Detection of COVID-19 cases through X-ray images using hybrid deep neural network

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Abstract

Purpose – The latest 2019 coronavirus (COVID-19), which first appeared in December 2019 in Wuhan’s city in China, rapidly spread around the world and became a pandemic. It has had a devastating impact on daily lives, the public’s health and the global economy. The positive cases must be identified as soon as possible to avoid further dissemination of this disease and swift care of patients affected. The need for supportive diagnostic instruments increased, as no specific automated toolkits are available. The latest results from radiology imaging techniques indicate that these photos provide valuable details on the virus COVID-19. User advanced artificial intelligence (AI) technologies and radiological imagery can help diagnose this condition accurately and help resolve the lack of specialist doctors in isolated areas. In this research, a new paradigm for automatic detection of COVID-19 with bare chest X-ray images is displayed. Images are presented. The proposed model DarkCovidNet is designed to provide correct binary classification diagnostics (COVID vs no detection) and multi-class (COVID vs no results vs pneumonia) classification. The implemented model computed the average precision for the binary and multi-class classification of 98.46% and 91.352%, respectively, and an average accuracy of 98.97% and 87.868%. The DarkNet model was used in this research as a classifier for a real-time object detection method only once. A total of 17 convolutional layers and different filters on each layer have been implemented. This platform can be used by the radiologists to verify their initial application screening and can also be used for screening patients through the cloud.

Design/methodology/approach – This study also uses the CNN-based model named Darknet-19 model, and this model will act as a platform for the real-time object detection system. The architecture of this system is designed in such a way that they can be able to detect real-time objects. This study has developed the DarkCovidNet model based on Darknet architecture with few layers and filters. So before discussing the DarkCovidNet model, look at the concept of Darknet architecture with their functionality. Typically, the DarkNet architecture consists of 5 pool layers though the max pool and 19 convolution layers. Assume as a convolution layer, and as a pooling layer.

Findings – The work discussed in this paper is used to diagnose the various radiology images and to develop a model that can accurately predict or classify the disease. The data set used in this work is the images bases on COVID-19 and non-COVID-19 taken from the various sources. The deep learning model named DarkCovidNet is applied to the data set, and these have shown signification performance in the case of binary classification and multi-class classification. During the multi-class classification, the model has shown an average accuracy 98.97% for the detection of COVID-19, whereas in a multi-class classification model has achieved an average accuracy of 87.868% during the classification of COVID-19, no detection and Pneumonia.

Research limitations/implications – One of the significant limitations of this work is that a limited number of chest X-ray images were used. It is observed that patients related to COVID-19 are increasing rapidly. In the future, the model on the larger data set which can be generated from the local hospitals will be implemented, and how the model is performing on the same will be checked.

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Primary paper: Originality/value - Deep learning technology has made significant changes in the field of AI by generating good results, especially in pattern recognition. A conventional CNN structure includes a convolution layer that extracts characteristics from the input using the filters it applies, a pooling layer that reduces calculation efficiency and the neural network’s completely connected layer. A CNN model is created by integrating one or more of these layers, and its internal parameters are modified to accomplish a specific mission, such as classification or object recognition. A typical CNN structure has a convolution layer that extracts features from the input with the filters it applies, a pooling layer to reduce the size for computational performance and a fully connected layer, which is a neural network. A CNN model is created by combining one or more such layers, and its internal parameters are adjusted to accomplish a particular task, such as classification or object recognition.

Keywords - Convolution layer, DarkNet, Maxpool, ResNet, Coronavirus (COVID-19), Sensitivity

Paper type - Research paper

1. Introduction

The virus name COVID-19, which started on 31 December 2019 with the unknown causes of pneumonia recorded in Wuhan, Chinese Hubei Province, has quickly become a pandemic (Wu et al., 2020). The disease is called COVID-19 and the SARS-CoV-2 virus (Yuvaraj et al., 2020). In 30 days, this new virus spread from Wuhan in no small part of China (Barry et al., 2020). By April 5, 2020, the USA, where the first seven cases were identified on January 20, 2020, exceeded more than 300,000 (Bialek et al., 2020). Most coronaviruses affect animals, but they can also be transmitted to humans due to their zoonotic nature.

Severe ARS-CoV (Coronavirus) and Middle East Respiratory Syndrome (MERS-CoV) have caused severe respiratory disease and human death (Li et al., 2020a). COVID-19 usually has a fever, poison, sore throat, headache, tiredness, abdominal discomfort and shortness of respiration (Singhal, 2020). A real-time reverse transcription-polymerase chain reaction (RT-PCR) is the popular test technique currently being used for COVID-19 diagnosis. The early diagnosis and treatment of chest radiological imaging such as computed tomography (CT) and X-rays have critical roles (Heenan et al., 2019). Due to low RT-PCR sensitivity of 60%–70%, while adverse results are obtained, symptoms can be identified by analyzing patients’ radiological images (Kanne et al., 2020). CT was reported to be a sensitive method for detecting COVID-19 pneumonia and can be regarded as a device for RT-PCR screening (Li et al., 2020b). CT findings are observed for a long time after symptoms start, and patients typically experience standard CT for the first 0–2 days. In a lung CT analysis of patients who have survived COVID-19 pneumonia, the most extensive lung disease is observed ten days after the onset of symptoms (Zhao et al., 2020). At the start of the pandemic, the Chinese health centers had inadequate test kits, which also yielded high levels of false-negative tests, which enabled doctors to make diagnoses based solely on CT findings. CT is commonly used to diagnose COVID-19 in countries like Turkey, where there are a small number of test kits available at the beginning of the pandemic.

Researchers suggest that it can be useful to combine clinical image features with laboratory findings to detect COVID-19 early on (Zhao et al., 2020). Radiological images from COVID-19 cases provide valuable diagnostic details. Some research finds improvements in chest X-rays and CT before COVID-19 symptoms started (Chan et al., 2020). Researchers also made fundamental advances in COVID-19 imaging research. Yoon et al. (2020) recorded that one in three studied patients in the lower left lung area had a single nodular opacity. The other two, by comparison, had an abnormal opacity of four and five lungs. Zhao et al. (2020) have found not only ground-glass opacities (GGOs) or mixed GGOs in most cases but also consolidation and lesion vascular dilations. Li and Xia (2020) stated that the typical CT characteristics of COVID-19 patients were GGO and consolidation, interlobular septal thickening and air bronchograms with or without vascular expansion. Another result is peripheral or multifocal GGO affecting both lungs in 50%–75% of patients.

Automated diagnostics machine learning (ML) methods in the medical sector have recently gained prominence by being an important tool for clinicians (Litjens et al., 2017). Deeper learning, a common research field of artificial intelligence (AI), allows the creation of end-to-end models to achieve expected input-data results without manual extraction of features. Deep learning techniques were used successfully for various problems including rhythm detection (Yildirim et al., 2018), classification of skin cancer (Esteva et al., 2017), breast cancer detection (Litjens et al., 2016), classification of brain disease (Liu et al., 2012), chest X-ray pneumonia detection (Khan et al., 2020) and lung segmentation (Mansoor et al., 2015). The rapid growth of the COVID-19 epidemic has needed expertise in this area – this increased interest in developing AI technology-based automated detection systems.

In this study, a profound research model for the automatic diagnosis of COVID-19 is proposed. Without any function extraction methods, the proposed model has an end to end architecture, and it requires bare chest X-ray images to return the diagnosis (Garg and Dhiman, 2020a). This model is equipped with 125 X-ray images of the pot that are not normal and have been quickly collected. In recovered patients, diagnostic tests conducted after 5–13 days are positive. This critical result tells us that the virus will continue to spread in healed patients. More accurate diagnostic methods are, therefore, required. One of the significant drawbacks of thoracic X-rays is that they cannot detect the early stages of COVID-19 because there is not enough sensitivity in GGO detection. But well-trained profound learning models can focus on points that the human eye cannot perceive and can reverse this perception.

2. Literature survey

ML and natural language processing use data-based models to identify, explain, and predict patterns. In recent years NLP has been very interested, particularly in Text Analytics (Arya et al., 2019). Classification is one of the essential tasks in Text Mining.
and can be performed using different algorithms (Romanyuk et al., 2020). Kumar et al. conducted the SWOT analysis of various supervised and unsupervised text classification algorithms to mining unstructured data (Kumar et al., 2018). Sentiment analysis, fraud detection, spam detection, etc. are the different text classification applications.

Deep learning has modified the medical outlook by providing excellent results to diabetes and Epilepsy. Sidhu et al. (2018) identified Epilepsy with ML, electroencephalogram (EEG) signals, used for the detection by artificial neural networks of normal and epileptic disorders. Sarwar et al. (2020) Diabetes diagnosis using computer and ensemble learning techniques found that ensemble techniques provided 98.60% accuracy. These can be useful for diagnosing and predicting COVID-19. Confirm and accurate diagnosis of COVID-19 can save millions of lives and generate large amounts of data to train ML models. ML can provide helpful feedback, particularly in diagnosis based on clinical text, X-ray images, etc.

According to Bullock et al. (2020), machine-learning can substitute for human knowledge by offering a detailed diagnosis. The optimal diagnosis will save time and can be economical as regular COVID-19 tests. X-rays and CT scans can be used to train the ML algorithm. Several measures in this respect are underway. Wang et al. (2020) created COVID-Net, a deep neural convolutionary network capable of diagnosing COVID-19 from chest X-rays. If the COVID-19 is identified in a human, it remains whether it is affected and how intensively. Not all positive COVID-19 patients need to be carefully treated. Being able to prognosis who is more seriously affected will help guide assistance and prepare the distribution and use of medical services – using data from only 29 patients in the Tongji Hospital in Wuhan, China, Yan et al. (2020) used ML to create a predictive prediction algorithm to predict an infected individual’s mortality risk. Jiang et al. (2020) proposed a model of master learning that can forecast a person with COVID-19 who can improve ARDS. The model proposed resulted in 80% precision. Samples of 53 patients have been used for their model training and are confined to two Chinese hospitals. ML may be used to diagnose COVID-19, which is not yet widely operational but needs a great deal of study. Since we do less work on diagnostics and text prediction, we have used ML and ensemble learning models to classify clinical reports into four virus groups.

Researchers have recently detected the imaging patterns on chest CT in chest CT to detect COVID-19 (Xie et al., 2020). Fang et al. (2020) examined RT-PCR sensitivity and chest CT sensitivity during COVID-19 detection. They studied the history of travel and the symptoms of two patients and found that chest CT’s sensitivity to COVID-19 detection is much higher than RT-PCR. Xie et al. (2020) also reported that 3% of 167 patients had COVID-19 negative RT-PCR. Chest CT, however, has greater sensitivity to COVID-19 detection than RT-PCR.

Bernheim et al. (2020) have examined 121 contaminated Chest CT patients from four Chinese sites. The relationship between CT scanning and onset of symptoms is determined. They find the severity of the disease increases with the time when symptoms start, and the signs of the disease are established. Recently, in Chest CT images, deep learning techniques have been used widely to detect acute pneumonia.

Li et al. (2020c) have developed a deep learning model called COVNet for the visual extraction of COVID-19 from chest CT. They used optical characteristics to differentiate between acquired pneumonia in the population and other pulmonary diseases. However, the seriousness of this disease cannot be classified by COVNet.

Guiolet et al. (2020) have developed an artificial CT analysis method to identify and quantify COVID-19. The machine automatically extracts opacity slices from the lungs. The device built was 98.2% responsive and 92.2% accurate. The device performance includes quantitative opacity calculation and an opacity 3D volume display (Dhiman et al., 2020). The system is good against the separation of pixels and the thickness of slices. Shan et al. (Xu et al., 2020) developed a VB-net profound learning framework for the automated segmentation of all pulmonary and chest CT sites.

Xu et al. (2020) developed a model prediction for the differential use of deep learning techniques for VICO-19 pneumonia and influenza-A viral pneumonia. For prediction, the CNN model was used. The overall accuracy of the prediction model was 86.7%.

Medhi et al. (2020) proposed an automated deep convolution neural network-based transference models in chest X-ray images to predict the COVID-19. For better prediction, they used InceptionV3, Inception-ResNetV2, and ResNet50 models. The pre-trained ResNet50 model provided 98% of the accuracy higher than (Xu et al., 2020). Sethy et al. (2020) developed an in-depth research model to detect X-ray images of COVID-19. They extracted deep features and passed them to the classification vector machine. The accuracy of 95.38% is higher than (Kanne et al., 2020; Li et al., 2020b) obtained from the proposed model. The detailed analysis found that the CT images of the chest could be used for the early detection of infected COVID-19 patients. Therefore, computational models for classifying COVID-19 patients in chest CT images have been used in this paper.

3. Proposed methodology

In this work, we have taken X-ray images from two different sources to diagnose COVID-19. Apostolopoulos and Mpiesiana (Wu et al., 2020) has worked on other datasets based on X-ray images related to Covid-19 (Apostolopoulos and Mpiesiana, 2020). Cohen, JP (Oh et al., 2020) created a COVID-19 X-ray image database using various open access sources. This database is updated continuously with photos that researchers from multiple regions share. The collection currently includes 127 X-ray images that are diagnosed with COVID-19.

X-ray images from two separate sources have been used to diagnose COVID-19 in this report. Cohen, JP created a COVID-19 X-ray image database using various open access sources. This database is updated continuously with photos that researchers from multiple regions share. The collection currently includes more than 900 X-ray images that are diagnosed with COVID-19. Figure 1 displays some COVID-19 cases from the report and expert results. There are 43 female and 82 male cases considered to be positive in the sample. Full metadata is not provided for all patients in this dataset. Age information for 26 positive COVID-19 subjects is given, and their average age is about 55 years. The database of ChestX-ray8 provided by Wang.
Deep learning technology has made significant changes in the field of Artificial Intelligence by generating good results, especially in pattern recognition (Srihari et al., 2020). A conventional CNN structure includes a convolution layer that extracts characteristics from the input using the filters it applies, a pooling layer that reduces calculation efficiency, and the neural network’s completely connected layer. A CNN model is created by integrating one or more of these layers, and its internal parameters are modified to accomplish a specific mission, such as classification or object recognition. A typical CNN structure has a convolution layer that extracts features from the input with the filters it applies, a pooling layer to reduce the size for computational performance, and a fully connected layer, which is a neural network. A CNN model is created by combining one or more such layers, and its internal parameters are adjusted to accomplish a particular task, such as classification or object recognition (Garg and Dhiman, 2020b).

This study also uses the CNN based model named Darknet-19 model, and this model will act as a platform for the real-time object detection system. The architecture of this system is designed in such a way so that they can be able to detect real-time objects. This study has developed the DarkCovidNet model based on Darknet architecture with few layers and filters. So before discussing the DarkCovidNet model, let us look at the concept of Darknet architecture with their functionality. Typically, the Darknet architecture consists of 5 pool layers though the max pool and 19 convolution layers. Assume as a convolution layer, and as a pooling layer, according to the Darknet, the layout will be as follows:

$$C_1 - M_1 - C_2 - M_2 - C_3 - C_4 - C_5 - M_3 - C_6 - C_7$$

$$- C_8 - M_4 - C_9 - C_{10} - C_{11} - C_{12} - C_{13}$$

$$- M_5 - C_{14} - C_{15} - C_{16} - C_{17} - C_{18} - C_{19}$$

In the above representation is the input convolution layer. The two dimensional operation of Convolution operation for the input sample $S$ (image) and kernel $k$ is defined as follows:

$$(S * k)(i, j) = \sum_{m} \sum_{n} k(m, n) S(i - m, j - n)$$

In the above equation (1), "*" denotes the discrete convolution operation and the matrix slides with a stride parameter over the input matrix. In the proposed DarkNet architecture, Leaky ReLu has been used as an activation function (Medhi et al., 2020). Leaky ReLu has been represented as:

$$f(x) = \begin{cases} 0.01x, & x < 0 \\ x, & x \geq 0 \end{cases}$$

A pictorial representation of the above equations (1) and (2) is shown in Figure 1 with Convolution layer C and Max pooling layer M. The deep learning model with several numbers of layers has been applied for extracting the features during the detection of real-time objects (Nair and Bhagat, 2019).

The proposed model is a solution for all those images, which is subtler because they encountered a problem during classification. The proposed model is shown in the Figure 2 consist of 17 convolution layers (Sethy et al., 2020). Each darknet layer contains one convolution layer followed by batch normalization with Leaky ReLU activation. In the three successive steps, the convolution layer has the same setup. To standardize the inputs, batch normalization is applied, and this also helps extend the stability and reduce the training time of the model. A variant of ReLU named Leaky ReLU is used for the prevention of dying neurons.

Contrary to ReLU or sigmoid functions with zero activation, LeakyReLU has a small value for the negative portion of its derivatives, and this is solved by epsilon value. Maxpool method is used in the proposed model as in the darknet model during the pooling operation. By using the filter, it downsizes an input by covering the maximum portion. This model works well in binary classification and multi-class classification. In the case of binary type, it performs the detection of COVID-19, while in multi-class type, it predicts the labels of the X-ray images of the chest as Pneumonia, COVID-19, or no detection. The proposed model consists of 1,748,352 parameters, and for weight updation, Adam optimizer has been used. Implementation is done by selecting the learning rate of 3e-3 and cross-entropy loss function.

Table 1 has shown the details of the proposed model, i.e. DarkCovidNet with the included number of layers and the parameters involved in the training process. Figure 2 has demonstrated the impact of DarkCovidNet model using the images of Chest X-ray. The same model is applied for both the classification i.e. binary and multi-class classification.

### 4. Results and discussion

The implementation of this work is done through using Python programming language. We have experimented with the use of the X-ray images in two separate situations to detect and
classify COVID-19. The DarkCovidNet deep learning model has been developed in the first place, which classifies X-ray images into three groups. The DarkCovidNet, second model based on Binary classification are applied to detect: COVID-19 and no-detection. The classification model’s efficiency is evaluated using 5-Cross-validation fold process, both for binary and triple grading problems. 80% of X-ray images are used for training and 20% is used for validation purpose. All the sections of the split k are folded to be used during the validation stage. The proposed model DarkCovidNet is trained using 100 epochs. The multi-class classification preparation and validation comparison table is given in Table 1.

Tables 2 and 3 will show the result achieved by implementing the model. Table 2 shows the multiclass-classification based on three classes, and Table 3 represents the binary classification. The parameters used for the performance evaluation of the algorithms are the accuracy, sensitivity, specificity, precision and the F1 score.

5. Conclusion and future work

The work discussed in this paper is used to diagnose the various radiology images and to develop a model that can accurately predict or classify the disease. The data set used in this work is the images bases on COVID-19 and non-COVID-19 taken from the various sources. The deep learning model named DarkCovidNet is applied to the dataset, and these have shown signification performance in the case of binary classification and multi-class classification. During the multi-class classification, the model has shown an average accuracy 98.97% for the detection of COVID-19, whereas in a multi-class classification model has achieved an average accuracy of 87.86 % during the classification of COVID-19, no detection and Pneumonia.

One of the significant limitations of this work is that we had used a limited number of chest X-ray images. It is observed that patients related to COVID-19 are increasing rapidly. In the future, we will implement the model on the larger dataset which can be generated from the local hospitals and check how the model is performing on the same. Let us look at Figure 3 which shows how the implemented model will work.
Figure 3  Performance evaluation of the DarkCovidNet model

References
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