Clinical Case Reports International

Review Article
Published: 27 Feb, 2023

COVID-19 Classification Models Based on Transfer Learning Approaches

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Abstract

WHO declared COVID-19 a pandemic in 2020. The virus can cause severe respiratory problems and affects the lungs. Timely precautions and accurate diagnosis is necessary to contain the spread of the virus. Diagnosis of COVID-19 was often misdiagnosed as Pneumonia and Tuberculosis (TB) in some cases. Accurate diagnosis is as important as timely diagnosis of this virus. For this purpose, multiple Machine Learning (ML) Deep Learning (DL), and Transfer Learning (TL) based approaches have been used. This paper analyzes transfer learning-based models that have been used, including classes of images, diseases, datasets, and accuracy.

Keywords: Transfer Learning; Machine Learning; Deep Learning; COVID-19; X-ray; CT; Lungs

Introduction

The World Health Organization (WHO) declared the spread of the Coronavirus infection a pandemic in March 2020, called the COVID-19 pandemic [1]. Coronavirus 2 (SARS-CoV-2) which causes severe acute respiratory syndrome [2] is to blame for the coronavirus pandemic. After initially starting in Wuhan, China, the virus later spread to every nation in the world [3].

The person who has the coronavirus can distribute it to others by coughing or sneezing respiratory droplets. These droplets have the potential to contaminate the surfaces, even more, speeding up the spread. People with the coronavirus may experience respiratory conditions ranging from minor to serious that may call for ventilation support [4]. When the COVID-19 pandemic hit the world, the first task which had to be tackled was the detection of the disease in its early stages so patients will be quarantined and the spread will be controlled.

At first, COVID was diagnosed using nasal swabs and Reverse Transcription Polymerase Chain Reaction (RT-PCR), but these methods had high false positive rates and were slow [5].

The researchers claimed that by using image processing and AI techniques, the process of detecting COVID-19 can be made faster and more accurate [6]. As all these diseases i.e. pneumonia, TB, and COVID-19 damaged a similar part of the lungs [7]. This became an issue as it caused misdiagnosis, which further lead to wrong treatment. The researchers used ML and DL to accurately classify COVID-19 from other lung diseases. For this purpose, chest X-rays and CT scan images were used. After this Transfer Learning [8] is used to get results more accurately and on time.

In this study, different Transfer learning models for classifying COVID-19 are discussed.

Transfer Learning

A transfer learning model takes parts of a trained machine learning model and applies them to a new, but similar, problem. Through transfer learning, the performance of a current task is improved by utilizing source data that are different from, but similar to, the target data. In a target task, the current problem is being solved. The source task is similar to the target task [9].

The purpose of the transfer is to use the experience gained in one task to improve performance in a similar but different one [10]. Transfer learning is employed in this study to identify some useful characteristics derived from a large amount of source data collected under one working condition, and then transfer these characteristics to a target task under a different working condition with only a limited amount of target data [9].

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Received Date: *06 Feb 2023*
Accepted Date: *22 Feb 2023*
Published Date: *27 Feb 2023*

Citation:
Khalid S. COVID-19 Classification Models Based on Transfer Learning Approaches. Clin Case Rep Int. 2023; 7: 1492.

Summary of Methodologies based on Image Type

Dataset description

The datasets were taken from public resources mostly from Kaggle and GitHub. Datasets taken contained CCOVID-19-positive Pneumonia, TB, and healthy images. In terms of radiological images, X-ray and chest CT scan images were used.

Models and methods

Authors in consideration have used transfer learning either as they were with increasing or decreasing layers, by an ensemble of two or more models, or in image preprocessing step by applying algorithms and filters.

Authors in [11] focused on feature extraction, dimension reduction, and classification of diseases using X-ray images. For feature extraction, authors ensemble deep Convolutional Neural Network CNN using Xception and InceptionResnetV2. The extracted features were then passed from a custom-made sparse autoencoder for reducing dimensionality and then Feed Forward Neural Network (FFNN) was used for classification. But a huge range of parameter values of sparse autoencoder was not experimented with and was neglected during the creation of the model.

Authors in [12] applied a modified lightweight CNN model for purpose of classification. The proposed CNN model contained four 2D convolutional layers and one fully connected layer with a MaxPooling 2D layer. The dropout regularization technique was also applied after each layer. A three-step process was proposed by [13]. The first step was segmentation which was done using C-GAN. The second step was feature extraction for which multiple deep transfer learning models and algorithms were used and the last step was classification which was done by machine learning classifiers. Final comparisons showed that VGG19 combined with Binary Robust Invariant Scalable Key-points (BRISK) algorithm [14] showed the highest accuracy.

Authors in [15] have used cGAN to generate images and these images were fed to CNN models (ResNet-50 [16], ResNet-101 [16], Xception, DenseNet-201 [17], DenseNet-169 [17]). SoftMax classifier was used in these models to classify images. This model is used to overcome data imbalances and overfitting. CNN models when using images without cGAN produced average testing accuracy of 90.71%, and when the images were generated with the help of cGAN, the testing accuracy of 92.17%. ResNet-50 [16] showed the best accuracy among these all. Though the dataset was still limited in this study the classes of COVID from different stages were taken which was a remarkable attempt in the said matter.

CNN-based model namely, CovFrameNet, is proposed by authors in [18]. SoftMax layer was used for classification purposes and deep learning regularization techniques were applied to avoid overfitting. In [19], ResNet-101 [16] is used as the backbone architecture. The weights of the image were extracted from the last layer of the architecture, and an average of these weights was calculated. That average weight was then used to generate a heatmap.

Authors have proposed an algorithm with a CNN model to increase the accuracy of COVID detection. A public dataset of CT images was used out of which 120 images were taken this study focuses on detecting Ground Glass Opacities from the CT images [20].

To increase the detection accuracy authors [21] have designed a lightweight CNN model, D2-CovidNet, by proposing feature-sensitive modules called Dual-Path Multiscale (DPM) feature fusion modules and Dense Depth-wise Separable (DDS) convolution modules as these have strong characterization capabilities and efficient computing abilities. In [22], authors have proposed an algorithm was proposed to classify COVID-19 accurately. Different pre-trained CNN models (SeresNext50, SeresNext101) along with Sparrow Search Algorithms (SpaSA) were used. Out of these models, MobileNetV3Large showed the best results. Similarly, in [23], the author has used Convolutional Neural Network (CNN), Zeiler and Fergus Network (ZFNet) [24], and Dense Convolutional Network-121 (DenseNet-121 [17]) architectures of deep convolutional neural network models to provide an accurate diagnosis of COVID-19 on binary classification. Out of these, customized CNN showed the best performance.

In [25], Ensemble learning was used to ensemble the transfer learning models i.e., EfficientNet, GoogLeNet, and XceptionNet. Which performed classification among taken images. Whereas, authors ensembled DenseNet-121 [17] and Resnet-50 [16] based on their orthogonal features and created and trained a deep learning network named DenResCov-19 in [26]. DenResCov-19 network is a concatenation of four blocks from ResNet-50 [16] and DenseNet-121 [17] with width, height, and frames of 58×58×256, 28×28×512, 14×14×1024, and 7×7×2048, respectively. A model was created in [27] created by the assembly of DenseNet, h5, and the Inception model. And results were demonstrated based on weights.

The authors have created a model named DeQueezeNet by ensemble DenseNet-121 [17] and SqueezeNet1.0 to increase the COVID-19 prediction efficiency by extracting various important features [28]. In [29], ResNet-50 [16] with 5 folds and 10 folds cross-validation to recognize COVID-19 is being used.

Three models i.e., InceptionV3, ResNet34, and DenseNet-201 [17] are being used in [30] and they were ensemble to detect COVID-19 more accurately using a bagging ensemble, called ET-NET.

Authors in [31] have combined DenseNet and Optimization of Transfer Learning Setting (OTLS) strategy to make the diagnosis of COVID more accurate. A Composite Learning Factor (CLF) was put to work to assign learning factors t different layers. It was observed that "201-IV" achieved better performance by using the proposed OTLS strategy.

In [32], the authors used a pre-trained transfer learning-based framework on the CheXnet model, which is trained in DenseNet-121 [17]. In [33], authors have ensemble three models named DCCNs, ResNet152V2, and VGG16 to tackle the sensitivity issue.

Authors in [34] have fine-tuned existing pre-trained deep learning models such as VGG16, VGG19, InceptionV3, ResNet-50 [16], ResNet50V2, InceptionResNetV2, Xception, and MobileNet on CT images and then these models were used to create a strong ensemble classifier that makes the further decision. Models were further divided into 5clf and 8clf. The results of 5clf showed better results than that of 8clf.

Authors in [35] have focused on feature extraction from R, G, and B areas of CT images using Empirical Wavelet Transformation. Then DenseNet121 [17] is used to classify these images based on COVID-19 and non-COVID. A classifier fusion strategy is proposed in [36] that fuses the predictions from the different classifiers via majority voting.

Apart from that authors have used pertained variants of the ResNet model to detect COVID with more accuracy. The results showed that ResNet-50 has outperformed other variants with a recall of 98.80%.

Limitations and Future Work

From this brief study following drawbacks have been found along with suggestions to improve them:

- Overfitting is the common one seen which can be avoided by more regularization techniques.
- Though models showed good accuracy there was no balance between accuracy and speed.
- Mostly the validation of the models is for only binary classification and three-class classification tasks.
- Models should be validated in one specific coherent.
- The major drawback of detecting COVID with ML techniques is the unavailability of public datasets. Researchers have used limited datasets.
- Imbalance in the dataset can be seen in work that has used large datasets.
- Another one is that accuracy of the model is affected when the test dataset has a different origin than that of validation.
- CXR and CT images have been separately used in most of the studies. The one in which both of them are used showed better results.
- Some of the models showed issues with feature extraction.
- Some datasets were from specific geographical regions which arise validity issues.

Conclusion

In this paper, transfer learning models and methods have been discussed which are used to detect and classify COVID-19 from other lung diseases using lung X-ray and CT scan images. The lung diseases in observation were Pneumonia and TB. Many models were used like CNN, Resnet, DenseNet, Xception, GoogleNet, VGG, and Alexnet. Lesser dataset caused overfitting and noisy images in the dataset resulted in lower accuracy. To remove noise and overcome overfitting image preprocessing techniques including data augmentation and cGAN were used. Ensemble learning and algorithms during different phases of the model are being used to boost classification accuracy. Models pretrained on ImageNet datasets were also considered to extract better results. In 2 class classification, MobileNetV3 showed better results, whereas, in 4 class classification with a larger dataset, ensemble learning has been proved to be better than other techniques with an average accuracy of more than 95%. It is concluded from the study that even though there is a lot of work done in this field. There still are drawbacks that can be improved by using different models and better approaches.

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