COVID-19 DETECTION - THE COMPARISON

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ABSTRACT

In December 2019, the first covid case was reported in China province. It has achieved a status as pandemic. This pandemic with continuously evolving transmission. Tracing the people who was a close contact with positive people and then quarantining them by some measures like seal-down. So, some other reliable measures have to be taken in order to control the cases of positivity.

Covid-19 is a larger epidemic, it covers several countries or spreads from one continent to another. The early detection of this disease is censorious to control the positivity cases unfurl and impermanence.

The speed and pace and of the transmission of severe acute respiratory syndrome coronavirus 2 also referred as Covid-19 have resulted in a global pandemic, with significant health, financial and other implications.

The global outbreak of novel coronavirus 2019 was declared by the World Health Organization on 30 January 2020. The clinical symptoms of covid-19 are predominantly pulmonary, although serious cardiovascular side effects were also observed in a number of patients.

Existing preventative solutions, include frequent hand wash using soap and water, hydro-alcoholic solution and digital technologies to detect and limit the spread of the virus and track the movement of quarantined peoples. Impact- millions of deaths, lockdown in cities, restricted movements, business losses, global economy slowdown.

Keywords - *CT, CNN, VGG16, Mobile net, Densenet121, Xception, Efficient net, NAS Net.*

1. INTRODUCTION

A larger epidemic includes the coronavirus disease 2019 (Covid-19), which is brought on by the coronavirus Z2 (SARS-CoV-2) that causes severe acute respiratory syndrome. The virus is quickly spreading and infecting more people. Actual head diagnosis Polymerase chain reaction test for reverse transcription. Additional quick and accessible diagnostic tools are required because the solution time and cost of this tes t are exorbitant.

The rapid increase in covid infection peoples is enormous. The healthcare system across world-wide with having only limited testing kits, so it is impossible for every covid patient with respiratory illness to test using normal techniques.

Those tests are also have long turn over time and very limited sensitivity. So, X-ray machines are already in use it may help to quarantine high risk covid affected patients stint test results are awaited.

The image-based diagnosis sequence for COVID-19, using a thoracic CT scan as an example. A technician instructs and assists each individual in posing on the patient bed, after which CT scan images are collected in a single breath-hold. The radiologists' best settings for the scans are used from the Depending on the patient's body type, the costophrenic angle may be superior to the upper thoracic inlet. Reconstructed CT images are then sent via picture archiving and communication systems (PACS) for additional analysis and diagnosis using the obtained data. An innovative method in the field of medical imaging called artificial intelligence (AI) made a significant contribution to the fight against COVID-19. In comparison to the traditional imaging workflow, which depends mainly on human labour, AI enables safer, more precise, and more effective imaging solutions. The specialised imaging platform, segmentation of the lung infection region, clinical evaluation and diagnosis, and basic and clinical research, are among the AI-powered applications in COVID-19Z. Furthermore, various commercial solutions have been created that successfully integrate AI into ZcombatZCOVID-19 and clearly demonstrate the technology's capabilities.

Due to the significance of AI in every part of COVID-19 image-based analysis, the focus of this review will be on how AI-enabled medical imaging contributes to the fight against disease. First, we'll go through intelligent imaging platforms for COVID-19, Next, we'll discuss popular machine learning techniques used in imaging workflow, including segmentation, diagnosis, and prognosis. A number of publicly accessible datasets are also discussed.

The increased likelihood of occupational virus exposure makes healthcare practitioners particularly vulnerable. Priority is provided to imaging specialists and technicians in order to prevent any dangerous viral interactions. Personal protection equipment (PPE) and specialised imaging facilities are also available and procedures may be considered, which are critical in reducing hazards and saving lives.

2. RESOURCES AND PROCEDURES

2.1 Experiment design

ConvNet's effectiveness on the database of images under consideration was assessed by a number of categorised tests, and ConvNet was compared to other models utilising the images' fundamental statistical properties, which can give accurate classification-related information. ConvNet research, statistical measurement experiments, and transfer learning studies were the three categories into which the experiments were divided.

2.2 Experiments with ConvNet.

ConvNet study focused COVID-19/Normal, COVID-19/Pneumonia, and COVID-19/Pneumonia/Normal are three subcategories. In order to assess the outcomes utilising different topologies and pre-processing techniques, they used four different network designs with differing numbers of convolutional and fully linked layers.

2.3 Experiments in Transferring Learning.

Unprocessed images, which performed best in ConvNet trials and statistical measurement studies, were compared to the previously described pre-trained networks.

33 filters are used in the VGG1613 CNN design, which also comprises 16 layers with weights. There are two entirely connected layers. After the convolutional layers, then a softmax for output. For the network, there are over 138 million parameters. Similar to VGG16, VGG1913 includes 19 layers with weights, which gives the network over 143 million parameters.

With its 50 residual layers, ResNet5014 aims to address issues like time consumption as the network gets deeper. Its foundation is a technique known as identity function that relies on skip connections across layers to improve model accuracy while shortening training times. More than 23 million trainable parameters are available.

42 layers and 24 million parameters make up Inception V315 Convolutions are factorised to lower the number of parameters without lowering network effectiveness. In Inception V3, new reduction was also suggested to cut down on the number of features.

53 layers and more than 3.4 million trainable parameters make up MobileNet-V216. It is made up of projection convolutions, expansion, and residual connections. The input tensor is expanded into a higher-channel tensor, filters are applied to the converted tensors using depth wise convolutions, and then the higher channels are projected to fewer tensors using projection convolutions.

Each layer is connected to every other layer in a feed forward manner via DenseNet12117. A fully connected layer comes after the first convolutional layer, while pooling and fully connected layers come after the remaining convolutional layers. More than 8 million trainable parameters are spread across 121 levels.

Each X-ray image was transmitted with the bare minimum of dimensions to the networks under consideration. The pre-processing was carried out on the pre-processing phases of the considered models to supply the models with the resulting images. After each model has been trained using pre-learned weights, the maximum Features were transferred to the fully connected layer when pooling was implemented (128). Similar to earlier research, the all experiments employed the eightfold cross-validation method experiments.

3. CRITERIA FOR MODEL EVALUATION

Different metrics, among them are classification accuracy, sensitivity (true positive rate), specificity, and ROC AUC, can be used to assess models. However, using either an accuracy or sensitivity/specificity criterion is insufficient, especially for data that is unbalanced; while one metric may yield higher ratings, other metrics may yield lower scores. There were two outcome classes in the COVID-19/Normal and COVID-19/Pneumonia studies, were compared using ROC AUC to evaluate the model's performance for statistical measurement was utilised in consideration of all the aforementioned criteria (labels). An evaluation of a model's performance is done using ROC AUC. The model with the higher ROC AUC score performs better in medical applications at differentiating between COVID-19-positive and COVID-19-negative patients. The responses are "positive" and "negative" findings.

$$\text{Accuracy} = (TP + TN) / (TP+TN+FP+FN) \qquad (a)$$

$$\text{Sensitivity} = TP / (TP + FN) \qquad (b)$$

$$\text{Specificity} = TN / (TN + FP) \qquad (c)$$

Where, FP and FN stand for false-positive and false-negative values, respectively, whereas TP and TN stand for true-positive and true-negative values.

4. RESULTS

In this section, the findings from ConvNet studies, statistical measurement experiments, and transfer learning experiments are presented.

4.1 Results of ConvNet Experiments

For the ConvNet studies, 38 tests were carried out in three groups individually, as was previously described.

4.2 COVID-19/Normal Experiments Results

Each experiment in this group trained without employing the data augmentation technique, which artificially inflates the training samples, on a total of 1808 images (225 COVID-19 and 1583 Normal).

4.3 COVID-19/Pneumonia Experiments Results

The second series of ConvNet tests, which employed a total of 4517 images (225 COVID-19 and 4292 Pneumonia for training), did not employ the data augmentation strategy, similar to the COVID-19/Normal research. Despite the fact that the second training set and the number of training photos were increased (the pneumonia set) is a challenging dataset for COVID-19 detection, similar results to those in the COVID-19/Normal tests were still attained.

4.4 COVID-19/Pneumonia/Normal Experiments Results

6200 pictures altogether (224 COVID-19, 4293 Pneumonia, and 1582 Normal) were trained for the three COVID-19 output classes in the most recent ConvNet research, Normal, and Pneumonia. The investigations in this group only employed the raw images with dimensions of 160120 and four potential ConvNet designs because the COVID-19/Normal and COVID-19/Pneumonia tests yielded better results without image pre-processing.

4.5 Learning Transfer Experiments

All experimental groups underwent comparisons. Pre-processing techniques were not used on the photos because ConvNet studies showed that the original images produced the best results. Transfer learning experiments were carried out in three groups, same like ConvNet experiments: COVID-19/Normal, COVID-19/Pneumonia, and COVID-19/Pneumonia/Normal.

In COVID19 or Pneumonia or Normal studies, the two models that would yield the best results in the COVID-19 or Normal and COVID-19 or Pneumonia groups were taken into consideration.

VGG19 and MobileNet-V2 produced the worst outcomes in the COVID-19/Normal category. They could only understand one class and were unable to categorise COVID-19 X-ray images. Results from ResNet-50 and VGG16 were notably superior to those from VGG19 and MobileNet-V2. ResNet-50 and VGG16's average ROC AUC values were calculated to be 65.78 and 72.64 percent, respectively. Inception-V3 outperformed other pre-trained networks in terms of results, while DenseNet121 achieved the greatest mean ROC AUC score in transfer learning experiments (96.48 %). Similar outcomes in the COVID-19/Pneumonia group were attained. ResNet50, MobileNet-V2, and VGG19 all saw an increase in their results, but they were still unable to match those of DenseNet121 and Inception V3. DenseNet121 (95.95%) and Inception V3 both received the highest mean ROC AUC score of COVID-19/Pneumonia classification in the transfer learning experiment (94.71 percent).

We implemented DenseNet121 and Inception V3 for the categorization of COVID 19/Pneumonia/Normal after taking into account the findings from the first two groups.

DenseNet121 surpassed Inception V3 in transfer learning trials, achieving a macro-averaged F1 score of 93.85 percent, compared to Inception V3's 93.14 percent, despite variable outcomes for the COVID-19, Pneumonia and Normal classes. The precision and recall scores were obtained.

Results Obtained in Transfer Learning Experiments for COVID-19/Normal and COVID-19/Pneumonia Classification

Experiment	Mean Sensitivity (%)	Mean Specificity (%)	Mean Accuracy (%)	Mean ROC AUC (%)	Mean Sensitivity (%)	Mean Specificity (%)	Mean Accuracy (%)	Mean ROC AUC (%)
VGG16	46.3	99.4	92.4	72.4	77.2	99.5	98.3	88.9
VGG19	08.4	100.0	88.5	54.1	70.5	99.8	98.5	85.7
InceptionV3	90.3	99.7	98.7	94.6	89.8	99.5	99.5	94.1
MobileNet-V2	08.1	100.0	87.1	54.0	68.9	99.9	97.7	84.4
ResNet50	31.6	100.0	91.5	65.8	59.6	100.0	97.8	79.6
DenseNet121	93.1	99.4	98.9	96.8	92.3	99.6	99.2	95.5

5. EXPERIMENT COMPARISONS

The deepest architecture in ConvNet experiments was used in the COVID-19/Normal classification, which yielded the highest mean specificity (when the pre-trained networks' 100.0 percent scores are excluded because they haven't learned another class) and mean accuracy results (99.78 and 99.11 percent, respectively). The performance of the evaluated ConvNet in the main performance measure for both classes, mean ROC AUC score, was therefore reduced as a result of the failure to deliver higher outcomes in terms of mean sensitivity. DenseNet121 achieved the highest mean sensitivity (93.92%), but other derived scores were insufficient to outperform other models in other criteria. The mean ROC AUC value for DenseNet121 was 96.48 percent.

ConvNet#1 managed to acquire the greatest mean ROC AUC score with 96.51 percent, despite the fact that it did not offer the best results in terms of sensitivity, specificity, and accuracy. The retrieved statistical data could not be used by machine learning classifiers to categorise COVID-19 in this experimental group with results that were adequate.

The macro-averaged F1scores for three-class experiments (COVID-19/ Pneumonia/ Normal) ranged from 92.70 to 94.10 percent. However, DenseNet121 outperformed ConvNet#1, ConvNet#3, ConvNet#4, and Inception V3 in terms of results. However, ConvNet#2 had the best results, with a macro-averaged F1score of 94.10 percent, followed by DenseNet121 with a score of 93.85 percent.

CONCLUSIONS

It is crucial for both doctors and patients to find COVID-19 in chest X-ray images in order to speed up diagnosis and cut expenditures. Deep learning and artificial intelligence are able to recognise images for the tasks taught. ConvNets were used in this study's studies to detect COVID-19 with great accuracy in chest X-ray pictures. For the classification, a number of groups—COVID-19 or Normal, COVID-19 or Pneumonia and COVID-19 or Pneumonia or Normal were taken into account.

Utilizing pictures and statistical data, various network topologies, cutting-edge pre-trained networks, and machine learning models were developed and assessed. It may be claimed that the studied architectures lower the computational cost with great performance when the amount of photos in the database and the COVID-19 detection time (average testing time = 0.03 s/image) are taken into consideration utilising ConvNets. With mean ROC AUC scores of 96.51 and 96.33 percent, respectively, the COVID-19 photos within the two-class COVID-19/Normal and COVID-19/Pneumonia categories were detected by the convolutional neural network with minimised convolutional and fully connected layers, according to the results. The second suggested structure, which had the second-lightest design, was also, had a macro-averaged F1score of 94.10 percent and was able to detect COVID-19 in three-class, COVID-19/Pneumonia/Normal pictures. As a result, the adoption of automated high-accuracy solutions based on AI may be able to help doctors diagnose COVID-19.

REFERENCE

[1] Mohamed Amine Ferrag, Lie Shu, senior member, IEEE and Kim-Kwang Raymond Choo, senior member, IEEE vol 8, no 9, September 2021 Fighting Covid-19 and Future Pandemics with the Internet of Things.
[2] J. P. Kanne, "Chest CT findings in 2019 novel coronavirus (2019-nCoV) infections from Wuhan, China: key points for the radiologist," Radiology, p. 200241, 2020.
[3] I. D. Apostol Poulos and T. Bessiana, "Covid-19: Automatic detection from X-Ray images utilizing transfer Learning with convolutional neural networks," arXiv:2003.11617, 2020.
[4] World Health Organization Coronavirus disease (COVID-2019) situation reports website", available online [10.4.2020] at https://www.who.int/emergencies/diseases/novel-coronavirus- 2019/situation-reports
[5] "SEWIO UWB Real-Time Location System (RTLS)", available online [5.4.2020] at https://www.sewio.net/real-time-location-system-rtls-onuwb/
[6] C. Sagonas, E. Antonakos, G, Tzimiropoulos, S. Zafeiriou, M. Pantic. 300 faces In-the-wild challenge: Database and results. Image and Vision Computing (IMAVIS), Special Issue on Facial Landmark Localisation "In-The-Wild". 2016.
[7] J.H. Lee, D. Kim, and M.K. Cho, Computed Tomography Apparatus and Method of Controlling X-ray by Using the Same, August 2021
[8] P. Forthmann and G. Pfleiderer Augmented Display Device for Use in a Medical Imaging Laboratory 25 march 2021
[9] Gunther correia bacillar, Mallikarjuna chandrappa, Rajlakshman Kulkarni, Soumava dey COVID-19 Chest X-ray Image Classification Using Deep Learning, July 19, 2021
[10] Pillalamarry Mahesh, Yakkala Gnana Prathyusha, Botlagunta Sahiti, S Nagendra COVID-19 Detection from Chest X-ray Using CNN, journal of physics conference series, ICMAICT 2020