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DETECTION OF COVID 19 FROM CHEST X RAY IMAGE USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT: The detection of severe acute respiratory syndrome coronavirus 2 (SARS CoV-2), which is responsible for coronavirus disease 2019 (COVID-19), using chest X-ray images has life-saving importance for both patients and doctors. In addition, in countries that are unable to purchase laboratory kits for testing, this becomes even more vital. In this study, we aimed to present the use of deep learning for the high-accuracy detection of COVID-19 using chest X-ray images. Publicly available X-ray images (1583 healthy, 4292 pneumonia, and 225 confirmed COVID-19) were used in the experiments, which involved the training of deep learning and machine learning classifiers. Thirty-eight experiments were performed using convolutional neural networks, 10 experiments were performed using five machine learning models, and 14 experiments were performed using the state-of-the-art pre-trained networks for transfer learning. Images and statistical data were considered separately in the experiments to evaluate the performances of models, and eightfold cross-validation was used. A mean sensitivity of 93.84%, mean specificity of 99.18%, mean accuracy of 98.50%, and mean receiver operating characteristics–area under the curve scores of 96.51% are achieved. A convolutional neural network without pre-processing and with minimized layers is capable of detecting COVID-19 in a limited number of, and in imbalanced, chest X-ray images.

***Keywords** – covid19, convolutional neural network.*

1. INTRODUCTION

At the end of 2019, humankind was faced with an epidemic—severe acute respiratory syndrome coronavirus 2 (SARS CoV-2)–related pneumonia, referred to as coronavirus disease 2019 (COVID-19)—that people did not expect to encounter in the current era of technology. While the COVID-19 outbreak started in Wuhan, China, the significant spread of the epidemic around the world has meant that the amount of equipment available to doctors fighting the disease is insufficient. At the time of writing (September 8, 2020), there have been more than 27,000,000 confirmed cases and more than 875,000 confirmed deaths worldwide.1 Considering the time required for diagnosis and the financial costs of the laboratory kits used for diagnosis, artificial intelligence (AI) and deep learning research and applications have been initiated to support doctors who aim to treat patients and fight the illness.2 Although rapid point-of-care COVID-19 tests are expected to be used in clinical settings at some point, for now, turnaround times for COVID-19 test results range from 3 to more than 48 hours, and probably not all countries will have access to those test kits that give results rapidly. According to a recently published multinational consensus statement by the Fleischner Society, one of the main recommendations is to use chest radiography for patients with COVID-19 in a resource-constrained environment when access to computed tomography (CT) is limited.3 The financial costs of the laboratory kits used for diagnosis, especially for developing and underdeveloped countries, are a significant issue

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when fighting the illness. According to their previously mentioned statement,3 the Fleischner Society recommends that medical practitioners use chest X-ray and CT in the management of COVID-19. In the end, the choice of imaging modality is left to the judgment of clinical teams at the point of care, accounting for the differing attributes of chest radiography and CT, local resources, and expertise. In this study, we propose the use of chest X-ray images over CT of the thorax, considering the latter's required diagnostic time. A CT scan of the thorax takes significantly more time than a chest X-ray scan does, and this means more contact duration with suspected or confirmed COVID-19 patients.

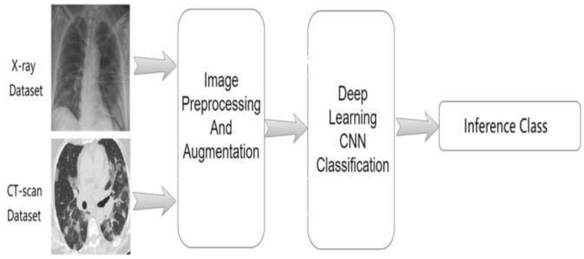

Fig.1: Example figure

Deep learning, which takes its name from the number of its hidden layers, has gained a special place in the field of AI by providing successful results for both image-based classification applications and regression problems during the past 10 years.7,8 The frequent use of deep convolutional neural networks (ConvNet, or CNNs)9 has enabled image-based applications to reach their peak in the past 5 years. Generally, CNNs that try to simulate biological aspects of human beings on computers required pre-processing of images or data before feeding them to the network. When the ConvNet was first invented, however, it was described as a neural network that requires minimal pre-processing of images before feeding them to the network, and a system that is capable of extracting the features from images to optimize the learning performance of the neural network.6 The ConvNet comprises both feature extraction and classification phases in a single network. A traditional ConvNet consists of three layers: convolution, pooling, and fully connected layers. Feature extraction is performed in the convolutional layer by applying masks, which is the process of dividing images into a predefined dimension of segments and using filters to extract features from the image. Then a feature map, which is the projection of features on the 2D map, is created by applying an activation function to the values obtained by the masks. The activation function activates the most knowledgeable neurons in a nonlinear way and reduces the computational cost of the neural network. Several activation functions are available in CNNs, and the rectified linear unit (ReLU) is the most commonly used activation function; it does not activate all the neurons at the same time, and therefore provides a faster convergence when the weights find the optimal values to produce the trained response during the training. A pooling operation is performed on the produced feature map to reduce the dimensions of the images. Finally, the feature map is flattened into a vector and sent to the fully connected layer. The convergence of the neural network and the classification of the input patterns are performed in the fully connected layer, and its principles are based on error backpropagation to update the weights within this layer.

2. LITERATURE REVIEW

HybridSN: Exploring 3-D–2-D CNN Feature Hierarchy for Hyperspectral Image Classification: Hyperspectral image (HSI) classification is widely used for the analysis of remotely sensed images. Hyperspectral imagery includes varying bands of images. Convolutional neural network (CNN) is one of the most frequently used deep learning-based methods for visual data processing. The use of CNN for HSI classification is also visible in recent works. These approaches are mostly based on 2-D CNN. On the other hand, the HSI classification performance is highly dependent on both spatial and spectral information. Very few methods have used the 3-D-CNN because of increased computational complexity. This letter proposes a hybrid spectral CNN (HybridSN) for HSI classification. In general, the HybridSN is a spectral–spatial 3-DCNN followed by spatial 2-D-CNN. The 3-D-CNN facilitates the joint spatial–spectral feature representation from a stack of spectral bands. The 2-D-CNN on top of the 3-D-CNN further learns more abstract-level spatial representation. Moreover, the use of hybrid CNNs reduces the complexity of the model compared to the

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use of 3-D-CNN alone. To test the performance of this hybrid approach, very rigorous HSI classification experiments are performed over Indian Pines, University of Pavia, and Salinas Scene remote sensing data sets. The results are compared with the stateof-the-art hand-crafted as well as end-to-end deep learning-based methods. A very satisfactory performance is obtained using the proposed HybridSN for HSI classification.

Prostate Cancer Nodal Staging: Using Deep Learning to Predict 68Ga-PSMA-Positivity from CT Imaging Alone:

Lymphatic spread determines treatment decisions in prostate cancer (PCa) patients. 68Ga-PSMA-PET/ CT can be performed, although cost remains high and availability is limited. Therefore, computed tomography (CT) continues to be the most used modality for PCa staging. We assessed if convolutional neural networks (CNNs) can be trained to determine 68Ga-PSMA-PET/CT-lymph node status from CT alone. In 549 patients with 68Ga-PSMA PET/CT imaging, 2616 lymph nodes were segmented. Using PET as a reference standard, three CNNs were trained. Training sets balanced for infltration status, lymph node location and additionally, masked images, were used for training. CNNs were evaluated using a separate test set and performance was compared to radiologists' assessments and random forest classifers. Heatmaps maps were used to identify the performance determining image regions. The CNNs performed with an Area-Under-the-Curve of 0.95 (status balanced) and 0.86 (location balanced, masked), compared to an AUC of 0.81 of experienced radiologists. Interestingly, CNNs used anatomical surroundings to increase their performance, "learning" the infltration probabilities of anatomical locations. In conclusion, CNNs have the potential to build a well performing CT-based biomarker for lymph node metastases in PCa, with diferent types of class balancing strongly afecting CNN performance.

The use of back propagation neural networks and 18F-Florbetapir PET for early detection of Alzheimer's disease using Alzheimer's Disease Neuroimaging Initiative database:

Amyloid beta (Aβ) plaques aggregation is considered as the "start" of the degenerative process that manifests years before the clinical symptoms appear in Alzheimer's Disease (AD). The aim of this study is to use back propagation neural networks (BPNNs) in 18F-florbetapir PET data for automated classification of four patient groups including AD, late mild cognitive impairment (LMCI), early mild cognitive impairment (EMCI), and significant memory concern (SMC), versus normal control (NC) for early AD detection. Five hundred images for AD, LMCI, EMCI, SMC, and NC, i.e., 100 images for each group, were used from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The results showed that the automated classification of NC/AD produced a high accuracy of 87.9%, while the results for the prodromal stages of the disease were 66.4%, 60.0%, and 52.9% for NC/LCMI, NC/EMCI and NC/SMC, respectively. The proposed method together with the image preparation steps can be used for early AD detection and classification with high accuracy using Aβ PET dataset.

Modeling Vehicle Interactions via Modified LSTM Models for Trajectory Prediction:

The long short-term memory (LSTM) model is one of the most commonly used vehicle trajectory predicting models. In this paper, we study two problems of the existing LSTM models for long-term trajectory prediction in dense traffic. First, the existing LSTM models cannot simultaneously describe the spatial interactions between different vehicles and the temporal relations between the trajectory time series. Thus, the existing models cannot accurately estimate the influence of the interactions in dense traffic. Second, the basic LSTM models often suffer from vanishing gradient problem and are, thus, hard to train for long time series. These two problems sometimes lead to large prediction errors in vehicle trajectory predicting. In this paper, we proposed a spatio-temporal LSTM-based trajectory prediction model (STLSTM) which includes two modifications. We embed spatial interactions into LSTM models to implicitly measure the interactions between neighboring vehicles. We also introduce shortcut connections between the inputs and the outputs of two consecutive LSTM layers to handle gradient vanishment. The proposed new model is evaluated on the I-80 and US-101 datasets. Results show that our new model has a higher trajectory predicting accuracy than one state-of-the-art model [maneuver-LSTM (M-LSTM)].

Advances in Intelligent Systems and Computing:

We are concerned with some important issues related to dynamic systems modeling, notably related to how to include aspects of human cognition in such models. We assume as a general perspective and a point of departure Yingxu Wang's cognitive informatics which is, roughly speaking, a multidisciplinary field within informatics, or computer science, that is based on results of cognitive and information sciences, and which deals with human information processing mechanisms and processes and their applications in broadly perceived computing. The emphasis is on processes in the human brain. However, in our work we advocate an approach which assumes the brain process-centered cognitive informatics to be the foundation, but—for our purposes—it may be proper to distinguish an "outer" cognitive informatics which explicitly makes reference not what proceeds "internally" in the brain, which is an area of interest of the traditional cognitive informatics, but what proceeds. And how, "externally," i.e., what people can see, judge, evaluate, etc., and what is clearly a result of cognitive information specific processes in the brain. Cognitive informatics constitutes a foundation of cognitive computing which synergistically employs tools and techniques from, e.g., information science, data sciences, computational sciences, computer science, artificial and computational intelligence, cybernetics, systems science, cognitive science, (neuro)psychology, brain science, linguistics, etc., to just mention a few. To show that the cognitive computing can yield an "added value," we consider—as an example of a dynamic systems modeling—a scenario-based dynamic regional development planning model. The region is characterized by seven life quality indicators related to economic, social, environmental, etc., qualities, which evolve over some planning horizon due to some investments, mostly by some regional or xi governmental agencies. There are investment scenarios over the planning horizon, which specify funds meant for the development of the particular life quality indexes, and some desired levels of these indexes, both objective, i.e., set by authorities, and subjective, i.e., perceived by the inhabitant groups. As a result of a particular investment scenario, the life quality indexes evolve over the planning horizon, and their temporal evolution is evaluated by the authorities and inhabitants. This evaluation has both an objective, i.e., against the "officially" set thresholds, and subjective, i.e., as perceived by various humans and their groups, aspects. We employ Kacprzyk's fuzzy dynamic programming-based approach to the modeling and planning/programming of sustainable regional development, with soft constraints and goals, but with a more sophisticated assessment of variability, stability, and balancedness of consecutive investments. The evaluation of the development quality measures and then their optimization are then proposed so that cognitive computing, notably by inclusion of some decision making, behavioral, social, etc., biases, in particular the so-called status quo and minimal change biases. We extend the model to include a more sophisticated analysis of variability of temporal evolution of some life quality indicators and a human perception of its goodness. We also mention how to reflect elements related to fairness. We show how the new elements of the regional development model proposed can change the best development scenarios derived.

3. METHODOLOGY

We study the end-to-end long-term trajectory prediction in dense traffic. The ''long-term'' here means that the model is capable to predict the trajectories of the entire process of nontrivial movements (movements except going straight) while keeping a low prediction error. The ''dense traffic'' here azmeans that every vehicle can influence trajectories of its surrounding vehicles, but the road is not fully blocked. In such scenarios, the motion of the vehicle is complicated due to the influence of surrounding vehicles.

Disadvantages:

- Accuracy is less

We aimed to present the use of deep learning for the high-accuracy detection of COVID-19 using chest X-ray images. Publicly available X-ray images (1583 healthy, 4292 pneumonia, and 225 confirmed COVID-19) were used in the experiments, which involved the training of deep learning and machine learning classifiers. Thirty-eight experiments were

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performed using convolutional neural networks, 10 experiments were performed using five machine learning models, and 14 experiments were performed using the state-of-the-art pre-trained networks for transfer learning. Images and statistical data were considered separately in the experiments to evaluate the performances of models, and eightfold cross-validation was used. A mean sensitivity of 93.84%, mean specificity of 99.18%, mean accuracy of 98.50%, and mean receiver operating characteristics–area under the curve scores of 96.51% are achieved. A convolutional neural network without pre-processing and with minimized layers is capable of detecting COVID-19 in a limited number of, and in imbalanced, chest X-ray images.

Advantages:

- Accuracy is high

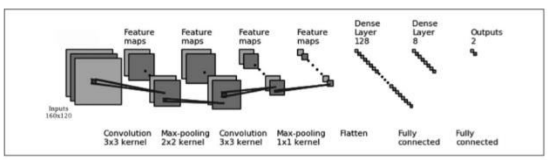

Fig.2: System architecture

MODULES:

In this project we have designed following modules

- Upload Covid-19 Chest X-ray Dataset
- Preprocess Dataset
- Model Generation
- Build CNN Covid-19 Model
- Upload Test Data & Predict Disease
- Accuracy Comparison Graph

4. IMPLEMENTATION

RESNET:

A residual neural network (ResNet) is an artificial neural network (ANN) of a kind that builds on constructs known from pyramidal cells in the cerebral cortex. Residual neural networks do this by utilizing skip connections, or shortcuts to jump over some layers. Typical ResNet models are implemented with double- or triple- layer skips that contain nonlinearities (ReLU) and batch normalization in between.[1] An additional weight matrix may be used to learn the skip weights; these models are known as HighwayNets.[2] Models with several parallel skips are referred to as DenseNets.[3] In the context of residual neural networks, a non-residual network may be described as a plain network. A reconstruction of a pyramidal cell. Soma and dendrites are labeled in red, axon arbor in blue. (1) Soma, (2) Basal dendrite, (3) Apical dendrite, (4) Axon, (5) Collateral axon. There are two main reasons to add skip connections: to avoid the problem of vanishing gradients, or to mitigate the Degradation (accuracy saturation) problem; where adding more layers to a suitably deep model leads to higher training error.[1] During training, the weights adapt to mute the upstream layer[clarification needed], and amplify the previously-skipped layer. In the simplest case, only the weights for the adjacent layer's connection are adapted, with no explicit weights for the upstream layer. This works best when a single nonlinear layer is stepped over, or when the intermediate layers are all linear. If not, then an explicit weight matrix should be learned for the skipped connection (a HighwayNet should be used). Skipping effectively simplifies the network, using fewer layers in the initial training stages[clarification needed]. This speeds learning by reducing the impact of vanishing gradients, as there are fewer layers to propagate through. The network then gradually restores the skipped layers as it learns the feature space. Towards the end of training, when all layers are expanded, it stays closer to the manifold[clarification needed] and thus learns faster. A neural network without residual parts explores more of the feature space. This makes it more vulnerable to perturbations that cause it to leave the manifold, and necessitates extra training data to recover.

VGG16:

VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR(Imagenet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers

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that have weights. This network is a pretty large network and it has about 138 million (approx) parameters.I am going to implement full VGG16 from scratch in Keras.

INCEPTION:

Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. It is based on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy, et. al. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concatinations, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. Loss is computed using Softmax.

DenseNet 121:

DenseNet (Dense Convolutional Network) is an architecture that focuses on making the deep learning networks go even deeper, but at the same time making them more efficient to train, by using shorter connections between the layers. DenseNet is a convolutional neural network where each layer is connected to all other layers that are deeper in the network, that is, the first layer is connected to the 2nd, 3rd, 4th and so on, the second layer is connected to the 3rd, 4th, 5th and so on. This is done to enable maximum information flow between the layers of the network. To preserve the feed-forward nature, each layer obtains inputs from all the previous layers and passes on its own feature maps to all the layers which will come after it. Unlike Resnets it does not combine features through summation but combines the features by concatenating them. So the 'ith' layer has 'i' inputs and consists of feature maps of all its preceding convolutional blocks. Its own feature maps are passed on to all the next 'I-i' layers. This introduces '(I(I+1))/2' connections in the network, rather than just 'I' connections as in traditional deep learning architectures. It hence requires fewer parameters than traditional convolutional neural networks, as there is no need to learn unimportant feature maps. DenseNet consists of two important blocks other than the basic convolutional and pooling layers. they are the Dense Blocks and the Transition layers.

CNN:

To build such automated opinion detection author is suggesting to build CNN model which can work like human brains. This CNN model can be generated for any services and we can make it to work like automated decision making without any human interactions. To suggest this technique author already describing concept to implement multiple models in which one model can detect or recognize human hand written digits and second model can detect sentiment from text sentences which can be given by human about government schemes. In our extension model we added another model which can detect sentiment from person face image. Person face expressions can describe sentiments better than words or sentences. So our extension work can predict sentiments from person face images.

To demonstrate how to build a convolutional neural network based image classifier, we shall build a 6 layer neural network that will identify and separate one image from other. This network that we shall build is a very small network that we can run on a CPU as well. Traditional neural networks that are very good at doing image classification have many more parameters and take a lot of time if trained on normal CPU. However, our objective is to show how to build a real-world convolutional neural network using TENSORFLOW.

Neural Networks are essentially mathematical models to solve an optimization problem. They are made of neurons, the basic computation unit of neural networks. A neuron takes an input (say x), do some computation on it (say: multiply it with a variable w and adds another variable b) to produce a value (say; z= wx+b). This value is passed to a non-linear function called activation function (f) to produce the final output(activation) of a neuron. There are many kinds of activation functions. One of the popular activation function is Sigmoid. The neuron which uses sigmoid function as an activation function will be called sigmoid neuron. Depending on the activation functions, neurons are named and there are many kinds of them like RELU, TanH.

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If you stack neurons in a single line, it's called a layer; which is the next building block of neural networks. See below image with layers

To predict image class multiple layers operate on each other to get best match layer and this process continues till no more improvement left.

5. EXPERIMENTAL RESULTS

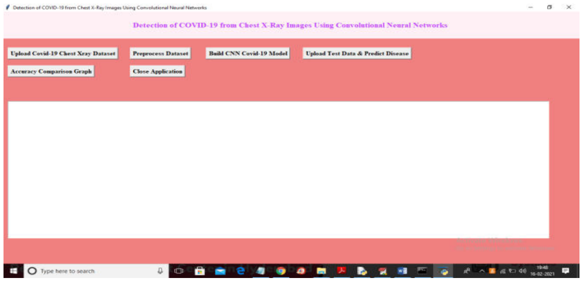

Fig.3: Home screen

Fig.4: Upload covid 19 chest x-ray dataset

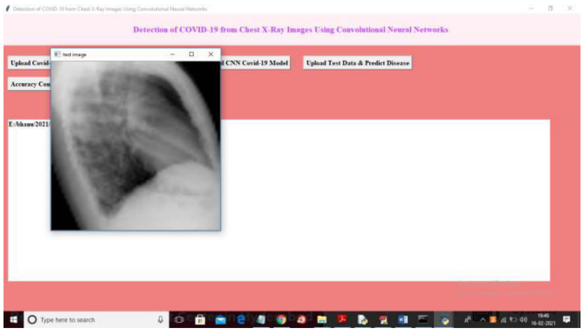

Fig.5: Preprocess dataset

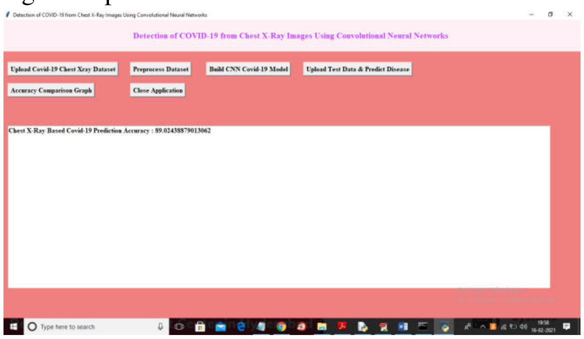

Fig.6: Build CNN covid-19 model

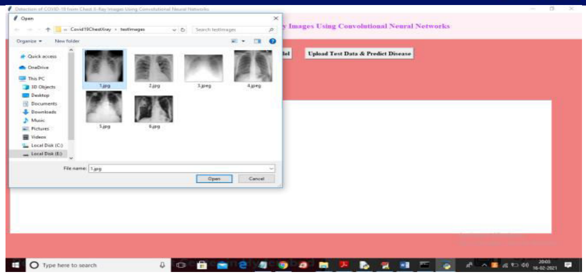

Fig.7: User input

Fig.8: Prediction result

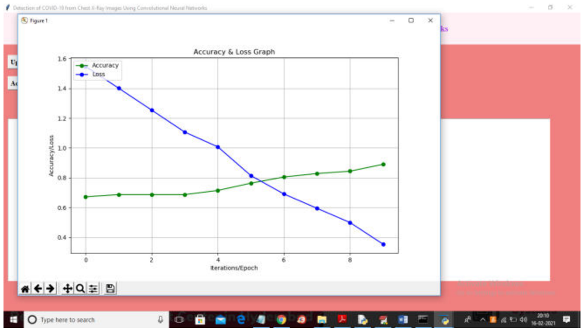

Fig.9: Accuracy comparison graph

6. CONCLUSION

Detection of COVID-19 from chest X-ray images is of vital importance for both doctors and patients to decrease the diagnostic time and reduce financial costs. Artificial intelligence and deep learning are capable of recognizing images for the tasks taught. In this study, several experiments were performed for the high-accuracy detection of COVID-19 in chest X-ray images using ConvNets. Various groups— COVID-19/Normal, COVID-19/Pneumonia, and COVID-19/Pneumonia/Normal— were considered for the classification. Different image dimensions, different network architectures, state-of-the-art pre-trained networks, and machine learning models were implemented and evaluated using images and statistical data. When the number of images in the database and the detection time of COVID-19 (average testing time = 0.03 s/image) are considered using ConvNets, it can be suggested that the considered architectures reduce the computational cost with high performance. The results showed that the convolutional neural network with minimized convolutional and fully connected layers is capable of detecting COVID-19 images within the two-class, COVID-19/Normal and COVID-19/Pneumonia classifications, with mean ROC AUC scores of 96.51 and 96.33%, respectively. In addition, the second proposed architecture, which had the second-lightest architecture, is capable of detecting COVID-19 in three-class, COVID-19/Pneumonia/Normal images, with a macro-averaged F1score of 94.10%. Therefore, the use of AI-based automated high-accuracy technologies may provide valuable assistance to doctors in diagnosing COVID-19. Further studies, based on the results obtained in this study, would provide more information about the use of CNN architectures with COVID-19 chest X-ray images and improve on the results of this study.

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