COVIDetect: A Desktop Application as a Diagnostic Tool for Novel Coronavirus (COVID-19) Pneumonia in Chest X-ray Images Using Convolutional Neural Network

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Abstract: The COVID-19 pandemic has heavily affected the well-being of people worldwide. Current diagnostic tools, like the RT-PCR, are expensive and time-consuming; thus, there is a need for cheaper and faster means of COVID-19 detection. This study proposes using a desktop application with a convolutional neural network (CNN) and visual analysis as a supplementary diagnostic tool for detecting COVID-19 pneumonia in chest X-ray images. The CNN used is a sequential Keras model that was trained and tested through eight epochs using an augmented dataset. Random data augmentation techniques applied were rotation and horizontal flipping, which increased the total images used to 13,584. Visual analysis was created using the Grad-CAM algorithm to determine patterns in chest X-ray images. These were implemented in a desktop application and evaluated by a professional pulmonologist. Results showed that the CNN achieved an average accuracy rate of 97.96% among the three classes, which was superior among related studies. The CNN also achieved a precision, recall, and F1-score of 99.67%, 99.62%, and 99.64% respectively for COVID-19 pneumonia, 99.26%, 94.83%, and 96.99% respectively for viral pneumonia, and 95.12%, 99.42%, and 97.22% respectively for normal chest X-ray images. Meanwhile, the visual analysis was also accurate, as evaluated by a professional pulmonologist, where patterns of haziness were determined. Hence, this could serve as an effective supplementary diagnostic tool for healthcare professionals for faster and more accurate diagnosis of COVID-19 and viral pneumonia patients.

Key Words: COVID-19; pneumonia; convolutional neural network; chest x-ray image; desktop application; Grad-CAM

1. INTRODUCTION

The Novel coronavirus or COVID-19 has become a global pandemic since 2020, caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Gunraj et al., 2020). The World Health Organization, as cited by Khan et al.t (2020), stated that a patient that is positive for COVID-19 may develop symptoms such as fever and dry cough, pneumonia, multi-organ failure, chest pain, loss of speech or movement, and death upon infection.

As of the present, several testing methods are used in testing COVID-19 among the possible carriers of the virus. However, these tests can be quite inaccurate as the most used testing method which is the RT-PCR test has a sensitivity rate of 71% to 98% and a specificity rate of 98% to 100% in COVID-19 diagnosis (Agarwal et al.,, 2020). Hence, there is a need for faster and more efficient means for COVID-19 detection.

Recently, studies have been done to further detect and analyze COVID-19 pneumonia using deep learning through chest X-ray images. Wang et al. (2020) suggested that chest X-rays are faster to operate than RT-PCR kits which take days to get results. The presence of X-ray machines in medical facilities adds to the availability and accessibility of the said testing method. Testing can also be done in a fixed X-ray machine instead of transporting the test kits from one location to another. However, present research on automated detection of COVID-19 pneumonia using deep learning techniques were challenged by the insufficient amount of identifiable chest X-rays since the outbreak was recent, possibly causing overfitting in some neural networks that would yield less accurate results.

Thus, this research study aimed to develop a convolutional neural network trained on an augmented dataset, implemented through a desktop application with visual analysis, as a low-cost, automatic, supplementary diagnostic tool for novel coronavirus (COVID-19) pneumonia and viral pneumonia from chest X-ray images utilizing deep learning techniques. Data augmentation will be implemented to a chest X-ray dataset to produce more images with different variations and obtain more accurate results.

To support this, the effectiveness of the developed model in terms of accuracy, precision, sensitivity, and F1 score in detecting the COVID-19, viral pneumonia and normal chest X-Ray images was determined. Additionally, the accuracy of the developed model was compared to other existing CNN models or architectures that also detected the same diseases. A qualitative feedback on the desktop application from an expert pulmonologist was also obtained to further assess its effectiveness.

This study may be deemed significant to COVID-19 positive patients as they can have a real-time assessment of the status of COVID-19 pneumonia if they are symptomatic. Also, medical frontliners, radiologists, and specialized virology doctors, can be greatly assisted through fast and automated detection of COVID-19 pneumonia by analyzing X-ray images among possible COVID-19 positive patients. Along with this, hospitals and specialized COVID-19 facilities can be benefited from this research as automated COVID-19 pneumonia detection can be done using X-rays and computers which are readily available across most health establishments.

2. METHODOLOGY

2.1. Development of Augmented Dataset

The dataset utilized in this study is the COVID-19 Radiography Database developed by Chowdhury et al. (2020), which is made up of 1200 COVID-19 pneumonia, 1,345 viral pneumonia, and 1,341 normal chest X-ray images. To maximize the size of the dataset, data augmentation was applied using scikit-image, where two transformational techniques were utilized: rotation and horizontal flipping. Using data augmentation, overfitting is significantly reduced from image processing models (Gunraj et al.,, 2020). This resulted in an augmented dataset that is composed of 13,584 chest X-ray images, as seen in Table 2.1.

Table 2.1. Number of Images Before and After Data Augmentation of the Dataset.

	Number of Images Before Augmentation	**Number of Images After Augmentation**
COVID-19 Pneumonia	1200	4205
Viral Pneumonia	1345	4697
Normal	1341	4682
Total	**3886**	**13,584**

2.2. Development of the Convolutional Neural Network (CNN)

A sequential CNN was constructed using Keras and Tensorflow, where its architecture is seen in Figure 2.1. The chest X-ray is inputted in the model and enters the rescaling layer, where its dimension is resized to 256 x 256. Afterward, it undergoes 3 repetitions of a convolutional layer and a max-pooling layer. A convolutional layer extracts the features from the images. Meanwhile, a max-pooling layer attains the maximum element from the feature map extracted by the convolutional layer. Lastly, it undergoes two dense or fully connected layers, which takes the output of the previous layers, then flattens and converts them into a single vector. The probability for each class is then calculated.

After constructing the convolutional neural network, the model ran through eight epochs for training and testing. 80% of the dataset was utilized for training the model, while the remaining 20% was utilized for testing the model.

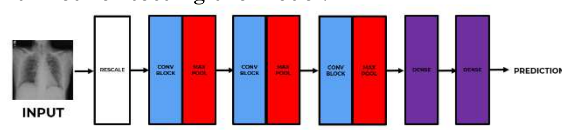

Figure 2.1. CNN Architecture of the Model

2.3. Development of the Desktop Application with Visual Analysis

The developed CNN was implemented through a desktop application using Tkinter. The user interface, as seen in Figure 2.2, shows the draft of the elements of the desktop application. The "Upload Chest X-ray Image" button allows users to upload chest X-ray images to be classified among the three groups. Once uploaded, the image would be seen in the left region, while a visual analysis using Gradient-weighted Class Activation Mapping (Grad-CAM) is provided on the right. The results of the classification would be provided at the classification label at the bottom side of the application.

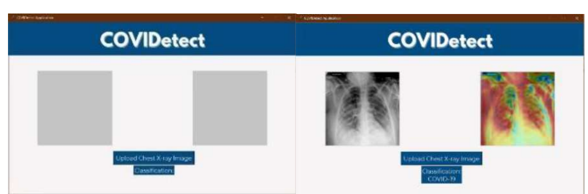

Figure 2.2. General User Interface of the Desktop Application

2.4. CNN and Desktop Application Evaluation

To assess the performance of the convolutional neural network, the following specific metrics were obtained: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These were visualized using a confusion matrix, which showed the true values of the specific metrics by arranging the data in terms of its classification.

Afterward, the following performance metrics were calculated: accuracy, precision, sensitivity and F1 score. These performance metrics assess the performance and effectiveness of the developed model in classifying the chest X-ray images. The formulas for these performance metrics are:

Accuracy = (TP+TN) / (TP+TN+FP+FN)
Precision = TP / (TP+FP)
Recall = TP / (TP + FN)
F1 Score = 2 x (Recall x Precision) / (Recall + Precision)

The average accuracy of the model was then compared to the average accuracy of other studies that classify the same groups.

Meanwhile, to assess the performance of the desktop application, a professional pulmonologist tested the application and evaluated it through an interview.

3. RESULTS AND DISCUSSION

The confusion matrix in Table 3.1 showed that the model predicted most chest X-ray images correctly. Therefore, it could be said that the developed model is successful in classifying these images efficiently since convolutional neural networks have the property of extracting similar features or patterns in the chest X-ray images (Khan et al., 2020). The convolutional layers in the model serve as successive filters in detecting significant features in an image. Meanwhile, max-pooling layers reduce the complexity of the image by returning only the maximum value of sub-regions in the image. Lastly, fully connected or dense layers are connected to previous layers and flatten the previous output to convert it into a single vector (Albawi et al., 2018).

Table 3.1. Confusion Matrix Result of COVIDetect in Classifying COVID19, Viral Pneumonia, and Normal Chest X-ray Images

Predicted Value

True Value	COVID19	Viral Pneumonia	Normal
COVID19	4189	8	8
Viral Pneumonia	12	4454	231
Normal	2	25	4655

Correctly Classified Images   Misclassified Images'

Overall, it has been observed that the convolutional neural network performed efficiently in classifying these images, where performance metrics obtained were above 90% for all classifications as seen in Table 4.2.

Table 4.2. Performance Metrics of the CNN in Classifying COVID-19, Viral Pneumonia, and Normal Chest X-ray Images

Class	Precision / Specificity	Recall / Sensitivity	F1 score	Average Accuracy
COVID-19	99.67%	99.62%	99.64%	97.96%
Viral Pneumonia	99.26%	94.83%	96.99%	
Normal	95.12%	99.42%	97.22%	

The high precision rate of 99.67% for COVID-19 is essential since this indicates that there would be fewer false-positive cases of misclassified COVID-19 diagnosis. Meanwhile, the high recall rate of 99.62% for COVID-19 is also necessary since this indicates that there would be less false-negative diagnosis of COVID-19. Decreasing the chances of these types of misdiagnosis would further decrease the spread of the COVID-19 virus in the community through immediate and proper detection (Wang et al, 2020). Meanwhile, high performance metrics were also obtained by the convolutional neural network for viral pneumonia and normal chest X-ray images, implying that it would also be less likely to misdiagnose normal patients and those with viral pneumonia.

The average accuracy of the developed model was then compared to related studies that detect the same classifications, as seen in Table 4.3. It has been observed that the results obtained by the model were relatively higher compared to other studies that detect the same three classes.

Table 4.3. Comparison of Average Accuracy with Other Related Studies

Study	Architecture	Average Accuracy for Three Classes (%)
COVIDetect	Keras - Sequential	97.96%
Apostolopoulos et al.	VGG-19	93.48%
Wang et al.	COVID-Net	93.3%
Apostolopoulos et al.	MobileNet v2	92.85%
Apostolopoulos et al.	Inception	92.85%
Apostolopoulos et al.	Xception	92.85%
Apostolopoulos et al.	Inception ResNet v2	92.85%
Khan et al.	CoroNet	89.60%

Despite using a simpler convolutional neural network, the obtained average accuracy in detecting the three classes was the highest among related models. This is possibly caused by the sequential neural network being trained on an augmented dataset.

Related studies face the challenge of using an insufficient number of COVID-19 chest X-ray images due to limited data available since the pandemic was recent. It could be observed that most studies that attained a relatively lower average accuracy used fewer images for training and testing their models. Apostolopoulos et al. (2020) made use of 305 COVID-19, 2780 pneumonia, and 1583 normal chest X-ray images for the use of 4 of their model architectures that attained 93.48% for VGG-19 and 92.85% for MobileNet v2, Inception, Xception, and Inception ResNet v2. Meanwhile, Khan et al. (2020) made use of 290 COVID-19, 327 viral pneumonia, and 310 normal chest X-ray images.

Through using data augmentation and developing an augmented dataset, this limitation is resolved. In a study by Wang & Perez (2017), they explored the use of data augmentation in the field of deep learning. Models that made use of small datasets often encounter overfitting since these do not generalize data well. Through data augmentation, more data is generated from the training data for an algorithm to perform better.

Through an evaluation of the COVIDetect desktop application by a professional pulmonologist, he stated that it accurately classifies COVID-19 and viral pneumonia, while there were minor misclassifications for normal chest X-ray images where these were misidentified as viral pneumonia. These misclassifications could be attributed to the haziness present in some normal chest X-ray images that were similar to those with viral pneumonia. Meanwhile, the visual analysis using Grad-CAM was also evaluated as accurate since the red spots effectively cover affected areas or areas with haziness.

Asides from the features of the desktop application, its usability and design were also assessed, and the professional pulmonologist stated that the application was simple, practical, and easy to use. He recommends adding the personal details of patients such as name and age, as well as including bacterial pneumonia in the application's classification.

4. CONCLUSION

Based on the gathered results and findings of the study, the following conclusions were drawn. First, the developed model achieved an average accuracy of 97.96% for detecting COVID-19 pneumonia, viral pneumonia, and normal chest X-ray images. Specifically, it achieved a precision, recall, and F1-score of 99.67%, 99.62%, 99.64% respectively for COVID-19 pneumonia, 99.26%, 94.83%, 96.99% respectively for viral pneumonia, and 99.26%, 94.83%, 96.99% respectively for normal chest X-ray images. Second, the developed model achieved the highest average accuracy compared to other related studies that detect the same classifications, mainly attributed to the CNN being trained on an augmented dataset. Lastly, the COVIDetect desktop application was evaluated by a professional pulmonologist and its CNN was assessed as accurate with minor misclassifications, while its visual analysis was also assessed as accurate since it effectively covers all affected areas with haziness. The application was also determined to be simple, practical, and easy to use.

Future studies might consider using different architectures for the construction of their CNN. It is also recommended to further expand the scope of the study by including bacterial pneumonia classification and detection of other COVID-19 variants such as the UK variant and P3 variant. Future researchers might also determine the severity of COVID-19 present in the chest X-ray images so people with severe COVID-19 disease can easily be diagnosed. Furthermore, other related methods which are equally available and accessible as chest X-ray image classification can be explored by future researchers. The study can also be improved once more training data are publicly available.

5. ACKNOWLEDGEMENTS

The researchers wish to extend their deepest gratitude and utmost appreciation and recognition to the following persons and institutions who have helped us in the finalization and completion of this research manuscript.

Dr. Allen Roxas, an expert pulmonologist at Mary Mediatrix Medical Center (MMMC) in Lipa City, for his valuable clarifications, insights, suggestions, recommendations, and additional knowledge that he has provided us during the interview with him as part of our methodology. The researchers are also grateful for him because of his accommodation and help in fulfilling one part of our methodology.

Ms. Amy U. Aclan, research adviser of the researchers, for her honest remarks and criticisms on the study that inspired the researchers to improve the desktop application and the research paper, and for her patience in checking and reviewing our manuscript throughout the research process.

Mrs. Cladys M. Falcunaya, research teacher of the researchers, for her consistent emotional support and constructive criticisms and suggestions regarding the study that helped the researchers to pursue this research study on a higher note.

Mr. and Mrs. Vicente and Imelda Arellano and Mr. and Mrs. Mon and Noemi Tolentino, the parents of the researchers, for their unending support and encouragement to the researchers in fulfilling their research requirements and responsibilities.

And most importantly to PSHS CALABARZON Region Campus, for their provision of high-quality research facilities and professionals to work with in accomplishing all the tasks needed for the completion of the research manuscript.

6. REFERENCES

Agarwal, N., Raheja, A., & Suri, A. (2020). Guidelines for Preoperative Testing for Neurosurgery in COVID-19 Era: Indian Viewpoint Amidst Global Practice. World Neurosurgery.

Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2018). Understanding of a convolutional neural network. Proceedings of 2017 International Conference on Engineering and Technology, ICET 2017, 2018-Janua, 1–6. doi: 10.1109/ICEngTechnol.2017.8308186

Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 43(2), 635–640. doi: 10.1007/s13246-020-00865-4

Böger, B., Fachi, M. M., Vilhena, R. O., Cobre, A. de F., Tonin, F. S., & Pontarolo, R. (2020). Systematic review with meta-analysis of the accuracy of diagnostic tests for COVID-19. American Journal of Infection Control. doi:10.1016/j.ajic.2020.07.011

Chouhan, V., Singh, S. K., Khamparia, A., Gupta, D., Tiwari, P., Moreira, C., Damaševičius, R., & de Albuquerque, V. H. C. (2020). A novel transfer learning-based approach for pneumonia detection in chest X-ray images. Applied Sciences (Switzerland), 10(2). https://doi.org/10.3390/app10020559

Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z., Islam, M. T. (2020). Can AI Help in Screening Viral and COVID-19 Pneumonia? IEEE Access, 8, 132665–132676. https://doi.org/10.1109/ACCESS.2020.3010287

Fang, Y., Zhang, H., Xie, J., Lin, M., Ying, L., Pang, P., & Ji, W. (2020). The sensitivity of Chest CT for COVID-19: Comparison to RT-PCR. Radiology, 296(2). https://doi.org/10.1148/radiol.2020200432

Gunraj, H., Wang, L., & Wong, A. (2020). COVIDNet-CT: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest CT Images. 1–12. Retrieved from http://arxiv.org/abs/2009.05383

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Identity mappings in deep residual networks. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9908 LNCS, 630–645. https://doi.org/10.1007/978-3-319-46493-0_38

Khan, A. I., Shah, J. L., & Bhat, M. M. (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest X-ray images. Computer Methods and Programs in Biomedicine, 196, 105581. https://doi.org/10.1016/j.cmpb.2020.105581

Magsambol, B. (2020, May 25). FAST FACTS: What's the difference between PCR, rapid antibody tests? Retrieved November 26, 2020, from https://www.rappler.com/newsbreak/iq/things-to-know-polymerase-chain-reaction-rapid-anti-body-tests

Mahmud, T., Rahman, M. A., & Fattah, S. A. (2020). CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. Computers in Biology and Medicine, 122(June), 103869. https://doi.org/10.1016/j.compbiomed.2020.103869

Rahman, T., Chowdhury, M. E. H., & Khandakar, A. (2020). Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-Ray.

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Ball, R. L., Langlotz, C., Shpanskaya, K., Lungren, M. P., & Ng, A. Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. ArXiv, 3–9.

Shibly, K. H., Dey, S. K., Islam, M. T. U., & Rahman, M. M. (2020). COVID faster R–CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-Ray images. Informatics in Medicine Unlocked, 20, 100405. https://doi.org/10.1016/j.imu.2020.100405

Sirazitdinov, I., Kholiavchenko, M., Mustafaev, T., Yixuan, Y., Kuleev, R., & Ibragimov, B. (2019). Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database. Computers and Electrical Engineering, 78, 388–399. https://doi.org/10.1016/j.compeleceng.2019.08.004

Wang, J., & Perez, L. (2017). The effectiveness of data augmentation in image classification using deep learning. ArXiv.

Wang, L., Lin, Z. Q., & Wong, A. (2020). COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. Scientific Reports, 10(1), 1–12. https://doi.org/10.1038/s41598-020-76550-z

World Health Organization. Philippines: WHO Coronavirus Disease (COVID-19) Dashboard. (2020). Retrieved October 01, 2020, from https://covid19.who.int/region/wpro/country/ph

World Health Organization. WHO Coronavirus Disease (COVID-19) Dashboard. (2020). Retrieved October 01, 2020, from https://covid19.who.int/