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**RESEARCH ARTICLE**

# DETECTION OF COVID-19 IN LOW ENERGY CHEST X-RAYS USING FAST R-CNN

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**Abstract:** In recent years, it has been shown that deep learning can produce similar performance increases in the domain of medical image analysis for object detection and segmentation tasks. Notable recent work includes important medical applications, for example, in the field of pulmonology (classification of lung diseases and detection of pulmonary nodules on CT images in this paper, we present a variation of CNNs, which works extremely well on a current data set — a customized architecture with optimal parameters. In our contribution, we focus on lowering the complexity of our network, while yet reaching a phenomenally high degree of accuracy. To achieve this aim, our model has been tailored for high performance and an easy design.

**Keywords:** component, formatting, style, styling, insert



## 1. Introduction

Radiology offers a crucial benefit when we monitor the way the illness progresses, and because of its availability it is a frequent approach (Song et al. 2020) (Shuja et al. 2020). In addition to biological procedures, the study of lung rays – such polymerase chain reaction (PCR), which permits the identification of infectious disorders – might therefore be immensely valuable particularly for nations with limited access to biomedical facilities. Given the successful use of deep learning architectures (DL architectures) in several areas, including medical image processing, this might boost our capacity to handle the difficulties of identifying the disease (Tartaglione et al. 2020).
In reality, the capacity and effect of these cutting-edge procedures are continually growing (Shi et al.

2020) (Karim et al.2020). Many academics now have an interest in the creation of deep neural networks (R-CNNs), which can accurately (and concurrently rapidly) identify COVID-19 symptoms (Victor et al.2020). A number of research have shown that R-CNNs, in particular convolutionary neural networks (CNNs), (Selvan et al.2020) recognize the symptoms of COVID19 in radiation (Alafif, 2020) effectively.

A number of recent research have been carried out employing Computer Tomography (CT) scans or X-rays to do a comparative analysis of pre-trained DL models used to grade COVID-19 in particular datasets (Khan et al. 2020), (He et al. 2016). However, the state-of-the-art research contributions mainly include 'transference learning' (Simonyan & Zisserman 2015) (Huang et al. 2017) as the automated identification strategy for COVID-19 symptoms. These contributions aim to establish new ways, although they have their own problems.

In general, the fundamental concern in regard to these methodologies is that the accuracy of these constructed models improves only at the expense of great complexity. In other words, considerable precision is gained, given the complexity of the systems increases.

## 2. Materials and Methods

### 2. 1. Covid-19



Coronaviruses are a broad family of viruses that may cause animals or people to get ill. Seven coronaviruses may cause infection in humans all around the globe, however these four human coronaviruses are usually infected: 229E, NL63, OC43 and HKU1. Air infections normally range from simple cold illnesses to more serious illnesses, such Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory syndrome (SARS) and infectious disorders caused lately by the coronavirus (COVID-19). (Goodfellow et al. 2017) This zoonotic sickness caused by severe acute coronavirus syndrome 2 (SARS-CoV-2). This infectious condition was previously designated New Coronavirus-Infected Pneumonia (NCIP) by WHO and was recognized a new coronavirus in 2019. (2019-nCoV). On 11 Feb 2020, the (WHO) formally renamed the COVID-19 (Corona Virus Disease-19) clinical condition reported in a tweet. In Wuhan, Hubei Province in China, the epidemic of COVID-19 caused by the 2019 new coronavirus (SARS-CoV-2) started in December 2019, and the current epidemic was an official pandemic. (Ai et al. 2020) As understanding about the virus has evolved fast, readers are recommended to continually update themselves (Fig. 1).

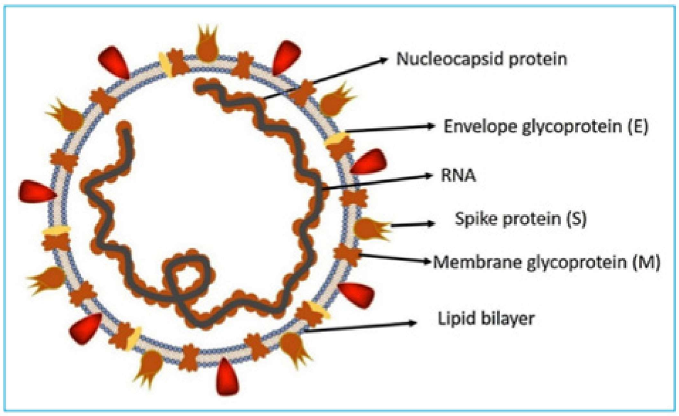


***Figure 1.*** *Covid-19 structure*

### 2.2. Fast R-CNN

The architectural selection utilized is based on the excellent results achieved with CNNs in the latest image classification projects of COVID-19 and excellent results in other comparable tasks with this kind of architecture (Selvan et al.2020), (Alafif, 2020), (Khan et al. 2020). We have adopted a single shot multibox detector network design as presented in (El Asnaoui et al. 2020) (SSD).

This design is designed for items detected by a single deep neural network in photos. This strategy discrete the bounding box output space into a series of default boxes spanning various aspect ratios and sizes by position of the characteristic map.

The network provides scores for the presence of each object category in every default box at the time of prediction and makes tweaks to the box to better fit the object form. The network also mixes predictions from numerous maps with varying resolutions to handle objects of diverse sizes organically. Experimental findings on many outstanding datasets demonstrate that SSD is equivalent to approaches that leverage more than one architecture for objects to be detected considerably quicker, while offering a unified training and inference framework.

In comparison with previous single-stage approaches, even with a lower input picture size (El Asnaoui et al. 2020), SSD is much more accurate. In this design, we employ VGG-16 (Vaid et al. 2020) as the basis network for extracting functions. This model is based on Fast R-CNN, too. We have various boxes with varied sizes and varying aspect ratios across the complete picture during training. SSD detects the box with more IOU compared to the reality of the ground.

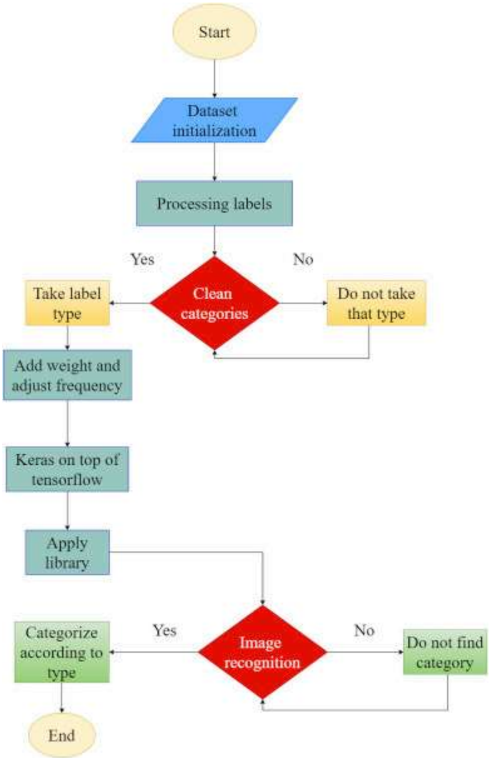


***Figure 2.*** *Fast R-CNN for Dataset Labelling.*



## 3. Proposed Method

In this work we train a variation of R-CNN called ResNet-50 CNN, with the ImageNet database conventional transfer learning algorithm, was employed. The validation accuracy of these networks has not surpassed 98% and some of them show a very low level of precision. In addition, ResNet-50 is used as the extractor of features and SVM as the classification in (Luz et al. 2020). This work is not a complete network and the low number of COVID-19 X-rays on the data set (25 pictures) does not provide the result that much value. With ResNet-18 modified, (Das et al. 2020) produces a deep convolutionary generative opposing network for synthetic data, but cannot create unusual synthetic data since a proposed network is independently trained for each class. The test accuracy for COVID-19 detection is 82.91 percent, the deep revolutionary auto-encoder methodology, is suggested by (Maguolo & Nanni 2021). After 3 times cross-validation, for the binary classification, a pooled ROC–AUC of 0.6902 is achieved. The Residual Neural Network (ResNet) model is an upgraded neural network version (CNN). ResNet offers shortcuts to address an issue across layers. This avoids distortion, as the network deepens and becomes more complicated. Bottleneck blocks are also utilized to speed up training in the ResNet (Hammoudi et al. 2020) model. ResNet50 is a 50-layer ImageNet dataset trained network. ImageNet is an image library with over 14 million photos from over 20,000 categories designed to compete for image recognition InceptionV3 is a kind of neural network model. It comprises multiple phases of convergence and maximum pooling. It includes a fully connected neural network in the final phase (Islam et al. 2020). As with the ResNet50 paradigm, ImageNet trains the network. The model comprises of a profound convolutionary network with the architecture Inception-ResNetV2, which was trained on the dataset ImageNet-2012. The input is a 299 to 299 picture and the output is a list of class probabilities computed. ResNet101 and ResNet152 are composed of 101 and 152 layers owing to the blocks of ResNet layered. A trained version of the network may be loaded from the ImageNet database on over one million images (Waheed et al. 2020). The network has therefore learnt a rich depiction of a variety of pictures. The network has a 224x224 picture input size.

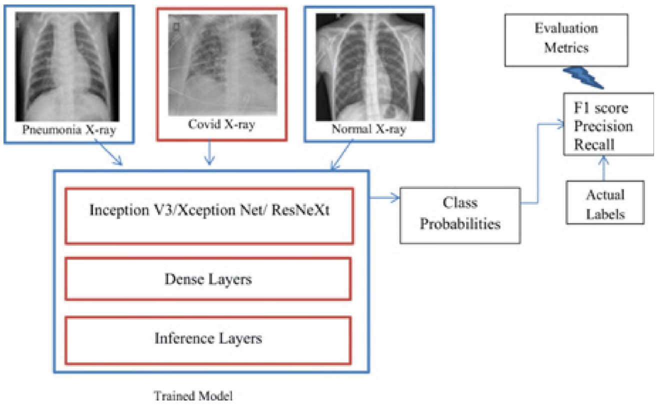


***Figure 3.*** *Inception, RESNET, Fast R-CNN Training on the Proposed Dataset.*

3 distinct binary classifications were carried out with 4 distinct classes (COVID-19, normal, viral pneumonia and bacterial pneumonia). The approach of 5-fold cross validation was utilized to get robust results using 5 separate, pre-trained models, InceptionV3, ResNet50, ResNet101, ResNet152 and Inception-ResNetV2 in this work. Although 80% of the data is allocated for training, the remaining 20% is for testing. This same procedure has proceeded till every 20% component has been evaluated. Figures 4 and 5 first of all, the accuracy and loss values in training process for Dataset-1 models including binary class-1 (COVID-19/normal classes). It is obvious that the ResNet50 model performs better than the other models. It is possible to say that the ResNet50 model obtains lower values between other models' losses. Figure 6 shows the detection performance of test data. Although there are many oscillations in certain models, some models are more stable. After the 15th epoch, the ResNet50 model seems to have less oscillation. Table 2 provides comprehensive performance numbers for each model fold value. The detection of the ResNet50 model in class COVID-19 is shown in Table 2 to be much higher than other models. The greatest overall performance is ResNet50 and ResNet101 with 96.1%. It is clear that additional normal data leads to improved performance in all models.

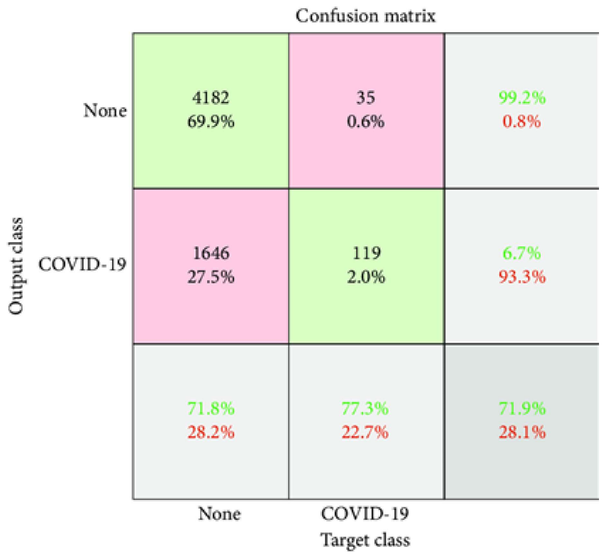


***Figure 4.*** *Covid-19 Detection F1 Score Confusion Matrix.*

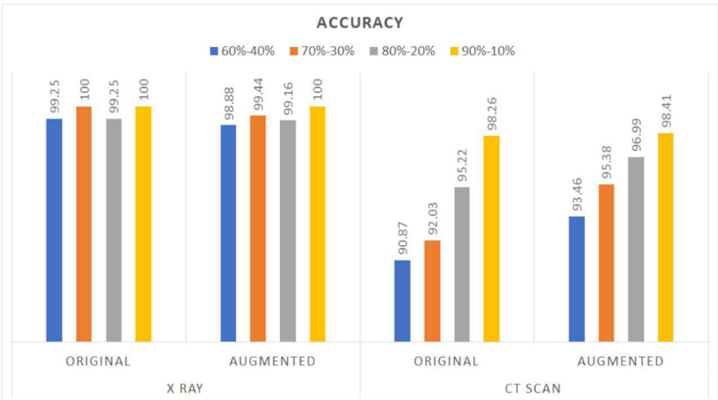


***Figure 5.*** *Accuracy and Error Rate of Each Dataset (CT and X-ray)*



## 4. Conclusions

A rapid diagnostic approach plays an important role in the fight against infectious illnesses and pandemic conditions such as the present COVID-19. Some drawbacks of the PCR test show that fast alternative approaches are needed in order to serve front-line specialists to make their diagnosis quick and precise. The development of R-CNN-based networks that can quickly and effectively recognize the symptoms of COVID-19 and, at the same time, have straightforward topologies is of considerable significance to researchers.

In this respect we compare remarkable methods to the binary classification of contaminated photos with the use of very accurate deep learning algorithms (a general framework that we called COVID-in-Depth CoDe).

We also suggest a variation of a convolutionary neural network that works exceptionally well with improved parameters on a recent dataset. The model shows an average performance accuracy of 99.90% for 5-fold cross validation, and 99.80% for the single COVID-19 identification. The 99% test accuracy shows that the model is very accurate. Furthermore, we use two external data sets to evaluate the performance of our model, while the results show that the model achieves 92.95% and 85.96% accuracy. The additional success here may be suggested by generalizing the CoDe Framework via the provision of relevant datasets for training the model, which may be sufficiently big and well-balanced.

This study may also be expanded to models that can recognize the phases of COVID19 development as a future effort. As the subject of this research is still in its infancy, we last note that the findings provided might be expanded in several ways. Authors and Affiliations

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