In [17]:

```
import cv2
import os
from tqdm import tqdm
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import glob
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import *
from tensorflow.keras.layers import *
from tensorflow.keras.models import *
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from tensorflow.keras.callbacks import *
```

In [18]:

```
imagePaths = []
for dirname, _, filenames in os.walk('/kaggle/input/covid19-radiography-database/COVID-19 Radiography Database/'):
    for filename in filenames:
        if (filename[-3:] == 'png'):
            imagePaths.append(os.path.join(dirname, filename))
```

In [19]:

```
imgSize = 224
```

In [20]:

```
X = []
Y = []
hmap = {'Viral Pneumonia': 'Pneumonia', 'NORMAL': 'Normal', 'COVID-19': 'Covid-19'}
for imagePath in tqdm(imagePaths):
    label = imagePath.split(os.path.sep)[-2]
    image = cv2.imread(imagePath)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image, (imgSize, imgSize))

    X.append(image)
    Y.append(hmap[label])
```

```
100%|██████████| 2905/2905 [00:42<00:00, 67.93it/s]
```

In [21]:

```
print('Covid-19:',Y.count('Covid-19'))
print('Normal:',Y.count('Normal'))
print('Pneumonia: ',Y.count('Pneumonia'))
```

```
Covid-19: 219
Normal: 1341
Pneumonia:  1345
```

In [22]:

```
le = LabelEncoder()
Y = le.fit_transform(Y)
Y = to_categorical(Y)
```

In [23]:

```
(trainX, testX, trainY, testY) = train_test_split(X, Y, test_size=0.20, stratify=Y, random_state=42)
```

In [24]:

```python
print(len(trainY))
ntimes = 6
trainY = trainY.tolist()
for i in tqdm(range(len(trainX))):
    if (trainY[i][0] == 1):
        trainX += [trainX[i]]*ntimes
        trainY += [trainY[i]]*ntimes

trainY = np.array(trainY)

print(len(trainY))
```

```
100%|██████████| 2324/2324 [00:00<00:00, 750505.27it/s]
```

```
2324
3374
```

In [25]:

```python
trainX = np.array(trainX).astype('float16')/255

testX = np.array(testX).astype('float16')/255
```

In [26]:

```python
trainAug = ImageDataGenerator(rotation_range=20, horizontal_flip = True,fill_mod
e="nearest")
```

In [27]:

```
best_val_acc = 0
best_train_acc = 0
def saveModel(epoch,logs):
    val_acc = logs['val_accuracy']
    train_acc = logs['accuracy']
    global best_val_acc
    global best_train_acc

    if val_acc > best_val_acc:
        best_val_acc = val_acc
        model_RN50.save('model_RN50.h5')
    elif val_acc == best_val_acc:
        if train_acc > best_train_acc:
            best_train_acc= train_acc
            model_RN50.save('model_RN50.h5')
```

Transfer Learning ResNet50

In [28]:

```
from keras.applications.resnet import ResNet50
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense, Flatten, GlobalAveragePooling2D, BatchNormalization

from tensorflow.python.keras.preprocessing.image import ImageDataGenerator
from tensorflow.python.keras.preprocessing.image import load_img, img_to_array

# resnet_weights_path = '../input/resnet50/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5'
# resnet_weights_path = 'imagenet'
```

In [29]:

```
from keras.layers import *
from keras.models import Sequential
from keras.applications.resnet50 import ResNet50

CLASS_COUNT = 3

base_model = ResNet50(
    weights='imagenet',
    include_top=False,
    input_shape=(224, 224, 3),
    pooling='avg',
)
model_RN50 = Sequential([
  base_model,
   Dense(CLASS_COUNT, activation='softmax'),
])
```

In [30]:

```
model_RN50.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
resnet50 (Model)             (None, 2048)              23587712  
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 6147      
=================================================================
Total params: 23,593,859
Trainable params: 23,540,739
Non-trainable params: 53,120
_________________________________________________________________
```

In [31]:

```
INIT_LR = 3e-2
EPOCHS = 50
BS = 32
```

In [32]:

```
opt = Adam(lr=INIT_LR, decay=INIT_LR / EPOCHS)
model_RN50.compile(loss="categorical_crossentropy", optimizer=opt, metrics=["accuracy"])
H = model_RN50.fit_generator(
    trainAug.flow(trainX, trainY, batch_size=BS),
    steps_per_epoch=len(trainX) // BS,
    validation_data=(testX, testY),
    validation_steps=len(testX) // BS,
    callbacks= [LambdaCallback(on_epoch_end=saveModel),
              ],
    epochs=EPOCHS)
```

```
Epoch 1/50
105/105 [==============================] - 61s 582ms/step - loss: 2.
3022 - accuracy: 0.4294 - val_loss: 65.2400 - val_accuracy: 0.2926
```

```
/opt/conda/lib/python3.7/site-packages/keras/engine/saving.py:165: U
serWarning: TensorFlow optimizers do not make it possible to access
optimizer attributes or optimizer state after instantiation. As a re
sult, we cannot save the optimizer as part of the model save file.Yo
u will have to compile your model again after loading it. Prefer usi
ng a Keras optimizer instead (see keras.io/optimizers).
  'TensorFlow optimizers do not '
```

```
Epoch 2/50
105/105 [==============================] - 50s 477ms/step - loss: 1.
0367 - accuracy: 0.5598 - val_loss: 1.6727 - val_accuracy: 0.0757
Epoch 3/50
105/105 [==============================] - 50s 478ms/step - loss: 0.
8105 - accuracy: 0.6391 - val_loss: 1.7449 - val_accuracy: 0.0757
Epoch 4/50
105/105 [==============================] - 50s 473ms/step - loss: 0.
7298 - accuracy: 0.6601 - val_loss: 1.2026 - val_accuracy: 0.3614
Epoch 5/50
105/105 [==============================] - 50s 480ms/step - loss: 0.
6914 - accuracy: 0.6825 - val_loss: 0.7474 - val_accuracy: 0.6575
Epoch 6/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
5715 - accuracy: 0.7504 - val_loss: 0.7800 - val_accuracy: 0.6196
Epoch 7/50
105/105 [==============================] - 50s 473ms/step - loss: 0.
3911 - accuracy: 0.8452 - val_loss: 9.9633 - val_accuracy: 0.4819
Epoch 8/50
105/105 [==============================] - 49s 471ms/step - loss: 0.
3115 - accuracy: 0.8866 - val_loss: 5.1758 - val_accuracy: 0.4854
Epoch 9/50
105/105 [==============================] - 50s 474ms/step - loss: 0.
2722 - accuracy: 0.9025 - val_loss: 6.5679 - val_accuracy: 0.4871
Epoch 10/50
105/105 [==============================] - 49s 469ms/step - loss: 0.
2579 - accuracy: 0.9162 - val_loss: 4.8288 - val_accuracy: 0.4905
Epoch 11/50
105/105 [==============================] - 49s 470ms/step - loss: 0.
2128 - accuracy: 0.9246 - val_loss: 0.2927 - val_accuracy: 0.9036
Epoch 12/50
105/105 [==============================] - 49s 464ms/step - loss: 0.
1817 - accuracy: 0.9360 - val_loss: 0.8422 - val_accuracy: 0.7780
Epoch 13/50
105/105 [==============================] - 49s 467ms/step - loss: 0.
1689 - accuracy: 0.9351 - val_loss: 4.7045 - val_accuracy: 0.5250
Epoch 14/50
105/105 [==============================] - 49s 465ms/step - loss: 0.
1801 - accuracy: 0.9354 - val_loss: 0.9558 - val_accuracy: 0.6971
Epoch 15/50
105/105 [==============================] - 49s 466ms/step - loss: 0.
1742 - accuracy: 0.9363 - val_loss: 1.0387 - val_accuracy: 0.7418
Epoch 16/50
105/105 [==============================] - 49s 469ms/step - loss: 0.
```

```
1654 - accuracy: 0.9426 - val_loss: 2.5037 - val_accuracy: 0.2857
Epoch 17/50
105/105 [==============================] - 49s 462ms/step - loss: 0.
1378 - accuracy: 0.9482 - val_loss: 0.4241 - val_accuracy: 0.8830
Epoch 18/50
105/105 [==============================] - 48s 459ms/step - loss: 0.
1408 - accuracy: 0.9461 - val_loss: 0.1545 - val_accuracy: 0.9587
Epoch 19/50
105/105 [==============================] - 49s 469ms/step - loss: 0.
1310 - accuracy: 0.9488 - val_loss: 0.4533 - val_accuracy: 0.8640
Epoch 20/50
105/105 [==============================] - 49s 467ms/step - loss: 0.
1296 - accuracy: 0.9500 - val_loss: 7.2879 - val_accuracy: 0.4750
Epoch 21/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
1320 - accuracy: 0.9510 - val_loss: 0.1480 - val_accuracy: 0.9415
Epoch 22/50
105/105 [==============================] - 49s 467ms/step - loss: 0.
1037 - accuracy: 0.9605 - val_loss: 0.5187 - val_accuracy: 0.8158
Epoch 23/50
105/105 [==============================] - 48s 458ms/step - loss: 0.
1178 - accuracy: 0.9566 - val_loss: 0.3889 - val_accuracy: 0.8451
Epoch 24/50
105/105 [==============================] - 49s 470ms/step - loss: 0.
1016 - accuracy: 0.9623 - val_loss: 0.1807 - val_accuracy: 0.9346
Epoch 25/50
105/105 [==============================] - 49s 466ms/step - loss: 0.
1020 - accuracy: 0.9608 - val_loss: 1.5885 - val_accuracy: 0.5318
Epoch 26/50
105/105 [==============================] - 49s 470ms/step - loss: 0.
0981 - accuracy: 0.9592 - val_loss: 0.4205 - val_accuracy: 0.8503
Epoch 27/50
105/105 [==============================] - 49s 464ms/step - loss: 0.
0915 - accuracy: 0.9666 - val_loss: 0.2879 - val_accuracy: 0.9105
Epoch 28/50
105/105 [==============================] - 49s 470ms/step - loss: 0.
0938 - accuracy: 0.9668 - val_loss: 1.0537 - val_accuracy: 0.7229
Epoch 29/50
105/105 [==============================] - 49s 466ms/step - loss: 0.
0852 - accuracy: 0.9679 - val_loss: 0.3275 - val_accuracy: 0.8830
Epoch 30/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
0841 - accuracy: 0.9687 - val_loss: 1.2515 - val_accuracy: 0.6472
Epoch 31/50
105/105 [==============================] - 49s 471ms/step - loss: 0.
```

```
0894 - accuracy: 0.9652 - val_loss: 0.7903 - val_accuracy: 0.7522
Epoch 32/50
105/105 [==============================] - 49s 469ms/step - loss: 0.
0722 - accuracy: 0.9744 - val_loss: 0.9790 - val_accuracy: 0.6299
Epoch 33/50
105/105 [==============================] - 49s 463ms/step - loss: 0.
0789 - accuracy: 0.9683 - val_loss: 2.6285 - val_accuracy: 0.5009
Epoch 34/50
105/105 [==============================] - 49s 464ms/step - loss: 0.
0876 - accuracy: 0.9682 - val_loss: 0.1449 - val_accuracy: 0.9466
Epoch 35/50
105/105 [==============================] - 49s 469ms/step - loss: 0.
0739 - accuracy: 0.9731 - val_loss: 5.4450 - val_accuracy: 0.5009
Epoch 36/50
105/105 [==============================] - 49s 470ms/step - loss: 0.
0735 - accuracy: 0.9722 - val_loss: 0.4032 - val_accuracy: 0.8933
Epoch 37/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
0842 - accuracy: 0.9671 - val_loss: 0.5420 - val_accuracy: 0.8176
Epoch 38/50
105/105 [==============================] - 49s 466ms/step - loss: 0.
0763 - accuracy: 0.9705 - val_loss: 0.2420 - val_accuracy: 0.9312
Epoch 39/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
0766 - accuracy: 0.9702 - val_loss: 0.5510 - val_accuracy: 0.8003
Epoch 42/50
105/105 [==============================] - 49s 467ms/step - loss: 0.
0618 - accuracy: 0.9767 - val_loss: 0.2558 - val_accuracy: 0.9260
Epoch 43/50
105/105 [==============================] - 49s 462ms/step - loss: 0.
0591 - accuracy: 0.9795 - val_loss: 0.3341 - val_accuracy: 0.8898
Epoch 44/50
105/105 [==============================] - 49s 468ms/step - loss: 0.
0512 - accuracy: 0.9823 - val_loss: 3.3527 - val_accuracy: 0.6213
Epoch 45/50
105/105 [==============================] - 48s 459ms/step - loss: 0.
0528 - accuracy: 0.9791 - val_loss: 0.7306 - val_accuracy: 0.8021
Epoch 46/50
105/105 [==============================] - 49s 465ms/step - loss: 0.
0601 - accuracy: 0.9758 - val_loss: 1.2285 - val_accuracy: 0.7935
Epoch 47/50
105/105 [==============================] - 49s 465ms/step - loss: 0.
0613 - accuracy: 0.9762 - val_loss: 0.9279 - val_accuracy: 0.7969
Epoch 48/50
105/105 [==============================] - 49s 464ms/step - loss: 0.
```

```
0530 - accuracy: 0.9823 - val_loss: 0.8137 - val_accuracy: 0.7745
Epoch 49/50
105/105 [==============================] - 49s 467ms/step - loss: 0.
0633 - accuracy: 0.9746 - val_loss: 0.2981 - val_accuracy: 0.9157
Epoch 50/50
105/105 [==============================] - 49s 465ms/step - loss: 0.
0703 - accuracy: 0.9741 - val_loss: 0.2136 - val_accuracy: 0.9329
```

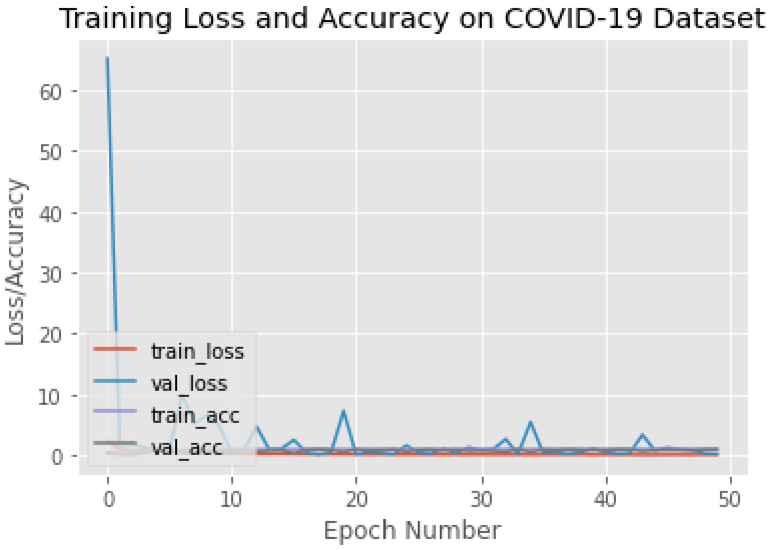
In [ ]:

In [33]:

```
N = EPOCHS
plt.style.use("ggplot")

plt.figure()
plt.plot(np.arange(0, N), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, N), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy on COVID-19 Dataset")
plt.xlabel("Epoch Number")
plt.ylabel("Loss/Accuracy")
plt.legend(loc="lower left")
plt.figure(figsize=(20,20))
```

Out[33]:

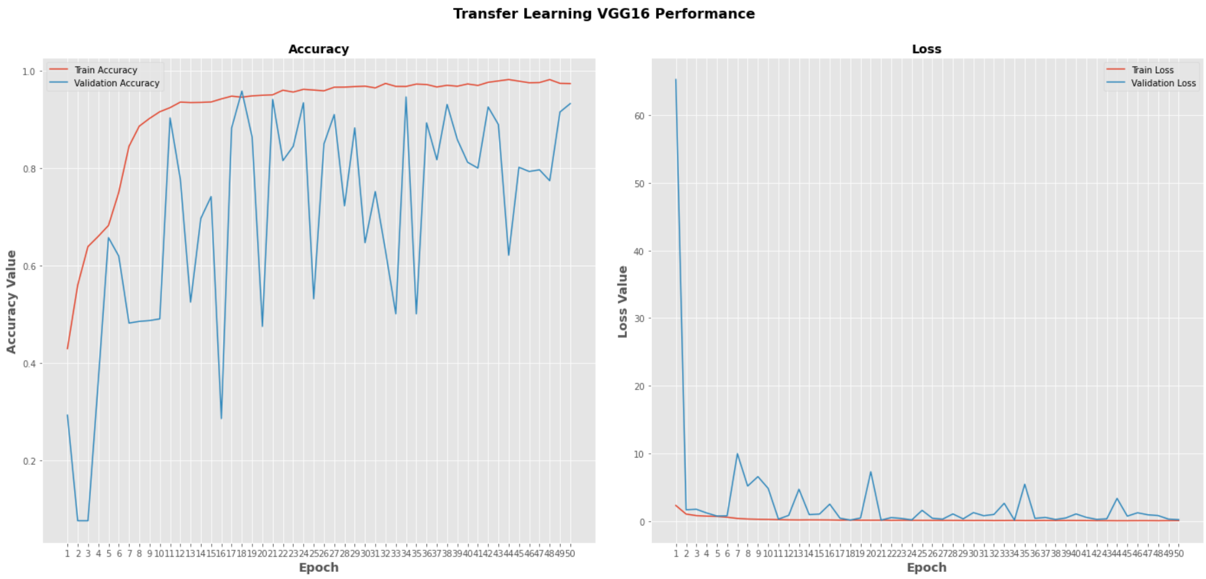
```
<Figure size 1440x1440 with 0 Axes>
```



```
<Figure size 1440x1440 with 0 Axes>
```

In [34]:

```
from sklearn.metrics import accuracy_score
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(24, 10))
t = f.suptitle('Transfer Learning VGG16 Performance', fontsize=16,fontweight='bold')
f.subplots_adjust(top=0.9, wspace=0.1)

max_epoch = len(H.history['accuracy'])+1
epoch_list = list(range(1,max_epoch))
ax1.plot(epoch_list, H.history['accuracy'], label='Train Accuracy')
ax1.plot(epoch_list, H.history['val_accuracy'], label='Validation Accuracy')
ax1.set_xticks(np.arange(1, max_epoch, 1))
ax1.set_ylabel('Accuracy Value',fontsize=14,fontweight='bold')
ax1.set_xlabel('Epoch',fontsize=14,fontweight='bold')
ax1.set_title('Accuracy', fontsize=14,fontweight='bold')
l1 = ax1.legend(loc="best")

ax2.plot(epoch_list, H.history['loss'], label='Train Loss')
ax2.plot(epoch_list, H.history['val_loss'], label='Validation Loss')
ax2.set_xticks(np.arange(1, max_epoch, 1))
ax2.set_ylabel('Loss Value',fontsize=14,fontweight='bold')
ax2.set_xlabel('Epoch',fontsize=14,fontweight='bold')
ax2.set_title('Loss',fontsize=14,fontweight='bold')
l2 = ax2.legend(loc="best")
```



In [35]:

```
# Load best model
# model= load_model('model.h5')
```

Result on train

In [36]:

```
predIdxs = model_RN50.predict(trainX, batch_size=BS)
predIdxs = np.argmax(predIdxs, axis=1)
print(classification_report(trainY.argmax(axis=1), predIdxs, target_names=le.cla
sses_, digits = 5))
```

```
              precision    recall  f1-score   support

    Covid-19    0.99190   1.00000   0.99593      1225
      Normal    0.98782   0.90680   0.94558      1073
   Pneumonia    0.91768   0.98420   0.94978      1076

    accuracy                        0.96532      3374
   macro avg    0.96580   0.96367   0.96376      3374
weighted avg    0.96693   0.96532   0.96520      3374
```

Result on test

In [37]:

```
predIdxs = model_RN50.predict(testX, batch_size=BS)
predIdxs = np.argmax(predIdxs, axis=1)
print(classification_report(testY.argmax(axis=1), predIdxs, target_names=le.classes_, digits = 5))
```

```
              precision    recall  f1-score   support

    Covid-19    0.84000   0.95455   0.89362        44
      Normal    0.99163   0.88433   0.93491       268
   Pneumonia    0.90068   0.97770   0.93761       269

    accuracy                        0.93287       581
   macro avg    0.91077   0.93886   0.92205       581
weighted avg    0.93804   0.93287   0.93303       581
```

In [38]:

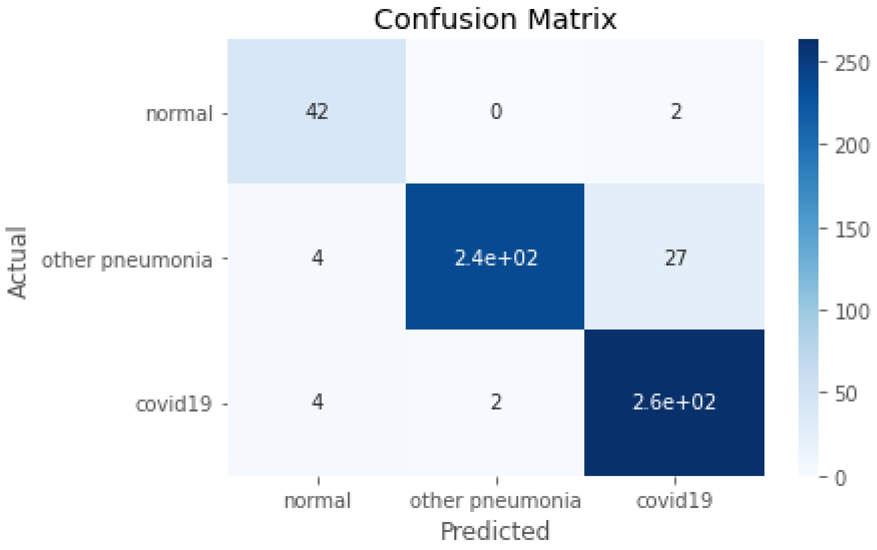
```
import sklearn.metrics as metrics
from PIL import Image
from tensorflow.keras.preprocessing.image import load_img, img_to_array
```

In [39]:

```
plt.figure()

ax = plt.subplot()

ax.set_title('Confusion Matrix')
pred = model_RN50.predict(testX)
pred=np.argmax(pred,axis=1)
# pred = model.predict_classes(X_test)
Y_TEST = np.argmax(testY, axis =1)
cm = metrics.confusion_matrix(Y_TEST,pred)
classes=['normal', 'other pneumonia', 'covid19']
sns.heatmap(cm, annot=True,xticklabels=classes, yticklabels=classes,cmap='Blues'
)

plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show
```

Out[39]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [40]:

```
img_size = (224,224)
dir_name = '../input/covid19-radiography-database/COVID-19 Radiography Database/
COVID-19'
img_list = glob.glob(dir_name + '/*')

list_covid = []
for img in img_list:
    temp_img = load_img(img,grayscale=True,target_size=(img_size))
    temp_img_array = img_to_array(temp_img) /255
    list_covid.append(temp_img_array)
list_covid = np.array(list_covid)
list_covid2 = list_covid.reshape(-1,50176)
df_covid=pd.DataFrame(list_covid2)
df_covid['label'] = np.full(df_covid.shape[0],2)
```

```
/opt/conda/lib/python3.7/site-packages/keras_preprocessing/image/uti
ls.py:107: UserWarning: grayscale is deprecated. Please use color_mo
de = "grayscale"
  warnings.warn('grayscale is deprecated. Please use '
```

In [41]:

```
img_size = (224,224)
dir_name2 = '../input/covid19-radiography-database/COVID-19 Radiography Databas
e//NORMAL'
img_list2 = glob.glob(dir_name2 + '/*')

list_normal = []
for img in img_list2[:150]:
    temp_img = load_img(img,grayscale=True,target_size=(img_size))
    temp_img_array = img_to_array(temp_img) /255
    list_normal.append(temp_img_array)
list_normal = np.array(list_normal)
list_normal2 = list_normal.reshape(-1,50176)
df_normal=pd.DataFrame(list_normal2)
df_normal['label'] = np.full(df_normal.shape[0],0)
```

In [42]:

```
img_size = (224,224)
dir_name3 = '../input/covid19-radiography-database/COVID-19 Radiography Database/Viral Pneumonia'
img_list3 = glob.glob(dir_name3 + '/*')

list_others = []
for img in img_list3[:150]:
    temp_img = load_img(img,grayscale=True,target_size=(img_size))
    temp_img_array = img_to_array(temp_img) /255
    list_others.append(temp_img_array)
list_others = np.array(list_others)
list_others2 = list_others.reshape(-1,50176)
df_others=pd.DataFrame(list_others2)
df_others['label'] = np.full(df_others.shape[0],1)
```

In [43]:

```
Df = pd.concat([df_covid, df_normal , df_others], ignore_index=True)
```

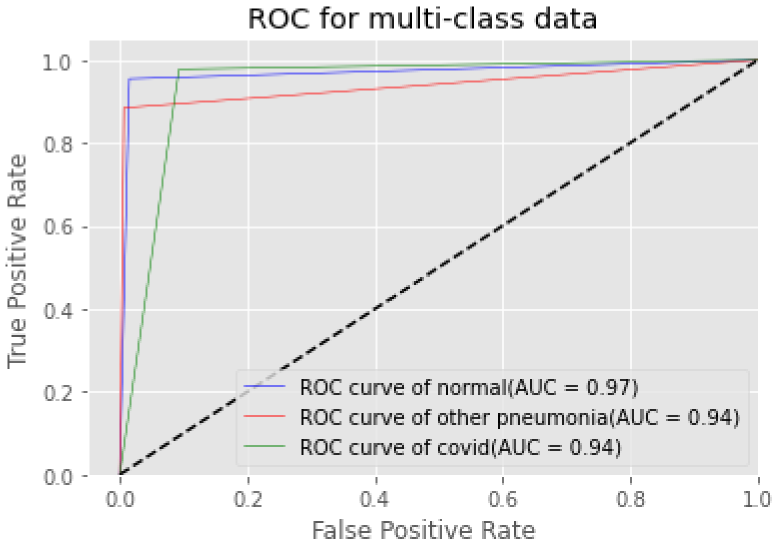
In [ ]:

In [44]:

```
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_curve, auc

PRED = to_categorical(pred)
y = Df['label'].values
# Binarize the output
y = label_binarize(y, classes=[0,1,2])
n_classes = y.shape[1]

fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
       fpr[i], tpr[i], _ = roc_curve(testY[:,i], PRED[:,i])
       roc_auc[i] = auc(fpr[i], tpr[i])
```

In [45]:

```
colors = ['blue', 'red', 'green']
cls = {0:'normal', 1:'other pneumonia', 2:'covid'}
for i, color ,c in zip(range(n_classes), colors, cls.values()):
    plt.plot(fpr[i], tpr[i], color=color, lw=0.5,
             label='ROC curve of '+c+ '(AUC = {1:0.2f})'
             ''.format(i, roc_auc[i]))
plt.plot([0, 1], [0, 1], 'k--',linestyle='--')
plt.xlim([-0.05, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC for multi-class data')
plt.legend(loc="lower right")
plt.show()
```



In [ ]:

```
```

In [ ]:

```
```

In [ ]:

```
```

In [ ]:

```
```