Journal of Engg. Research Vol.9 No. (4A) pp. 87-97 DOI:10.36909/jer.12233

COVID-XIX-Net: Deep learning empirical comparison between X-ray imaging and POCUS for COVID-19 detection

Marwa Kandil, Ali Kelkawi, Imtiaz Ahmad and Mohammed Al-Failakawi*

Computer Engineering Department, College of Engineering & Petroleum, Kuwait University, Kuwait
** Corresponding Author : alfailakawi.m@ku.edu.kw*

Submitted ***:*** 18/11/2020
Revised ***:*** 13/04/2021
Accepted ***:*** 25/04/2021

ABSTRACT

The novel COVID-19 virus has been spreading vigorously through the world, starting a pandemic that was never experienced before in our modern era. It is an infectious disease caused by severe acute respiratory syndrome and carries symptoms such as cough, fever, and shortness of breath. In March 2020, the World Health Organization recognized COVID-19 as a pandemic, with more than 130 million cases in over 200 countries and over 2.8 million deaths since its discovery. With a limited number of test kits available worldwide and the rapid spread of the disease on a daily basis, alternative means of detection are needed. The use of X-ray imaging, CT scans, and lung point-of-care ultrasound (POCUS) facilitated early diagnosis of COVID-19 cases. In this study, we leverage InceptionV3 and ResBlocks in building a deep convolutional neural network model, COVID-XIX-Net, to aid in the detection of COVID-19 positive cases through the detection of pneumonic patterns in chest X-ray images and ultrasound scans. COVID-XIX-Net is a multiclass classification model that classifies images into one of 3 classes: healthy, bacterial pneumonia, and COVID-19-induced pneumonic lungs. The proposed model architecture aims at accurately diagnosing COVID-19 cases while maintaining a low number of parameters. COVID-XIX-Net is tested on a balanced X-ray dataset composed of 1,011 images, and an imbalanced ultrasound dataset composed of 1,103 images. After training, cross-validation, and testing, COVID-XIX-Net achieved an accuracy of 99.9% with precision and recall of 0.99 for the X-ray dataset, and an accuracy, precision, and recall of 89.9%, 0.97, and 0.90, respectively, for the case of ultrasound dataset. Results are compared against recent literature showing promising results and great potential with only 24.6M parameters. This work can be further developed and trained to assist medical practitioners in diagnosing COVID-19 cases.

Keywords: COVID-19; Deep learning; Convolutional neural network; X-ray imaging; Ultrasound.

INTRODUCTION

Since its emergence in December 2019 in Wuhan, China, the novel coronavirus (COVID-19) has been rapidly spreading worldwide, with upwards of 130 million cases in total and 2.8 million deaths (Worldometers, 2020). As of 11 March 2020, the World Health Organization (WHO) has recognized the disease as a pandemic due to its rapid and wide spreading. Such alarming numbers are causing a tremendous strain on the health sector, with an increasing demand for intensive care units, medical professionals and medical supplies. Deep learning algorithms, namely convolutional neural networks, have recently been used in radiology to help radiologists in making informed decisions as well as automatically detecting and classifying certain features (Abdelhafiz et al., 2019; Ma et al., 2019; Zhang and Sejdić, 2019). While the fight against COVID-19 is mainly taking place on the medical front, the aim of research in artificial intelligence is to assist medical professionals in making informed decisions in a more timely fashion by automating different processes (Bullock et al., 2020; Shi et al., 2020, Nguyen, 2020; Dong et al, 2020).

One of the key factors in reducing the number of infectious cases is through the detection and containment of COVID-19 positive cases. Currently, this is done by using reverse transcription-polymerase chain reaction (RT-PCR) test kits (Ai et al., 2020). This sensitive tool is able to detect the RNA of the virus in swabs taken from the mouth or nose. Many countries have now adopted this testing strategy as their primary method of testing for COVID-19. However, one downside to RT-PCR tests is the time and resources needed to collect, transport and process the samples, leading to prolonged waiting times for results, during which patients run the risk of infecting others. Therefore, a faster method of screening suspected cases is needed.

Several phenomena in the lungs have been linked to possible infection with COVID-19, with medical practitioners using X-ray imaging, CT scans and lung point-of-care ultrasound (POCUS) in diagnosing COVID-19 cases. Automating the process of detection through the use of artificial intelligence may prove to be an effective method of speeding up the process of making more accurate predictions about the presence of COVID-19 in patients (Chowdhury, 2020). In this study, we propose a deep convolutional neural network multiclass classifier and apply it to chest X-ray and ultrasound images to distinguish between healthy, pneumonic and COVID-19-induced pneumonic lungs. We introduce COVID-XIX-Net, a deep CNN model that utilizes InceptionV3 and native ResBlocks as submodels to reduce complexity of the problem while maintaining high classification performance in two datasets of X-ray images and ultrasound scans. Our contributions are summarized as follows:

1. We conduct an empirical study comparing the effectiveness of COVID-19 detection in chest X-ray images and lung point-of-care ultrasound scans using deep learning techniques.
2. We propose a novel model that utilizes the strong classification power of InceptionV3 with Residual Blocks in a deep convolutional neural network to maintain high classification performance with low number of parameters.
3. We perform multiclass classification by the proposed model on two datasets of X-ray images and ultrasound scans.
4. We conduct a comparative study between X-ray and ultrasound datasets on correctly diagnosing COVID-19 cases based on multiple performance metrics and recent state-of-the-art models.

The rest of the paper is organized as follows: Section 2 reviews related works in the field of COVID-19 detection. Section 3 discusses the proposed framework for the detection and classification of COVID-19 cases. Section 4 presents the results obtained from the classification model and compares it with existing work in the literature. Finally, we summarize the paper and discuss future work in section 5.

RELATED WORKS

Despite the novelty of the disease at hand, there have been efforts to incorporate artificial intelligence in the fight against COVID-19. In this section, we review a number of related works in this field (Shi et al, 2020; Nguyen, 2020). While there are a variety of techniques relating to CT scans, we focus mainly on works related to classification of chest X-ray images and point of care ultrasound images.

Wang and Wong (2020) introduced COVID-Net, an open-source deep CNN aimed at detecting COVID-19 cases through chest X-ray scans. Zhang et al. (2020) developed a deep anomaly detection model for scanning chest

X-ray images and classify them into one of two classes: COVID-19 and non-COVID-19. Hall et al. (2020) used a pretrained ResNet50 model to train a deep learning classifier to detect COVID-19 cases from chest X-ray images. Ghoshal and Tucker (2020) investigated a Drop weights based Bayesian Convolutional Neural Network to diagnose COVID-19 based on chest X-ray scans. Narin et al. (2020) developed an automatic detection system for COVID-19 using chest X-ray images by detecting pneumonia. Afshar et al. (2020) presented COVID-CAPS, a framework built on Capsule Networks to identify COVID-19 cases out of four possible cases (normal, bacterial pneumonia, non-COVID-19 viral pneumonia, and COVID-19 viral pneumonia) from chest X-ray images using small datasets. Luz et al. (2020) proposed a modification of the EfficientNet architecture for classifying chest X-ray images. Oh et al. (2020) proposed a patch-based CNN for classifying chest X-ray images. Karim et al. (2020) proposed DeepCOVIDExplainer, a deep learning framework for prediction of COVID-19 based on chest X-ray images into one of three pneumonic classes: normal, bacterial and COVID-19. Farooq and Hafeez (2020) design COVID-ResNet, which leverages a pretrained ResNet50 architecture to classify chest X-ray images into one of four classes: normal, bacterial pneumonia, non-COVID-19 viral pneumonia, and COVID-19 viral pneumonia. Born et al. (2020) proposed POCOVID-Net, a novel approach using deep learning to classify lung point-of-care ultrasounds into one of three classes: healthy, pneumonia and COVID-19. Panwar et al. (2020) proposed nCOVnet, a deep learning binary classifier for the detection of COVID-19 cases from chest X-ray images. Kassani et al. (2020) compared between different deep learning models for automatic COVID-19 detection based on chest X-ray images and CT scans. Waheed et al. (2020) discussed CovidGAN, a data augmentation technique to assist in improving COVID-19 detection rates from chest X-ray images. Kadry et al. (2020) implemented a machine learning system to detect COVID-19 infection using CT scan slices. Kroft et al. (2019) assessed the effectiveness of using ultra-low-dose CT compared with chest X-ray images in diagnosing chest pathology. Yang et al. (2020) built a COVID-CT dataset to address the difficulty of obtaining open-source dataset of CT scans, applying AI methodology for diagnosing COVID-19 cases. Rajaraman et al. (2020) developed a custom CNN with iteratively pruned models and used ensemble methods in detecting COVID-19 in chest X-ray images. Alam et al. (2021) proposed a feature fusion system for detecting COVID-19 from chest X-ray images.

Numerous other works in the literature have also attempted to address the issue of COVID-19 detection using artificial intelligence (Ulhaq et al, 2020; Latif et al., 2020; Hanumanthu, 2020). In this study, we focus our attention on chest X-ray image and lung point-of-care classifiers with more than two classes to maintain a certain level of complexity and generalization to the problem. In observing these works, we note that performing correct diagnosis of COVID-19 is very critical and misdiagnosis could lead to further spreading of the disease or death. However, maintaining high performance usually means increasing the cost of computations. Our proposed model aims to achieve a higher classification accuracy and recall for COVID-19 class using larger datasets while maintaining a low complexity neural network.

PROPOSED MODEL AND DATASET

In this section, we discuss the dataset used, preprocessing stage techniques, the proposed model architecture and experimental setup.

Dataset

In this study, two separate datasets were used for chest X-ray images and ultrasound scans that contains 3 classes of COVID-19, bacterial pneumonia, and healthy patients. For chest X-ray, images of 337 positive COVID-19 patients have been collected from Github repository shared by Dr. Joseph Cohen and open source Kaggle dataset shared by a research team from Qatar University (Cohen et al, 2020; Chowdhury et al., 2020). In addition, chest X-ray images of 337 patients diagnosed with bacterial pneumonia and 337 healthy patients were obtained from open Kaggle dataset (Kermany et al, 2018). The ultrasound dataset has been collected from GitHub repository developed by Born et. al

(2020). The dataset was collected from video frames of ultrasound scans using Linear and Convex probes for all three classes. A total of 1,103 images with 654 for COVID-19, 277 for bacterial pneumonia and 172 healthy patients. Both datasets were randomly split into 80% for training and 20% for testing. Furthermore, the training datasets were further split to 80% training and 20% validation sets for cross-validation. Since COVID-19 is quite recent, both datasets are limited in number which could result in overfitting of COVID-XIX-Net. Therefore, data augmentation techniques are used on the training and validation batches to enlarge the datasets, reduce overfitting and reduce the imbalance of the ultrasound dataset. Initially, all X-ray images and ultrasound scans were resized to 299×299×3 pixels per image. Data augmentation techniques used include standard normalization, horizontal and vertical flip, rotation (0° ± 50°), zooming (0% ± 10%), shearing (0% ± 25%), width shifting (0% ± 20%), height shifting (0% ± 20%), and channel shifting (0% ± 20%). Sample images of the X-ray and ultrasound datasets are shown in Figure 1.

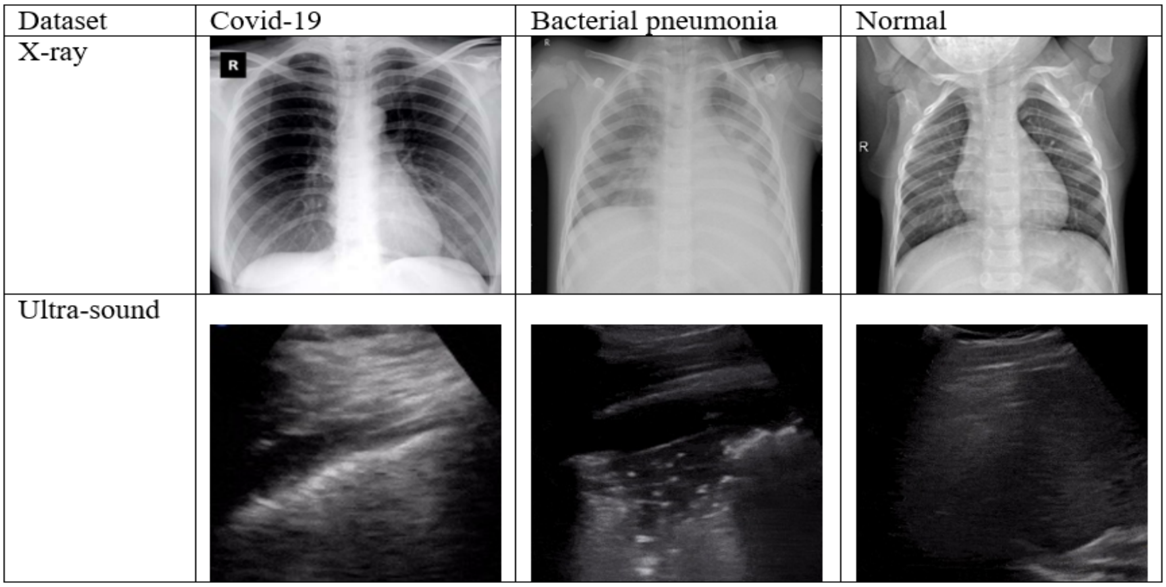


Figure 1: Chest X-ray and ultrasound dataset samples.

Proposed Model

Many deep Convolutional Neural Network (CNN) networks use different combinations of layers to reduce the complexity of computations and extract more features from visual imagery, such as X-ray images and CT-scans. For example, Inception model allows parallel filters to operate on the image to reduce the number of network parameters (Szegedy et al., 2015). Another widely known deep CNN model is the Residual Network model (ResNet), which utilizes a jump connection between the original input and convolution layers to reduce the problem of vanishing gradient (He et al., 2016). Combining both inception and residual blocks techniques was also explored before in Inception ResNet network to improve performance but incurred higher computational cost (Szegedy et al., 2016a). It is important to reduce the number of parameters required for training to reduce computational cost while maintaining high performance. In this research, we propose COVID-XIX Net that utilizes InceptionV3 and native residual blocks as submodels along with a fully connected neural network classifier block to classify X-ray and ultrasound images separately while maintaining low number of parameters yet high performance. The proposed model preforms multiclass classification according to 3 labels: COVID-19, bacterial pneumonia, and healthy patients. The architecture of our model is shown in Figure 2 and details of each block are shown in Figure 3. The stem block consists of InceptionV3 model, a powerful multiclass classification CNN developed by Google that maximizes feature extraction and reduces network complexity (Szegedy et al., 2016b). We used InceptionV3 as it consists of blocks of multiple smaller filters to replace larger filters that are very expensive computationally. According to Szegedy et al. (2016b) there are three different inception modules used within its 42-layers NN generating a total of 24M parameters. An intermediate Batch Normalization (BN) layer is used to normalize the convoluted feature values and stabilize the learning process. The second submodel contains 8 x 2D Convolution layers (2DConv) with kernel size of 3×3, 2D MaxPooling, BN, and dropout layers to extract remaining features. Since the stem block and the second submodel contain a total of 50 layers, the model will face vanishing gradient issue. Two simple native residual blocks (ResBlocks) were used to form jump connections and use identity function where the original input is added to two 2DConv layers of 3×3 filters to prevent any loss of information caused by the problem of vanishing gradient. The structure was inspired by He et al. (2016) original residual block. The final submodel is the classifier model which consists of 8 x 2D Conv with kernel size of 3×3 to reduce the number of parameters thus reduce the complexity of the problem. The generated 2D matrix passes through a flattening layer to be converted into a vector that is fed into a fully connected NN with output of 3 classes.

Experimental Setup

The proposed model was developed with Python 3.6 language using Tensor-Flow and Keras libraries and trained over GPU through Google Co-labs notebooks. Random subsampling cross-validation was used during training of COVID-XIX-Net with the X-ray and ultrasound datasets such that the training datasets are divided into 80% for training and 20% for validation. Data augmentation techniques mentioned earlier were used with training and validation sets. The model was trained over 150 epochs with a batch size of 15 with learning rate 0.0001, Adam optimizer and categorical cross entropy loss function. The top layers of InceptionV3 were not included, but the model was pretrained with ImageNet dataset, and learned weights were transferred for further training over the X-ray and ultrasound datasets.

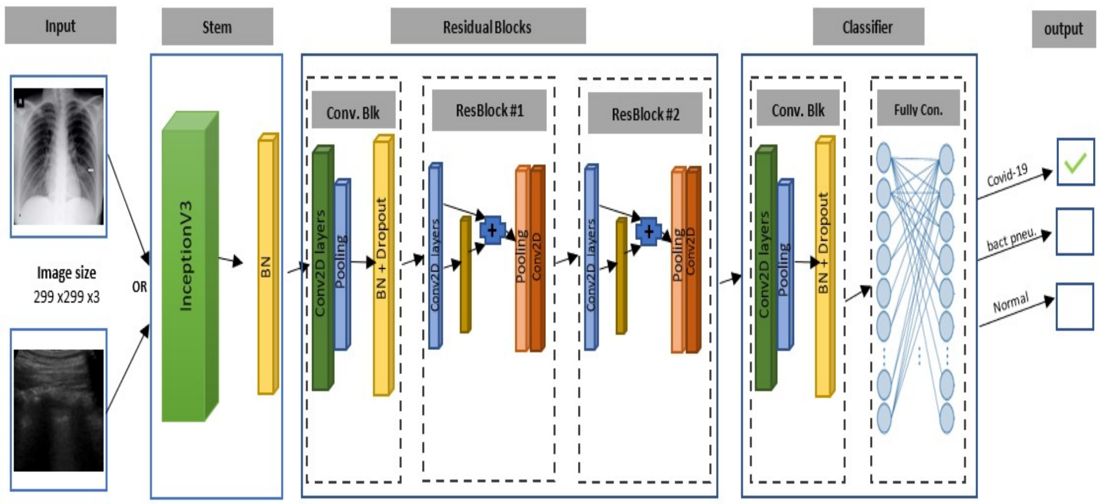


Figure 2: Proposed COVID-XIX-Net model architecture.

Blocks	Layer Type	Output size
Stem Block	InceptionV3 + ImageNet	8 X 8 X 2048
	BN	8 X 8 X 2048
ResBlocks	8 X Conv2D (8,16,32,64) @3x3 + ReLU	8 X 8 X (8 or 16 or 32 or 64)
	MaxPooling2D	4 X 4 X 64
	BN + Dropout (0.3)	4 X 4 X 64
	ResBlock (64) @ 3x3	4 X 4 X 64
	ResBlock (128) @ 3x3	4 X 4 X 128
Classifier Block	8 X Conv2D (64,128,256) @ 3x3 + ReLU	4 X 4 X (64 or 128 or 256)
	MaxPooling2D	2 X 2 X 256
	BN + Dropout (0.3)	2 X 2 X 256
	Fully Connected (512) + ReLU	1 X 1 X 512
	Dense (3) + SoftMax	1 X 1 X 3

Figure 3: COVID-XIX-Net model architecture details. InceptionV3 model developed by Szegedy et al. (2016). BN stands for Batch Normalization layer. The number after the symbol "@", e.g. 3X3, denotes the kernel size of the convolution layer or the residual block.

RESULTS AND EVALUATION

This section presents the performance of COVID-XIX-Net and quantitative metrics used for evaluation. COVID-XIX-Net performance is compared against multiple recent state-of-the-art models and existing deep CNN models.

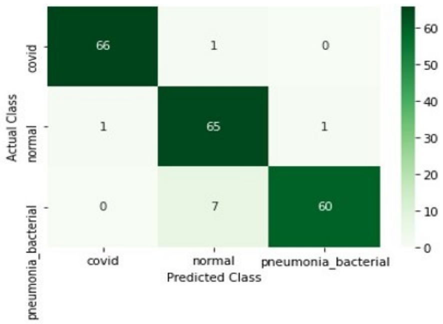
COVID-XIX-Net Results

The model was evaluated on the test sets and the generated average accuracy, average loss and execution time per image are presented in Table 2. As shown in Table 2, the accuracy of the X-ray dataset is better than that of the ultrasound dataset as COVID-XIX Net managed to generate more correct predictions from the X-ray dataset in less time. The ultrasound dataset generated higher loss value which can be attributed to the imbalance in ultrasound dataset. Accuracy alone is normally not enough for a multiclass classification problem; therefore precision, sensitivity and F1-score were considered as shown in Table 2 as they are very critical for diagnosing COVID-19. Moreover, a confusion matrix was generated to visualize the performance of the trained model in classifying the 3 classes. The results are encouraging as shown in Figures 4a and 4b. For the both datasets, COVID-19 class has the highest results when compared to the normal and pneumonia classes. This means that COVID-XIX-Net is better at correctly identifying and classifying evidence of COVID-19 in X-ray images and ultrasound scans. For ultrasound dataset, COVID-19 was the major class in this set, whereas normal and pneumonia were minor classes. It is apparent that this imbalance resulted in much lower precision and recall values where many of the samples were misclassified as COVID-19. The results show clearly that COVID-XIX-Net model performed better when using X-ray dataset compared to the ultrasound dataset, yet, the limited datasets could have affected the performance.

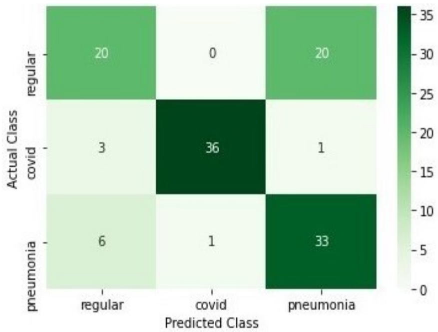
To further evaluate the proposed model, COVID-XIX-Net is compared against multiple existing models and state-of-the-art methods that used either X-ray or ultrasound datasets for multiclass classification of COVID-19. A comparison study of F1-score and execution time for COVID-19 class of multiple existing models is represented in Figure 5. As shown, COVID-XIX-Net achieved the highest F1-score with a reasonable prediction time per image using both X-ray and ultrasound datasets when compared to different deep CNN models. Table 4 presents a comparison study between state-of-the-art models and COVID-XIX-Net. As shown, COVID-Net achieved lower number of parameters compared to COVID-XIX Net, however, the model performance was lower than COVID-XIX-Net. This shows that the difference in complexity allowed COVID-XIX-Net to perform more accurate diagnosis of COVID-19 cases. The use of InceptionV3 and ResBlocks in COVID-XIX-Net architecture allowed the model to outperform Inception-V3, COVID-ResNet, EfficientNet and COVID-ResNet in correctly diagnosing COVID-19 cases while maintaining fair complexity. For the ultrasound dataset, COVID-XIX-Net has higher precision value of 0.97 than POCOVID-Net which indicates more positive COVID-19 cases were diagnosed correctly. This evaluation shows that the proposed COVID-XIX-Net has very promising results while maintaining a simple architecture and reasonable number of parameters.

Table 2: Performance metrics for X-ray and ultrasound datasets.

Dataset	Classes	Precision	Recall	F1-score	Accuracy	Loss	Time
X-ray	COVID-19	0.99	0.99	0.99	99.9%	0.0315	3.55
	Normal	0.89	0.97	0.93			
	Bacterial Pneumonia	0.98	0.90	0.94			
Ultrasound	COVID-19	0.97	0.90	0.94	89.0%	0.354	4.15
	Normal	0.69	0.50	0.58			
	Bacterial Pneumonia	0.61	0.82	0.70			

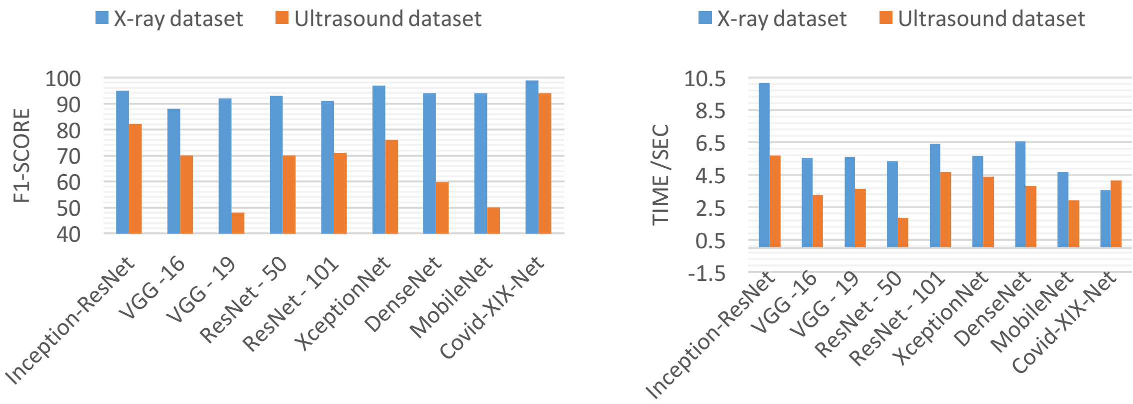


(a) Confusion matrix for X-ray dataset



(b) Confusion matrix for ultrasound dataset

Figure 4: Confusion matrices.



(a) F1-score comparison chart

(b) Execution time comparison chart

Figure 5: Comparison charts.

Table 3: Comparison between COVID-XIX-Net and state-of-the-art models.

Paper	Model	Dataset	Params (M)	Precision	Recall	F1-Score	Accuracy
Wang and Wong (2020)	COVID-Net	X-ray	**11.7**	0.989	0.910	0.947	0.933
Born et al. (2020)	POCOVID-Net	Ultrasound	14.7	0.880	**0.960**	0.920	0.980
Proposed Model	COVID-XIX-Net	X-ray	24.6	0.99	0.99	0.99	**0.999**
		Ultrasound	24.6	**0.970**	0.9	**0.940**	0.89
Rajaraman et al. (2020)	Inception-V3	X-ray	40.6	0.974	0.975	0.974	0.974
Farooq and Hafeez (2020)	COVID-ResNet	X-ray	25.6	**1**	**1**	**1**	0.962
Luz et al. (2020)	EfficientNet	X-ray	30.5	0.906	0.935	0.920	0.922

CONCLUSION

In this study, we introduced COVID-XIX-Net, a deep convolutional neural network built to perform multiclass classification of X-ray images and ultrasound scans into 3 classes: healthy, bacterial pneumonia, and COVID-19-induced pneumonic lungs. COVID-XIX-Net architecture benefits from the low number of parameters and classification power offered by the InceptionV3 while reducing the vanishing gradient problem of the deep network using ResBlocks. Comparison study was carried out against recent existing and state-of-the-art models, where COVID-XIX-Net proved high performance in both datasets with precision of 0.99 and 0.97 respectively for the X-ray and ultrasound datasets. The results showed that the proposed model performed better with X-ray dataset than the ultrasound dataset. Future directions of this research include collecting a larger dataset for chest X-ray images and ultrasound scans of COVID-19 patients. Finally, identifying infected areas and measuring their dimensions in the lungs will be the next scope of this research.

REFERENCES

Worldometers, 2020. COVID-19 Coronavirus Pandemic.

Abdelhafiz, D., Yang, C., Ammar, R. and Nabavi, S., 2019. Deep convolutional neural networks for mammography: advances, challenges and applications. *BMC bioinformatics*, *20*(11), p.281.

Ma, J., Song, Y., Tian, X., Hua, Y., Zhang, R. and Wu, J., 2019. Survey on deep learning for pulmonary medical imaging. *Frontiers of Medicine*, pp.1-20.

Zhang, Z. and Sejdić, E., 2019. Radiological images and machine learning: Trends, perspectives, and prospects. *Computers in biology and medicine*, *108*, pp.354-370.

Bullock, J., Pham, K.H., Lam, C.S.N. and Luengo-Oroz, M., 2020. Mapping the landscape of artificial intelligence applications against COVID-19. *arXiv preprint arXiv:2003.11336*.

Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., He, K., Shi, Y. and Shen, D., 2020. Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for covid-19. *IEEE reviews in biomedical engineering*.

Nguyen, T.T., 2020. Artificial intelligence in the battle against coronavirus (COVID-19): a survey and future research directions. *Preprint, DOI*, *10*.

Dong, D., Tang, Z., Wang, S., Hui, H., Gong, L., Lu, Y., Xue, Z., Liao, H., Chen, F., Yang, F. and Jin, R., 2020. The role of imaging in the detection and management of COVID-19: a review. *IEEE reviews in biomedical engineering*.

Ai, T., Yang, Z., Hou, H., Zhan, C., Chen, C., Lv, W., Tao, Q., Sun, Z. and Xia, L., 2020. Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. *Radiology*, p.200642.

Chowdhury, M.E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M.A., Mahbub, Z.B., Islam, K.R., Khan, M.S., Iqbal, A., Al-Emadi, N. and Reaz, M.B.I., 2020. Can AI help in screening viral and COVID-19 pneumonia?. *arXiv preprint arXiv:2003.13145*.

Born, J., Brändle, G., Cossio, M., Disdier, M., Goulet, J., Roulin, J. and Wiedemann, N., 2020. POCOVID-Net: automatic detection of COVID-19 from a new lung ultrasound imaging dataset (POCUS). *arXiv preprint arXiv:2004.12084*.

Wang, L. and Wong, A., 2020. 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*.

Zhang, J., Xie, Y., Li, Y., Shen, C. and Xia, Y., 2020. Covid-19 screening on chest x-ray images using deep learning based anomaly detection. *arXiv preprint arXiv:2003.12338*.

Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M. and Summers, R.M., 2017. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2097-2106).

Hall, L.O., Paul, R., Goldgof, D.B. and Goldgof, G.M., 2020. Finding covid-19 from chest x-rays using deep learning on a small dataset. *arXiv preprint arXiv:2004.02060*.

Ghoshal, B. and Tucker, A., 2020. Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. *arXiv preprint arXiv:2003.10769*.

Narin, A., Kaya, C. and Pamuk, Z., 2020. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *arXiv preprint arXiv:2003.10849*.

Afshar, P., Heidarian, S., Naderkhani, F., Oikonomou, A., Plataniotis, K.N. and Mohammadi, A., 2020. Covid-caps: A capsule network-based framework for identification of covid-19 cases from x-ray images. *arXiv preprint arXiv:2004.02696*.

Luz, E., Silva, P.L., Silva, R. and Moreira, G., 2020. Towards an efficient deep learning model for covid-19 patterns detection in x-ray images. *arXiv preprint arXiv:2004.05717*.

Oh, Y., Park, S. and Ye, J.C., 2020. Deep learning covid-19 features on cxr using limited training data sets. *IEEE Transactions on Medical Imaging*

Karim, M., Döhmen, T., Rebholz-Schuhmann, D., Decker, S., Cochez, M. and Beyan, O., 2020. Deepcovidexplainer: Explainable covid-19 predictions based on chest x-ray images. *arXiv preprint arXiv:2004.04582*.

Farooq, M. and Hafeez, A., 2020. Covid-resnet: A deep learning framework for screening of covid19 from radiographs. *arXiv preprint arXiv:2003.14395*.

Panwar, H., Gupta, P.K., Siddiqui, M.K., Morales-Menendez, R. and Singh, V., 2020. Application of Deep Learning for Fast Detection of COVID-19 in X-Rays using nCOVnet. *Chaos, Solitons & Fractals*, p.109944.

Kassani, S.H., Kassasni, P.H., Wesolowski, M.J., Schneider, K.A. and Deters, R., 2020. Automatic Detection of Coronavirus Disease (COVID-19) in X-ray and CT Images: A Machine Learning-Based Approach. *arXiv preprint arXiv:2004.10641*.

Waheed, A., Goyal, M., Gupta, D., Khanna, A., Al-Turjman, F. and Pinheiro, P.R., 2020. Covidgan: Data augmentation using auxiliary classifier gan for improved covid-19 detection. *IEEE Access*, *8*, pp.91916-91923.

Ulhaq, A., Khan, A., Gomes, D. and Pau, M., 2020. Computer Vision for COVID-19 Control: A Survey. *arXiv preprint arXiv:2004.09420*.

Latif, S., Usman, M., Manzoor, S., Iqbal, W., Qadir, J., Tyson, G., Castro, I., Razi, A., Boulos, M.N.K., Weller, A. and Crowcroft, J., 2020. Leveraging Data Science To Combat COVID-19: A Comprehensive Review.

rekha Hanumanthu, S., 2020. Role of Intelligent Computing in COVID-19 Prognosis: A State-of-the-Art Review. *Chaos, Solitons & Fractals*, p.109947.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1-9).

He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

Szegedy, C., Ioffe, S., Vanhoucke, V. and Alemi, A., 2016a. Inception-v4, inception-resnet and the impact of residual connections on learning. *arXiv preprint arXiv:1602.07261*.

Cohen, J.P., Morrison, P., Dao, L., Roth, K., Duong, T.Q. and Ghassemi, M., 2020. Covid-19 image data collection: Prospective predictions are the future. *arXiv preprint arXiv:2006.11988*.

Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F. and Dong, J., 2018. Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, *172*(5), pp.1122-1131.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., 2016b. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).

Kadry, S., Rajinikanth, V., Rho, S., Raja, N. S. M., Rao, V. S., & Thanaraj, K. P., 2020. Development of a machine-learning system to classify lung ct scan images into normal/covid-19 class. *arXiv preprint arXiv:2004.13122*.

Kroft, L. J., van der Velden, L., Girón, I. H., Roelofs, J. J., de Roos, A., & Geleijns, J., 2019. Added value of ultra–low-dose computed tomography, dose equivalent to chest x-ray radiography, for diagnosing chest pathology. *Journal of thoracic imaging*, *34*(3), 179.

Yang, X., He, X., Zhao, J., Zhang, Y., Zhang, S., & Xie, P., 2020. COVID-CT-Dataset: a CT image dataset about COVID-19. *arXiv preprint arXiv:2003.13865*.

Rajaraman, S., Siegelman, J., Alderson, P. O., Folio, L. S., Folio, L. R., & Antani, S. K., 2020. Iteratively pruned deep learning ensembles for covid-19 detection in chest x-rays. *IEEE Access*, *8*, 115041-115050.

Alam, N. A., Ahsan, M. M., Based, M. A., Haider, J., & Kowalski, M., 2021. COVID-19 Detection from Chest X-Ray images using Feature Fusion and Deep learning. *Sensors*, *21*(4).