COVID-19 detection based on convolution neural networks from CT-scan images: a review

Walat Ramadhan Ibrahim, Mayyadah Ramiz Mahmood
Department of Computer Science, Faculty of Science, University of Zakho, Kurdistan Region, Iraq

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ABSTRACT

The COVID-19 outbreak has been affecting the health of people all around the world. With the number of confirmed cases and deaths still rising daily, so the main aim is to detect positive cases as soon as and provide them with the necessary treatment. The utilization of imaging data including chest x-rays and computed tomography (CT) was proven that is would be beneficial for quickly diagnosing COVID-19. Since Computerized Tomography provides a huge number of images, recognizing these visual traits would be difficult and take enormous amounts of time for radiologists so automated diagnosis technologies including deep learning (DL) models are recently for COVID-19 screening in CT scans. This review paper presents different researches which used deep learning approaches including various models of convolutional neural networks (CNN) used in image classification tasks well, and large training, like ResNet, VGG, AlexNet, LeNet, GoogleNet, and others for COVID-19 diagnosing and severity assessments using chest CT images. As a result, automated COVID-19 analysis on CT images is essential to save medical personnel and essential time for disease prevention.

Corresponding Author:

Mayyadah Ramiz Mahmood
Department of Computer Science, Faculty of Science, University of Zakho
Duhok, Iraq
Email: mayyadah.mahmood@uoz.edu.krd

1. INTRODUCTION

Serious acute respiratory syndrome the novel coronavirus disease of 2019 is caused by Coronavirus 2 (also known as COVID-19) [1]. What first came to exist in Wuhan is in the Chinese province of Hubei [2]. And the infection went on a global level from there. The World Health Organization (WHO) classified it an epidemic in March 2020 [3]. Till December, 1st, 2020, the number of cases that have been confirmed was around 64 million, and 1.5 million were diseased globally [4]. COVID-19 causes tiredness and inflamed lungs with high body temperatures, lack of smell and taste with coughing as well. COVID-19 usually spread from an infected to a non-infected man through physical contact like touching and coughing [5].

In the meantime, the best technique to diagnose the disease is the reverse transcription polymerase chain reaction (RT-PCR) [6], yet the mentioned test is still not accurate enough to stop the spread and put a definite ending to the pandemic [7]. A test that comes out negative and which is a false result can cause infection to spread in large areas for the negative test, but the infected patient was, in reality, infected and unable to get correctly diagnosed [8]. To improve the test results radiology images are used [9]. Chest radiographs, as well as computed tomography (CT) scans, play a crucial role in identifying the virus through imaging the lungs. Certain cases got diagnosed with CT scans before the RT-PCR could help diagnose the infected individual [10]. Skilled radiologists are in low supply during the pandemic, making it harder to diagnose potentially infected patients in time. Furthermore, because the COVID-19 epidemic is new, It is challenging to gather useful data on chest X-ray (CXR) images [11]. As a result, automated diagnosis technologies are commonly demanded [12]. Deep learning (DL) models for automated image processing have the potential to maximize the role of radiological images for an accurate and rapid diagnosis of COVID-19 [13]. Because of the huge various parameters, convolutional neural networks (CNNs) may readily overfit on small datasets; hence, generalization effectiveness is related to the amount of labeled data [14]. CNN uses a hierarchical design to automatically extract deep features, which is particularly successful in a variety of visual applications and tasks including image denoising and object recognition [15], then classification [16]. Many research projects have been carried out intensely and rapidly to create artificial intelligence (AI) techniques for reacting to the COVID-19 global outbreak. This review presents some relevant work on COVID-19 classification using a chest CT image.

Goel *et al*. [17] introduce an optimized convolutional neural network (OptCoNet) on chest X-rays for automated detection of COVID-19. The components for feature extraction and categorization make up the CNN architecture. The grey wolf optimizer (GWO) method was used to optimize CNN's hyperparameters. The data consisted of lung X-rays from healthy and individuals suffering from pneumonia obtained from public sources. In total, there were 2700 photos, with 900 of them being COVID-19 photographs. According to the writers, the improved CNN model beats state-of-the-art methods. The calculated results were accuracy 97.78%, sensitivity 97.75%, specificity 96.25%, precision 92.88%, and F1-score 95.25%.

Polsinelli *et al*. [18] SqueezeNet -based convolutional neural model was presented for the efficient classification of COVID-19 computed tomography (CT) pictures from further pneumonia and/or healthy CT scans. Original SqueezeNet's performance is outperformed by the planned CNN-2. CNN-2 obtained an accuracy of 87.55% and a sensitivity of 81.95% while being 85.01% specific and, 86.2% precise with an F1-Score of 86.2%. By using effective pre-processing methods without graphics processing unit (GPU) acceleration, the method's performance can be significantly improved.

Horry *et al*. [19] on various medical images (x-ray, CT, ultrasound), a deep learning-based COVID-19 detection system based on the VGG19 model was constructed, with a precision of up to 86% for X-Ray, 100% for Ultrasound, and 84% for CT scans. Song *et al* [20] collected CT-scans of 88 patients with COVID-19 and 100 patients with bacterial pneumonia, as well as 86 normal people obtained from two Chin hospitals, and utilized these data to develop a deep learning-based CT-diagnosing system for identifying COVID-19 patients from chest CT -scans. the testing findings revealed that this model could successfully distinguish COVID-19 patients from bacterial pneumonia patients. With an AUC of 95%, sensitivity of 96 %, and precision of 79%, this study was conducted at the initial stage of the COVID-19 pandemic, so there was a problem of shortage of samples to develop such a deep learning prototype. In addition to the effect of the batch, this approach performed well on datasets from the source data from the hospital which collects it but it was not able of forecasting the external data right away directly.

Islam and Matin in [21] for identifying COVID-19 in chest CT, a basic convolution neural network (CNN) model was employed, followed by a LeNet-5 CNN model. They train and test on a CT data set that includes 349 COVID-19 CT scan frames of the lungs and 397 Non-COVID-19 CT scan frames. For COVID-19 detection, the obtained results were 86.06 % accurate, and F1 scored 87 %, 85% precise, and recalling ratio of 89 %, and an area beneath the curve of ROC of 0.86. Garain *et al*. [22] CT scans were used to develop a three-layer DCSNN for COVID-19 screening. For the potential-based model, the method received an F1 score of 99%. The proposed SNN-based model outperforms standard deep learning models on chest CT images, but it requires more time to train. The current approach, on the other hand, is more efficient than previous deep learning models. Zhang *et al.* [23] created a new technique (DenseNet-OTLS) for recognizing COVID-19 patients from chest CT scans that mixes DenseNet with an optimized transfer learning setting (OTLS) strategy. The dataset was made up of 320 images from 142 positive COVID-19 patients and another 320 images from 142 negative COVID-19 patients. Optimization of the composite learning factor setting (CLFS) and optimization of the DenseNet structure are both parts of the OTLS. The proposed OTLS approach has a sensitivity of 96.35, a precision of 96.29, a specificity of 96.25, and an accuracy of 96.30. The suggested DenseNet-OTLS technique outperformed other methods in diagnosing COVID-19.

Ouyang *et al*. [24] for chest CT scans diagnosing COVID-19, a new 3D convolutional network with an online attention module is proposed by the authors. They train and validate using multi-center CT data from different hospitals, totaling 2186 CT images from a total of 1588 different patients. A comparable dataset of 2796 CT images from 2057 sick individuals was utilized for the testing stage. by the researcher 3D ResNet34 architecture with an attention module is offered. Due to the lack of class balance in the training data, two models were used, one with uniform sampling and one with a size-balanced sample. The predictions from the two models are then integrated by transfer learning approach usage. accuracy, AUC, specificity, sensitivity,and F1 score were reported as 86.9 %, 0.944, 87.5 %, 90.1 %, and 82.0 %, respectively.

Wang *et al*. [25] have suggested a novel collaborative learning framework for reliably identifying COVID-19 from a variety of data sets with disparities in distribution. A network was split into two sections: one with a lightweight architecture and four distinct convolution layers, and the other with the learning blocks of denser connections. The SARS-CoV-2 and COVID-CT dataset were utilized in this study to evaluate a combined learning system. The dataset included 2,482 CT scans from 120 sick individuals, 1,230 of whom were non-COVID but complaining of various symptoms of lung infectious diseases and 1252 of whom were COVID-19. The COVID CT dataset included clinical findings from 397 CT scans from 171 persons with no COVID-19 features and 349 CT pictures from 216 persons with COVID-19. Both datasets have been computed for evaluation metrics. The SARS-CoV-2 data set outperformed the COVID-CT dataset regarding the outcomes. The whole accuracy was 90%, with 85% recall, 95% precision, and 90% F1 score.

Hasan *et al*. [26] predict COVID-19 patients from CT images using DenseNet-121-based CNN. The results were 92% accurate and had a 95% recall rate, demonstrating good performance for COVID-19 prediction. Pham [27] presented the findings of COVID-19 classification research with sixteen CNNs that had been pre-trained. In this study, data augmentation is replaced by transfer learning resulting in higher classification rates in this experiment. The dataset was randomly split between training and testing data (80% and 20%, respectively), with MobileNet-v2 achieving the maximum achieved an accuracy of 95%, ResNet-18 achieving the highest sensitivity of 98%, DenseNet-201 achieving the highest specificity of 96 %, and MobileNet-v2 achieving the highest F1-score of 96%. MobileNet-v2, ShuffleNet, ResNet-18, and DenseNet-201 were all distinct networks.

Pathak *et al*. [28] deep transfer learning (DTL) was utilized to create a classification model for a COVID-19-infected patient. The data set included 413 pictures of COVID-19-infected persons and 439 images of healthy people or non-COVID19 pneumonia. The dataset's training and testing ratios were set at 60% and 40%, respectively. The suggested model achieves up to 96.2264% training accuracy and 93.0189% testing accuracy. which concludes that the already present COVID-19 test equipment can easily be replaced by this model. Zhang *et al.* [29] developed an AI technique using a large computed tomography (CT) database of 3,777 patients to identify COVID-19 pneumonia and distinguish it from healthy controls and other forms of pneumonia using the convolutional neural network ResNet-18 model, the authors explored the relevance of detecting important clinical indicators. For COVID-19, their suggested approach obtained a Sensitivity of 94.93%, Specificity of 91.13%, AUC of 0.981, Sensitivity of 94.93%, AUC of 0.981, and Accuracy of 92.49%.

Perumal *et al*. [30] suggest increasing the dataset quality and quantity to implement the deep learning method on CT images and chest radiographs. The significance of categorizing radiological pictures at an initial stage of the disease is demonstrated. Deep transfer learning and self-supervised techniques are proposed to avoid the costly manual labeling of huge data samples. Deep transfer learning approaches for both CT images and CXRs were investigated for numerous lung infections in conjunction with SARSCOV. The suggested model surpasses other current models by producing a recall of 90%, precision of 91%, and accuracy of 93% utilizing VGG-16 and transfer learning.

Wang *et al.* [31] developed a new multi-task prior-attention learning method for implementing COVID-19 screening in 3D images from chest CT scans. They got CT scans from 4657 people, with 936 normal scans, 2406 scans with virus-induced interstitial lung disease, and 1315 scans with COVID-19. The PARL block was designed as a single model framework for end-to-end training by bringing double ResNet-based branches together. The experimental findings showed that this approach outperformed other cutting-edge COVID-19 screening methods with accuracy of 93.3%, specificity of 95.5%, and sensitivity of 87.6%.

Loey *et al.* [32] Researchers employed a mix of classical data augmentations and CGAN with deep transfer learning to detect COVID-19 in limited lung CT scan pictures. To detect individuals infected with SARSCOV2 using chest tomography, researchers used a dataset of 742 CT scan photos and five distinct CNN-based models (GoogleNet, ResNet50, AlexNet, VGGNet19, and VGGNet16). In all tested deep transfer models, classical data augmentations combined with CGAN improve classification outcomes. With a testing accuracy of 82.91%, a sensitivity of 77.66%, and a specificity of 87.62%, the results show that ResNet50 is the best model for diagnosing SARSCOV2 from a constrained dataset using traditional data augmentation.

Wang *et al.* [33] According to the hypothesis of this work, artificial intelligence algorithms may be able to generate specific graphical characteristics of COVID-19. To develop the approach, they used a dataset of 1065 CT scans of cases with COVID-19 and without COVID-19 pneumonia to update the original transfer-learning model, which was then internally and externally validated. Internal validation demonstrated 89.5% accuracy, 87% sensitivity, and 88% specificity respectively. The external testing dataset demonstrated a total accuracy of 79.3 %, a sensitivity of 67%, and a specificity of 83% Furthermore, the first two nucleic acid test results in 54 COVID-19 images were negative, and the algorithm correctly forecasted 46 as COVID-19 positive with an accuracy of 85.2%.

The evaluation matrices in Table 1 (in *appendix*) show the results of different CNN model architectures in terms of COVID-19 test results accuracy, as well as the differences between the results of each author, which researchers had reviewed about.

2. METHODS
2.1. Convolutional neural network (CNN)
CNN is a particular kind of neural network [34]. With a unique topology that was inspired by biological research [35]. In 1998 Fukushima first introduced it, and they have a broad range of applications in activity identification, phrase classification, biometrics and text recognizing, detecting and localizing objects, scanned results' analysis, and so on. They are composed of neurons, each of which has a weight that can be learned ait sownown favoring. The network contains a single input and single output layer, as well as other hidden layers, the latter of which includes layers of convolution, pooling, a fully connected (FC), and numerous normalizing layers [36].

2.2. Explanation of the structure of every CNN layer
2.2.1. Convolutional layer
The Convolution Layer is the simplest basic but also the most significant in a CNN. It essentially goes by convolving or multiplying the matrix of pixels created for the provided image or object to build a map of activation for the current image. The fundamental advantage of activation maps is that they store all of the differentiating qualities of a particular image thus reducing the amount of data that must be processed. The data is convolved with the help of a matrix that serves as a feature detector. The feature detector is, in essence, a collection of values that are machine-compatible. By altering the threshold value of the feature detector one can get a wide variety of picture permutations. To train the convoluted model and achieve the most accurate results possible in each layer, backpropagation is also utilized. Depth and padding are determined by the lowest error set [37].

2.2.2. Pooling
Pooling is a key phase in lowering the dimensions of the map of activation, retaining just the necessary elements while minimizing spatial invariance. As a result, the model's learnable features are reduced [38]. This contributes to the resolution of the overfitting issue. Pooling enables CNN to absorb all of the distinct resolutions and sides of an image, allowing it to effectively detect the provided item even if its form is distorted or at a different angle. Pooling may be classified into several categories, including maximum pooling, average pooling, stochastic pooling, and spatial pyramid pooling [37]. The most prominent of them is max pooling [39]. Max pooling divides the image into several parts as rectangular sub-regions and just gives back the highest value from within that sub-region [40]. 2×2 is one most commonly used sizes in max-pooling [41]. The operation of Max pooling is shown in Figure 1.

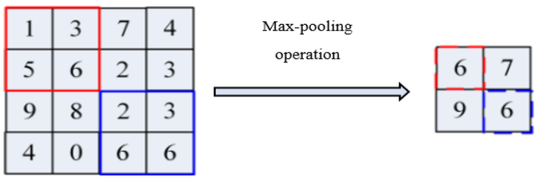

Figure 1. Operation of max-pooling [40]

2.2.3. Fully connected layer
This is the final layer that is sent to the neural network (the final layer is a classifier that outputs the identification result [42]. In general, matrices are made flat before being passed on to neurons. It is difficult to keep up with the data after the current point owing to the inclusion of a large number of hidden layers with varied weights for each neuron's output. All data reasoning and computation are done here.

2.3. CNN 1
The CNN architecture has two main parts. The convolution for feature extraction and a fully connected layer that utilizes the image class. The most popular CNN architecture [43], [44]. Include LeNet [41], GoogleNet [45], ResNet, VGG-16, AlexNet [46], MobileNetV2 and DenseNet.

2.3.1. LeNet
LeNet is one of the first CNN, and it has been mostly used for recognizing and distinguishing digits. Yan LeCun published this design in 1998, and it is based on the MNIST database. This network's main design contains convolution of a (5x5) size on the input, followed by an average pooling of (2x2) with a stride of a twice repeated 2, and is eventually terminated with two layers fully connected. The last input to the FCN has

the dimensions 120x1x1. The number of parameters considered is around 60,000 [41], [47]. The details are illustrated in Figure 2.

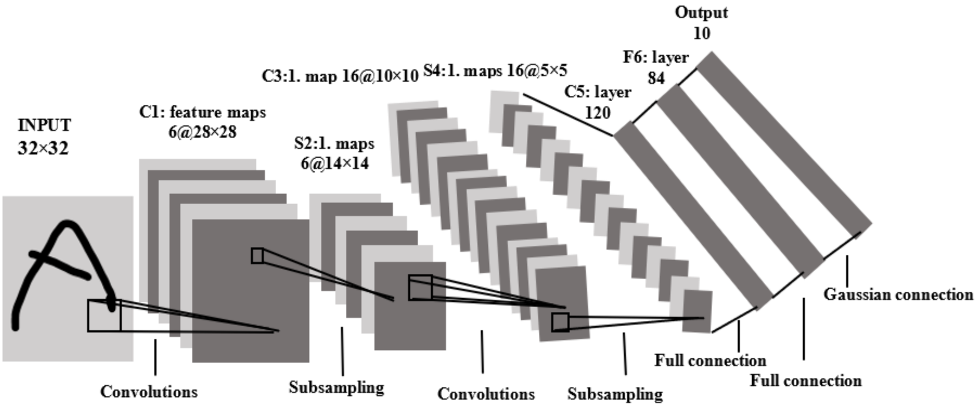

Figure 2. LeNet architecture [41]

2.3.2. VGG-16

VGG is an abbreviation for Visual Geometric Group [48]. Which was created by VGG at the University of Oxford [36]. This network debuted at the ILSVRC 2014 competition [49]. Where it was a runner-up but was well-recognized and accepted. This network has around 138 million parameters [50]. There are 16 convolutional layers in total [51]. In addition, there are two completely linked layers with 4096 hidden levels each. The VGG-16 design is shown in Figure 3.

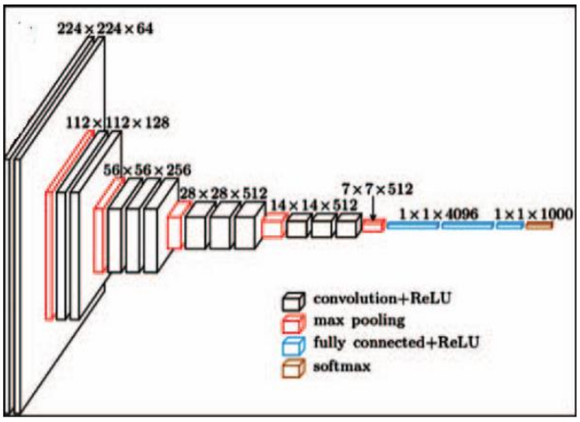

Figure 3. The basic architecture of VGG-16 [49]

2.3.3. Google Net

In 2014 GoogLeNet achieved first place in the ImageNet competition (ILSVRC) [52]. Christian Szegedy introduced the network structure idea. The structure is based on LeNet and AlexNet framework structures, with depth and width adjustments network. The architecture includes 22 network layers. It employs a novel parallel structure, which drastically shortens the training cycle. The VGGNet and GoogLeNet have pushed the research boom of deep learning to the peak [53].

2.3.4. DenseNet

DenseNet, a logical expansion of ResNet, improves performance by recombining each layer feature map with the preceding layer within a dense block. This allows layers that follow afterward of the network to directly exploit previous levels' features, promoting feature reuse throughout the network [51]. All previous layers' feature maps would be used as inputs for each layer, and their feature maps would be used as inputs into all subsequent layers, which helps to ease the vanishing gradient problem, feature reuse, and minimize the number of parameters [54]. Shown in Figure 4.

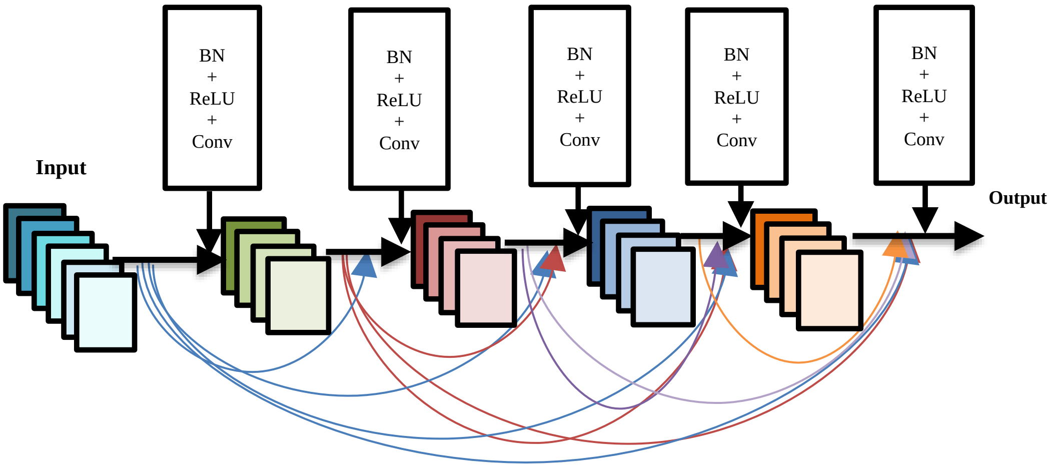

Figure 4. The architecture of dense blocks in DenseNet [55]

2.3.5. Microsoft ResNet

ResNet, or deep residual network, won the ImageNet competition in 2015, outperforming the accuracy of humans for the first time with a rate of error of roughly 3.6%. It is a 152-layer model that uses a single remarkable model to provide advanced traces in classification, localization, and detection. Residual block: It overcomes the difficulty of deep model training by building identity skip linkages between layers, allowing inputs to be copied to the next layer. The goal of this method is for the next layer to learn something new and unique from the input of the preceding layer [36].

3. DISCUSSION

In the previous section, all that is discussed in the paper is work from 2 years ago related to the studies from various types of CNN models for COVID-19 diagnosis and severity detection from chest CT images. The authors in the [19], [30], and [32] applied VGG models only or with another model or with transfer learning to a variety of datasets to identify COVID-19 from CT-Scan samples. The results came out better with 93% accuracy and 91% precision [30]. Zhang *et al*. [23] and Hasan *et al*. [26] DenseNet was used, the accuracy resulted in 92% while the sensitivity resulted in 95% a result in [26], while in [23] the COVID-19 diagnosis results are higher. The researchers in [24], [29], and, [31] only used the ResNet model or some other models or methods for different datasets which resulted in a 93.3% accuracy in [31] which is higher than the results from [24] and [29]. The favored method from [17] out of the other method results because it resulted in the highest accuracy out of all the studies that we had reviewed which was an accuracy of 97.78% and high sensitivity of 97.75%. Goel *et al*. [17] used the proposed CNN to extract feature and classification components with the grey wolf optimizer to optimize the CNN hyperparameters, for this reason, it is better than other methods.

4. CONCLUSION

This current review gives a comprehensive summary of state-of-the deep learning uses for combating the COVID-19 pandemic, to identify and detect COVID-19 disease in its early stages using chest HRCT images. The CNN and its modified models were identified to be the most commonly employed for COVID-19 pandemic prediction. The included studies have shown that DL approaches have a considerable influence on early COVID-19 identification with a high accuracy rate. However, the majority of the proposed ways and methods are still in the early stages of development, necessitating extra substantial research.

APPENDIX

Table 1. COVID-19 CT-Scan images detection based on CNN modles

Ref	Dataset	Methods	Results
[17]	COVID-19: 900 CT images Non-COVID:1800 CT images	optimized convolutional neural network (OptCoNet)	Acc. 97.78% Prec. 92.88% Sens. 97.75% Spec. 96.25% F1-score. 95.25%.
[18]	Zhao et al. dataset: COVID-19 360 CT scans Non-COVID: 397 CT scans. Italian dataset: 100 CT scans of COVID-19	SqueezeNet's based-CNN	Acc. 85.03 % Prec. 85.01 % Sens. 87.55 % Spec. 81.95 % F1-score. 86.20 %
[19]	COVID-19: 140 X-ray images Non-COVID:60683 X-ray images COVID-19: 399 Ultrasound images Non-COVID:512 Ultrasound images COVID-19: 349 CT images Non-COVID:397 CT images	VGG19	Prec. 86% F1-score.87% (X-ray) Prec. 100% F1-score. 99% (Ultrasound) Prec. 84% F1-score. 78% (CT)
[20]	COVID-19: 777 CT images Non-COVID:1213 CT images	Pre-trained ResNet50 - based DRENet	Prec. 79% Sens. 96% AUC. 95%
[21]	COVID-19: 349 CT images Non-COVID:397 CT images	basic CNN model + LeNet-5 CNN model	Acc. 86.06 % Prec. 85 % Sens. 89 % F1-score. 87 % AUC. 86 %
[22]	COVID-19: 349 CT scan images Non- COVID- 19: 397 CT scan images	Three-layer DCSNN	F1 score. 99 %
[23]	COVID-19: 320 CT images Non-COVID: 320 CT images	DenseNet-OTLS	Acc. 96.30 % Prec. 96.29 % Sens. 96.35 % Spec. 96.25 %
[24]	Train and validate dataset 2186 CT images Test dataset 2796 CT images	3D ResNet34 + an online attention module	Acc. 87.5% Sens. 86.9% Spec. 90.1% F1 score. 82.0% AUC. 94.4%
[25]	Dataset 1 COVID-19: 1252 CT images Non-COVID:1230 CT images Dataset 2 COVID-19: 349 CT images Non-COVID: 397 CT images	collaborative learning framework	Acc. 90.83% Prec. 95.75% Sens. 85.89% F1 score. 90.87% AUC. 96.24% Acc. 78.69% Prec. 78.02%A Sens. 79.71% F1 score. 78.83% AUC. 85.32%
[26]	COVID-19: 1252 CT images Non-COVID: 1230 CT images	DenseNet-121 based-convolutional neural networks (CNN)	Acc. 92 % Sens. 95 %
[27]	COVID-19: 349 CT images Non-OVID: 397 CT images	Sixteen pre-trained CNNs	Acc. 95 % (MobileNet-v2) Sens. 98% (ResNet-18) Spec. 96 % (DenseNet-201) F1-score 96 % (MobileNet-v2)
[28]	COVID-19: 413 CT images Non-COVID:439 CT images	Deep Transfer Learning (DTL)	Acc. 96.2264 % (Training accuracy) Acc. 93.0189 % (testing accuracy).

Table 1. COVID-19 CT-Scan images detection based on CNN modles (*continue*)

Ref	Dataset	Methods	Results
[29]	Total data: 617,775 CT images	CNN ResNet-18 model	Acc. 92.49 % Sens. 94.93 % Spec. 91.13 % AUC. 98.1 %
[30]	Large chest x-ray and CT images dataset	VGG-16 +transfer learning.	Acc. 93% prec. 91% Sens. 90%
[31]	COVID-19: 1315 CT images Non-COVID: 3342CT images	3D-ResNets + prior-attention mechanism	Acc. 93.3% Sens. 87.6% Spec. 95.5%
[32]	Total data: 742 CT-scan images	CGAN + five different deep CNN-based models (AlexNet, VGGNet16, VGGNet19, GoogleNet, and ResNet50)	Testing Acc. 82.91% Sens. 77.66% Spec. 87.62%
[33]	Total data: 1065 CT images	Modified inception transfer-learning model	Internal validation Acc. 89.5%, Spec. 88% Sens. 87%. The external testing Acc. 79.3 % spec. 83% Sens. 67%

REFERENCES

[1] A. Narin, C. Kaya, and Z. Pamuk, “Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks,” *Pattern Analysis and Applications*, vol. 24, no. 3, pp. 1207–1220, Aug. 2021, doi: 10.1007/s10044-021-00984-y.

[2] V. Ravi, H. Narasimhan, C. Chakraborty, and T. D. Pham, “Deep learning-based meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images,” *Multimedia Systems*, vol. 28, no. 4, pp. 1401–1415, Aug. 2022, doi: 10.1007/s00530-021-00826-1.

[3] S. Rajaraman, J. Siegelman, P. O. Alderson, L. S. Folio, L. R. Folio, and S. K. Antani, “Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-Rays,” *IEEE Access*, vol. 8, pp. 115041–115050, 2020, doi: 10.1109/ACCESS.2020.3003810.

[4] J. F. W. Chan *et al.*, “A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster,” *The Lancet*, vol. 395, no. 10223, pp. 514–523, Feb. 2020, doi: 10.1016/S0140-6736(20)30154-9.

[5] R. Murugan and T. Goel, “E-DiCoNet: Extreme learning machine based classifier for diagnosis of COVID-19 using deep convolutional network,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 9, pp. 8887–8898, Sep. 2021, doi: 10.1007/s12652-020-02688-3.

[6] T. Ai *et al.*, “Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 Cases,” *Radiology*, vol. 296, no. 2, pp. E32–E40, Aug. 2020, doi: 10.1148/radiol.2020200642.

[7] Y. Fang *et al.*, “Sensitivity of chest CT for COVID-19: Comparison to RT-PCR,” *Radiology*, vol. 296, no. 2, pp. E115–E117, Aug. 2020, doi: 10.1148/radiol.2020200432.

[8] Y. H. Wu *et al.*, “JCS: an explainable COVID-19 diagnosis system by joint classification and segmentation,” *IEEE Transactions on Image Processing*, vol. 30, pp. 3113–3126, 2021, doi: 10.1109/TIP.2021.3058783.

[9] Y. Wang, H. Hou, W. Wang, and W. Wang, “Combination of CT and RT-PCR in the screening or diagnosis of COVID-19,” *Journal of Global Health*, vol. 10, no. 1, Jun. 2020, doi: 10.7189/jogh.10.010347.

[10] Y. Peng, Y. Tang, S. Lee, Y. Zhu, R. M. Summers, and Z. Lu, “COVID-19-CT-CXR: a freely accessible and weakly labeled chest X-Ray and CT Image Collection on COVID-19 from biomedical literature,” *IEEE Transactions on Big Data*, vol. 7, no. 1, pp. 3–12, Mar. 2021, doi: 10.1109/TBDATA.2020.3035935.

[11] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro, “CovidGAN: data augmentation using auxiliary classifier GAN for improved COVID-19 detection,” *IEEE Access*, vol. 8, pp. 91916–91923, 2020, doi: 10.1109/ACCESS.2020.2994762.

[12] S. Tabik *et al.*, “COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on chest X-Ray images,” *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 12, pp. 3595–3605, Dec. 2020, doi: 10.1109/JBHI.2020.3037127.

[13] G. Litjens *et al.*, “A survey on deep learning in medical image analysis,” *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[14] N. Tajbakhsh *et al.*, “Convolutional neural networks for medical image analysis: full training or fine tuning?,” *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1299–1312, 2016, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/26978662/.

[15] K. Adam, I. I. Mohd, and Y. M. Younis, “The impact of the soft errors in convolutional neural network on GPUS: Alexnet as case study,” *Procedia Computer Science*, vol. 182, pp. 89–94, 2021, doi: 10.1016/j.procs.2021.02.012.

[16] M. R. Mahmood and M. B. Abdulrazzaq, “Performance evaluation of chi-square and relief-F feature selection for facial expression recognition,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 3, pp. 1470–1478, 2022, doi: 10.11591/ijeecs.v27.i3.pp1470-1478.

[17] T. Goel, R. Murugan, S. Mirjalili, and D. K. Chakrabartty, “OptCoNet: an optimized convolutional neural network for an automatic diagnosis of COVID-19,” *Applied Intelligence*, vol. 51, no. 3, pp. 1351–1366, 2021, doi: 10.1007/s10489-020-01904-z.

[18] M. Polsinelli, L. Cinque, and G. Placidi, “A light CNN for detecting COVID-19 from CT scans of the chest,” *Pattern Recognition Letters*, vol. 140, pp. 95–100, 2020, doi: 10.1016/j.patrec.2020.10.001.

[19] M. J. Horry *et al.*, “COVID-19 detection through transfer learning using multimodal imaging data,” *IEEE Access*, vol. 8, pp. 149808–149824, 2020, doi: 10.1109/ACCESS.2020.3016780.

[20] Y. Song *et al.*, “Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT Images,” *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 6, pp. 2775–2780, Nov. 2021, doi: 10.1109/TCBB.2021.3065361.

[21] M. R. Islam and A. Matin, “Detection of COVID 19 from CT Image by the Novel LeNet-5 CNN architecture,” in *ICCIT 2020 - 23rd International Conference on Computer and Information Technology, Proceedings*, Dec. 2020, pp. 1–5, doi: 10.1109/ICCIT51783.2020.9392723.

[22] A. Garain, A. Basu, F. Giampaolo, J. D. Velasquez, and R. Sarkar, “Detection of COVID-19 from CT scan images: A spiking neural network-based approach,” *Neural Computing and Applications*, vol. 33, no. 19, pp. 12591–12604, Oct. 2021, doi: 10.1007/s00521-021-05910-1.

[23] Y. D. Zhang, S. C. Satapathy, X. Zhang, and S. H. Wang, “COVID-19 Diagnosis via densenet and optimization of transfer learning setting,” *Cognitive Computation*, Jan. 2021, doi: 10.1007/s12559-020-09776-8.

[24] X. Ouyang *et al.*, “Dual-sampling attention network for diagnosis of COVID-19 from community acquired pneumonia,” *IEEE Transactions on Medical Imaging*, vol. 39, no. 8, pp. 2595–2605, Aug. 2020, doi: 10.1109/TMI.2020.2995508.

[25] Z. Wang, Q. Liu, and Q. Dou, “Contrastive cross-site learning with redesigned Net for COVID-19 CT classification,” *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 10, pp. 2806–2813, Oct. 2020, doi: 10.1109/JBHI.2020.3023246.

[26] N. Hasan, Y. Bao, A. Shawon, and Y. Huang, “DenseNet convolutional neural networks application for predicting COVID-19 using CT image,” *SN Computer Science*, vol. 2, no. 5, p. 389, Sep. 2021, doi: 10.1007/s42979-021-00782-7.

[27] T. D. Pham, “A comprehensive study on classification of COVID-19 on computed tomography with pretrained convolutional neural networks,” *Scientific Reports*, vol. 10, no. 1, 2020, doi: 10.1038/s41598-020-74164-z.

[28] Y. Pathak, P. K. Shukla, A. Tiwari, S. Stalin, S. Singh, and P. K. Shukla, “Deep transfer learning based classification model for COVID-19 disease,” *IRBM*, vol. 43, no. 2, pp. 87–92, Apr. 2022, doi: 10.1016/j.irbm.2020.05.003.

[29] K. Zhang *et al.*, “Clinically applicable ai system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography,” *Cell*, vol. 182, no. 5, p. 1360, Sep. 2020, doi: 10.1016/j.cell.2020.08.029.

[30] V. Perumal, V. Narayanan, and S. J. S. Rajasekar, “Detection of COVID-19 using CXR and CT images using transfer learning and Haralick features,” *Applied Intelligence*, vol. 51, no. 1, pp. 341–358, Jan. 2021, doi: 10.1007/s10489-020-01831-z.

[31] J. Wang *et al.*, “Prior-attention residual learning for more discriminative COVID-19 screening in CT images,” *IEEE Transactions on Medical Imaging*, vol. 39, no. 8, pp. 2572–2583, Aug. 2020, doi: 10.1109/TMI.2020.2994908.

[32] M. Loey, G. Manogaran, and N. E. M. Khalifa, “A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19 from chest CT radiography digital images,” *Neural Computing and Applications*, pp. 1–13, Oct. 2020, doi: 10.1007/s00521-020-05437-x.

[33] S. Wang *et al.*, “A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19),” *European Radiology*, vol. 31, no. 8, pp. 6096–6104, Aug. 2021, doi: 10.1007/s00330-021-07715-1.

[34] R. A. Nugroho, A. S. Nugraha, A. Al Rasyid, and F. W. Rahayu, “Improvement on KNN using genetic algorithm and combined feature extraction to identify COVID-19 sufferers based on CT scan image,” *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1581–1587, Oct. 2021, doi: 10.12928/TELKOMNIKA.v19i5.18535.

[35] J. Wang, X. Song, L. Sun, W. Huang, and J. Wang, “A novel cubic convolutional neural network for hyperspectral image classification,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 4133–4148, 2020, doi: 10.1109/JSTARS.2020.3008949.

[36] A. Dhillon and G. K. Verma, “Convolutional neural network: a review of models, methodologies and applications to object detection,” *Progress in Artificial Intelligence*, vol. 9, no. 2, pp. 85–112, Jun. 2020, doi: 10.1007/s13748-019-00203-0.

[37] H. Chen *et al.*, “A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources,” *Agricultural Water Management*, vol. 240, p. 106303, Oct. 2020, doi: 10.1016/j.agwat.2020.106303.

[38] M. R. Mahmood, M. B. Abdulrazzaq, S. R. M. Zeebaree, A. K. Ibrahim, R. R. Zebari, and H. I. Dino, “Classification techniques' performance evaluation for facial expression recognition,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 2, pp. 1176–1184, Feb. 2020, doi: 10.11591/ijeecs.v21.i2.pp1176-1184.

[39] F. Guo, R. He, and J. Dang, “Implicit discourse relation recognition via a BiLSTM-CNN architecture with dynamic chunk-based max pooling,” *IEEE Access*, vol. 7, pp. 169281–169292, 2019, doi: 10.1109/ACCESS.2019.2954988.

[40] Y. Zhang, S. Xiang, X. Guo, A. Wen, and Y. Hao, “The winner-take-all mechanism for all-optical systems of pattern recognition and max-pooling operation,” *Journal of Lightwave Technology*, vol. 38, no. 18, pp. 5071–5077, Sep. 2020, doi: 10.1109/JLT.2020.3000670.

[41] S. Albawi, T. A. M. Mohammed, and S. Alzawi, “Layers of a convolutional neural network,” *Icet2017*, pp. 1–6, 2017.

[42] W. Qian *et al.*, “UAV and a deep convolutional neural network for monitoring invasive alien plants in the wild,” *Computers and Electronics in Agriculture*, vol. 174, p. 105519, Jul. 2020, doi: 10.1016/j.compag.2020.105519.

[43] M. Lv, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, “Maize leaf disease identification based on feature enhancement and DMS-robust alexnet,” *IEEE Access*, vol. 8, pp. 57952–57966, 2020, doi: 10.1109/ACCESS.2020.2982443.

[44] S. Serte and H. Demirel, “Deep learning for diagnosis of COVID-19 using 3D CT scans,” *Computers in Biology and Medicine*, vol. 132, p. 104306, May 2021, doi: 10.1016/j.compbiomed.2021.104306.

[45] G. Zeng, Y. He, Z. Yu, X. Yang, R. Yang, and L. Zhang, “Preparation of novel high copper ions removal membranes by embedding organosilane-functionalized multi-walled carbon nanotube,” *Journal of Chemical Technology and Biotechnology*, vol. 91, no. 8, pp. 2322–2330, Aug. 2016, doi: 10.1002/jctb.4820.

[46] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[47] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2323, 1998, doi: 10.1109/5.726791.

[48] S. Karen and Z. Andrew, “Very deep convolutional networks for large-scale image recognition,” in *3rd International Conference on Learning Representations, ICLR 2015-Conference Track Proceedings*, 2015, pp. 14, [Online]. Available: https://www.researchgate.net/publication/265385906_Very_Deep_Convolutional_Networks_for_Large-Scale_Image_Recognition%0A.

[49] T. Kaur and T. K. Gandhi, “Automated brain image classification based on VGG-16 and transfer learning,” in *Proceedings - 2019 International Conference on Information Technology, ICIT 2019*, Dec. 2019, pp. 94–98, doi: 10.1109/ICIT48102.2019.00023.

[50] I. Hammad and K. El-Sankary, “Impact of approximate multipliers on VGG deep learning network,” *IEEE Access*, vol. 6, pp. 60438–60444, 2018, doi: 10.1109/ACCESS.2018.2875376.

[51] J. A. R. Navarrete and F. Otremba, “A computational scheme for assessing driving,” *Advances in Intelligent Systems and Computing*, vol. 997, pp. 44–58, 2019, doi: 10.1007/978-3-030-22871-2_4.

[52] C. Lin, Y. Li, H. Liu, Q. Huang, Y. Li, and Q. Cai, "Power enterprise asset estimation algorithm based on improved GoogLeNet," in *2020 Chinese Automation Congress (CAC)*, Nov. 2020, pp. 883–887, doi: 10.1109/CAC51589.2020.9326547.
[53] F. Yuesheng *et al.*, "Circular fruit and vegetable classification based on optimized GoogLeNet," *IEEE Access*, vol. 9, pp. 113599–113611, 2021, doi: 10.1109/ACCESS.2021.3105112.
[54] M. Zeng and N. Xiao, "Effective combination of DenseNet and BiLSTM for keyword spotting," *IEEE Access*, vol. 7, pp. 10767–10775, 2019, doi: 10.1109/ACCESS.2019.2891838.
[55] Z. Wu, H. Chen, Y. Lei, and H. Xiong, "Recognizing automatic link establishment behaviors of a short-wave radio station by an improved unidimensional densenet," *IEEE Access*, vol. 8, pp. 96055–96064, 2020, doi: 10.1109/ACCESS.2020.2997380.

BIOGRAPHIES OF AUTHORS

Walat Ramadhan Ibrahim received the B.Sc. degree from the Department of Computer Science from University of Duhok, Duhok, Iraq, in 2005, where she is currently pursuing the M.Sc. degree. She is also working with the Department of Electrical and Computer Engineering, Duhok University. Her research revolves around machine learning, deep learning and, image recognition. She can be contacted at email: Walat.Ebrahim@stud.uoz.edu.krd.

Mayyadah Ramiz Mahmood is Lecturer at Department of Computer Science, Faculty of Science, University of Zakho, Kurdistan Region-Iraq. She Holds a PhD degree in Computer Science with specialization in image processing and artificial intelligence. Her research areas are image processing, artificial intelligence, machine learning, data mining and pattern recognition. She can be contacted at email: mayyadah.mahmood@uoz.edu.krd.