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Original Article

Diagnosing Corona Virus Using Chest X-Ray Images

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Abstract:

Corona Virus continues to possess it effects on the people lives across the world. The screening of infected persons is vital step because it is a fast and low-cost way. Chest X-ray images plays a major crucial role and it is used for examination in detection of CORONA VIRUS (COVID-19). Here radiological chest X-rays are easily available with low cost only. In this, we are using a Convolutional Neural Network (CNN) based solution that will benefit in detection of the Covid19 Positive patients using radiography chest X-Ray images. To test the efficiency of the solution, we are using public available X-Ray images of Corona Virus Positive cases and negative cases. Images of Positive Corona Virus patients and pictures of healthy person images are divided into testing images and trainable images. The solution which we are providing will give good results in classification accuracy within the test set-up. The GUI application can be used on any computer and performed by any medical examiner or technician to determine Corona Virus positive patients using radiography X-ray images. The result will be shown or provided by this application is accurate.

Keywords: Corona Virus, X-Ray Images, Diagnosing

Introduction:

The leading cause of the global COVID-19 pandemic is the SARS-CoV-2 virus. Therefore, it has become necessary to find means that would effectively achieve early detection of people with COVID-19 and provide them with the care needed on time. In addition, all medical measures and precautions must be taken to separate patients infected with COVID-19 from other patients to reduce the spread of the disease or its fatal symptoms. The number of deaths due to coronavirus reached 6,517,058 based on global measures [1]. Furthermore, COVID-19 poses a severe challenge due to its ease of transmission and global lack of definitively viable therapies [2]. Many vaccines have been proven to expose users to many complications, including blood clots. COVID-19 infection goes through three stages: the incubation period, acute COVID-19, and finally, COVID-19 recovery. The incubation period is the period between the actual infection with the disease and the onset of symptoms in the patient. Acute COVID-19 is the time when the symptoms appear, such as fever, cough, fatigue, headache, congestion, or runny nose, among other COVID-19 symptoms. In addition, an essential step in the fight against this fatal illness would be a successful screening and diagnosis procedure to treat affected patients. In addition, an effective strategy in the fight against COVID-19 may be early detection utilizing chest X-ray pictures [3]. Therefore, effective and early COVID-19 diagnosis based on the symptoms and chest X-ray images will help to mitigate the coronavirus outbreak. Moreover, it will assist healthcare systems, including doctors, nurses, and medical staff, in protecting vulnerable patients. Artificial intelligence (AI) has been instrumental in the steady transition from laboratory to clinical and public health applications. AI provides a wide range of approaches for analyzing complex data to advance understanding of the subject of COVID-19 [4,5,6,7]. AI employs machine learning (ML) and deep learning (DL) to produce algorithms that can be used in the clinical and biomedical fields for patient classification and stratification based on the pairing and processing of a wide range of available data sources, such as heart disease detection [8], polycystic ovary syndrome detection [9], and chronic kidney disease detection [10]. The most significant contribution is using AI to detect patients at higher risk early to treat those patients and control disease transmission. Furthermore, AI can help governments to manage the pandemic by early notification of COVID-19 outbreaks [11]. An ensemble classifier combines the results of several classifiers in a way that enables component models to balance out the deficiencies of each other. Ensemble learning has three types, stacking [12,13], bagging [14], and boosting, which use a generic meta-approach in predictive performance by integrating predictions from different models, improving the general prediction of DL. Stacking involves combining weak algorithms into a meta-model that can make better predictions [12,13].

There are two types of stacking ensembles: heterogeneous and homogeneous. The heterogeneous ensemble uses a variety of classifiers, while the homogeneous ensemble uses the same base model repeatedly. An ensemble of heterogeneous agents may perform better than an ensemble of homogeneous agents because of the combination of their biased decisions. In our work, we develop homogeneous stacking ensemble models to detect COVID-19. Therefore, rapid diagnosis based on symptoms with accurate prediction is the essential AI-based solution to control the spread of the pandemic. Some related research work has been done on COVID-19 diagnosis. However, experimental research still needs to be done using ensemble learning for COVID-19 diagnosis. On the other hand, COVID-19 can induce pneumonia, which is caused by lung inflammation triggered by bacterial or viral infection. Consequently, researchers, specialists, and companies have used medical images (i.e., chest X-ray and computed tomography (CT)) for early diagnosis of COVID-19 patients. Hundreds of chest X-ray have been used to investigate the nature of pneumonia due to COVID-19 infection (see Figure 1). According to the context of this paper, DL models have been proposed to study chest X-ray images to benefit the detection of COVID-19. Researchers have used DL classifiers, in particular, to classify COVID-19 using chest X-rays images. For example, CNN models have been used to learn the pattern of COVID-19 infection from radiological X-ray images [15,16]. In particular, CNN models help to draw a clear distinction between non-tangible elements in the X-ray that can expose COVID-19 infection.

Background:

Beginning in December of 2019, a novel, Human coronavirus emerged in Wuhan, China [17]. Though similar to the previous SARS and MERS viruses, this virus proved to be more infectious and quickly became a global pandemic. Causing pneumonia-like symptoms, a total of 2,552,687 deaths have been attributed to this virus as of March 3, 2021 [17]. The elderly are especially vulnerable to this virus [18]. Routine testing for this virus usually involves a nasopharyngeal or oropharyngeal swab [19]. The sample is then sent to an outside facility for determination of viral load by polymerase chain reaction (PCR) [19]. Some rapid tests exist but are not used as prevalently [20]. This test is time consuming, taking several days for results to be returned. It also expends valuable reagents and testing kits that are in limited supply. A faster, less expensive modality for diagnosing the novel coronavirus (COVID19) would be valuable in hospital settings when patients are too sick to wait for answers. Rapid chemical testing for COVID19 has been made available but suffers from the same problem of consuming reagents and test kits . Additionally, rapid antigen tests have less sensitive compared to other tests [20].

Other researchers have been explored the marks left by COVID19 on radiographic images of the patient's lungs. COVID19 presents radiologically like an atypical or organizing pneumonia, but also has some distinctive characteristics [20]. On plain-film x-ray, patchy or diffuse opacities with the texture of consolidation or ground-glass may be visible, but the unique imaging features of COVID19 are much more apparent in a CT scan [21]. CT scans of COVID19 infected patients show ground-glass opacities, crazy paving, airspace consolidation, bronchovascular thickening, and traction bronchiectasis [12]. Given these distinctive findings, machine learning algorithms have been developed to diagnose cases of the virus with CT data [22]. A meta-analysis of machine learning models used for diagnosis of COVID19 based on medical imaging found 18 papers applying deep-learning to CT scans. These deep-learning models performed well on their respective datasets with reported area-under the receiver operating characteristic curve (AUROC) between 0.7 and 1.0 [23].

However, CT scans come with their own problems. Compared to a plain-film x-ray, CT scans use much larger amounts of radiation, presenting higher risk to the patient. For this reason, physicians use them sparingly. A diagnostic algorithm for COVID19 infection using a plain-film chest x-ray as its input would greatly economize the patient's radiation exposure. The same meta-analysis found 22 papers using deep-learning to analyze plain-film chest x-rays [24]. These models also exhibited good performance on their datasets with accuracies ranging from 0.88 to 0.99 [25]. Our goal is to improve upon the existing technology for deep-learning diagnosis of COVID19 using chest x-rays by including larger number of images in the training set and incorporating a transfer learning approach. We will use a pre-trained CheXNet model to extract imaging features from chest x-rays for use in a downstream. This approach was used by this research group previously for predicting the etiology of acute shortness of breath in an ER setting [26].

Detecting COVID-19 Using Symptoms

The authors used ML and DL algorithms to detect COVID-19. For example, in [6], the authors used the gradient-boosting (GBoost) model for COVID-19 patient detection. They evaluated the model using AUC. In [17], the authors proposed a DL model technique called gray level co-occurrence matrix (GLCM) based on CNN. The authors in [18] contrasted widely employed feature extraction techniques for COVID-19 automatic categorization based on DL. The authors applied a group of deep CNNs, including InceptionV3, InceptionResNetV2, MobileNet, DenseNet, Xception, ResNet, VGGNet, and NASNet. In [27], the authors developed a predictive algorithm based on a trained DL model using 8427 COVID-19 patient records. In [28], the authors used the ML models: XBoost, AdaBoost, RF, and ExtraTrees with 337 COVID-19 patients. Jamshidi et al. [29] summarized different models, including hybrid DL approaches and ML approaches, for calculating and forecasting complicated occurrences focused on the spread of COVID-19. In [30], the authors used ML techniques to detect mortality risks in COVID-19 using a dataset collected from the UK Biobank. The authors of [31] used KNN, SVM, LR, multilayer perceptual neural networks (MLP), LSTM, and GRU for COVID-19 diagnosis. They used the COVID-19 dataset from Kaggle that includes some features and symptoms for their experiment. In , the authors used LR, NB, RF, DT, and gradient boosters for COVID-19 diagnosis based on some symptoms. They used the COVID-19 dataset from Kaggle that includes some features and symptoms. The results showed that KNN achieved the highest accuracy. In [32], the authors Used RF, SVM, MLP and XGB, and LR to predict COVID-19 for children based on collected data that include some of the symptoms. Previous studies used regular ML and DL models. However, they did not use ensemble stacking based on LSTM and GRU. In our study, we proposed stacking ensemble DL models for detecting COVID-19. The proposed model combined LSTM and GRU with SVM as a meta-learner for detecting COVID-19.

The Detection of COVID-19 Using Chest X-rays

Several studies have used transfer learning on chest X-ray images to identify COVID-19 patients. Here, we focus only on issues directly relevant to our suggestion. In [33], X-ray images of the chest were analyzed using three pre-trained models for extracting features and detecting COVID-19. A variety of data augmentation techniques, such as random rotation and noise, were employed. VGG16 achieved the best results. In [34], A total of 100 chest X-ray images was analyzed by the author to detect COVID-19 using three pre-trained CNNs, Inception-ResNetV2, InceptionV3, and ResNetV2. ResNet50 registered the highest result. In [34], the authors proposed CNN models (COVID-Net) and proposed a new design pattern called residual projection extension-projection extension (PEPX). The authors of [35] proposed a concatenation-based CNN (Concat_CNN) model to detect COVID-19 from chest X-rays images. A comparison was made between Concat_CNN and the following transfer models: VGG16, InceptionV3, Resnet50, and DenseNet121. Concat_CNN registered the best results. In , the authors suggested a CNN employing Softmax classifier and ML (SVM and RF). In , the authors presented a hybrid CNN model using Xception and ResNet101 to extract COVID-19 characteristics from chest X-rays. In , the authors proposed new ML models to detect COVID-19 from chest X-ray images. They used fractional multichannel exponent moments to extract features from images. In [34], the authors presented a DL model and employed SqueezNet with a modified output layer to categorize X-ray pictures into COVID-19, normal, and pneumonia.

System Analysis:

Existing System:

Regional-CNN(R-CNN): This was one of the earlier methods of CNN where the model, first it searches for areas where objects may exist through selective search algorithm and extract candidate boxes. The algorithm assigns object scores with likeliness of the region containing the required features. Then use CNN to calculate the features of each box and extract the features of each box, and the extracted features are classified with help of classifier, and finally, the output results are displayed as malignant or benign.

-Dimensional CNN: Convolutional layer where images are translated into feature-map data by convolutional kernels or filters. In a 3D CNN, the kernels move through three dimensions of data (height, length, and depth) and produce 3D maps. Pooling layer, a filter mov es across the convolutional output to take either the average or the weighted average or the maximum value. The goal of pooling layer is to progressively reduce the spatial size of the matrix to reduce the number of parameters and to control over fitting. Fully-connected layer, where a SoftMax function is used to get probabilities as it pushes the values between 0 and 1. Batch normalization is used to improve the training speed and to reduce over fitting.

Proposed System:

Deep learning in smart health analytics is a prominent interdisciplinary field that merges computer science, biomedical engineering, health sciences, and bioinformatics. Various medical imaging devices have a dedicated image and signal analysis and processing module, on which deep learning based models can be implemented to provide accurate, real time inferences.

Deep-Convolutional Neural Networks (CNN): The proposed method uses Deep

Convolutional Neural Networks to detect the corona virus based on the Chest X-Ray images. The proposed model involves the following stages. Pre-Processing is the first stage, lung regions are extracted from CT image and in that region each slice is segmented to get tumors.

Convolutional Neural Networks (CNN) is composed of several kinds of layers

(i) Convolutional layer: creates a feature map to predict the class probabilities for each feature by applying a filter that scans the whole image, few pixels at a time. (ii) Pooling layer (down-sampling): scales down the amount of information the convolutional layer generated for each feature and maintains the most essential information (the process of the convolutional and pooling layers usually repeats several times). (iii) Fully connected input layer: flattens the outputs generated by previous layers to turn them into a single vector that can be used as an input for the next layer. (iv) Fully connected layer: Applies weights over the input generated by the feature analysis to predict an accurate label. Generates the final probabilities to determine a class for the image.

Advantages:

- The large dataset helps to easily classify the corona virus.
- The rate of error and efficiency is much higher than that most other methods.
- The performance is much better compared to existing methods.
- Rate of false positives and negatives is greatly reduced in the proposed method.
- The System combines both detection and classification of corona virus

Conclusion:

We believe that this computer-aided diagnostic tool can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This could be highly useful in a pandemic, where the burden of disease and the need for preventive measures do not match the availability of resources. Deep learning has become a dominant method in a variety of complex tasks such as image classification and object detection. The proposed Deep CNN model provides better accuracy and achieves better performance. The results demonstrate that transfer learning proved to be effective, showed robust performance and easily deployable approach for COVID-19 detection. The detection of corona virus pneumonia infected patients using chest X-ray radiographs and gives a classification accuracy of more than 90%. This computer-aided diagnostic tool can significantly improve the speed and accuracy of diagnosing cases with COVID-19.

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