COVID-19 Classification using DCNNs and Exploration Correlation using Canonical Correlation Analysis

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***Abstract*— Coronavirus disease (COVID-19) has rapidly spread among people living in many countries. Chest radiography (CXR) image is an alternative diagnosis option to observe COVID-19. However, CXR usually requires an expert radiologist to distinguish the lesion from viral pneumonia and COVID-19 because the symptoms of COVID-19 pneumonia may be similar to other types of viral pneumonia. In this study, three different convolutional neural network based models (VGG19, ResNet50, and InceptionV3) have been proposed for the detection of coronavirus pneumonia infected patient using chest X-ray. In addition, this studies can potentially find the correlation between COVID-19 pneumonia and viral pneumonia using canonical correlation analysis. Considering the performance results obtained the best performance as an accuracy of 0.97, sensitivity of 0.97, specificity of 0.93, and F1-score value of 0.97 for VGG19 pre-trained model. The experiment results also show that the viral lesion of Viral pneumonia and COVID-19 is less similarity.**

Keywords*— *COVID-19 classification; deep convolution neuron networks; canonical correlation analysis

I. INTRODUCTION

Coronavirus disease (COVID-19) is an infectious disease that spread throughout the world. Although the government is restrictions, flight restrictions, social distancing, and increasing awareness of hygiene, the virus is spread very rapid rate. Most of the people infected with the COVID-19 are mild to moderate respiratory illness, while some people are deadly pneumonia. The effective screening and immediate medical response for the infected patients are important to treat with stopping the spread of COVID-19 disease. Reverse Transcription Polymerase chain reaction (RT-PCR) test on respiratory specimens is the gold standard screening method for testing the COVID-19 patients [1] but it is a complicated, laborious and time-consuming process with a positivity rate of only 63 %. Moreover, there has a limitation to the shortage of its supply that leads to delay in disease prevention efforts [2]. The clinical symptoms analysis is the diagnosis tools of COVID-19 such as epidemiological history and positive radiographic images (computed tomography (CT) /Chest radiograph (CXR)) as well as positive pathogenic testing. The clinical symptoms such as bronchopneumonia causing fever, cough, dyspnea, and respiratory failure with acute respiratory distress syndrome (ARDS) are characteristics of severe COVID-19 infection [3-6]. Although radiographic images (typical CXR) may help early screening of suspected cases, the images of various viral pneumonia are similar, and they overlap with other infectious and inflammatory lung diseases. Therefore, it is difficult for radiologists to distinguish COVID-19 from other viral pneumonias. The automated CT image analysis tools to distinguish patients with coronavirus from viral pneumonia have been developed. Deep learning techniques are mostly used to reveal image features. Specifically, Deep Convolutional Neural Networks (DCNNs) has been proven extremely beneficial in feature extraction on chest X-Rays. However, DCNNs have some limitations in insufficiency of available datasets and time-consuming. Therefore, concept of transfer learning in deep learning framework was introduced by Vikash et al.[7] for the detection of pneumonia. For example, Residual neural network (ResNet) model is an improved version of the convolutional neural network (CNN) to prevent the distortion that occurs as the network gets deeper and more complex [8]. InceptionV3 and Inception-ResNetV2 are the kind of convolutional neural network model that consists of numerous convolution and maximum pooling steps [9]. All pre-trained models were trained on the ImageNet-2012 dataset that trained more than 14 million images belonging to more than 20 thousand categories created for image recognition competitions [10].

Inspired by the pre-trained, the many pre-trained models have developed. Xianghong et al. [11] proposed VGG16 model for lung regions identification and different types of pneumonia classification. Recently, several studies have reported deep - learning based COVID-19 pneumonia detection. For instance, Linda et al.[12]introduced COVID - Net for the detection of COVID-19 cases from the chest X-ray images with an accuracy of 83.5%. Ayrton [13] used a small dataset of 339 images for training and testing using ResNet50 based deep transfer learning technique and reported the validation accuracy of 96.2%. Although previous studies are successful when using the transfer learning concept, questions have been exploring about any similarities or differences between COVID-19 pneumonia and viral pneumonia.

II. RELATED WORKS

In the last few years, deep learning has achieved state-of-the-art results in many fields of computer vision, such as object detection and classification [14]. Many deep learning models not only applied in image recognition but also applied on various medical imaging fields like tissue classification in

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histopathology and histology images [15]. Deep learning methods can perform well at the cost of large amount of data set [16]. The performance of a deep CNN lies in the trainable features in different layers [17-18]. These are used to extract discriminative features at different level of abstraction [19]. However, training a deep CNN often requires computational resources. To address these challenges, transfer learning [20] is introduced to pre-trained followed by a specific task. Transfer learning allows the domains, tasks, and distributions used in training and testing to be different. For example, we may find that learning to recognize cat might help to recognize Prionailurus. It can apply previous knowledge to solve new problems faster or better solutions, and it has been proved that the transferring features outperform the random weights [21]. Several medical applications, such as chest pathology identification [22], breast mass detection and classification [23], have been reported that exciting models such as ResNet [24], GoogLeNet [25] and VGGNet [26] are significantly increase classification accuracy. Previous studies demonstrated that the transferring of different layers in deep CNNs trained with ImageNet dataset, which widely experienced as the source dataset in most transfer learning cases, show better performance than other standard approaches such as medical image datasets [27-28], X-ray security screening images [29]. However, a few of studies are available using deep learning for COVID-19 classification.

Motivated by applicability of transfer learning of DCNNs, this paper makes the following contributions. It shows that transfer learning can be employed for COVID-19 classification. It shows that features extracted from pre-trained models for domain specific tasks can be successfully used for the COVID-19 chest x-ray image. One of the most challenging problems in the machine learning is the overfitting problem. To address this problem, pre-trained models on a large benchmark from related domain specific tasks was used to extract COVID-19 chest x-ray image. We also compared three popular pre-trained CNN architectures (VGGNet, Inception, and ResNet) for COVID-19 classification. In addition, the correlation between normal, viral pneumonia, and COVID-19 was explored to find the significant information.

III. Materials and Methods

A. Datasets

The experiment dataset consist of 1000 COVID-19 chest X-ray images obtained from the open source GitHub repository shared by Dr. Joseph Cohen [24]. In addition, 1000 normal chest X-ray images and 1000 viral pneumonia were selected from Kaggle repository called "Chest X-Ray Images (Pneumonia)" [25]. The image sizes are 256 x256 pixel. Fig 1 shows representative chest X-ray images of normal, viral pneumonia, and COVID-19 patients respectively. The dataset was randomly split into two independent datasets with 70% for training and 30% for testing.

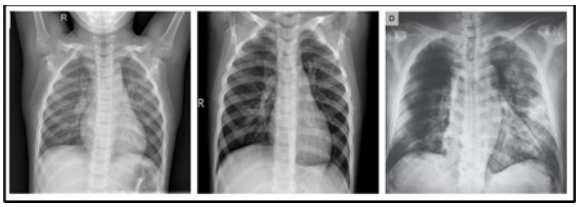

Fig.1. Representative Chest X-ray images of normal, viral pneumonia, and COVID-19

B. Deep Transfer Learning

In this study, we built deep convolutional neural network (CNN) based VGG19, ResNet152V2, and InceptionV3 models for the classification of COVID-19 Chest X-ray images to normal, Viral Pneumonia, and COVID-19 classes. In addition, transfer learning technique that was realized by using ImageNet data was applied to overcome the insufficient data and training time. Fig 2 show the schematic representation of conventional CNN including pre-trained VGG19, ResNet152V2, and InceptionV3 models for the prediction of COVID-19 x-ray images.

VGGNet show the depth of the network that is a critical component for good performance. Residual neural network (ResNet) model gets deeper and more complex that improves convolutional neural network (CNN) [8]. InceptionV3 is a kind of convolutional neural network model. It consists of numerous convolution and maximum pooling steps. All deep convolutional network architecture was trained on the ImageNet-2012 dataset. Although the transfer learning technique using ImageNet data was applied to overcome the insufficient data and training time, the proposed framework included the DCNNs top layers to learn more accurate hierarchical abstract features from the original input data.

C. Experiment setup

DCNNs models were trained using Python programming language on a Google Colaboratory with Ubuntu 16.04 operating system using Tesla K80 GPU graphics card. The models were trained with random initialization weights using the Adam optimizer. The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing. It is generally regarded as being robust to the choice of hyper parameters. The batch size was set to 32 as a for-loop iterating over one or more samples and making predictions. In the case of mini-batch gradient descent, popular batch sizes include 32, 64, and 128 samples. The smallest batch size was sufficient compared to the expected output variables and an error is calculated. The default learning rate was set to 1e-5. These numbers may provide decent results. The number of epochs in the experiment was tested to 10,100, 500, 1000, and larger. The experiment found that the model error over time did not change when using more than 100 epochs.

D. Evaluation of the performance

Confusion matrices were used to evaluate the model performance. These matrices computed sensitivity (true positive rate), specificity (true negative rate) and accuracy of models.

E. Exploration of correlation analysis via canonical correlation analysis

Because of the symptoms of COVID-19 pneumonia may be similar to other types of viral pneumonia, many studies are underway to determine how COVID-19 pneumonia differs from other types of pneumonia. Information from this study can potentially find the correlation between COVID-19 and viral pneumonia. To explore the correlation, the canonical correlation analysis was used to measure the distance of linear relationships between COVID-19 and viral pneumonia x-ray images. Canonical Correlation Analysis (CCA) is a general procedure for finding the relationships between two sets of random variables based on analyzing the cross-covariance matrix.

X-ray image features were extracted using DCNNs. The image features from the last layer were used for prediction using softmax activation function, while the image features from previous layer were used for exploration of the correlation. The features were defined as:

$$X_i^1 = [x_1^1, x_2^1, x_3^1, \dots, x_n^1],$$
$$X_i^2 = [x_1^2, x_2^2, x_3^2, \dots, x_n^2],$$
$$X_i^3 = [x_1^3, x_2^3, x_3^3, \dots, x_n^3]$$

where X_i^1 is the normal x-ray image, X_i^2 is the viral pneumonia x-ray image, and X_i^3 is the COVID-19 x-ray image. CCA aims to identify linear relationships between two random vectors. The idea is to find two vectors $w_1 \in R^p$ and $w_2 \in R^q$, so that the random variables $w_1^T \cdot X^1$ and $w_2^T \cdot X^2$ are maximum correlated ($w_1^T$and w_2^T map the random vectors to random variables, by computing weighted sums of vector components). By using the sample matrix notation $X^1$and X^2 this problem can be formulated as the following optimization problem:

$$\rho = \underset{w_1 \in R^p, w_2 \in R^q}{\text{maximize}} \frac{w_1^T Cov(X^1, X^2) w_2}{\sqrt{(w_1^T Cov(X^1) w_1)(w_2^T Cov(X^2) w_2)}}$$

where $Cov(X^1)$ and $Cov(X^2)$ are estimated of variances of $X^1$and X^2, and $Cov(X^1, X^2)$ is covariance between $X^1$and X^2. The optimization problem can be solved to a generalized eigenvalue problem:

$$[C_{22}^{-1} C_{21} C_{11}^{-1} C_{12} - \lambda I] w_i = 0$$

$$\begin{bmatrix} C_{11}^{-1} - \lambda & C_{12} \\ C_{21} & C_{22}^{-1} - \lambda \end{bmatrix} = 0$$

$$(C_{11}^{-1} - \lambda)(C_{22}^{-1} - \lambda) - (C_{21})(C_{12}) = 0$$

where C_{11} , C_{22}, and C_{12} are covariance matrix of the features X^1 and X^1, X^2 and X^2, then X^1 and X^2, and I is the identity matrix. The λ was calculated using following equation:

$$\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

where $i \in \{1, 2, 3, \dots, n\}$, n is the number of x-ray image features. for instance, if the first matrix $X_1 \in R^{256 \times 256}$ and the second matrix $X_2 \in R^{256 \times 256}$, the covariant matrix are 256×256, the eigenvalue compose of $\lambda_1 to\, \lambda_{256}$, the eigenvector compose of $W_1 \in R^{256 \times 256}$ and $W_2 \in R^{256 \times 256}$, while if we have n matrix, the covariant metric are $C_i \in R^{n \times n}$, the eigenvalue compose of $\lambda_1, \lambda_2, \dots, \lambda_n$, the weight matrix compose of $W_i \in R^{n \times n}$.

This model maps the features into the new space. This process like a dimension reduction method. It finds a new vector that can use instead of old variables. The new vectors were calculated:

$$V_i = w_i^T X_i$$

where w_i^T is the weight based on the largest λ that is the optimal weight vector.

CCA develops a canonical vector that maximizes the correlation coefficient between the two canonical vectors. It measures the strength of the relationship between the two canonical variates. The CCA correlation was measured the pair of x-ray image as:

CCA(Normal, Viral pneumonia),
CCA(Normal, COVID-19),
CCA(Viral pneumonia, COVID-19),

When the correlation coefficient is close to 1 or −1, their correlation is the strongest. The correlation coefficient is close to 0, their correlation is weak.

IV. Result and Discussion

A. Classification performance

These models were trained on the training data and tested them on the test data. The performance and diagnostic efficiency were analyzed as shown in table 1.

1)Performance comparison between accuracy and time complexity of different pre-trained model having different number of trainable parameters: Generally, the time complexity is the network learning time [30]. VGG19 has the highest trainable parameter followed by ResNet152V2. InceptionV3 has the lowest trainable parameter. Consequently, VGG19 use the highest training time followed by ResNet152V2 and InceptionV3. The experiment results show that a network having large number of parameters shows a very large time complexity. These results are consistent with many studies. For instance, Panchal et al [31], they reported that the minimum number of hidden layers for the problems due to which network needs very less time to be trained. Huang et al [32], they demonstrated that if the problem is small and linear, the time complexity will be gained.

2)Diagnosis efficiency comparison of different pre-trained model: It was observed that It was observed that VGG19 showed the best performance for classifying images. The comparisons of three models using the test data are shown in Table 1. We have obtained the best performance as an accuracy of 0.97, sensitivity of 0.97, specificity of 0.93, and F1-score value of 0.97 for VGG19 pre-trained model. The low performance values have been yielded an accuracy of 0.96, sensitivity of 0.97, specificity of 0.93, and F1-score value of 0.95 for ResNet152V2. The lowest performance values have been yielded an accuracy of 0.95, sensitivity of 0.97, specificity of 0.92, and F1-score value of 0.95 for InceptionV3.

TABLE I PERFORMANCE COMPARISONS

Model	Trainable parameters	Training time	Sensitivity	Specificity	Accuracy	F1-score
VGG19	139,570×1000	15m47s	0.98	0.95	0.98	0.98
ResNet152V2	58,187×1000	5m26s	0.97	0.93	0.96	0.95
InceptionV3	21,768×1000	3m16s	0.97	0.92	0.95	0.95

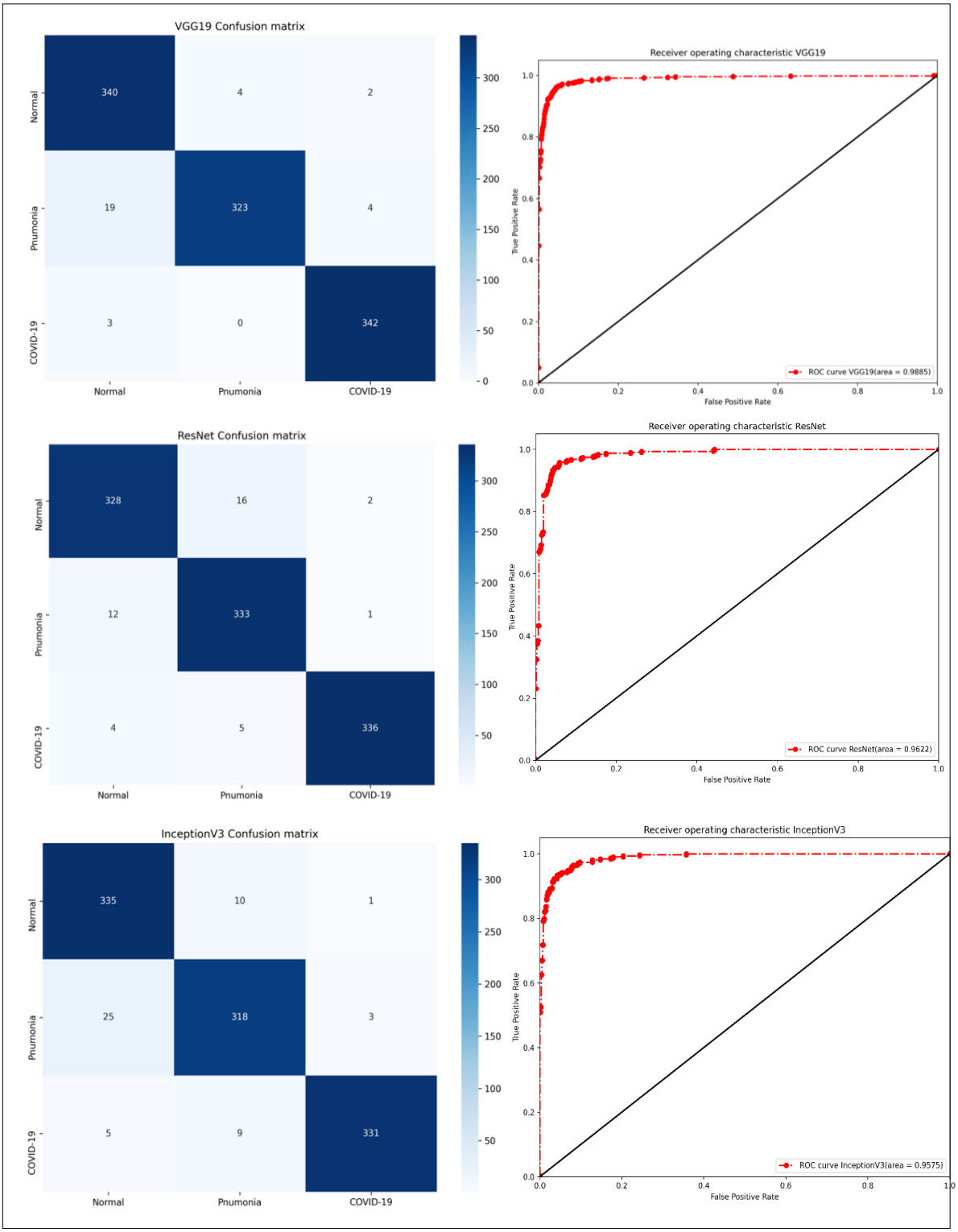

Figure 2 The confusion matrix and ROC plots obtained using pre-trained models

Confusion matrix of Normal, Viral Pneumonia, and COVID-19 were analyzed. Firstly, VGG19 classified 340 of the Normal as true positive, 323 of Viral Pneumonia as true positive, and 342 of the COVID-19 as true positive. ResNet classified 328 of the Normal as true positive, 323 of Viral Pneumonia as true positive, and 336 of the COVID-19 as true positive. InceptionV3 classified 335 of the Normal as true positive, 318 of Viral Pneumonia as true positive, and 331 of the COVID-19 as true positive.

The experiment results show that networks having large number of trainable parameters normally show high accuracy even for the large and complex problems. These results are consistent with many studies [33]. These studies demonstrated that a good result in the Neural network very large number of trainable parameters and neurons should be required.

B. Correlation exporation

The symptoms of COVID-19 pneumonia may be similar to other types of viral pneumonia. Information from these studies could potentially explain in correlation between viral pneumonia and COVID-19 x-ray images. Section III shows the pre-trained models to extract the image features observing by which areas in the convolutional layers activated on an image. VGG19 model was used to analyze the correlation because it obtains the best classification performance.

TABLE II CANONICAL CORRELATION ANALYSIS COMPARISONS

	Normal	Viral Pneumonia	COVID-19
Normal	1	0.71	0.66
Viral Pneumonia	0.71	1	0.60
COVID-19	0.66	0.60	1

Table II shows the canonical correlation analysis of Normal, Viral pneumonia, and COVID-19 features from DCNNs. The highest similarity is 0.71 for Normal and Viral pneumonia followed by Normal and COVID-19 is 0.66. The lowest similarity is 0.60 for Viral pneumonia and COVID-19. The experiment results show that the viral lesion of Normal and Viral pneumonia is similar than Normal and COVID-19. In the other hand, the viral lesion of Viral pneumonia and COVID-19 is less similarity. The symptoms of COVID-19 pneumonia may be similar to other types of viral pneumonia. Information from this study may potentially explain that depending on the type of pneumonia, lesions appear differently in the lungs. This result is consistent with an article released July 9 in the American Journal of Roentgenology [34] [ref new article]. They found that most COVID-19 lesions appear in the peripheral zone close to the pleura, while lesions from influenza virus pneumonia are more apt to show mucoid impaction and pleural effusion. They were also concluded that the most features between viral pneumonia and COVID-19 are overlap, but some statistical differences did emerge.

V. CONCLUSSION

In this study, we proposed a deep transfer learning approach to classify Normal, Viral pneumonia, and COVID-19 using chest X-ray images. Three models such as VGG19, ResNet, and InceptionV3 were compared. It was observed that VGG19 outperforms other two different networks. Since the COVID-19 is an infection of the lungs, many questions have been exploring about any similarities or differences between COVID-19 pneumonia and viral pneumonia. This study not only show the transfer learning can be employed for COVID-19 classification but also potentially explained the correlation between COVID-19 pneumonia and viral pneumonia. In subsequent studies, we believe that this knowledge can play in helping to develop the computer aided diagnostic tool and can significantly improve the accuracy of diagnosing cases with COVID - 19.

VI. REFERENCES

[1] W. Wang, Y. Xu, R. Gao, R. Lu, K. Han, G. Wu, et al., "Detection of SARS-CoV-2 in Different Types of Clinical Specimens," Jama, 2020.

[2] T. Yang, Y.-C. Wang, C.-F. Shen, and C.-M. Cheng, "Point-of-Care RNA-Based Diagnostic Device for COVID-19," ed: Multidisciplinary Digital Publishing Institute, 2020.

[3] D. Wang, B. Hu, C. Hu, F. Zhu, X. Liu, J. Zhang, et al., "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China," Jama, 2020.

[4] N. Chen, M. Zhou, X. Dong, J. Qu, F. Gong, Y. Han, et al., "Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study," The Lancet, vol. 395, pp. 507-513, 2020.

[5] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, et al., "Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia," New England Journal of Medicine, 2020.

[6] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, et al., "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China," The Lancet, vol. 395, pp. 497-506, 2020.

[7] V. Chouhan, S. K. Singh, A. Khamparia, D. Gupta, P. Tiwari, C. Moreira, et al., "A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images," Applied Sciences, vol. 10, p. 559, 2020.

[8] Wu, Z., Shen, C., and Van Den Hengel, "A. Wider or Deeper: Revisiting the ResNet Model for Visual Recognition," Pattern Recognition, 90: 119-133, 2019.

[9] Ahn, J. M., Kim, S., Ahn, K. S., Cho, S. H., Lee, K. B., and Kim, U. S. "A deep learning model for the detection of both advanced and early glaucoma using fundus photography," PLoS ONE 13(11): e0207982, 2018.

[10] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C. and Fei-Fei, L. "ImageNet Large Scale Visual Recognition Challenge," International Journal of Computer Vision, 115: 211-252, 2015.

[11] X. Gu, L. Pan, H. Liang, and R. Yang, "Classification of bacterial and viral childhood pneumonia using deep learning in chest radiography," in Proceedings of the 3rd International Conference on Multimedia and Image Processing, 2018, pp. 88-93.

[12] A. w. Linda wang, "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest Radiography Images," 2020.

[13] A. S. Joaquin. "Using Deep Learning to detect Pneumonia caused by NCOV-19 from X-Ray Images," Available: https://towardsdatascience.com/using-deep-learning-to-detect-ncov-19-from-x-rayimages-1a89701d1acd, 2020.

[14] Shwartz-Ziv, R.; Tishby, N. "Opening the black box of deep neural networks via information," arXiv, 2017; arXiv:1703.00810.

[15] Saxe, A.; Bansal, Y.; Dapello, J.; Advani, M.; Kolchinsky, A., "On the Information bottleneck theory of deep Learning," In Proceedings of the International Conference on Learning Representations, Vancouver, BC, Canada, 30 April–3 May 2018.
[16] Vasudevan, S. "Dynamic learning rate using Mutual Information," arXiv, 2018; arXiv:1805.07249.
[17] Hodas, N.O.; Stinis, P. "Doing the impossible: Why neural networks can be trained at all," arXiv, 2018; arXiv:1805.04928.
[18] Hjelm, R.D.; Fedorov, A.; Lavoie-Marchildon, S.; Grewal, K.; Trischler, A.; Bengio, Y, "Learning deep representations by mutual information estimation and maximization," arXiv, 2018; arXiv:1808.06670.
[19] Bullock, A. Luccioni, K. Pham, C. Lam and M. Luengo-Oroz, "Mapping the Landscape of Artificial Intelligence Applications against COVID-19", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2003.11336. [Accessed: 24- May- 2020].
[20] Ai, T. et al., "Correlation of Chest CT and RT-PCR Testing in Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases", Radiology, p. 200642, 2020. Available: 10.1148/radiol.2020200642.
[21] Ghoshal, B. and Tucker, A., "Estimating Uncertainty and Interpretability in Deep Learning for Coronavirus (COVID-19) Detection'", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2003.10769.
[22] Narin, A., Kaya, C. and Pamuk, Z., "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks," arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2003.10849.
[23] Wang, L. and Wong, A., "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2003.09871.
[24] Open database of COVID-19 cases with chest X-ray or CT images https://github.com/ieee8023/covid-chestxray-dataset
[25] Chest X-Ray Images (Pneumonia) https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
[26] Belghazi, M. et al., "MINE: Mutual Information Neural Estimation", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/1801.04062. [Accessed: 28- May- 2020].
[27] Reunanen, J. Search strategies. In Guyon, I. Gunn, S. Nikravesh, M. and Zadeh, L. editors, Feature Extraction: Foundations and Applications, Studies in Fuzziness & Soft Computing, chapter 4, pages 119{136. Springer, 2006.
[28] Wang, L. and Wong, A. "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-ray Images," arXiv:2003.09871 (2020).
[29] Karim, M. Döhmen, T. Rebholz-Schuhmann, D. Decker, S. Cochez M. and Beyan, O. "DeepCOVIDExplainer: Explainable COVID-19 Predictions Based on Chest X-ray Images", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2004.04582. [Accessed: 28- May- 2020].
[30] D. Xiao, B. Li and Y. Mao, "A Multiple Hidden Layers Extreme Learning Machine Method and Its Application", Mathematical Problems in Engineering, vol. 2017, pp. 1-10, 2017. Available: 10.1155/2017/4670187.
[31] G. Panchal, A. Ganatra, Y. Kosta and D. Panchal, "Behaviour Analysis of Multilayer Perceptronswith Multiple Hidden Neurons and Hidden Layers", International Journal of Computer Theory and Engineering, pp. 332-337, 2011. Available: 10.7763/ijcte.2011.v3.328.
[32] N. Guliyev and V. Ismailov, "Approximation capability of two hidden layer feedforward neural networks with fixed weights", Neurocomputing, vol. 316, pp. 262-269, 2018. Available: 10.1016/j.neucom.2018.07.075.
[33] K. Almustafa, "Prediction of heart disease and classifiers' sensitivity analysis", BMC Bioinformatics, vol. 21, no. 1, 2020. Available: 10.1186/s12859-020-03626-y.
[34] L. Lin et al., "CT Manifestations of Coronavirus Disease (COVID-19) Pneumonia and Influenza Virus Pneumonia: A Comparative Study", *American Journal of Roentgenology*, vol. 216, no. 1, pp. 71-79, 2021. Available: 10.2214/ajr.20.23304.