2022 27th International Computer Conference, Computer Society of Iran (CSICC), Tehran, Iran

An Artificial Intelligence System for Detecting the Types of the Epidemic from X-rays

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2022 27th International Computer Conference, Computer Society of Iran (CSICC) | 978-1-6654-8027-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/CSICC55295.2022.9780523

Abstract— Since the beginning of the COVID-19 pandemic, many lives have been in danger. The visual geometry group network (VGGNet) is used in this research as a model to identify epidemic types. The dataset consisted of 12068 chest X-ray images extracted from the Kaggle website and evaluated in 4 classes: Pulmonary tuberculosis, normal lung, pneumonia, and Covid 19. We have used the VGGNet architecture to diagnose and classify the mentioned disease using the chest X-ray images. To assess the performance of these classes, the parameters such as accuracy, specificity, and sensitivity are measured. Regarding the measured parameters, the accuracy, specificity, and sensitivity values were 0.97, 0.96, and 0.98, respectively. This system can differentiate among these diseases by accurately diagnosing differences in patients' X-ray images. The results showed that the VGG16 model could be more effective than VGG19 in diagnosing epidemics. The VGG16 based technique can facilitate the rapid diagnosis of patients and increase their chances of recovery. The findings also showed that the proposed model based on chest X-ray images is more accurate, simpler, and less expensive than computed tomography (CT) images.

Keywords— *Deep learning; COVID-19; Image classification; Chest X-ray images*

I. INTRODUCTION

Coronavirus 2019, or COVID-19, is a virus that causes severe pneumonia with varying degrees of severity depending on the patient's immune system. This pathogen was originally discovered in the Chinese city of Wuhan in December 2019 [1, 2]. At the start of their illness, COVID-19 patients develop symptoms such as fever, dry cough, myalgia, lethargy, dyspnea, and anorexia. Acute respiratory distress syndrome (ARDS), arrhythmia, and shock develop due to these symptoms. COVID-19 causes a moderate respiratory infection that can be treated without antibiotics. People with medical issues such as diabetes, chronic respiratory disorders, and cardiovascular diseases, on the other hand, are more susceptible to contracting the virus [3, 4].

As the number of patients with Covid-19 grows, clinicians are looking for more reliable and quick detection techniques and viral and antibody testing options. X-rays and computed tomography (CT) scans are commonly available and inexpensive in public health facilities, emergency rooms, and rural clinics. They are used to detect COVID-19-induced lung infections [5] quickly. The RT-PCR method is time-consuming and has a 60–70 percent low sensitivity. By evaluating images of patients' lungs to detect the harmful effects of COVID-19, early treatment can be ensured. CT scanning, in particular, maybe a more sensitive method for detecting COVID-19 pneumonia and could be used as a screening tool alongside RT-PRC. Lung pathological changes CT scans are frequently performed for an extended time after the onset of symptoms [5].

As a result, doctors are encouraged to base their choices only on the results of X-rays and chest CT scans, which are often used to identify Covid-19 in countries where testing kits are scarce. A combination of clinical imaging characteristics and laboratory data, according to researchers, may aid in the early diagnosis of COVID-19 [5]. Modern machine learning and data mining techniques, such as Convolutional Neural Network (CNN), can be used in conjunction with CT and X-ray scan images of the lungs to accurately and quickly detect the condition, minimizing the problem of testing kit scarcity.

Using transfer learning, this research suggests using deep learning to detect the presence of COVID-19 in X-ray pictures. It is also suggested that the VGG-16 and VGG-19 convolutional neural networks be upgraded to achieve this purpose. This article may serve as a tip for the radiologist to locate the X-ray areas of interest right away.

The following is how the paper is structured: Section 2 summarizes pertinent research, Section 3 elucidates the approach, and Section 4 presents experimental findings, including performance evaluation and comparison. In the concluding section, the study's conclusion is delivered, which will be used in future publications.

II. RELATED WORK

Several machine learning methods are applied for the automated classification of digital medical images. Machine learning pattern recognition can determine visual features used for detection, diagnosis, or classification. The coaching styles of machine learning algorithms are frequently classified: supervised, unsupervised, and reinforcement learning. Supervised learning entails accumulating experience with usable images and applying that knowledge to predict new images that have not been seen before (test data) [1, 2]. A deep learning approach for COVID-19 identification has been proposed by researchers in [6, 7]. Zhang et al. [8] used the DenseNet network with COVID-19 RNA sequences to predict which existing antivirals can benefit COVID-19-affected patients.

Opacities in the correct space were discovered in a severe COVID-19 patient, according to Kong et al. [9]. Yoon et al. [10, 11] also found that one out of three patients exhibited one nodular opacity in the left lower lung region. In both lungs, the opposing two exhibited four and five irregular opacities. In recent years, the Convolutional Neural Network (CNN) has become one of the most well-known methods in artificial intelligence (AI). MRI [12, 13], X-ray [14], CT scans [15], Ultrasonography [16], and other medical image analyses have all shown success with CNN. In addition to linguistic communication processing [17], computer vision [18], audio recognition [19], and speech recognition [20], CNN has had much success.

III. Proposed Method

This paper uses the transfer learning method to train a convolutional neural network (CNN). A pre-trained CNN network from the ImageNet database with preserved weights was loaded and trained on the dataset used in this study using the transfer learning approach. The advantage of employing the transfer learning method to train the CNN is that the network's first layers are already taught, which would otherwise be difficult to teach due to the vanishing gradient problem. On the other hand, the network has already acquired basic aspects such as detecting shape, image edges, etc. As a result, the pre-trained model benefits from the knowledge gained from the images in the existing database's basic learning features. The steps of the proposed method showed in figure 1.

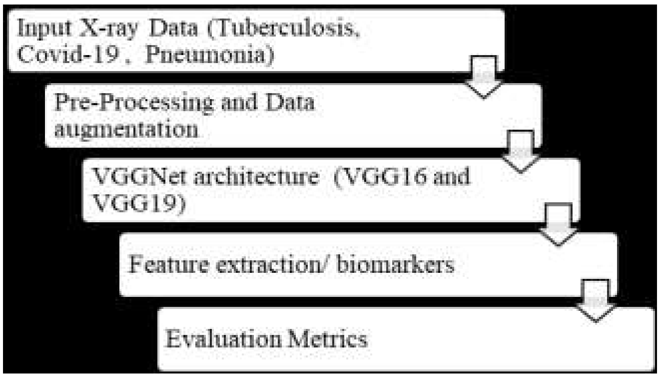

Fig 1. Show the steps of the proposed method

Because just the network's final layers must be trained, his coaching method decreases computing time [1,2,4,6,10,11].

Figure 1 depicts the entire flow diagram illustrating the suggested method's steps. Figure 2 depicts the exploitable architecture that we customized for our needs. We use data augmentation to confirm that the suggested models generalize by rotating the random image fifteen degrees clockwise or counterclockwise.

A. *Transfer* learning

Transfer learning is a process in which a model trained on one problem is used to predict labels for a second problem [22]. The most significant advantage of using transfer learning is reducing the time required to train a neural network model. Furthermore, it may result in fewer generalization errors. The major issue should be linked to the secondary issue. We use the expertise of a model trained for generic picture detection to solve the problem of lung illness identification in this example.

VGG19 could be a VGG model with 19 members (16 convolution layers, three fully connected layers, 5 MaxPool layers, and 1 SoftMax layer). Other VGG variations include VGG11 and VGG16. VGG19 has a FLOP count of 19.6 billion. VGG-19 could be a 19-layer deep convolutional neural network. You will import a pre-trained version of the network from the ImageNet database [12, 13, 23], which has been trained on over 1,000,000 images.

We use fine-tuning to apply transfer learning. We set up the VGGNet model for fine-tuning by instantiating the VGG19 network with pre-trained weights on ImageNet and removing the fully connected layer head. Then, to predict the classes, we design a replacement fully-connected layer head with the following layers AveragePooling2D, Flatten, Dense, Dropout, and a final Dense with the "softmax" activation. It is added on top of VGG19. The convolutional weights of VGG19 are then frozen, and just the fully connected layer head is trained, completing our fine-tuning setup. The structure of the proposed method showed in figure 2.

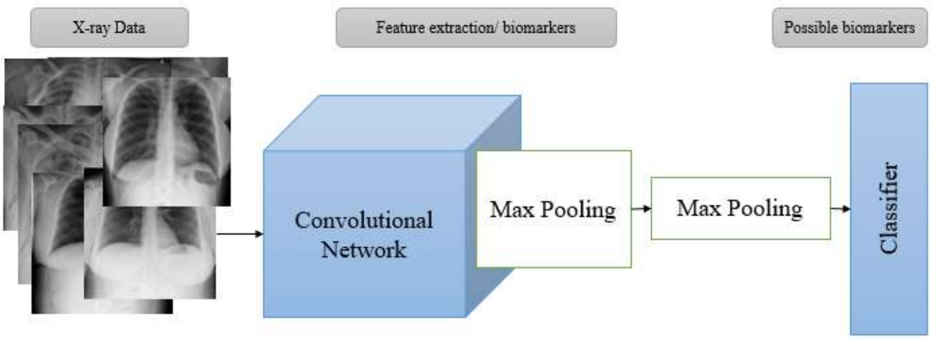

Fig.2. Structure of proposed method

B. *Pre-processing*

Pre-processing is considered a widespread process in computer vision applications. Preprocessing techniques emphasize the image aspect, which can help the recognition process or even be helpful in the deep learning training phase. The preprocessing procedure applied to the images extracted from DICOM files is as follows:

- Normalizing the pixel values of images.

• Cropping the images to remove any zero-valued pixels surrounding the images.

We transformed all images into a standard length of 224 x 224 pixels because the data set is not uniform, and the X-ray images are of varying sizes. RGB reordering was used for this, and as a result, the final input to the proposed model is 224 224 3 pictures. Since the information set is limited, we did the information augmentation using a 20-degree rotation range. The X-ray images were turned horizontally and vertically, greatly expanding the available data. With identical data sets, this data collection can coach on additional ideas.

Our AI system is being tested and evaluated using a dataset of 12,068 chest X-rays 75% of the database images were selected for training the model, 15% for testing, and 10% for evaluation. There are separate sets for training and testing and do not interfere with the patients.

C. Data augmentation

Data augmentation is a technique that allows you to increase the amount of information you have greatly. Figure 3 depicts the distribution of X-ray pictures in each of the four classifications, namely normal/healthy, pneumonia caused by viral, bacterial, and COVID-19 infection, as acquired from both databases. As a result, augmentation techniques enhance the number of photos of COVID-19 and other classes, preventing the model from overfitting. This study used rotation and Gaussian blur as information augmentation techniques [1, 2].

D. Proposed Method

Innovation

This paper uses the transfer learning method to train a convolutional neural network (CNN). This paper offers an upgraded convolutional neural network VGG-16 and VGG-19 that uses deep learning to achieve this purpose.

The proposed x-ray-based epidemic screening methodology is described. We modified the VGGNet architecture and used X-ray images from healthy and SAR-CoV-2 and pneumonia-infected patients to train the models. The x-ray pictures are derived from the datasets mentioned in the preceding section and are subjected to the pre-processing steps outlined below. The proposed method is intended to determine if chest x-rays are normal or show signs of lung illness.

We use a deep learning network based on the VGG-19 and VGG16 (i.e., Visual Geometry Group) model [2] and transfer learning to develop the (first and second) model.

In-network depth has been improved as compared to typical convolutional neural networks. It has a better structure than one since it alternates between many convolutions and nonlinear activation layers. The layer structure can better extract image features, apply Maxpooling for low sampling, and use the linear unit (ReLU) as the activation function, selecting the most significant value in the image area as the site's pooled value.

IV. Results

A. Dataset

This section describes the three datasets considered during this work. These are the three most enormous public datasets to the most effective of our knowledge.

- Tuberculosis (TB) Chest X-ray Database

A team of academics from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh has created a database of chest X-ray photos for Tuberculosis (TB) positive cases and normal shots. The database for this paper contains 3047 (TB) photographs and 3047 representative images. The TB database is collected from the source:https://www.kaggle.com/tawsifurrahman/tuberculosis-tb-chest-xray-dataset.

- Covid-19 Chest X-ray Database

RADIOGRAPHY DATABASE FOR COVID-19 (Winner of the COVID-19 Dataset Award by Kaggle Community) Researchers from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh, in partnership with collaborators from Pakistan and Malaysia and medical practitioners, have established a database of COVID-19 positive cases, as well as normal and virus infection images. 3006 Covid-19 photos were used to generate the database for this paper. The database is collected from https://www.kaggle.com/tawsifurrahman/covid19-radiography-database.

- Pneumonia Chest X-ray Database

The pneumonia database used 3060 validated Chest X-Ray images as our dataset to identify this lung infection. The database is collected from https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

- Final regards

The detailed information about the collected dataset and the identified issues are summarized in Table I. This section presents the relation between the number of images and patients for each class.

TABLE I. Datasets distribution.

Classes	DR condition	NO. of image
0	Normal	3047
1	Covid-19	3006
2	Pneumonia	3060
3	Tuberculosis	3047

B. Evaluation Metrics

Various criteria are accustomed to analyzing the performance of deep learning algorithms developed to detect and classify lung nodes. To analyze the performance of our proposed CNN model, we calculated accuracy, sensitivity, and specificity.

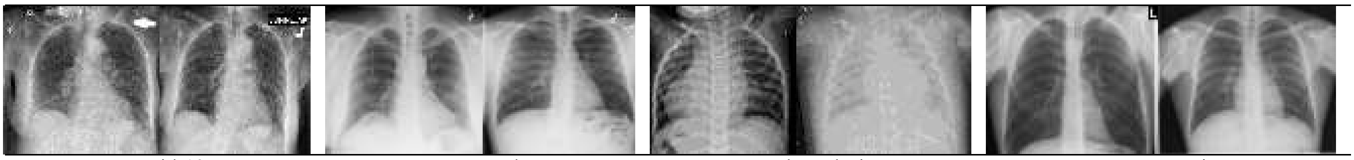

Fig.3. Examples of images used

Accuracy: Indicate the class's number of "correct predictions made" divided by the number of "total predictions made" by the same category [24-27, 33-35].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Sensitivity: Real positive rate: If the person's result is positive, the model will be positive in a small percentage of situations, as estimated below.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Specificity: Real negative rate: If the result damages the individual, the model will also be a negative result in a small percentage of situations, as estimated by the formula below [24-27, 33-35].

$$Specificity = \frac{\text{TN}}{\text{TN+FP}} \quad (3)$$

TABLE II. Confusion Matrix.

Confusion Matrix		**Classified As:**	
		Negative	Positive
Actual Class	Negative	TN	FP
	Positive	FN	TP

As its name implies, the Confusion Matrix gives us a matrix as output and describes the complete performance of the model.

TABLE III. SOFTWARE REQUIREMENTS.

Distribution	**Anaconda Navigator and Google Colab**
API	Keras
Library	Tensor Flow, OpenCV
Packages	Matplotlib, NumPyNumPy, pandas, sci-kit learn
Language	Python 3.7
IDE	Jupyter Notebook
GPU Architecture	Google Colab
Applications	labeling, TensorBoard

C. *Experimental Analysis*

Using images from the three most frequent medical imaging modes: X-Ray, Ultrasound, and CT scan, this study reveals how transfer learning from deep learning models is commonly utilized to diagnose COVID-19. The idea is to provide a second set of eyes to overburdened medical professionals using smart, deep learning picture classification algorithms. In this section, we discuss the experiment we ran to assess the performance of the offered approaches in terms of:

- Differentiation between a normal chest X-ray and one associated with lung illnesses.
- Differentiation of a pneumonia-related chest X-ray from COVID-19.

TABLE IV. VGGNET architecture results in different parameters.

	Optimizer	Batch size	Epochs	Loss	Sensitivity	Specific	Accuracy
VGG19	Adam	32	20	0.6532	0.6515	0.6942	0.7217
	Adam	32	5	0.6969	0.6836	0.6913	0.7231
	Adam	16	10	1.3865	0.1403	0.1013	0.2493
	RMS prop	32	20	0.2502	0.7826	0.7327	0.7797
VGG16	RMS prop	64	15	0.5762	0.7326	0.7592	0.7679
	Adam	32	50	0.0598	0.9826	0.9689	0.9799

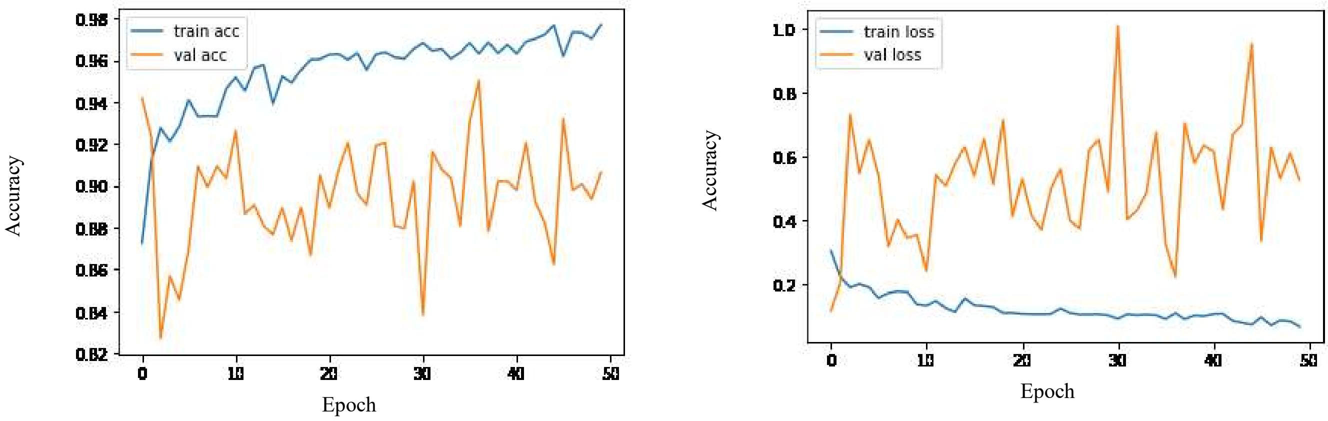

Fig.4. Result of VGG16

During the training of the CNN model, Figure 4 shows the classification accuracy and loss curves in a train and a validation set. Table IV summarizes the experiment's findings in terms of performance metrics—convergence graphs of loss functions for several transfer learning methods. The training and validation loss convergence curves are denoted by "train" and "Val," respectively. Figure 5 shows the classification by the VGG16 algorithm using the covid-19 X-ray image as an input.

D. *Result of Radiologist:*

For further studies, the research team compared the performance of artificial intelligence with the reports presented by radiologists. To do this, many real data was prepared by radiologists and used to validate the model. The result showed that this system performs better than master radiologists and slightly lower than specialists. This system helps to reduce the workload of doctors. Studies show that radiologists need an average of 6.5 minutes to scan CT images, while artificial intelligence does it in 2.73 seconds for one image. According to the results shown in this article, the performance of artificial intelligence in diagnosing pneumonia was slightly lower than radiologists. The table below shows the accuracy of the existing model relative to the actual data. (This data is not used in model training.).

TABLE V. Accuracy of the existing model relative to the actual data.

	Sample	Radiologist			Model AI					
		NPV	PPV	Time	NPV	PPV	Accuracy	Sensitivity	Specific	Time
Normal	50	0	50	15 Min	15	45	92%	89%	86%	3 Min
Covid-19	50	7	43	15 Min	21	39	88%	90%	83%	3 Min
Pneumonia	50	8	42	15 Min	19	41	91%	88%	90%	3 Min
Tuberculosis	50	19	31	15 Min	16	34	82%	80%	81%	3 Min

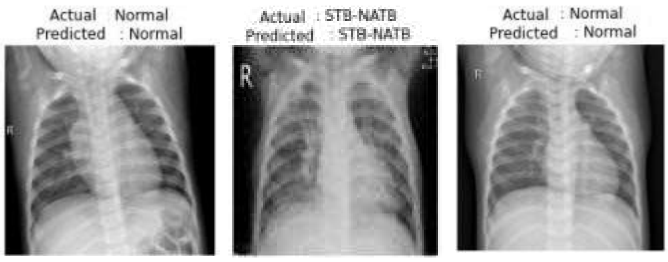

Fig.5. Result of predicting new sample with VGG-NET

V. Discussion

By processing chest X-ray images and providing them as input to the model, deep learning can be a significant tool in the medical business for diagnosing disorders. Pneumonia, TB, and COVID-19 were all found on normal chest X-rays. This study presents a system based on artificial intelligence that can accurately distinguish covid-19 from pulmonary tuberculosis and pneumonia. In such a situation where errors in the diagnosis of Covid-19 are relatively common, the proposed system can help identify people with Covid-19 to physicians. This system may be important to hospitals not equipped with CT devices.

Deeper models, such as VGG-19, suffered from overfitting concerns and could not accurately model the variations between the categories, resulting in performance loss. We chose the best-performing VGG-16 model for future investigation of viral infection in the COVID-19, Pneumonia, and Tuberculosis collections.

The presented method is a potential alternative diagnostic tool for detecting COVID-19 instances. Finally, the current research implies that by utilizing deep learning models, it should be possible to see COVID-19 since all recent investigations have shown encouraging outcomes. The great accuracy reported by multiple methods suggests that deep learning models detect something in photos, allowing deep networks to classify images correctly. Whether the results of deep learning algorithms can be used to make a trustworthy diagnosis will have to wait.

TABLE V. Accuracy comparison of our proposed model vs. existing models.

Study	Model	Accuracy (%)
Debabrata Dansana et al [28].	VGG-19	91%
Chiranjibi Sitaula et al [29].	VGG16	87.49
Ayan KumarDas et al. [30].	VGG-16	97.67
Ki-Sun Lee [31].	VGG-16	95.9%
Shamik Tiwari,Anurag Jain [32].	VGG-CapsNet	92%
This paper (VGG16)	VGG16	97.99%

Furthermore, the exponential rise in COVID-19 patients is straining healthcare systems worldwide. Traditional procedures cannot be used to test each patient with the disorder due to the limited number of testing kits available (RT-PCR). Despite this, the tests take a long time to complete and have low sensitivity. While test results are awaited, high-risk quarantine patients may benefit from detecting suspected COVID-19 infections on a chest X-ray. There is no need to transport the samples because most healthcare systems already have X-Ray equipment, and the most current X-Ray systems have already been digitized. VGGNET was trained using three open-source datasets and new approaches for classifying X-ray images into four categories: regular, pneumonia, tuberculosis, and COVID-19.

VI. Conclusion

Due to the disease's early stage, the number of labeled data points gathered was limited. As a result, the dataset's scale was lowered, as was the number of data points utilized. There is a chance you will end up overfitting. When the dataset size is increased, greater results are often obtained. Our current proposal comprises two separate models capable of handling the categorization mentioned above tasks. In the future, an architecture might be built to group the chest X-rays within the indicated classes successfully. For the classification tasks, we used the VGG-16 and VGG-19 models.

As indicated in Table IV, we tried a variety of models and got varying degrees of accuracy. In summary, the upgraded network model's precision for detecting epidemic categories has increased by 97.99 percent, and its sensitivity rate has increased by 98.26 percent. This improvement impact is well acknowledged to be quite strong. Furthermore, the parameters have been substantially lowered, and the upgraded VGG-16 for finding epidemic detection categories has much promise and provides a positive guarantee prior to admission to the hospital. We hope that our well-trained network can assist with medical diagnostics. The study also has a disadvantage because it only used a small number of COVID-19 X-ray pictures. I hope that larger datasets from COVID-19 from our local hospitals become available in the future, and using them increases the accuracy of our proposed network.

Available Code: All computational tools developed during this work can be found in a repository available at https://github.com/Jafar-Abdollahi/An-artificial-intelligence-system-for-detecting-the-types-of-the-epidemic-from-X-rays- which, includes a tutorial for the usage of the proposed tools.

REFERENCE

[1] Hussain, E., Hasan, M., Rahman, M. A., Lee, I., Tamanna, T., & Parvez, M. Z. (2021). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. Chaos, Solitons & Fractals, 142, 110495.

[2] Kamal, K. C., Yin, Z., Wu, M., & Wu, Z. (2021). Evaluation of deep learning-based approaches for COVID-19 classification based on chest X-ray images. Signal, Image and Video Processing, 1-8.

[3] Xiao, J., Wang, J., Cao, S., & Li, B. (2020, April). Application of a novel and improved VGG-19 network in the detection of workers wearing masks. In Journal of Physics: Conference Series (Vol. 1518, No. 1, p. 012041). IOP Publishing.

[4] Jain, G., Mittal, D., Thakur, D., & Mittal, M. K. (2020). A deep learning approach to detect Covid-19 coronavirus with X-Ray images. Biocybernetics and biomedical engineering, 40(4), 1391-1405.

[5] Hussain, E., Hasan, M., Rahman, M. A., Lee, I., Tamanna, T., & Parvez, M. Z. (2021). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. Chaos, Solitons & Fractals, 142, 110495.

[6] Kamal, K. C., Yin, Z., Wu, M., & Wu, Z. (2021). Evaluation of deep learning-based approaches for COVID-19 classification based on chest X-ray images. Signal, Image and Video Processing, 1-8.

[7] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, et al., A deep learning algorithm using ct images to screen for corona virus disease (covid-19), medRxiv (2020).

[8] Zhang, K. M. Saravanan, Y. Yang, M. T. Hossain, J. Li, X. Ren, Y. Wei, Deep learning based drug screening for novel coronavirus 2019-ncov (2020).

[9] W. Kong, P.P. Agarwal Chest imaging appearance of COVID-19 infection Radiology, 2 (1) (2020)

[10] Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 43(2), 635-640.

[11] S.H. Yoon, K.H. Lee, J. Radiol, et al. Chest radiographic and CT findings of the 2019 novel coronavirus disease (COVID-19): analysis of nine patients treated in Korea Korean, 21 (4) (2020), pp. 494-500.

[12] L. Zou, J. Zheng, C. Miao, M.J. Mckeown, Z.J. Wang 3D CNN based automatic diagnosis of attention deficit hyperactivity disorder using functional and structural MRI IEEE Access, 5 (2017), pp. 23626-23636

[13] Canayaz, M. (2021). MH-COVIDNet: Diagnosis of COVID-19 using deep neural networks and meta-heuristic-based feature selection on X-ray images. Biomedical Signal Processing and Control, 64, 102257.

[14] Liu, et al. TX-CNN: Detecting tuberculosis in chest x-ray images using convolutional neural network IEEE International conference on image processing (ICIP), Beijing (2017), pp. 2314-2318

[15] X. Zhao, L. Liu, S. Qi, Y. Teng, J. Li, W. Qian Agile convolutional neural network for pulmonary nodule classification using CT images Int J CARS, 13 (2018), pp. 585-595

[16] Liu, W. Li, N. Zhao, et al. Integrate domain knowledge in training CNN for ultrasonography breast cancer diagnosis Frangi A., Schnabel J., Davatzikos C., Alberola-López C., Alberola-Fichtinger G. (Eds.), Medical image computing and computer assisted intervention – MICCAI 2018. MICCAI 2018. Lecture Notes in Computer Science, vol. 11071, Springer, Cham (2018)

[17] A.M. Alayba, V. Palade, M. England, R. Iqbal A combined CNN and LSTM model for arabic sentiment analysis Holzinger A., Kieseberg P., Tjoa A., Weippl E. (Eds.), International cross-domain conference for machine learning and knowledge extraction, CD-MAKE Lecture Notes in Computer Science, vol. 11015, Springer, Cham (2018)

[18] X. Peng, C. Schmid Multi-region two-stream r-CNN for action detection Leibe B., Matas J., Sebe N., Welling M. (Eds.), Computer vision – ECCV 2016, ECCV, Lecture Notes in Computer Science, vol. 9908, Springer, Cham (2016)

[19] S. Zhang, S. Zhang, T. Huang, W. Gao, Q. Tian Learning affective features with a hybrid deep model for audio–visual emotion recognition IEEE Trans Circuits SystVideo Technol, 28 (10) (2018), pp. 3030-3043

[20] O. Abdel-Hamid, A. Mohamed, H. Jiang, G. Penn Applying convolutional neural networks concepts to hybrid NN-HMM model for speech recognition 2012 IEEE International conference on acoustics, Speech and Signal Processing (ICASSP), Kyoto (2012), pp. 4277-4280

[21] Dey, N., Zhang, Y. D., Rajinikanth, V., Pugalenthi, R., & Raja, N. S. M. (2021). Customized VGG19 architecture for pneumonia detection in chest X-rays. Pattern Recognition Letters, 143, 67-74.

[22] Shaha, M., & Pawar, M. (2018, March). Transfer learning for image classification. In 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 656-660). IEEE.

[23] ImageNet. http://www.image-net.org

[24] Abdollahi, J., Moghaddam, B. N., & Parvar, M. E. (2019). Improving diabetes diagnosis in smart health using genetic-based Ensemble learning algorithm. Approach to IoT Infrastructure. Future Gen Distrib Systems J, 1, 23-30.

[25] Abdollahi, J. A review of Deep learning methods in the study, prediction and management of COVID-19.

[26] Abdollahi, J., Keshandehghan, A., Gardaneh, M., Panahi, Y., & Gardaneh, M. (2020). Accurate detection of breast cancer metastasis using a hybrid model of artificial intelligence algorithm. Archives of Breast Cancer, 18-24.

[27] Abdollahi, J., & Nouri-Moghaddam, B. (2022). Hybrid stacked ensemble combined with genetic algorithms for diabetes prediction. Iran Journal of Computer Science, 1-16.

[28] Dansana, D., Kumar, R., Bhattacharjee, A., Hemanth, D. J., Gupta, D., Khanna, A., & Castillo, O. (2020). Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing, 1-9.

[29] Sitaula, C., & Hossain, M. B. (2021). Attention-based VGG-16 model for COVID-19 chest X-ray image classification. Applied Intelligence, 51(5), 2850-2863.

[30] Das, A. K., Kalam, S., Kumar, C., & Sinha, D. (2021). TLCoV-An automated Covid-19 screening model using Transfer Learning from chest X-ray images. Chaos, Solitons & Fractals, 144, 110713.

[31] Lee, K. S., Kim, J. Y., Jeon, E. T., Choi, W. S., Kim, N. H., & Lee, K. Y. (2020). Evaluation of scalability and degree of fine-tuning of deep convolutional neural networks for COVID-19 screening on chest X-ray images using explainable deep-learning algorithm. Journal of Personalized Medicine, 10(4), 213.

[32] Tiwari, S., & Jain, A. (2021). Convolutional capsule network for COVID - 19 detection using radiography images. International Journal of Imaging Systems and Technology, 31(2), 525-539.

[33] abdollahi jafar, amani firouz, mohammadnia alireza, amani paniz, fattahzadeh-ardalani ghasem. Using Stacking methods based Genetic Algorithm to predict the time between symptom onset and hospital arrival in stroke patients and its related factors. JBE. 2022;8(1):8-23.

[34] Abdollahi, J., & Nouri-Moghaddam, B. (2021). Feature selection for medical diagnosis: Evaluation for using a hybrid Stacked-Genetic approach in the diagnosis of heart disease. arXiv preprint arXiv:2103.08175.

[35] Abdollahi, J., Nouri-Moghaddam, B., & Ghazanfari, M. (2021). Deep Neural Network Based Ensemble learning Algorithms for the healthcare system (diagnosis of chronic diseases). arXiv preprint arXiv:2103.08182.