

Automatic Detection of COVID-19 from Chest X-ray Images with Convolutional Neural Networks

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Abstract—Deep Learning has improved multi-fold in recent years and it has been playing a great role in image classification which also includes medical imaging. Convolutional Neural Networks (CNN) has been performing well in detecting many diseases including Coronary Artery Disease, Malaria, Alzheimer's disease, different dental diseases, and Parkinson's disease. Like other cases, CNN has a substantial prospect in detecting COVID-19 patients with medical images like chest X-rays and CTs. Coronavirus or COVID-19 has been declared a global pandemic by the World Health Organization (WHO). Till July 11, 2020, the total COVID-19 confirmed cases are 12.32 M and deaths are 0.556 M worldwide. Detecting Corona positive patients is very important in preventing the spread of this virus. On this conquest, a CNN model is proposed to detect COVID-19 patients from chest X-ray images. This model is evaluated with a comparative analysis of two other CNN models. The proposed model performs with an accuracy of 97.56% and a precision of 95.34%. This model gives the Receiver Operating Characteristic (ROC) curve area of 0.976 and F1-score of 97.61. It can be improved further by increasing the dataset for training the model.

Index Terms—COVID-19, Coronavirus, CNN, Deep Learning, COVID-19 Detection.

I. INTRODUCTION

CNN is a Deep Learning (DL) algorithm that is being vastly used for image and document analysis [1] [2]. With the recent development of Artificial Intelligence (AI), CNN has also grown forth and vice versa. Moreover, CNN has already shown promising performances in real-world scenarios like face recognition, scene labeling, image classification, action recognition, human pose estimation, and document analysis [3]. CNN has also been successful in solving the medical image classification [4].

The world has been enduring the formidable outbreak of Coronavirus or COVID-19 which was first detected in December 2019. It is a potential zoonotic disease with the estimated mortality rate of 2%-5% [5]. According to the scientific brief of the WHO, the modes of transmission of COVID-19 involve respiratory droplets the size of greater than 5-10 μm . This also involves potential airborne transmission [6]. So, the growth

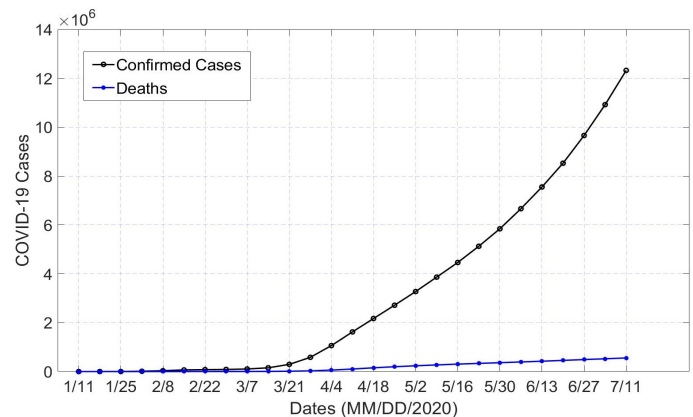


Fig. 1. Time-series graph of world-wide total confirmed cases and deaths due to COVID-19

factor of this disease is also very high with the estimation of 12.32 M confirmed cases and 0.556 M deaths worldwide as of July 11, 2020 [7]. Fig 1 shows the time-series graph of the total confirmed COVID-19 cases and deaths all over the world [7].

This graph shows the severity of the situation. The number of confirmed cases were only 41 on January 11, 2020 which increased almost thousand times to 43,109 in one month (February 11, 2020). This disease spread fast in the next three months taking the confirmed cases count to 4.04 M on May 11, 2020 which is almost 94 times the count on February 11, 2020. Even after taking so much precautions of wearing masks and maintaining social distancing, the affected patient count increased 3 times in the next two months taking the count to 12.32 M on July 11, 2020. It is a matter of hope that the growth factor is decreasing day by day due to mass consciousness. Detecting the COVID-19 positive patients and taking necessary steps accordingly is one of the important aspects of fighting against this global pandemic. WHO listed a few rapid and detailed diagnostic tests for COVID-19 detection

including genisig Real-Time PCR Coronavirus (COVID-19) testing and cobas SARS-CoV-2 for use on the cobas 6800/8800 systems [8]. These tests take a lot of time and money whereas CNN can play a major role in automatic positive patient detection. This can save both time and money which will eventually save lives. Moreover, this can add an extra layer of validation as none of the prevailing tests offer 100% accuracy.

CNN is an Artificial Neural Network (ANN) which is first conceptualized in the year of 1943. It is inspired from the human nervous system [9] [10]. Hubel and Wiesel first pointed out that animal visual cortex cells play an important role in detecting lights in the receptive fields [11]. This later inspired to model neocognitron which is considered to be the predecessor of CNN [12]. With very little preprocessing, CNN perceives the images from their visual pattern which makes it precise and popular in image classification. Alexnet, ZFNet, VGGNet are few prominent CNN model for image classification which perform really well in practical scenarios [13] [14] [15].

Like other image classifications, CNN has been performing really well with medical imaging also. For recent years, it has been used vastly for a different disease or anomaly detection [16] [17]. CNN does the diagnosis of Coronary Artery Disease (CAD), recognition of stages from bright-field microscopy images of malaria-infected blood, detection of Parkinson's disease from electroencephalogram (EEG) signals [18] [19] [20]. Researchers have also proposed different CNN models to classify dental images, detect skin diseases, the study of Alzheimer's disease, and many other diseases [21] [22] [23]. CNN can also play a great role in COVID-19 detection from CT or X-ray images. In this paper, a CNN model is proposed to detect COVID-19 positive patients from chest X-ray images. With very little time and resources, this model successfully detects coronavirus patients with high accuracy. This can help to implement testing of COVID-19 on a much greater scale which would really save both money and time.

Section 2 describes the related works, the proposed model is presented in section 3, section 4 describes the results and analysis and finally, the paper is concluded in section 5.

II. RELATED WORKS

Extensive research work is going on for classifying COVID-19 patient image data. Few researchers have proposed different DL models for classifying chest x-ray images whereas some others have taken CT images into consideration. Narin et. al proposed three pretrained CNN models based on ResNet50, InceptionV3 and Inception-ResNetV2 for detecting COVID-19 patient from chest X-ray radiographs [24]. It is found that ResNet 50 gives the classifying accuracy of 98% whereas InceptionV3 and Inception-ResNetV2 perform with the accuracy of 97% and 87% respectively. But these models have taken only 100 images (50 COVID-19 and 50 normal Chest X-rays) into consideration for training which might result in declined accuracy for a higher number of training images. Zhang et al. propose a DL model for Coronavirus patient screening using their chest X-ray images [25]. This research group has

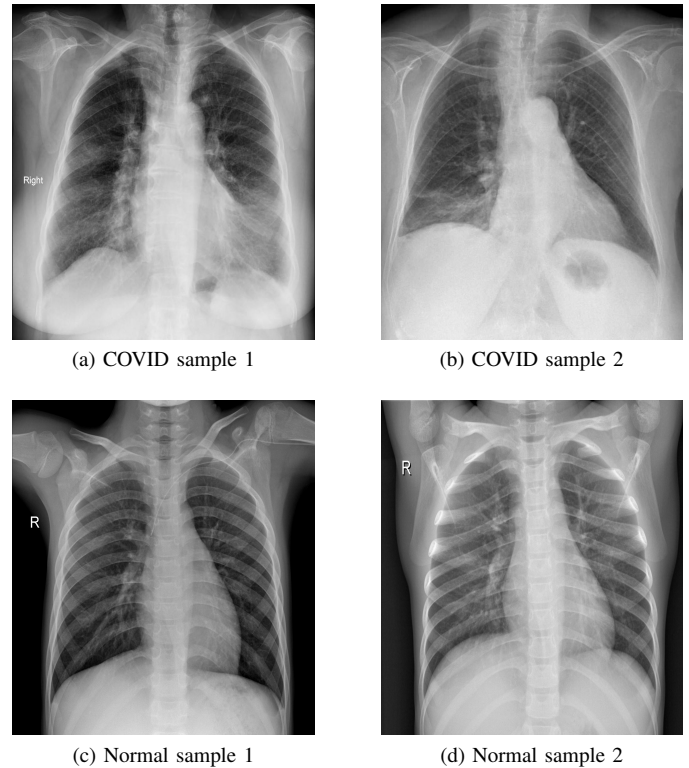


Fig. 2. (a) and (b) are the PA view of the chest X-rays of COVID-19 positive patients whereas (c) and (d) are of COVID-19 negative people

used 100 chest X-ray images of 70 COVID-19 patients and 1431 X-ray images of other pneumonia patients where they are classified as COVID-19 and non-COVID-19 respectively. This model is formed of three main parts: backbone networks, classification head, and anomaly detection head. The backbone network is a 18 residual CNN layer pre-trained on ImageNet dataset and it is mentionable that ImageNet provides a huge number of a generalized dataset for image classifications. This model can diagnosis COVID-19 and non-COVID-19 patients with an accuracy of 96% and 70.65% respectively. Hall et al. also worked on finding COVID-19 patients from a small set of chest X-ray images with DL [26]. They have used pre-trained ResNet50 and VGG 16 along with their own CNN and this model generates the overall accuracy of 91.24%. Sethy and Behea have also utilized deep features for Coronavirus disease detection [27]. Their model is based on ResNet50 plus SVM which achieved the accuracy and F1-score of 95.38% and 91.41% respectively. Apostolopoulos and Mpesiana utilized CNN transfer learning for detecting COVID-19 with X-ray images [28]. This work has considered 224 chest X-ray images of COVID-19 infected people, 714 images with Pneumonia and 504 images of normal people for training their model. This model achieved the accuracy of 96.78% and sensitivity and specificity of 98.66% and 96.46% respectively. Li et al. used the patients' chest CT images for detecting COVID-19 with the developed CNN architecture called COVNet [29]. This research group has obtained sensitivity, specificity and

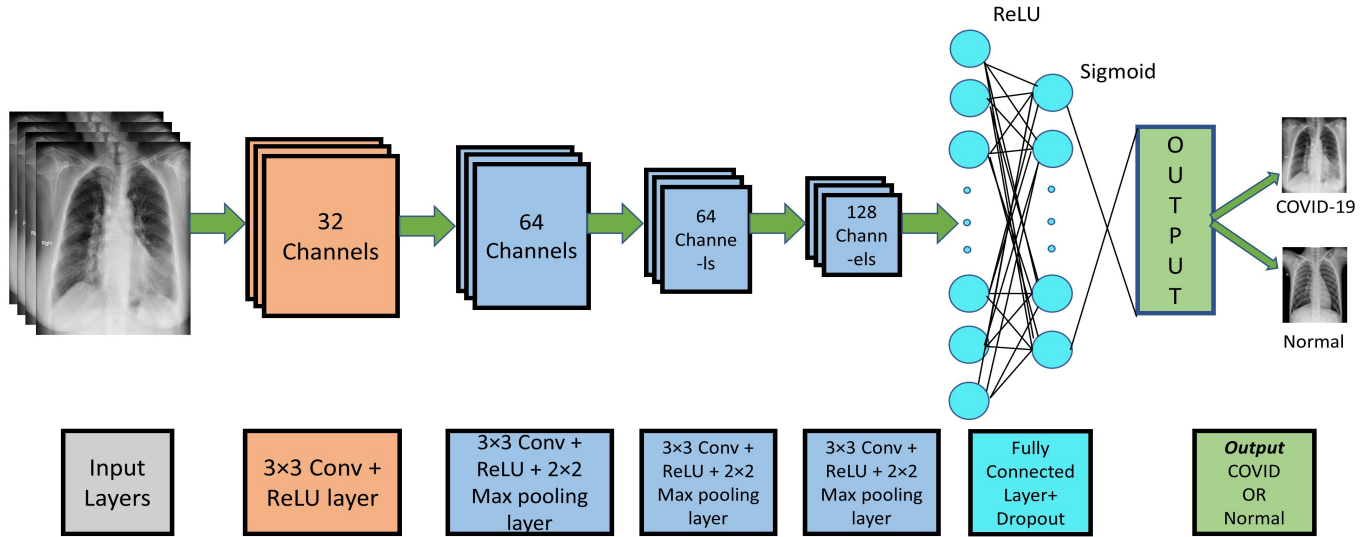


Fig. 3. Workflow diagram of the proposed CNN model for COVID-19 detection

Area Under the Receiver Operating Curve (AUC) of 90%, 96% and 0.96 respectively. Other researchers have also put an effort to detect COVID-19 patient from chest X-ray images in [30] [31].

Most of the discussed research works in detecting COVID-19 use pretrained models for their model architecture. These models are pretrained on more generalized dataset like ImageNet which might not achieve high accuracy with this medical imaging with bigger dataset. So, a sequential CNN model is proposed that is computationally efficient due to its simplicity in architecture. Moreover this is trained from scratch with the relevant dataset.

III. PROPOSED CNN MODEL FOR COVID-19 DETECTION

A. Dataset Modeling

For training the proposed model, 165 chest X-ray images of COVID-19 patients are used which are obtained from open Github repository by Cohen et al. [32]. This repository contains patients' chest X-ray images of COVID-19, SARS, ARDS, Pneumocystis, Streptococcus, Chlamydomydia, E.Coli, Legionella, Varicella, Lipoid, Bacterial, Pneumonia, Mycoplasma Bacterial Pneumonia, Klebsiella and Influenza. For training, only the COVID-19 positive X-rays have been taken into consideration and the patient age ranges from 12-93 years. The training needs the normal or non-COVID-19 chest X-rays also which is obtained from Kaggle dataset naming "Chest X-ray Images (pneumonia)" [33]. This repository contains 5863 images in two categories- normal and pneumonia. But we have taken 165 (same number as the COVID-19 chest X-ray images) normal chest X-ray images for the training purpose. The whole dataset is primarily split into two categories: training and validation maintaining the ratio of 80% and 20% respectively. Each group of training and validation dataset contains two subcategories: 'Normal' and

'COVID-19', containing the respective types of X-ray images. So, for the training, both the subcategories- 'Normal' and 'COVID-19' contain 165 chest X-ray images each whereas, the validation dataset contains 41 images for each of the 'Normal' and 'COVID-19' sub-categories. For maintaining unanimity and the image quality at the same time, all the images are converted to 224×224 pixels. Moreover, all the X-ray images that are used for training and validation of the model are in Posteroanterior (PA) chest view. Fig. 2 presents the sample of PA views of the X-ray images of both COVID-19 positive and negative cases from the training dataset.

B. CNN Modeling

CNN has been playing a great role in classifying images, in particular medical images. This has opened new windows of opportunities and made the disease detection much more convenient. It also successfully detects recent novel Coronavirus with higher accuracy. One of the constraints that researchers encounter is a limited dataset for training their model. Being a novel disease, the chest X-ray dataset of COVID-19 positive patients is also limited. Therefore, to avoid overfitting, a sequential CNN model is proposed for classifying X-ray images. Fig 3 depicts the proposed CNN model for COVID-19 detection. This model has 4 main components : (i) input layers (ii) convolutional layers (iii) fully connected layers and (iv) output layers.

The tuned data set is fed into the input layers of the model. This model is trained on 165 X-ray images of each category: normal and COVID-19. It has four convolutional layers, first one is a 2D convolutional layer with 3×3 kernels and Rectified Linear Unit (ReLU) activation function. ReLU is one of the most popular and effective activation functions that are being widely used in DL. ReLU does not activate all the

neurons at the same time making it computationally efficient in comparison to other activation functions like tanh.

The next three layers are 2D convolutional layer along with the ReLU activation function and Max pooling. Max pooling accumulates the features of the convolutional layer by convolving filters over it. It reduces the computational cost as it minimizes the number of parameters thus it helps to avoid overfitting. In each of three layers a 2×2 Max pooling layer is added after the convolutional layer to avoid overfitting and to make the model computationally efficient. In the next step of the model, the output of the convolutional layers is converted to a long 1D feature vector by a flatten layer. This output from the flatten layer is feed to the fully connected layer with dropout. In a fully connected layer, every input neuron is connected to every activation unit of the next layer. All the input features are passed through the ReLU activation function and this layer categorizes the images to the assigned labels. The Sigmoid activation function makes the classification decision depending on the classification label of the neurons. Finally, in the output layer, it is declared if the input X-ray image is COVID-19 positive or normal.

IV. RESULTS AND ANALYSIS

The proposed model is trained for 25 epochs with 10 steps per epoch with the training dataset described in previous section. This model is named as Model 1. For comparative analysis, two more models are also trained with three and five convolutional layers instead of the 4 convolutional layer structure of Model 1. These two models are named Model 2 and Model 3 respectively. In this section, the proposed model (Model 1) is analyzed along with Model 2 and Model 3. The models are trained with a learning rate of 10^{-4} and a batch size of 32. All the training images are resized to 224×224 pixels. Moreover, to avoid overfitting of the models data augmentation is used which includes random cropping and random horizontal flipping. These three models are trained and validated with the same dataset and machine. The validation accuracy and corresponding epochs for all the three models are plotted in Fig 4.

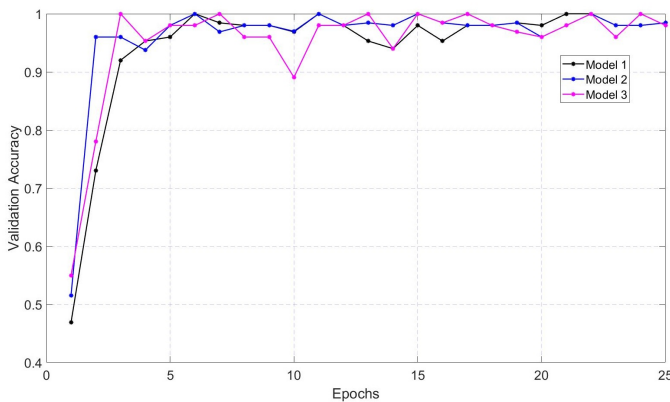


Fig. 4. The validation accuracy and corresponding epochs for all the three models

The overall accuracy is 0.9756, 0.9634, and 0.9634 for Model 1, Model 2, and Model 3 respectively. It clearly shows that the proposed model (Model 1) performs better than the other two in terms of accuracy. The performance of the models is more evident from the metrics like precision, recall, and F-1 score. These performance metrics are calculated from the possible outcomes of the validation dataset which is obtained by the confusion matrix. A confusion matrix has four different outcomes: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). In this case, TP denotes the number of Corona positive patients detected as positive, TN denotes the number of Corona negative cases detected as negative, FP presents the number of cases which are actually negative but detected as Corona positive and FN gives the cases which are actually Corona positive but detected as negative.

Receiver Operating Characteristics (ROC) curve represents the performance of the classifier at different threshold values which plot the TP rates vs FP rates. The confusion matrix and corresponding ROCs of Model 1, Model 2 and Model 3 are presented in Fig 5, Fig 6 and Fig 7 respectively. Top left square of the matrices denotes the TP cases and top right denotes the FN cases whereas bottom left and right squares present the FP and TN cases respectively.

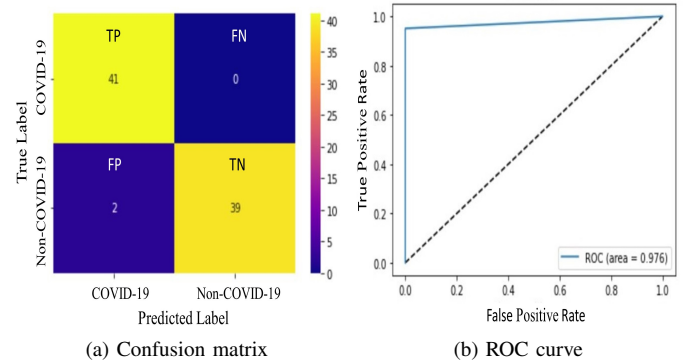


Fig. 5. (a) Confusion matrix and (b) ROC curve of Model 1

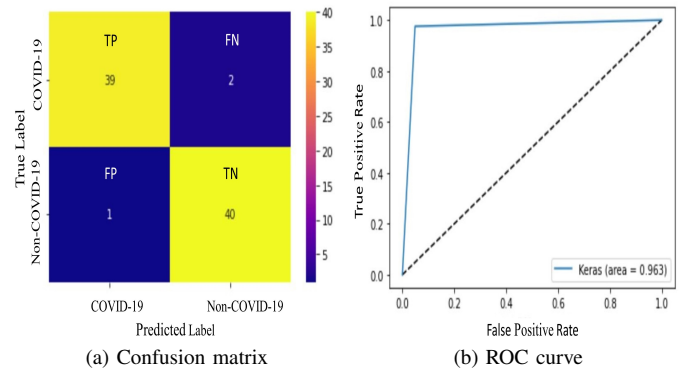


Fig. 6. (a) Confusion matrix and (b) ROC curve of Model 2

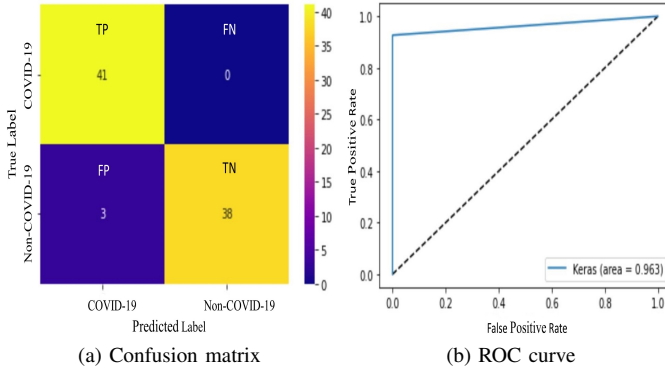


Fig. 7. (a) Confusion matrix and (b) ROC curve of Model 3

Model 1 detects 41 TP and 39 TN cases, Model 2 finds 39 TP and 40 TN cases whereas, Model 3 detects 41 TP and 38 TN cases. The ROC curve areas of Model 1, 2 and 3 are respectively 0.976, 0.963, 0.963. It is evident from the confusion matrix and ROC curves that Model 1 performs better in terms of case detection.

Accuracy defines how close the generated result is close to the actual value whereas precision measures the percentage of the relevant results. Recall or sensitivity is another important factor for evaluating a CNN model. It is defined by the percentage of the total relevant results that a model can correctly classify. F1-score combines both precision and recall and it is designated as the weighted average of these two. Equation 1-4 represents accuracy, precision, recall, and F1 score respectively.

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

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 \text{ Score} = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \quad (4)$$

Table I shows the confusion matrix parameters, accuracy, precision, recall and F1-score of the mentioned three models.

The F1-score of the Model 1, 2, and 3 are 97.61, 96.29, 96.46 respectively. The overall performance and also the F1-score of the proposed model (Model 1) show better performance than that of the other two. The accuracy of the proposed model is 97.56% with the precision and recall value of 95.34% and 100% respectively. The overall performance including accuracy and F1-score can be improved further by training the model with a larger dataset.

TABLE I
CONFUSION MATRIX PARAMETERS AND PERFORMANCE METRICS OF THE MODELS

Model	TP	TN	FP	FN	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Model 1	41	39	2	0	97.56	95.34	100	97.61
Model 2	39	40	1	2	96.34	97.5	95.12	96.29
Model 3	41	38	3	0	96.34	93.18	100	96.46

V. CONCLUSION

Mass testing and early detection of COVID-19 play an important role in preventing the spread of this recent global pandemic. Time, cost, and accuracy are the few major factors in any disease detection process specially COVID-19. To address these issues, a CNN based model is proposed in this paper for detecting COVID-19 cases from patients' chest X-rays. A set of 330 chest X-ray images which are equally divided into two classes: 'COVID-19' and 'Normal', are used for training the model. Similarly, an equally divided image set of 82 chest X-rays are used for validation of the model. This model performs with accuracy and precision of 97.56% and 95.34% respectively. Moreover, this model is compared to the other two CNN models with a different number of convolutional layers. The comparative studies show better F1-score and overall performance of the proposed model (Model 1) than that of other two. This model can be improved further with the availability of the larger dataset. So, CNN has great prospects in detecting COVID-19 with very limited time, resources, and costs. Though the proposed model shows promising results, it is in no way clinically tested. This model needs further improvements and clinical testing for it to work in clinical diagnosis.

REFERENCES

- [1] P. Y. Simard, D. Steinkraus, J. C. Platt *et al.*, "Best practices for convolutional neural networks applied to visual document analysis" in *Icdar*, vol. 3, no. 2003, 2003.
- [2] K. O'Shea and R. Nash, "An introduction to convolutional neural networks" *arXiv preprint arXiv:1511.08458*, 2015.
- [3] A. Bhandare, M. Bhide, P. Gokhale, and R. Chandavarkar, "Applications of convolutional neural networks" *International Journal of Computer Science and Information Technologies*, vol. 7, no. 5, pp. 2206–2215, 2016.
- [4] K. Suzuki, "Overview of deep learning in medical imaging" *Radiological physics and technology*, vol. 10, no. 3, pp. 257–273, 2017.
- [5] Y.-C. Wu, C.-S. Chen, and Y.-J. Chan, "The outbreak of covid-19: An overview" *Journal of the Chinese medical association*, vol. 83, no. 3, p. 217, 2020.
- [6] W. H. O., "Modes of transmission of virus causing covid-19: implications for ipc precaution recommendations: scientific brief, 27 march 2020" World Health Organization, Tech. Rep., 2020.
- [7] W. H. O. coronavirus disease (COVID-19) dashboard. Geneva: World health organization, 2020. [Online]. Available: <https://covid19.who.int/>
- [8] W. H. O. coronavirus disease (COVID-19) newsroom. Geneva: world-healthorganization2020. [Online]. Available: <https://www.who.int/news-room/detail/07-04-2020-who-lists-two-covid-19-tests-for-emergency-use>
- [9] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity" *The bulletin of mathematical biophysics*, vol. 5, no. 4, pp. 115–133, 1943.

- [10] M. Liang and X. Hu, "Recurrent convolutional neural network for object recognition" in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 3367–3375.
- [11] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, G. Wang, J. Cai *et al.*, "Recent advances in convolutional neural networks" *Pattern Recognition*, vol. 77, pp. 354–377, 2018.
- [12] K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position" *Biological cybernetics*, vol. 36, no. 4, pp. 193–202, 1980.
- [13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.
- [14] M. D. Zeiler and R. Fergus, "Visualizing and understanding convolutional networks" in *European conference on computer vision*. Springer, 2014, pp. 818–833.
- [15] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition" *arXiv preprint arXiv:1409.1556*, 2014.
- [16] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghahfaridian, J. A. Van Der Laak, B. Van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis" *Medical image analysis*, vol. 42, pp. 60–88, 2017.
- [17] A. S. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on mri" *Zeitschrift für Medizinische Physik*, vol. 29, no. 2, pp. 102–127, 2019.
- [18] J. Hung and A. Carpenter, "Applying faster r-cnn for object detection on malaria images" in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2017, pp. 56–61.
- [19] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan, and C. K. Chua, "Automated detection of coronary artery disease using different durations of ecg segments with convolutional neural network" *Knowledge-Based Systems*, vol. 132, pp. 62–71, 2017.
- [20] S. L. Oh, Y. Hagiwara, U. Raghavendra, R. Yuvaraj, N. Arunkumar, M. Murugappan, and U. R. Acharya, "A deep learning approach for parkinson's disease diagnosis from eeg signals" *Neural Computing and Applications*, pp. 1–7, 2018.
- [21] S. A. Prajapati, R. Nagaraj, and S. Mitra, "Classification of dental diseases using cnn and transfer learning" in *2017 5th International Symposium on Computational and Business Intelligence (ISCBI)*. IEEE, 2017, pp. 70–74.
- [22] H. Liao, "A deep learning approach to universal skin disease classification" *University of Rochester Department of Computer Science, CSC*, 2016.
- [23] E. Hosseini-Asl, R. Keynton, and A. El-Baz, "Alzheimer's disease diagnostics by adaptation of 3d convolutional network" in *2016 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2016, pp. 126–130.
- [24] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks" *arXiv preprint arXiv:2003.10849*, 2020.
- [25] J. Zhang, Y. Xie, Y. Li, C. Shen, and Y. Xia, "Covid-19 screening on chest x-ray images using deep learning based anomaly detection" *arXiv preprint arXiv:2003.12338*, 2020.
- [26] L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, "Finding covid-19 from chest x-rays using deep learning on a small dataset" *arXiv preprint arXiv:2004.02060*, 2020.
- [27] P. K. Sethy and S. K. Behera, "Detection of coronavirus disease (covid-19) based on deep features" *Preprints*, vol. 2020030300, p. 2020, 2020.
- [28] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks" *Physical and Engineering Sciences in Medicine*, p. 1, 2020.
- [29] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song *et al.*, "Artificial intelligence distinguishes covid-19 from community acquired pneumonia on chest ct" *Radiology*, p. 200905, 2020.
- [30] P. Afshar, S. Heidarian, F. Naderkhani, A. Oikonomou, K. N. Plataniotis, and A. Mohammadi, "Covid-caps: A capsule network-based framework for identification of covid-19 cases from x-ray images" *arXiv preprint arXiv:2004.02696*, 2020.
- [31] L. Wang and A. Wong, "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images" *arXiv preprint arXiv:2003.09871*, 2020.
- [32] J. P. Cohen, P. Morrison, and L. Dao, "Covid-19 image data collection" *arXiv 2003.11597*, 2020. [Online]. Available: <https://github.com/ieee8023/covid-chestxray-dataset>
- [33] P. Mooney. Chest x-ray images (pneumonia). [Online]. Available: <https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia>