ISSN: 0974-5823 Vol. 6 No. 3 December, 2021

International Journal of Mechanical Engineering

# COVID-19 identification and investigation using Machine Learning on chest X-ray Imaging

Pratibha Sambhakar
M. Tech. Scholar
School of Engineering and I.T.,
MATS University, Raipur

Apurv Verma
Assistant Professor
School of Engineering and I.T.,
MATS University, Raipur

Dr. Abhishek Badholia
Associate Professor
School of Engineering and I.T.,
MATS University, Raipur

**Abstract:** The key purpose of the research is to examine and analyse various deep learning improved strategies for spotting COVID-19 in X-ray and CT-scan medical pictures. In this research, we employed 4 efficient pretrained CNN algorithms for the COVID-19 CT-scan for categorization job. The suggested Fast.AI ResNet framework was meant to automatically choose the appropriate architecture, preprocessing, and training settings for the algorithms. The correctness and F1-measure in the recognition of COVID-19 utilizing CT-scan pictures were both more than 96 percent. Furthermore, we used transmission learning approaches to overwhelmed the lack of data and shorten the training time. The upgraded VGG16 deep transfer learning architecture was used to perform two and more class categorization of X-ray pictures. Enhanced VGG16 detected X-ray pictures from COVID-19 and pneumonia with a high precision of 99 percent. The method's accuracy and authenticity were evaluated using well known large - scale dataset from X-ray and Computed tomography scan. The suggested approaches outperform alternative appropriate methodologies in the research towards COVID-19 detection. In our judgement, this study can assist virologists and radiologists achieve cheaper and improved diagnoses in the fight against COVID-19 pandemic.

**Keywords:** CNN, Chest X-ray, COVID-19, Machine Learning;

## 1. Introduction

As we all know COVID-19 is a serious disease that kills a considerable number of individuals daily. This sickness impacts more than one country, and the entire globe has suffered as a result of this viral disease. Several viruses (such as SARS [1], MERS, Flu, and others) have entered the scene in the last decade, however they only last a few days or months. Numerous experts are studying on all of these viruses, and only a handful of them have been diagnosed due to the existence of vaccinations developed by specialists. At the moment, the entire globe is plagued by COVID-19 illness, and the most crucial point is that no one country's experts can develop a vaccine for it [2]. Meanwhile, several more forecasts have emerged, like plasma treatment, X-ray imaging, and various others, however the precise cure to this fatal condition has yet to be discovered [3].

X-ray pictures of fit and COVID-19 afflicted patients were made accessible for analysis in various repository such as Github and Kaggle. COVID-19 is an infectious sickness that has become a pandemic and poses a worldwide threat to mankind [4]. It is crucial to distinguish COVID-19 infected patients from healthy people. To decrease the danger of patients who are not infected with COVID-19, dialysis of COVID-19 infected patients must be performed with greater caution and under very stringent protocols.

The unique coronavirus illness began as a throat infection, and victims suddenly had difficulties breathing. The COVID-19 disease is a secret adversary that no one can defeat. To safeguard healthy individuals, COVID-19 infected patients must be isolated, undergo thorough screening, and take necessary precautions with prevention. This virus spreads by a chain mechanism [5] that begins when one person comes into touch with a COVID-19 sick individual. Healthcare workers are critical in diagnosing this pandemic. Many other measures have been implemented to mitigate the effects of COVID-19. Medical imaging [6] is another approach for assessing and forecasting COVID-19's effects on the human body. Through the use of CT and X-ray pictures, healthy persons and COVID-19 sick person may be studied in simultaneously.

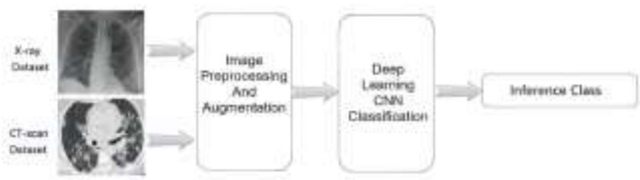


Figure 1:

The acquired data is analyzed with the aid of CNN, a machine learning technology. The study emphasizes on using CNN paradigm to categorize X-ray pictures for COVID infected persons [8]. We sought to illustrate parallels to prior research in the domain and explore for suitable task models that may be evaluated further to verify their utility in actual circumstances.

This paper's key contributions are as described in the following:

- The algorithms' validity was assessed applying our suggested model on 3 familiar public X-ray and CT-scan set of images data.
- Use transfer learning, which is used to solve the overfitting difficulties suppressed by deep learning's limited quantity of training pictures. Due to the unavailability of a publicly

available COVID-19 datasets, we created one with 3616 chest X-ray pictures of COVID-19 confirmed individuals.

- In terms of numerous performance criteria such as correctness, f1-score, precision, and recall, the suggested Fast.AI system outperformed earlier efforts. All of the indicators have greatly improved.
- After a thorough assessment to evaluate the suggested approaches, we discovered that the suggested VGG16 deep learning model performs very well on 2 & 3-class classification problems, with the top model achieving an accuracy of 99 percent.

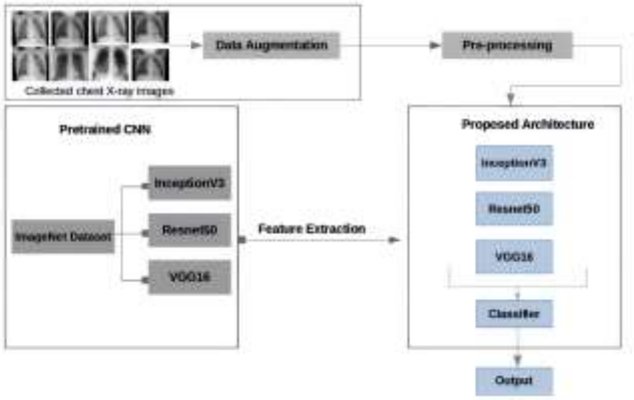


**Figure 2: COVID-19 comparison to non-COVID-19 Chest X-ray picture categorization**

## 2. Proposed Models

Transfer-learning, Fast.AI, and CNN architectures are all examples of artificial intelligence. Numerous deep learning nets are utilized to properly analyze COVID-19 [9]. Among them, CNN is the primary approach for COVID-19 illness categorization, segmentation, and predictions. In Figure 1, COVID-19 deep learning-based diagnostic architecture shown in which the software employs a deeplearning based-system to identify whether the pictures of the person's presumed respiratory system are healthy, contain bacterial meningitis, or have COVID-19 [10].

We employed deep learning to train X-ray and CT-scan pictures individually as part of our effort. The upgraded VGG16 deep transfer learning models are used to perform COVID-19 X-ray binary and multi-class classification; the model performance exhibits promising results and is straightforward to deploy [11, 12].

[1]. VGG16: It is a CNN paradigm which, suggests its development in 2014, is still regarded as one of the finest for image classification today. Convolutional layers are layered with 3x3 filters and 2x2 max-pooling layers. The rely activation function is implemented among these layers [13]. After that, there are three completely linked layers that hold the majority of the network's parameters. The probability for each categorization of pulmonary symptoms are calculated using a SoftMax function [14, 15].

[2]. Transfer Learning: We also used ImageNet data to apply a transmit training approach on a dataset that was significantly smaller [16]. It cuts down on the amount of time deep learning techniques need to train. The ImageNet-trained model has been released, and it may be used to fine-tune various sets of data [17]. It's straightforward to use the transmit training program to the labeled set of data in the particular problem case as it adapts well to various data collections [18]. Our suggested VGG16 model is skilled across 20 epochs with a bunch extent of 32 in this study. With Keras' Image Data Generator, all picture is randomly updated in each epoch [19]. The underlying neural networks of Dense Layer have been ice-covered in order to retain ImageNet masses through-out the Modeling process [20]. To prevent overfitting in the model, dropouts is used in the fully linked layers. Model is proficient to produce various metrics. Decrease the dropout if the overfitting is much healthier but the metrics are too dramatically improved [21]. Raise the dropouts if the overfitting is still severe. The drop ratios of 0.3 and 0.2 were applied in our scenario.

[3]. ResNet: Input-layer, four subsequent layer, as well as an output-layer make up the ResNet Architecture. Each stage reflects a step in the process that we are following in order. It takes data from prior phases, runs one step of the CNN, and outputs the results [22]. ResNet is separated in five phases, the first of which may be thought of as a pre-processing of INPUT, and the remaining four of which are made up of a Bottleneck and have a more comparable architecture [23]. In this layer, we successfully reduce the input width and height by four times while increasing the channel size to 64 [24]. The only difference between the residual blocks and the down-sampling blocks would be the stride of the convolutions, which in this instance would be 1.

## 3. Experimental setup

The VGG16 model was used in three situations for the experimental component. In the first case, photos of normal individuals were combined with patients identified using COVID-19 to create a classification model. Inside the 2nd case, we established a method to differentiate COVID-19 from other Lung disease in sick people with abnormal X-ray images. As in 3rd instance, 3 categories were assumed: COVID-19, Healthy, and Pneumonia.

The Python language was used to create these three situations. To supervise the frameworks, equipment, repositories, and resources of TensorFlow 2.0, we utilised one unrestricted deep learning framework. For the sake of repeating the experiments, all of the essential applications remained wrapped consuming the Docker platform. The container also incorporated and enclosed the essential libraries to execute each model on GPUs.

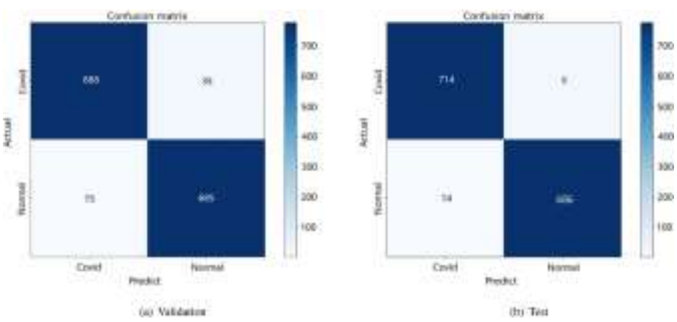


**Figure 3:** Error matrix for VGG16 on X-ray dataset: COVID-normal.

We employed the Fast.AI ResNet50 and Fast.AI ResNet152 algorithms for the CT-scan images investigations. These were running on Google Collaboratory, which has a more powerful GPU.

All the information was gathered from openly published training data that complied with the organizational and/or leading research bodies' ethical requirements, as well as the Helsinki Statement and its subsequent modifications or equivalent proper regulations.

## 4. Result Analysis

**COVID19/normal X-ray picture results:** The findings of the upgraded VGG16 model for the categorization of COVID-19/normal on validation and test data are shown in Table 1 [25]. The test photos were never used to train or modify hyper-parameters, but the performance is indeed higher than the validation pictures, with our model obtaining up to 98 percent correctness, 99 percent recall, 98 percent accuracy, and 98.8 percent F1-score [26].

The VGG16 model's training and validation accuracy and loss [27]. As can be observed, the model converges successfully since the gap among the training and authentication arches is small.

COVID19/pneumonia X-ray picture results: The findings of the updated VGG16 model for the categorization of and COVID-19/pneumonia on validation and test data are shown in Table 2. As can be seen, the validation and training dataset results are both accurate with a really high correctness of 99 percent, recall and Precise are likewise over 99 percent [28]. As we explain in "Discussion," these findings outperform those of other research in the literature.

The Error matrix of authentication and testing dataset for 2-class categorization using COVID-19/pneumonia is shown in Figure 4. This model, as can be seen, also converges effectively. The VGG16 model's training, validation, and loss accuracy [29]. The categorization of COVID-19 or pneumonia accurateness plan shows that after epoch 10, the exactness begins to stabilise at 99.5 percent aimed at exercise and authentication data, resp. It is revealed that training and confirmation losses are comparable. The model is well-fitting and avoids excessively.

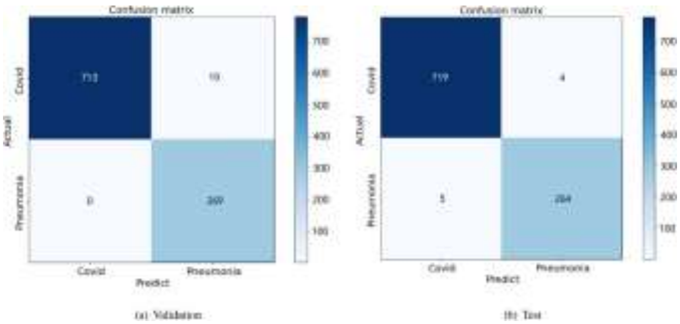


Figure 4: Error matrix for VGG16 on X-ray data-set

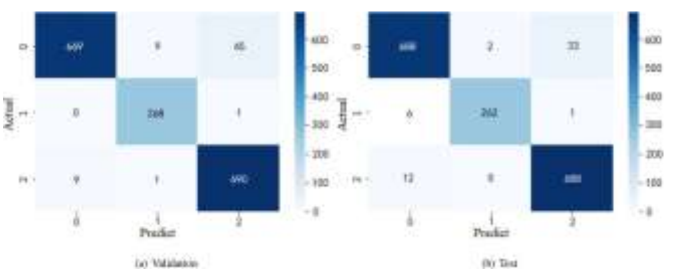


Figure 5: X-ray dataset 3-class categorization

We ran the 3-class categorization experiment to improve the validity of the models. Table 3 presents the findings of our model using validation and test data for the three-class scenario of COVID-19/pneumonia/normal. We can see our suggested technique performs well on 3-class classification, with precision of 97 percent. Furthermore, this obtains a high precision of 99 percent for the COVID-19 class in the validation data and a high accuracy for other class in dataset. It implies that valid affirmative projections might be classified as favorable across all categories. However, in both tests, some COVID-19 photos were incorrectly labelled as Normal. We examined these photos and discovered that because these individuals had silent illnesses, their X-ray images were difficult to identify. To address this issue, the number of images of this type in the collection should be raised and classified for further investigation.

CNN algorithms without Fast.AI. the outcomes of employing CNN models to scan CT images without the Fast.AI framework. VGG16 had the most accuracy, at 92 percent. It implies that the VGG16 model recognized the greatest number of COVID-19 CT-scan pictures among all positives. The DenseNet121 model surpasses other models in terms of accuracy, recall, and F1-score by 83.7 percent, 98.2 percent, and 86.7 percent, correspondingly.

We then use Fast.AI to execute the CNN models using CT-scan pictures Categorization. Fast. AI's Interpretation function displays several erroneously recognized example photos [30]. To prevent the algorithm getting learned forever, that consumes computational assets and decreases effectiveness, we used an early-stopping technique for hyper-parameter tweaking. Fast.AI records the outcomes of each hyper-training parameters and then delivers the set of data before over-fitting begins [31]. Table 5 illustrates the outcomes of the operations.

Table 1. CNN model output deprived of Fast. AI.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| VGG16 | 77 | 92 | 60 | 73 |
| DenseNet121 | 83.7 | 77.7 | 98.2 | 86.7 |
| ResNet50 | 81 | 84 | 77 | 80 |
| ResNet152 | 80 | 89 | 70 | 78 |

Table 2. CNN architecture output from Fast.AI.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Fast.AI ResNet50 | 96.3 | 97.6 | 95.2 | 96.4 |
| Fast.AI ResNet152 | 96.2 | 95.7 | 97.2 | 96.4 |

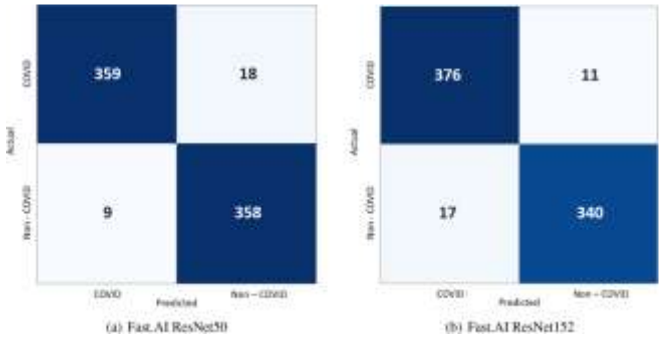


Figure 6: Fast.AI ResNet confusion matrix using CT-scan datasets.

Fast.AI ResNet50 and Fast.AI ResNet152's confusion matrix is shown in Fig-6 [32]. The Fast.AI ResNet50 model accurately categorizes 359 photos as COVID-Positive and 357 photos as COVID-Negative. As a result, our algorithm accurately categorized 717 photos out of a total of 27. Nine of the 27 misclassified photos are projected as COVID-Positive while being COVID- Negative, indicating Type I inaccuracy [33]. Finally, 18 photos had Type II errors, which meant that images that were COVID-Positive were expected to be COVID-Negative.

We can see that after implementing Fast.AI, the suggested approaches function more effectively than last. As a result, we recommend combining FAST.AI with any ResNet model [34].

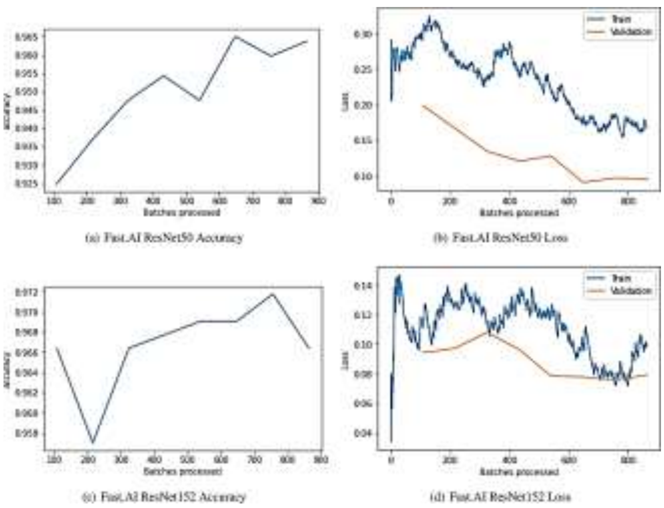


**Figure 7: Accuracy and Loss [1]**

One of the most common imaging techniques applied in COVID-19 studies is X-ray data. CT-scans pictures give higher resolution 3D picture for COVID-19 sensing and recognition. There are various studies that use chest X-rays to diagnose COVID-19, with single or many categories [35]. Raw data is used in certain studies, whereas feature extraction is used in others. In addition, the quantity of photos used in the research differs. The CNN is the most popular method used in the investigations (CNN). Table 7 compares our suggested CNN models to numerous previous research papers employed in COVID-19 identification and evaluation [36].

In the COVID-19 of X-ray image detection experiment, our suggested model upgraded VGG16 had a higher accuracy and a wider dataset than those in prior works. Table 6 shows that RG28 has the best accuracy. Our VGG16 model only requires 20 epochs of training and has a simple network layout. Shalbaf 29 is unique in that it proposes classifying CT pictures using a group of 5 CNN and a majority vote at the conclusion. Because they have to perform the 5 CNN algorithms for a single image, the calculation takes substantially longer and is much more expensive. On CT-scan pictures, Rahim The COVID-19 precision is just approximately 81 percent, despite the model's 98 percent accurateness on more than 7986 test photos. The amount of COVID-19 photos in the test is significantly fewer than the number of images in regular tests. For network performance testing, they have 450 COVID-19 pictures and 7800 regular photos. The picture numbers in the two groups are vastly different in size. In the categorization, we pick photos of nearly the same rating.

We tested the model on two settings and with the third biggest datasets in contrast to prior techniques. Table 7 displays our system's finest X-ray and CT scan picture outcomes. They are, as can be seen, superior to the majority of the techniques provided.

COVID-19's automated categorization would be highly useful in promoting the screening process in clinical practice because bacterial and viral Pneumonia indications are identical. We employed a deep learning technique to identify radiological markers that differentiate COVID-19 from ordinary viral pneumonia in our research. It's interesting that our model can discriminate Pneumonia, particularly viral pneumonia, from COVID-19 with such high accuracy (99%). More medical studies, in our perspective, is required to further evaluate and enhance the model's validity. The sooner serious instances are identified, the more likely therapy will be successful.

Furthermore, using the upgraded VGG16 model of binary categorization, the avg rates of evaluating correctness is 98.5 percent, while the avg rates of precise, recall, and F1-score are 98.5 percent, 99 percent, and 98.8 percent, correspondingly. For the three-class classification problem, the correctness, precise, recall, and F1-score are all over 97 percent. As a consequence, the findings show that the upgraded VGG16 model has a lot of potential. Our improved VGG16 and Fast.AI ResNet models have shown to be successful in COVID-19 sufferers with different pneumonias and healthier persons. The suggested methods favour the identification, resulting in increased accuracy.

To summarize, we believe that the concept of merging deep learning and machine learning has progressed significantly, and that it may be a valuable tool for clinical practitioners and radiologists to aid diagnostics of COVID-19 situations.

## 5. Conclusion

The major objective of the research was to study & explain various Deep learning algorithms for diagnosing COVID-19 using medical photos. For multi and binary class categorization challenges, we created many Sets of data from Govt. sources, like X-Ray and CT-Scan pictures. The upgraded CNN algorithms' correctness is at all times over 98 percent, and the error matrix indicate extremely few false instances for binary categorization of X-ray pictures, allowing us to adapt the models to achieve a better amount of precision than prior research. The findings show that characteristics gained from upgraded deep learning techniques may be included into our work to create a useful model.

One of the paper's key conclusions is that by using extra open datasets, data fusion models might improve diagnostics and predictive performances even more. The other is that our models might successfully support virologists in diagnosing COVID-19 and radiologists in the battle against COVID-19 outbreaks, arriving at vital medical diagnoses in min., that may be extremely in their treatments.

We have already been performing on multi-criteria categorization to separate photos from sets of data containing individuals with lung issues owing to a variety of illnesses, such as TB, AIDS, COVID-19, and others, as future study areas. Furthermore, we were unable to locate databases containing metadata describing illness phases that may be used to determine the intensity of symptoms. We intend to work on this in collaboration with experts at a few Madrid hospitals.

## REFRENCE


[1]. Dandi Yang, Cristhian Martinez, Lara Visuña, Hardev Khandhar, Chintan Bhatt, Jesus Carretero. "Detection and analysis of COVID-19 in medical images using deep learning techniques", Scientific Reports, 2021. https://doi.org/10.1038/s41598-021-99015-3.

[2]. Sohrabi, C. et al. World health organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). Int. J. Surg. 76, 71–76 (2020).

[3]. World Health Organization. Weekly epidemiological update on COVID-19—29 June 2021, 46th edn. (2021). https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-1929-june-2021.

[4]. Sandri, T. L. et al. Complementary methods for SARS-CoV-2 diagnosis in times of material shortage. Sci. Rep. 11, 1–8 (2021).

[5]. Elsharkawy, M. et al. Early assessment of lung function in coronavirus patients using invariant markers from chest X-rays images. Sci. Rep. 11, 1–11 (2021).

[6]. Asnaoui, K. E., Chawki, Y. & Idri, A. Automated methods for detection and classification pneumonia based on X-ray images using deep learning. arXiv preprint arXiv:2003.14363 (2020).

[7]. Yao, Z. et al. A machine learning-based pulmonary venous obstruction prediction model using clinical data and CT image. Int. J. Comput. Assist. Radiol. Surg. 16, 609–617 (2021).

[8]. Bhandary, A. et al. Deep-learning framework to detect lung abnormality—A study with chest X-ray and lung CT scan images. Pattern Recognit. Lett. 129, 271–278 (2020).

[9]. Kuchana, M. et al. Ai aiding in diagnosing, tracking recovery of COVID-19 using deep learning on chest CT scans. Multimed. Tools Appl. 80, 9161–9175 (2021).

[10]. Alshazly, H., Linse, C., Abdalla, M., Barth, E. & Martinetz, T. Covid-nets. Deep CNN architectures for detecting COVID-19 using chest CT scans. medRxiv (2021).

[11]. Joaquin, A. Using deep learning to detect pneumonia caused by ncov-19 from X-ray images. https://towardsdatascience.com/using-deep-learning-to-detect-ncov-19-from-x-ray-images-1a89701d1acd (2020).

[12]. Wang, D., Mo, J., Zhou, G., Xu, L. & Liu, Y. An efficient mixture of deep and machine learning models for COVID-19 diagnosis in chest X-ray images. PLoS One 15, e0242535 (2020).

[13]. Autee, P., Bagwe, S., Shah, V. & Srivastava, K. Stacknet-denvis: A multi-layer perceptron stacked ensembling approach for COVID-19 detection using X-ray images. Phys. Eng. Sci. Med., 1–16 (2020).

[14]. Ko, H. et al. Artificial intelligence can predict the mortality of COVID-19 patients at the admission time using routine blood samples. J. Med. Internet Res. (2020).

[15]. Bandyopadhyay, S. & Dutta, S. Associating unemployment with panic attack using stacked-RNN model during COVID-19. Pre-printshttps://doi.org/10.20944/preprints202006.0242.v1 (2020).

[16]. Shoeibi, A. et al. Automated detection and forecasting of COVID-19 using deep learning techniques: A review. arXiv preprint arXiv:2007.10785 (2020).

[17]. Howard, J. & Gugger, S. Fastai: A layered API for deep learning. Information 11, 108 (2020).

[18]. Soares, E., Angelov, P., Biaso, S., Higa Froes, M. & Kanda Abe, D. SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification. medRxiv (2020).

[19]. Babukarthik, R., Adiga, V. A. K., Sambasivam, G., Chandramohan, D. & Amudhavel, J. Prediction of COVID-19 using genetic deep learning convolutional neural network (GDCNN). IEEE Access 8, 177647–177666 (2020).

[20]. Shalbaf, A. & Vafaeezadeh, M. Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans. Int. J. Comput. Assist. Radiol. Surg. 16, 115–123 (2020).

[21]. Rahimzadeh, M., Attar, A. & Sakhaei, S. M. A fully automated deep learning-based network for detecting COVID-19 from a new and large lung CT scan dataset. Biomed. Signal Process. Control 68, 102588 (2021).

[22]. Khan, S. H., Sohail, A. & Khan, A. COVID-19 detection in chest X-ray images using a new channel boosted CNN. arXiv preprint arXiv:2012.05073 (2020).

[23]. Sakib, S., Tazrin, T., Fouda, M. M., Fadlullah, Z. M. & Guizani, M. DL-CRC: Deep learning-based chest radiograph classification for COVID-19 detection: A novel approach. IEEE Access 8, 171575–171589 (2020).

[24]. Jaiswal, A., Gianchandani, N., Singh, D., Kumar, V. & Kaur, M. Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. J. Biomol. Struct. Dyn., 1–8 (2020).

[25]. Ismael, A. M. & Şengür, A. Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Syst. Appl. 164, 114054 (2021).

[26]. Gomes, J. C. et al. IKONOS: An intelligent tool to support diagnosis of COVID-19 by texture analysis of X-ray images. Res. Biomed. Eng., 1–14 (2020).

[27]. Majeed, T., Rashid, R., Ali, D. & Asaad, A. COVID-19 detection using CNN transfer learning from X-ray images. medRxiv (2020).

[28]. Misra, S. et al. Multi-channel transfer learning of chest X-ray images for screening of COVID-19. Electronics 9, 1388 (2020).

[29]. Ozturk, T. et al. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput. Biol. Med. 121, 103792 (2020).

[30]. Kermany, D. S. et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell 172, 1122–1131 (2018).

[31]. Han, S., Mao, H. & Dally, W. J. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. arXiv preprint arXiv:1510.00149 (2015).

[32]. Amin, J., Sharif, M., Yasmin, M. & Fernandes, S. L. Big data analysis for brain tumor detection: Deep convolutional neural networks. Future Gener. Comput. Syst. 87, 290–297 (2018).

[33]. Pastur-Romay, L. A., Cedrón, F., Pazos, A. & Porto-Pazos, A. B. Deep artificial neural networks and neuromorphic chips for big data analysis: Pharmaceutical and bioinformatics applications. Int. J. Mol. Sci. 17, 1313 (2016).

[34]. Goceri, E. & Goceri, N. Deep learning in medical image analysis: Recent advances and future trends. IADIS Digital. Library (2017).

[35]. Litjens, G. et al. A survey on deep learning in medical image analysis. Med. Image Anal. 42, 60–88 (2017).

[36]. He, T. et al. Bag of tricks for image classification with convolutional neural networks. arXiv:1812.01187 [cs.CV] (2018).