12990
weighted avg	0.98	0.98	0.98	12990



Testing

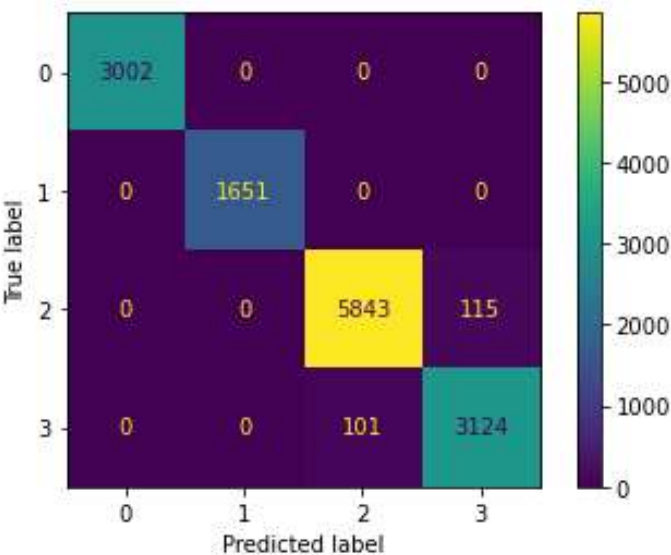
	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	2819
Normal	1.00	1.00	1.00	1557
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weighted avg	0.98	0.98	0.98	12990



Random Forest

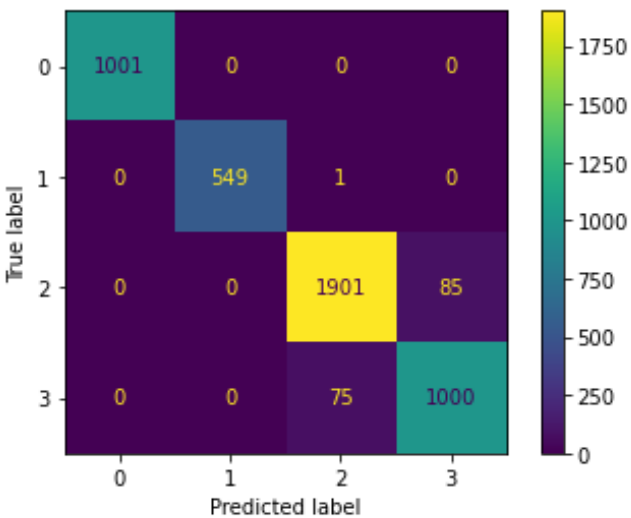
Training

	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	3002
Normal	1.00	1.00	1.00	1651
Other	0.98	0.98	0.98	5958
pneumonia	0.96	0.97	0.97	3225
accuracy			0.98	13836
macro avg	0.99	0.99	0.99	13836
weighted avg	0.98	0.98	0.98	13836



Testing

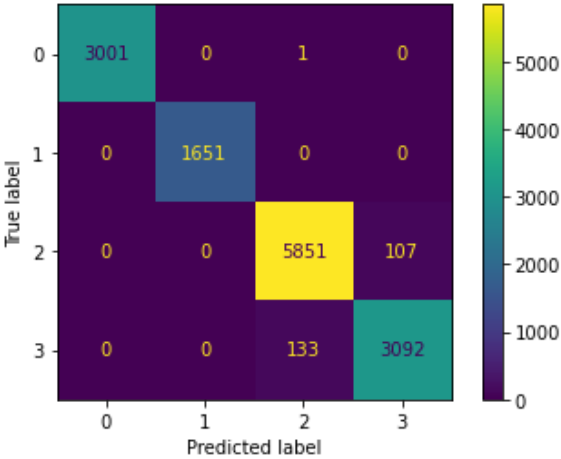
	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	1001
Normal	1.00	1.00	1.00	550
Other	0.96	0.96	0.96	1986
pneumonia	0.92	0.93	0.93	1075
accuracy			0.97	4612
macro avg	0.97	0.97	0.97	4612
weighted avg	0.97	0.97	0.97	4612



KNN

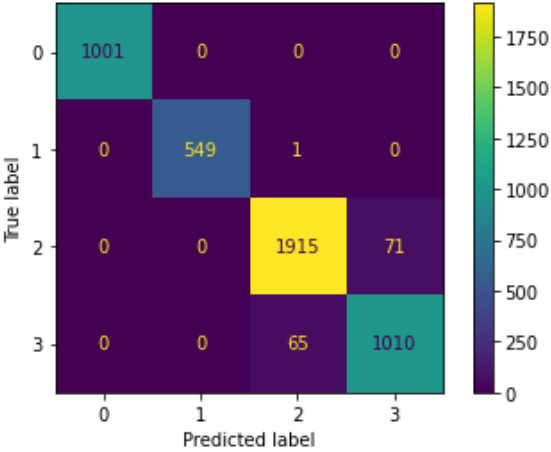
Training

	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	3002
Normal	1.00	1.00	1.00	1651
Other	0.98	0.98	0.98	5958
pneumonia	0.97	0.96	0.96	3225
accuracy			0.98	13836
macro avg	0.99	0.99	0.99	13836
weighted avg	0.98	0.98	0.98	13836



Testing

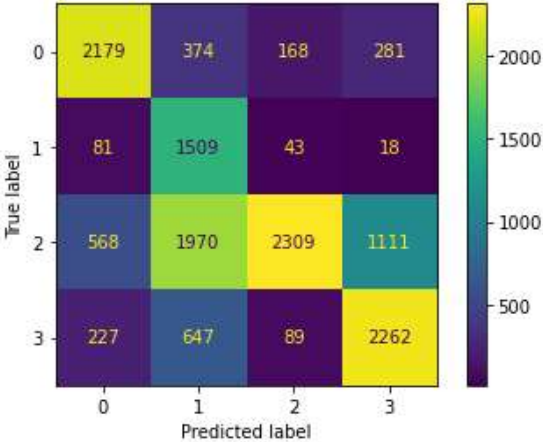
	precision	recall	f1-score	support
Covid	1.00	1.00	1.00	1001
Normal	1.00	1.00	1.00	550
Other	0.97	0.96	0.97	1986
pneumonia	0.93	0.94	0.94	1075
accuracy			0.97	4612
macro avg	0.98	0.98	0.98	4612
weighted avg	0.97	0.97	0.97	4612



Naïve Bayes

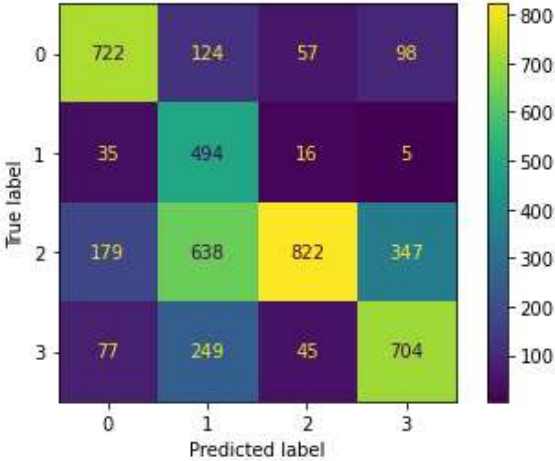
Training

	precision	recall	f1-score	support
Covid	0.71	0.73	0.72	3002
Normal	0.34	0.91	0.49	1651
Other	0.89	0.39	0.54	5958
pneumonia	0.62	0.70	0.66	3225
accuracy			0.60	13836
macro avg	0.64	0.68	0.60	13836
weighted avg	0.72	0.60	0.60	13836

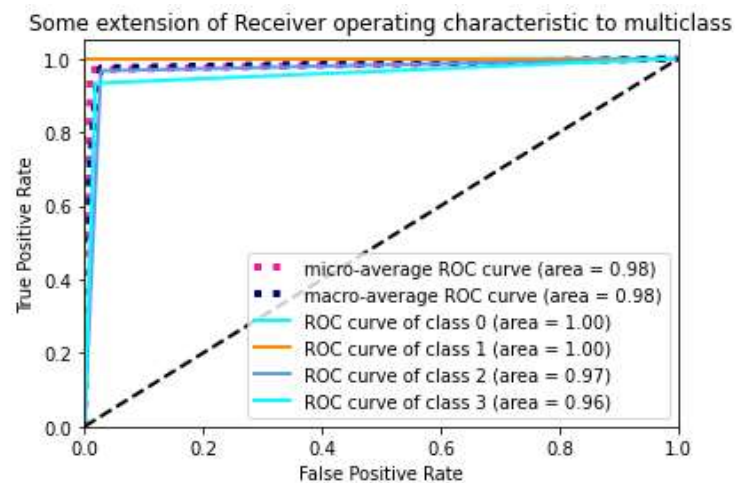


Testing

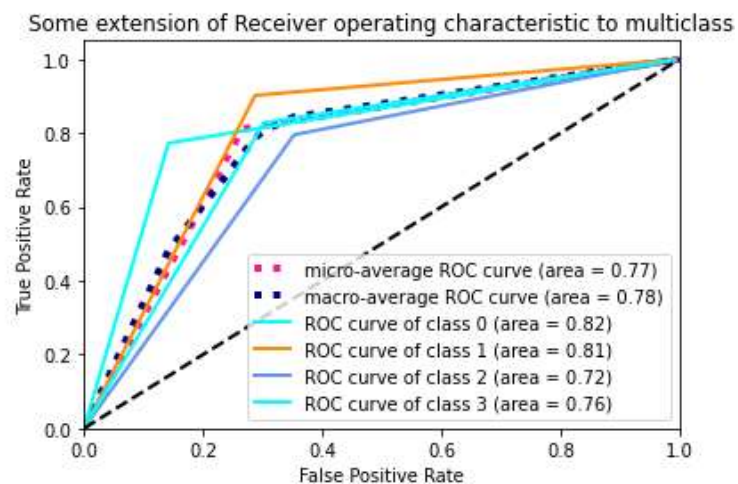
	precision	recall	f1-score	support
Covid	0.71	0.72	0.72	1001
Normal	0.33	0.90	0.48	550
Other	0.87	0.41	0.56	1986
pneumonia	0.61	0.65	0.63	1075
accuracy			0.59	4612
macro avg	0.63	0.67	0.60	4612
weighted avg	0.71	0.59	0.60	4612



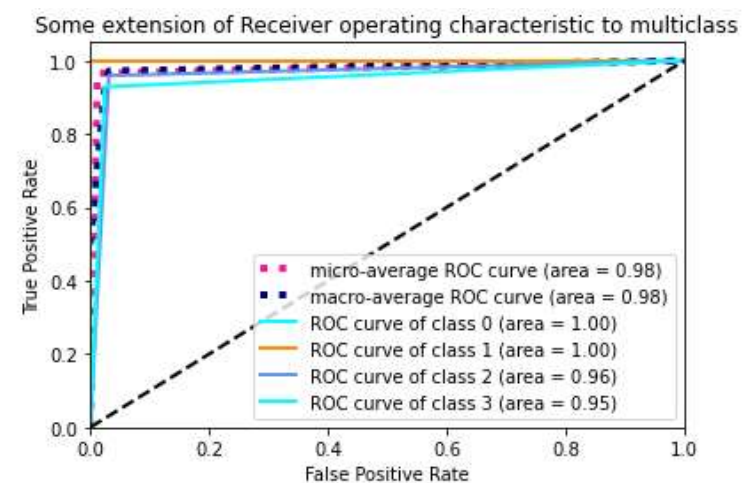
KNN ROC



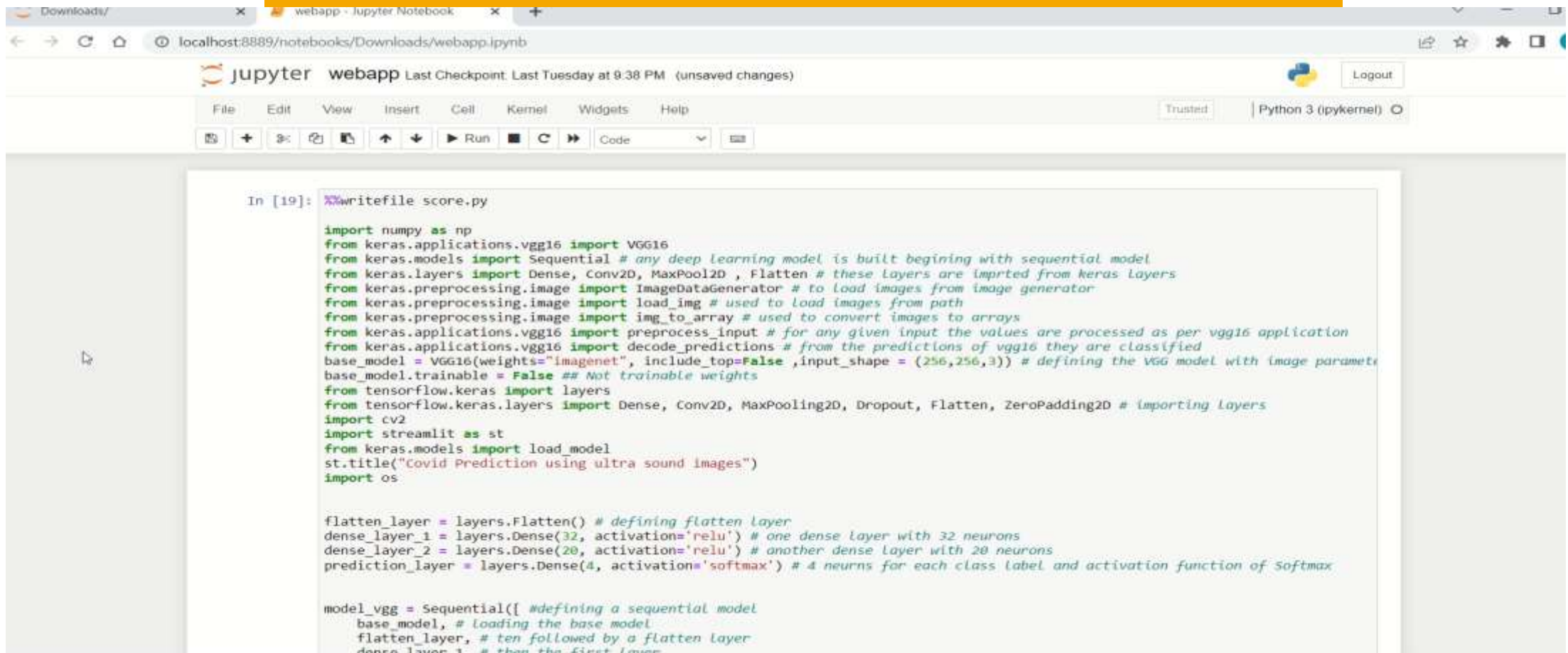
Naïve Bayes ROC



Random Forest ROC



Web App Demonstration



The screenshot displays a Jupyter Notebook interface in a web browser. The browser's address bar shows the URL `localhost:8889/notebooks/Downloads/webapp.ipynb`. The Jupyter interface includes a top bar with the 'jupyter webapp' logo, a 'Last Checkpoint' timestamp, and a 'Logout' button. Below this is a menu bar with options like 'File', 'Edit', 'View', 'Insert', 'Cell', 'Kernel', 'Widgets', and 'Help'. A toolbar with icons for file operations and execution is also present. The main area shows a code cell with the following Python code:

```
In [19]: %%writefile score.py

import numpy as np
from keras.applications.vgg16 import VGG16
from keras.models import Sequential # any deep learning model is built begining with sequential model
from keras.layers import Dense, Conv2D, MaxPool2D , Flatten # these layers are imprted from keras Layers
from keras.preprocessing.image import ImageDataGenerator # to load images from image generator
from keras.preprocessing.image import load_img # used to load images from path
from keras.preprocessing.image import img_to_array # used to convert images to arrays
from keras.applications.vgg16 import preprocess_input # for any given input the values are processed as per vgg16 application
from keras.applications.vgg16 import decode_predictions # from the predictions of vgg16 they are classified
base_model = VGG16(weights="imagenet", include_top=False ,input_shape = (256,256,3)) # defining the VGG model with image parameters
base_model.trainable = False ## Not trainable weights
from tensorflow.keras import layers
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Dropout, Flatten, ZeroPadding2D # importing layers
import cv2
import streamlit as st
from keras.models import load_model
st.title("Covid Prediction using ultra sound images")
import os

flatten_layer = layers.Flatten() # defining flatten layer
dense_layer_1 = layers.Dense(32, activation='relu') # one dense layer with 32 neurons
dense_layer_2 = layers.Dense(20, activation='relu') # another dense layer with 20 neurons
prediction_layer = layers.Dense(4, activation='softmax') # 4 neurns for each class label and activation function of Softmax

model_vgg = Sequential([ #defining a sequential model
    base_model, # loading the base model
    flatten_layer, # ten followed by a flatten layer
    dense_layer_1, # then the first layer
```

Conclusions



Training stage allowed us to adjust the models to establish a higher degree of accuracy as compared to previous works, as the accuracy of the enhanced VGG16 model is 98% and the confusion matrices show very few false cases for multi classification of LUS images.



The results demonstrate that the features derived from the enhanced deep learning models could be integrated into our work to build an effective model.

Conclusions



The other is that our models could effectively assist the virologists to diagnose COVID-19 and help the radiologists in the struggle against the outbreak of COVID-19, arriving in the diagnosis of critical patients in few minutes, which could be very important in their treatment.



We do not aim to eliminate the role of medical professionals but provide an evidence-based second opinion to fasten the treatment and increase reliability.

Recommendations

As future research lines we can work on multi-criteria classification to distinguish images from datasets mixing patients with lung problems due to several possible diseases, such as tuberculosis, AIDS, COVID-19, etc.

we have not found datasets with metadata including stages of the disease to diagnostic the severity of the symptoms. It would be a suggestion to work with doctors in this aspect to understand the severity from image.

We also emphasize that larger and more diverse image datasets are needed in order to evaluate the methods in a more realistic manner.

We should work closely with diagnostics with the real time scenrio and understand the need for prediction and train the models for minimizing the human errors besides providing fast and accurate predictions.

References

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<https://www.frontiersin.org/articles/10.3389/frai.2022.912022/full>

<https://www.sciencedirect.com/science/article/pii/S2352914820305773>

Thank You

