<Corona detection using chest x-ray>

Mathematical programming-2

Report

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# **INTRODUCTION**

# Coronavirus related respiratory illness usually manifests clinically as pneumonia with predominant imaging findings of an atypical or organizing pneumonia. Plain radiography is very helpful for COVID-19 disease assessment and follow-up. It gives an accurate insight into the disease course

# We aimed to determine the COVID-19 disease course using chest X-ray (CXR) scoring system and correlate these with patients’ age, and outcome

# Corona - COVID19 virus affects the respiratory system of healthy individual & Chest X -Ray is one of the important imaging methods to identify the corona virus.

# With the Chest X - Ray dataset, Develop a Machine Learning Model to classify the X Rays of Healthy vs Pneumonia (Corona) affected patients & this model powers the AI application to test the Corona Virus in Faster Phase.

# **Literature Survey**

Artificial intelligence approaches have repeatedly given accurate and dependable outcomes in applications that use image-based data. Using deep learning techniques, researchers have been investigating and analyzing chest X-ray images to identify COVID-19 in recent years.

In [[35](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8614951/#B35-biology-10-01174)], the images were normalized to extract enhanced features, which were then fed into image classification algorithms utilizing deep learning techniques. Five cutting-edge CNN systems, VGG19, MobileNetV2, Inception, Xception, and InceptionResNetV2, on a transfer-learning scenario, were tested to detect COVID-19 from control and pneumonia images. Experiments were conducted in two parts: one with 224 COVID-19 pictures, 700 bacterial pneumonia images, and 504 control images, and another with the prior normal and COVID-19 data but 714 instances of bacterial and viral pneumonia. In the two- and three-class classifications, the MobileNetV2 net had the greatest results, with 96.78% and 94.72% accuracy, respectively.

In [[36](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8614951/#B36-biology-10-01174)], both VGG16 CNN and Resnet50, which were trained on color camera images from ImageNet, were utilized to perform transfer learning. To assess the feasibility of utilizing chest X-rays to diagnose COVID-19, 10-fold cross-validation was performed to obtain an overall accuracy of 89.2%.

Three CNN architectures (ResNet50, InceptionV3, and InceptionRes-NetV2) were evaluated in relation to COVID-19 identification in [[37](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8614951/#B37-biology-10-01174)], utilizing a database of just 50 controls and 50 COVID-19 cases. ResNet50 achieved the highest accuracy of 98%.

In [[38](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8614951/#B38-biology-10-01174)], a successful performance in diagnosis accuracy found in this research demonstrates that deep CNNs could correctly and efficiently distinguish 21,152 normal and abnormal chest radiographs. The CNN model pre-trained on datasets of adult patients and fine-tuned on pediatric patients obtained an accuracy of 94.64%, a sensitivity of 96.5% and a specificity of 92.86% for normal versus pneumonia categorization.

# **Methodology**

### **Dataset Preparation**

# A chest X-ray database was used to experiment with this study. This database is currently one of the popular public X-ray databases, containing 3616 COVID-19 cases along with 10,192 healthy, 6012 lung opacity and 1345 viral pneumonia images. However, only COVID-19 (3616) and healthy (10,192) X-ray images were extracted for this study. As a result, the dataset includes studies of COVID-19 and healthy individuals with a matrix resolution of 299 × 299 system for scene-text removal, was used to remove annotations from certain images. EnsNet is capable of automatically removing all of the text or annotation from an image without any prior knowledge . Data augmentation and image enhancement techniques are performed to enhance the quantity and variety of images given to the classifier for classification. Image augmentations used include horizontal flip, rotation, width shift and height shift on all the extracted data from the original dataset.

### **Model Selection**

One of the main goals of this research is to obtain appropriate classification results utilizing freely available data (increased to high volume data by using enhancement techniques) with the combined transfer learning models. This research was undertaken to choose a CNN-based deep learning model that is appropriate for COVID-19 image classification investigation. The primary aim is to propose a modified novel deep-learning-based CNN model to gain the highest accuracy on a large volume of chest X-ray data with minimal compilation time and compare the modified novel approach (accuracy, efficiency, compilation time) with existing deep learning models on the same dataset.

1. VGG19 and VGG16

The Visual Geometry Group is abbreviated as VGG. VGG16 is built using multiple 33 kernel-sized filters sequentially (11 and 5 in the first and second convolutional layers, respectively). VGG’s input is set to a 224 × 244 RGB picture. The VGG-19 convolutional neural network was trained using over a million pictures from the ImageNet database. The network has a depth of 19 layers and is capable of classifying images of multiple classes. The VGG architectures’ primary concept is to keep the convolution size modest and constant while designing an extremely deep network.

InceptionV3

InceptionV3 makes use of label smoothing, factorized 7 × 7 convolutions, and an auxiliary classifier to transmit label information down the network, as well as batch normalization for sidehead layers. It features smaller convolutions for quicker training and lower grid size to overcome computational cost constraints. Numerous optimization methods have been proposed for an InceptionV3 model in order to relax the restrictions and facilitate model adaptability. Factorized convolutions, regularization, dimension reduction, and parallelized calculations are all included in the methods.

ResNet50 and 101

ResNet50’s architecture is divided into 4 stages. The network may accept an input image with a height, width of multiples of 32, and channel width. The network may accept an input image with a height, width of multiples of 32, and channel width Each ResNet architecture conducts initial convolution and max-pooling with a kernel size of 7 × 7 and 3 × 3, respectively. Each 2-layer block is replaced with this 3-layer bottleneck block in the 34-layer net, resulting in a 50-layer ResNet. A 101-layer ResNet is created by adding additional 3-layer blocks.

GoogLeNet

GoogLeNet is a deep convolutional neural network with 22 layers and almost 12× fewer parameters compared to Inception architecture. However, by adding more layers, the number of parameters grows, and the network may overfit. The pre-trained network accepts images with a resolution of 224 × 224. In GoogLeNet, global average pooling was utilized instead of a fully linked layer. The architecture makes use of the Activation, AveragePooling2D, and Dense layers.

MobileNetV2

MobileNetV2 introduces a new module with an inverted residual structure. With MobileNetV2, state-of-the-art object recognition and semantic segmentation are accomplished. MobileNetV2’s architecture begins with a fully convolutional layer with 32 filters and 19 residual bottleneck layers. Typically, the network requires 300 million multiply-add operations and utilizes 3.4 million parameters. Accuracy is increased by removing ReLU6 from the output of each bottleneck module.

AlexNet

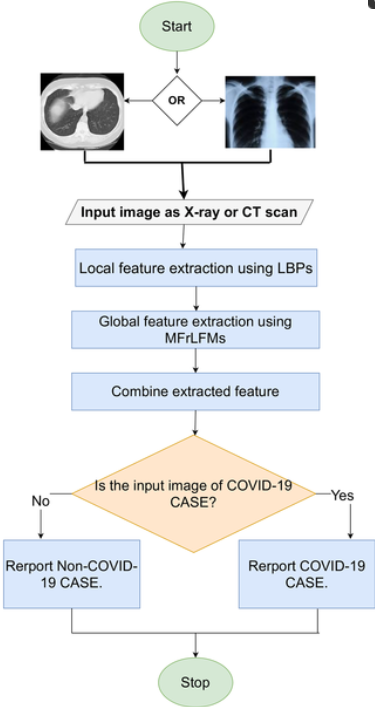
AlexNet is made up of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Each convolutional layer is composed of convolutional filters and a ReLU nonlinear activation function. Max pooling is accomplished using the pooling layers. Due to the existence of completely linked layers, the input size 224 × 224 × 3 is fixed. If the input picture is grayscale, it is converted to RGB by duplicating the single channel to create a three-channel RGB image. AlexNet’s total parameter count is 60 million, with a batch size of 128.

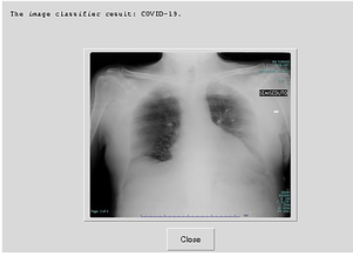
### **Modified MobileNet V2 Architecture**

The modified MobileNetV2 that has been proposed is not only compact in size but also computationally efficient, leading to enhanced performance on both large and small data sets.

Seven convolutional layers formed the bulk of the bottleneck residual block in the modified model. The final two layers that were previously included in the initial generation of MobileNet: a depth-wise convolution filtering the inputs and a 1 × 1 pointwise convolution layer. Though, this layer 1 × 1 role has shifted. The main concept is to use 3 × 3 depth-separable convolution filters followed by 1 × 1 subsequent convolution filters instead of the usual 3 × 3. The new design uses fewer operations and parameters to achieve the same filtering and combining process as traditional convolution. In MobileNetV1, the pointwise convolution had to either double or maintain the number of channels. In MobileNetV2, pointwise convolution has the opposite effect: it decreases the number of available channels. The first new feature was introduced by the expansion layer. The expansion layer is a 1 × 1 convolution. Its function is to increase the number of channels in the image data before proceeding to depth-wise convolution. As a result, since it performs the reverse of the projection layer, this expansion layer always has more output channels than input channels. [Table 4](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8614951/table/biology-10-01174-t004/) shows the architecture of modified MobileNetV2.

Flowchart :





# **CODE IMPLEMENTATION**

# from sklearn.metrics import confusion\_matrix, roc\_curve

# import seaborn as sns

# import numpy as np

# import matplotlib.pyplot as plt

# import cv2

# from glob import glob

# def plot\_images(images, title):

# nrows, ncols = 5, 8

# figsize = [10, 6]

# fig, ax = plt.subplots(nrows=nrows, ncols=ncols, figsize=figsize, facecolor=(1, 1, 1))

# for i, axi in enumerate(ax.flat):

# axi.imshow(images[i])

# axi.set\_axis\_off()

# plt.suptitle(title, fontsize=24)

# plt.tight\_layout(pad=0.2, rect=[0, 0, 1, 0.9])

# plt.show()

# plot\_images(covid\_images, 'Positive COVID-19 Chest X-ray')

# plot\_images(noncovid\_images, 'Negative COVID-19 Chest X-ray')

# inception = InceptionV3(weights="imagenet", include\_top=False,

# input\_tensor=Input(shape=(224, 224, 3)))

# outputs = inception.output

# outputs = Flatten(name="flatten")(outputs)

# outputs = Dropout(0.5)(outputs)

# outputs = Dense(2, activation="softmax")(outputs)

# model = Model(inputs=inception.input, outputs=outputs)

# for layer in inception.layers:

# layer.trainable = False

# model.compile(

# loss='categorical\_crossentropy',

# optimizer='adam',

# metrics=['accuracy']

# )

# train\_aug = ImageDataGenerator(

# rotation\_range=20,

# width\_shift\_range=0.2,

# height\_shift\_range=0.2,

# horizontal\_flip=True

# )

# **CONCLUSION**

# The chest X-ray images (COVID-19, healthy) were mostly applied to analyze lung problems. The study attempts to understand the specific strengths and weaknesses of common deep learning models in order to identify COVID-19 with acceptable accuracy. This is critical for a doctor’s decision-making, since each has benefits and drawbacks. Furthermore, when time, resources, and the patient’s condition are restricted, the doctor may be forced to make a choice based on only one modality. In this work, deep learning techniques were used for automatic COVID-19 detection from chest X-ray images. For this, twelve different models were implemented. Among them, eleven models are existing CNN models while the last one is modified MobileNetV2, a novel approach suggested in the study for more accurate classification with the least compilation time. In this study, authors have shown that the existing methods, when trained and tested on a large dataset, are outperformance by the proposed modified model in COVID-19 detection.

# The classification accuracy of the modified MobileNetV2 model is 98% in 2 h 50 min 21 s. The precision, recall, sensitivity, and F1 score of the model are 97%, 98%, 97% and 97%, respectively. Compared to the proposed model, the highest performance achieved by the existing models is from MobileNetV2. The existing MobileNetV2 model has an accuracy of 97% in classifying COVID-19 and healthy chest X-rays in 5 h 42 min 34 s. The precision, recall, sensitivity, and F1 score of this model are 96%, 97%, 96% and 96%, respectively. Furthermore, the Wilcoxon signed-rank test done in the study confirms the validity of the findings. These findings will assist doctors in choosing suitable models for various image analysis methods, which will be important when time and resources are limited in a pandemic scenario like the present COVID-19.

# **FUTURE WORK**

# As future work, the proposed method could be implemented on a dataset with more classes of pulmonary diseases such as asthma, chronic obstructive pulmonary disease, pulmonary fibrosis, pneumonia, lung cancer and COVID-19.

# Additionally, from the literature review, it was observed that there is a lack of proper feature extraction processes from image data. Therefore, a feature extraction technique will also be included in future work.

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