A COVID-19 CXR Image Recognition Method Based on Deep Transfer Learning

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***Abstract*— Although the immediate threat of the coronavirus disease 2019 (COVID-19) has been significantly mitigated through widespread vaccination efforts and public health measures, ongoing observation and preparedness remain crucial in managing potential future outbreaks and ensuring global health security. Our research focuses on using a transfer learning-based convolutional neural network (CNN) to distinguish and classify chest X-ray images (CXR) of patients with COVID-19, pneumonia, and relatively normal lungs. The proposed transfer learning model, named NewNet, integrates features from CXR images and deep learning model, AlexNet [1]. Training of the transfer learning CNN model was conducted using two datasets: the Kaggle CXR dataset [2] and the dataset collected by Joseph et al. [3]. The experimental results indicate that the NewNet model achieves an average accuracy of 96.82% for classifying COVID-19 CXR images, 92.94% for pneumonia, and 96.32% for normal cases. Thus, through the transfer learning technique, the proposed NewNet deep learning network demonstrates improved accuracy in diagnosing COVID-19.**

Keywords*— *Transfer Learning (TL), Coronavirus Disease 2019 (COVID-19), Machine Learning (ML), Deep Learning (DL), Convolution Neural Network (CNN).

I. INTRODUCTION

The rapid spread of the coronavirus disease has caused significant detrimental impacts to the world, particularly in regions with limited medical resources and lower healthcare standards. The primary diagnostic approach for COVID-19 involves reverse transcriptase polymerase chain reaction (RT-PCR), known for its specificity. However, there is still a lack of detections kits in many countries due to the lasting disruption of supply chains and high demand [4]. Moreover, its diminished sensitivity raises the likelihood of false negative results, presenting significant challenges to effective COVID-19 prevention initiatives. In areas with limited medical resources, there is a need to find a rapid, dependable, and cost-effective detection method. Chest X-ray (CXR) is widely recognized as the predominant imaging test for diagnosing heart and chest diseases [5]. In comparison to CT scans, CXR involves lower levels of ionizing radiation [6].

Identifying diseases through chest radiographs poses a highly demanding challenge, requiring a specific level of expertise and meticulous observation. COVID-19 exhibits certain radiological features detectable through CXR. However, relying on manual film reading for analyzing these characteristics not only consumes significant medical staff time, but also introduces the risk of errors arises from visual fatigue and other related issues. Hence, it is imperative to explore methods for automating the CXR detection process.

Recently, there has been an increasing investigation of computer-aided detection systems as a means to reduce dependency on medical staff and aid in diagnoses. Machine learning (ML) approaches have become ubiquitous in numerous medical fields, showing positive results [7]. Deep learning (DL) approaches, in particular, have garnered attention in clinical imaging due to their feature extraction capabilities, allowing them to discern patterns, orientation, and boundaries effectively. Convolutional Neural Networks (CNNs) is a prominent branch of deep learning technology which excel in tasks involving image feature extraction and learning [8]. The performance of the convolutional neural network (CNN) model depends on variables like the size of the training dataset and the architecture of the layers. Given the limitations in the size of medical imaging datasets and the time-consuming nature of collecting such data, a more robust approach to deep learning should be investigated.

The adoption of transfer learning is recommended for the training of the CNN model [9], [10]. Transfer learning is a machine learning technique that involves applying knowledge acquired from training a model on one task to a different yet related task. In the context of neural networks utilizing transfer learning, the training process occurs in two stages. Initially, the network undergoes training on the ImageNet dataset, which comprises over 1000 images. Subsequently, fine-tuning occurs, where the pretrained network is further trained on the specific dataset of interest. Typically, the initial layers of the model are trained to learn basic features like edges, corners, and curves, while the final layers concentrate on capturing more advanced features.

We are motivated to develop transfer learning based machine learning and deep learning methods to address the challenges in the COVID-19 CXR (chest X-ray) image recognition problem, such as (1) Limited Annotated Data for COVID-19: Annotated datasets for COVID-19 CXR images may be limited, making it challenging to train deep neural networks from scratch. Transfer learning allows leveraging pre-trained models on large datasets, such as general medical images, and fine-tuning them on the limited COVID-19 CXR dataset. (2) Knowledge Transfer from General Medical Images: Pre-trained models on general medical images can capture valuable features and patterns that are relevant to CXR analysis. Transfer learning allows the model to inherit knowledge from broader medical contexts and adapt it to the specific characteristics of COVID-19 CXR images. (3) Accelerated Model Training: Training deep neural networks from scratch requires significant computational resources and time. Transfer learning accelerates the training process by starting with a model that has already learned meaningful representations. Fine-tuning this pre-trained model on COVID-19 CXR images requires fewer iterations and computational resources.

The contribution of this paper is an accurate transfer learning-based method for recognizing CXR images of COVID-19 and pneumonia. This will aid medical professionals in diagnosis and minimize dependency on user interpretation. In this paper, we present an innovative method to aid in the diagnosis of COVID-19 patients. This includes augmenting CXR images and identifying distinctive features. Next, we train a convolutional neural network (CNN), which is entitled NewNet, to detect COVID-19, normal, and pneumonia, based on the differences in CXR images. Our goal is to enhance the accuracy and robustness of COVID-19 detection, thereby contributing to more efficient and effective medical diagnoses.

The paper is structured into several sections, with Section I providing an introduction to the research. Section II presents a review of existing works within the field. Following this, Section III goes into data preparation for training and testing the proposed transfer learning model. Section IV expands upon the proposed model's algorithm and architecture, In Section V, the results obtained from the developed model are detailed and compared with existing methods and model results. Section VI serves as the conclusion of the paper and future work.

II. Literature Review

In recent years, deep learning techniques have seen extensive application in medical image analysis, particularly in tasks such as detection and classification. Transfer learning techniques were employed by Misra et al. [9] and Justin et al. [11] on brightness-mode ultrasound images and elastograms. Their approach involved combining AlexNet with other neural network models to discern between benign and malignant breast cancers, achieving an overall accuracy of 86.39% and 88%, respectively.

Two convolutional neural network models, namely VGG-16 and VGG-19, have been pre-trained using transfer learning for the automatic classification of patients into COVID-19, normal, or pneumonia categories [12]. The utilization of the ESIHE image enhancement technique with the VGG-16 model demonstrated the highest accuracy, achieving a noteworthy 92.17%. Bai and Zhang employed AlexNet as the foundation for a novel transfer learning algorithm, achieving accuracies of 95.15% and 92.47% in the detection of corn disease and rice disease, respectively [13]. By utilizing Dilated Convolutional Neural Networks and transfer learning for feature extaction, Kumar et al. was able to provide a CNN architecture for detection of COVID-19 using a combination of two datasets of chest X-ray images and CT scans [14]. The best classification accuracy achieved on Chest CT images is 91.6%.

Researchers have been advocating for using deep learning methodologies to facilitate the detection of lesions in Chest X-ray (CXR) images, thereby conserving medical resources and enhancing diagnostic efficiency [15]-[17]. For instance, Tang et al. [15] investigated five pre-trained state-of-the-art CNN models (DarkNet-19, ResNet-101, SqueezeNet, VGG-16, and VGG-19) to determine the best CNN for detection of COVID-19. Tang et al. used transfer learning to modify the pre-trained CNN models to classify CXR images between COVID-19 and normal lungs. Shelke et al. [16] introduced a classification model for categorizing chest X-ray (CXR) images into four classes: normal, pneumonia, tuberculosis (TB), and COVID-19. Subsequently, the COVID-19 images were further categorized based on severity, distinguishing between mild, medium, and severe cases. The VGG-16 model employed achieved a high test accuracy of 95.9% for the classification of pneumonia, TB, and normal lung conditions. In addition, the severity of COVID-19 cases was classified using ResNet-18, resulting in an accuracy of 76%.

III. Data Preparation

The datasets that will be used to conduct experiments are from Kaggle dataset [2] and Joseph dataset [3]. Both datasets contain more than 1000 CXR images of patients with COVID-19, pneumonia, or healthy lungs. A significant challenge in image detection, particularly in public datasets such as COVID-19 detection, is the variation in image sizes across different sources. This variability poses a hindrance to feeding deep learning (DL) models effectively, as these models typically require uniform image sizes for optimal performance. Without preprocessing the data from diverse sets to standardize image dimensions, leveraging DL for disease detection becomes impractical. For this research, we pre-processed the dataset using the MATLAB. We add the datasets into a shared folder and use the resizing feature of MATLAB to ensure they are uniform in dimensions. In the pre-trained AlexNet network, the input to the network is a batch of RGB images with dimensions of 227-by-227-by-3. The 227-by-227 represents the image's dimensions and the 3 represents the image’s number of channels for color (red, green, blue). After the images are homogenized in size and are in a readable image format, we can use them for training and testing the NewNet model.

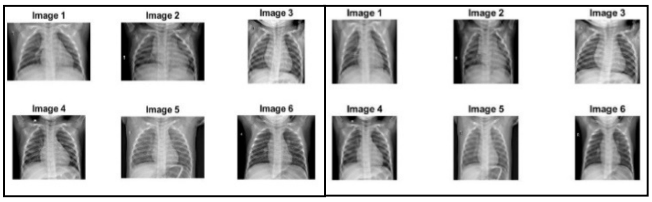
A. Kaggle and Joseph et al. CXR Dataset

The Kaggle CXR dataset [2] contains 2 classes of data including Normal, and Pneumonia affected lungs. Out of the two categories of images mentioned above, 351 images and 600 images were chosen, respectively. The sizes of the CXR images vary, as illustrated in Figure 1a. Following data preprocessing, we standardized all the images to 227-by-227-by-3 dimensions, as depicted in Figure 1b.

The dataset, compiled and curated by Joseph et al., includes a total of 428 chest X-ray (CXR) and computed tomography (CT) images depicting patients infected with either COVID-19 or other forms of pneumonia. From this dataset, 428 CXR images specifically from COVID-19 patients were selected. The initial CXR images exhibit variations in sizes (Fig 2. a), and through preprocessing, all images were standardized to dimensions of 227 x 227 x 3 (Fig 2. b). Table I outlines the distribution of images for each class and provides the overall count for the entire dataset.

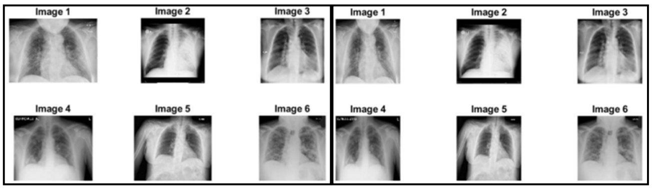
TABLE I. KAGGLE AND JOSEPH ET AL. CXR DATASET

CXR Dataset from Kaggle [2] and Joseph [3]	Number of images used	The initial dimensions of the images	Dimensions of the resized images
Normal	351	Varying	227 x 227 x3
Pneumonia	600	Varying	227 x 227 x 3
COVID-19	428	Varying	227 x 227 x 3
Total	1379		



(a) (b)

Fig. 1. Kaggle CXR data: (a) The initial dimensions of the images; (b) Dimensions of the resized images.



(a) (b)

Fig. 2. Joseph et al. CXR data: (a) The initial dimensions of the images; (b) Dimensions of the resized images.

IV. PROPOSED METHODOLOGY

In this paper, we used the pre-trained AlexNet [1], which is a prominent convolutional neural network. Utilizing GPU acceleration during training increases its speed compared to alternative models. AlexNet, designed primarily by Alex Krizhevsky, was developed with the primary objective of classifying large amounts of images into one-thousand object classes, including items such as keyboards, coffee mugs, pencils, and various animals. Because of this, the network has been trained to distinguish a large array of features across numerous images.

The utilized AlexNet model comprises eight crucial layers, with the first five layers from the bottom designated as convolutional layers, and the subsequent three layers at the top identified as fully connected (FC) layers, as illustrated in Figure 3. In addition, to mitigate the potential overfitting problems, pooling layers are incorporated after the second, third, and fifth convolutional layers.

A. Transfer Learning Architecture

Transfer learning is used for our proposed model of NewNet. Transfer learning uses a pre-trained model, which in our case is AlexNet, to recognize patterns and features. Since AlexNet was training on more than 1000 distinct images, we leverage this learned knowledge and adapt it to our combined datasets. This process involved substituting the ultimate layer of the pre-trained model with a new layer.

In addition, we replaced training and testing images used for AlexNet with CXR images from our datasets after the images were resized. This was done in the input layer. The fully-connected (FC) layer that was used in AlexNet to classify images into 1000 distinct labels was replaced with 3 classes: COVID-19, normal, and pneumonia. Fig 3. shows the proposed NewNet transfer learning model architecture.

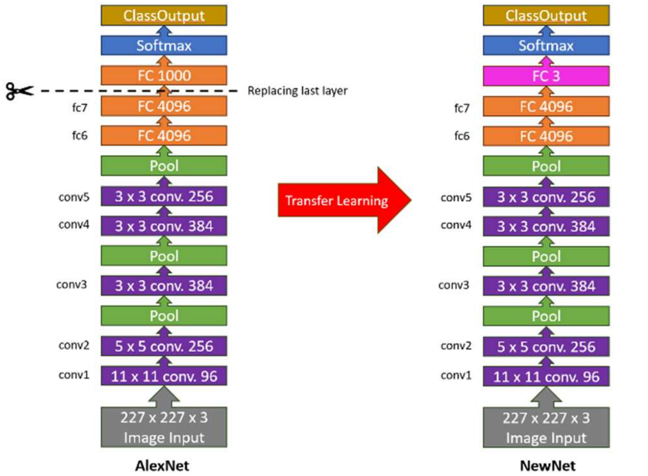


Fig. 3. Proposed transfer learning from AlexNet to NewNet.

In Fig. 3, for AlexNet, FC 1000 refers to the last fully connected layer which contains 1000 neurons. This layer is responsible for producing the final output for classification across 1000 different classification classes, i.e. labels. For example, there are labels in AlexNet for shark, vulture, mug, and keyboard. In the proposed NewNet, FC 3 refers to the last fully connected layer in the network, which contains 3 neurons. This layer produces the final output for classification across 3 different labels. We replace the FC 1000 with FC 3 since the task at hand involves a different number of classes. It is more efficient to have a final FC layer with 3 neurons instead of 1000. This adjustment reduces the model's complexity and computational resources, making it more suitable for the task at hand.

B. Proposed Algorithm

The proposed CNN, NewNet, operates through a sequential process. Initially, images or data are inputted into the network, progressing through each layer successively. Features are gradually extracted throughout this process, enabling the model to discern the distinguishing characteristics of each class. Therefore, the trained model becomes increasingly adept at classifying new images accurately.

Convolutional layers are important in the proposed architecture. Convolutional layers perform feature extraction by applying filters to input images. These filters traverse the image, calculating dot products between the filter weights and the corresponding pixel values in the input. The output of this layer highlights patterns and features present in the image. It is important to include integrate batch normalization layers between convolutional layers and nonlinear activation functions when training convolutional neural networks. To do this, we implemented ReLU (Rectified Linear Unit) layers into our proposed architecture. This allows for faster processing and reduces the network's reliance on initialization conditions. The ReLU layer within the network employs the Rectified Linear Unit (ReLU) activation function on the input data. This function transforms negative values into zero, preserving positive values unchanged. This process contributes to enhancing the network's capacity for learning and predicting the provided data. Following the ReLU layer, the rectified feature map undergoes pooling. Pooling is a downsampling procedure that decreases the dimensionality of the feature map. In this network, max pooling is utilized, selecting the maximum value within a filter and transferring it to the new pooling feature map. Following the convolutional and pooling layers, fully connected (FC) layers are commonly included in neural network architectures. FC layers are named so because every neuron within the layer establishes connections with neurons within the layer before. Fully Connected (FC) layers primarily serve to link the features extracted by preceding layers across the entire image. This connection aids the neural network in discerning more features. The final FC layer unifies the acquired features to classify the CXR images effectively.

A problem that can occur when training a neural network such as NewNet is overfitting. Overfitting can cause suboptimal performance and results when new data is introduced. To address this issue of overfitting, a layer technique known as "Dropout" can be used. The Dropout layer functions by randomly deactivating (converting to 0) a portion of input units during each training step, determined by a specified frequency called the "rate." This approach helps prevent the neural network from overly depending on specific input units or features, thus mitigating overfitting. The SoftMax layer is an important component in neural network architectures, typically used as the final layer for classification tasks. Its primary function is to convert raw output values, often referred to as logits or scores, into probabilities for each class in a mutually exclusive set. This allows the neural network to make predictions by identifying the class with the highest probability as the predicted class label. The final layer in the NewNet convolutional neural network is the ClassOutput layer, also referred to as the classification layer. This layer's role is to acquire the probabilities of the output classification from the SoftMax layer, assigning a probability value to each class for every input image. Leveraging these output probabilities, the ClassOutput layer identifies the class for each input image and computes the associated loss.

V. Experimental Results

A. CXR Dataset and Validation

The CXR data set used consists of three classes of images of chest X-rays, including COVID-19, Normal, and Pneumonia. The training and validation data is shown in Table II. The dataset is divided into training and validation sets, constituting 70% and 30% of the data, respectively.

TABLE II. CXR DATASET DETAILS FOR THE PROPOSED ALGORITHM

CXR Dataset	Number of images	Training data (70%)	Validation data (30%)
COVID-19	428	300	128
Pneumonia	600	420	180
Normal	351	254	97
	1379 (total)		

During the training process, the cross-entropy loss function is utilized along with the Adam optimizer, set to a learning rate of 0.0001. The training spans 16 epochs. Moreover, the training images undergo resizing to dimensions of 227-by-227-by-3 and augmentation to augment the dataset: this involves random vertical flipping and random translations of up to 20 pixels both horizontally and vertically. The incorporation of data augmentation serves to mitigate overfitting by preventing the network from memorizing specific details of the training images. The experiment was run for five tests, and of the five tests, the best validation accuracy result obtained is 99.15%. Each run, data augmentation was implemented, and the algorithm randomly selected training and validation data. The results for the five tests are shown in Table III.

TABLE III. NEWNET RESULTS FOR CXR DATASET

	Test 1	Test 2	Test 3	Test 4	Test 5	Average
Accuracy	99.15%	98.33%	92.47%	96.9%	96.23%	**96.62%**

B. Evaluation Criteria of Model

Concerning the criteria for model evaluation, we adhered to the commonly employed standards in medical image classification models. These criteria encompass accuracy, precision, sensitivity, specificity, and F1-score. These criteria serve as benchmarks for evaluating model performance. Below are the formulas for these evaluation criteria, where TP represents true positive, FP represents false positive, FN represents false negative, and TN represents true negative:

$$\text{Accuracy} = \frac{T_P+T_N}{T_P+T_N+F_P+F_N}$$

$$\text{Precision} = \frac{T_P}{T_P+F_P}$$

$$\text{Sensitivity} = \frac{T_P}{T_P+F_N}$$

$$\text{Specificity} = \frac{T_N}{T_N+F_P}$$

$$\text{F1-score} = \frac{2T_P}{2T_P+F_P+F_N}$$

C. Experimental Results and Analysis

Figure 4 depicts the confusion matrix illustrating the validation results of the transfer learning model, with an average accuracy of 96.62% in correct predictions. The diagonal cells, in terms of both numbers and percentages, represent correctly classified observations, while off-diagonal cells indicate instances that are incorrectly classified. The rightmost column displays the percentages of accurately and inaccurately classified instances for the predicted class. the bottom row indicates the percentages of each class that are correctly and incorrectly classified.

As depicted in Figure 4, the sensitivity of COVID-19 is 98.9%, with 89 images correctly identified out of 90 tested images. Additionally, from 76 images tested, NewNet was able to detect 69 images of the Normal class, resulting in 90.8%. Finally, out of 126 images tested, 123 were detected by NewNet as the Pneumonia class which results in 97.6% success rate.

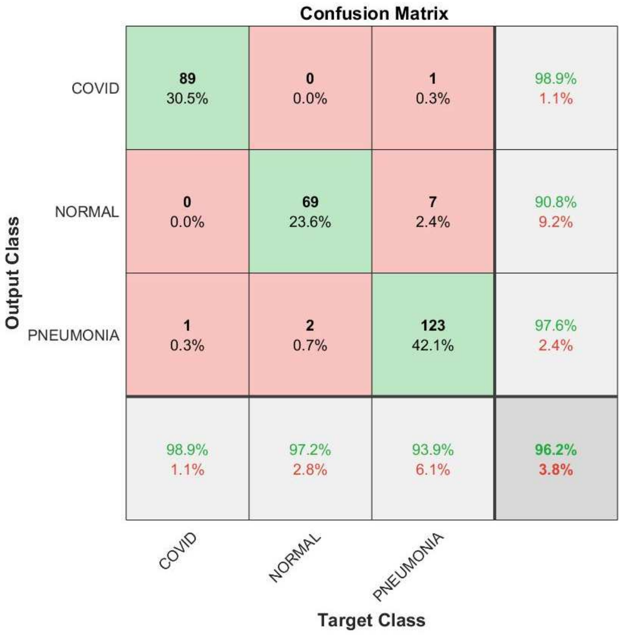


Fig. 4. The confusion matrix for NewNet from Test 5.

Figure 5 illustrates the testing results of NewNet on chest X-ray images from the merged dataset. The NewNet transfer learning model can differentiate the three categories of images. The predicted NewNet labels are either COVID-19, Normal, or Pneumonia.

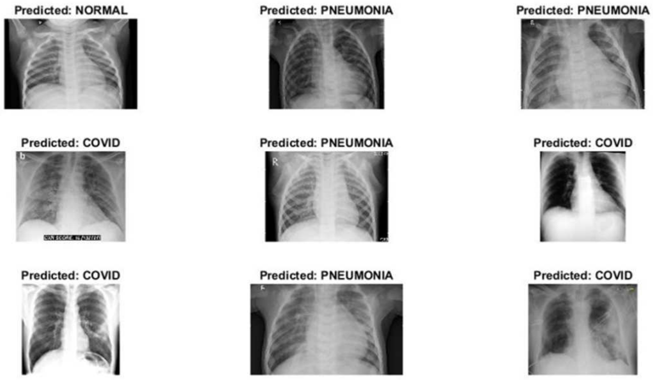


Fig. 5. NewNet classification of chest X-Ray images.

To demonstrate classification capability of the NewNet model, we compared the evaluation criteria with several state-of-the-art models, including VGG19 [18], GoogleNet [19], ResNet50 [20], and DenseNet121 [21], which served as the control group. The control group encompassed several lightweight networks, including SqueezeNet1.0 [22], MobileNet [23], ShuffleNet [24], MobileNetV2 [25], and ShuffleNetV2 [26].

The evaluation metrics for these cutting-edge models are presented in Table IV. The assessment criteria encompass accuracy, precision, sensitivity, specificity, and F1-score of each state-of-the-art model, as well as our own model. Since the model was run for five tests, the average result for each criterion was calculated. Our NewNet results for accuracy, precision, sensitivity, specificity, and F1-score for COVID-19 CXR images are 96.82%, 91.55%, 97.89%, 96.49% and 94.50% respectively.

These results show that NewNet is comparable to the state-of-the-art models and even leads in accuracy, sensitivity and F1-score. As an example, ResNet50 [19] from the control group has the highest accuracy among traditional networks in our experiment at 93.53%. It is less than our proposed network, NewNet, by 3.29%.

TABLE IV. ACCURACY, PRECISION, SENSITIVITY, SPECIFICITY, AND F1-SCORE OF THE PROPOSED METHOD AND 9 BASELINES

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
VGG19 [18]	93.11	96.09	92.93	96.47	93.02
GoogleNet [19]	92.56	95.29	91.56	95.78	92.06
ResNet50 [20]	93.53	96.01	93.15	96.53	93.34
DenseNet121 [21]	93.11	95.98	92.75	96.38	92.92
SqueezeNet1.0 [22]	67.91	45.83	50.51	64.16	57.93
MobileNet [23]	88.53	90.14	87.25	91.84	87.89
ShuffleNet [24]	87.02	90.08	86.17	92.31	86.59
MobileNetV2 [25]	89.26	91.89	88.51	93.16	88.89
ShuffleNetV2 [26]	92.01	91.92	91.74	96.29	91.87
NewNet (our method)	**96.82**	**91.55**	**97.89**	**96.49**	**94.50**

VI. CONCLUSION

In this paper, a transfer learning model, named NewNet, was constructed based on an AlexNet model to recognize COVID-19 CXR images accurately and effectively. The NewNet model, as proposed, extracts features from chest X-rays and compares them with features obtained from training images. To assess the performance of the proposed model, two datasets are employed. For the experiment, 351 CXR images of normal patients, 600 CXR images of pneumonia patients and 428 images of COVID-19 patients were used from the Kaggle and Joseph et al. datasets. Results show that NewNet has the highest classification accuracy for the COVID-19 images used for testing, which was 96.82%. Additionally, the precision, sensitivity, specificity, and F1-score are 91.55%, 97.89%, 96.49%, and 94.50% respectively. Hence, by using our NewNet model for the detection of COVID-19 CXR images, it can help medical staff by significantly increasing diagnostic efficiency and aiding in detection and isolation of COVID-19 patients.

VII. FUTURE WORK

Despite the comparable performance of the proposed NewNet to traditional networks, further clinical research and testing are required. With additional training and testing, NewNet can be further improved to be used within the medical field.

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REFERENCES

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," "*Proceedings of the 25th International Conference on Neural Information Processing Systems*", vol. 1, pp. 1097–1105, 2012.

[2] Chest X-Ray Images (Pneumonia). Available online: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia. 2020.

[3] J.P. Cohen, P. Morrison, L. Dao, Covid-19 image data collection, 2020.

[4] X., Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, J. Liu, "Chest CT fortypical 2019-ncov pneumonia: relationship to negative RT-PCR testing," *Radiology*, vol. 296, no. 2, 2020.

[5] M.Y. Ng, E.Y. Lee, J. Yang, F. Yang, M.D. Kuo, "Imaging profile of theCOVID-19 infection: radiologic findings and literature review," *Radiol. Car-diothorac. Imaging*, vol. 2, no. 1, 2020.

[6] S. Latif, M. Usman, S. Manzoor, W. Iqbal, J. Crowcroft, "Leveraging data science to combat COVID-19: a comprehensive review," *IEEE Transactions on Artificial Intelligence*, vol. 1, no. 1, pp. 85-103, 2020, doi: 10.1109/TAI.2020.3020521.

[7] M. K. Santos, et al. "Artificial intelligence, machine learning, computer-aided diagnosis, and radiomics: advances in imaging towards to precision medicine," *Radiologia Brasileira*, vol. 52, no. 6, pp. 387-396, 2019. https://doi.org/10.1590/0100-3984.2019.0049

[8] W. Wang, Y. Yang, X. Wang, W.J. Wang, J. Li, "The development of con-volution neural network and its application in image classification: a survey," *Opt. Eng.*, vol. 58, no. 4, 2019.

[9] S. Misra et al., "Ensemble transfer learning of elastography and B-mode breast ultrasound images," 2021, arXiv:2102.08567.

[10] J. An, N. Zhang, W. Mahmoud, "Transfer learning-based deep learning model for corn leaf disease classification," *18th International Symposium on Neural Networks (ISNN 2024)*, Weihai, China, July 11-14, 2024.

[11] J. An, T. Abdus-Shakur and M. Denis, "Quantitative assessment of tissue stiffness using transfer learning ultrasound elastography: a breast cancer phantom study," *IEEE Sensors Letters*, vol. 7, no. 10, pp. 1-4, Oct. 2023, Art no. 7005504, doi: 10.1109/LSENS.2023.3307102.

[12] F. N. Shaari, A. S. Abdul Nasir, and W. A. Mustafa, "Variant histogram equalization based enhancement to transfer learning in detection of COVID-19 chest x-ray images," *2023 IEEE 2nd National Biomedical Engineering Conference (NBEC)*, Melaka, Malaysia, 2023, pp. 158-163, doi: 10.1109/NBEC58134.2023.10352580.

[13] F. Bai, W. H. Mahmoud and N. Zhang, "Deep learning-based plant disease image recognition for cyber-physical systems," *2023 13th International Conference on Information Science and Technology (ICIST)*, Cairo, Egypt, 2023, pp. 1-8, doi: 10.1109/ICIST59754.2023.10367187.

[14] S. Kumar, K. Abhishek, Kritika and K. Singh, "COVID-19 detection from chest x-rays and CT scans using dilated convolutional neural networks," *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, Bhopal, India, 2021, pp. 369-374, doi: 10.1109/CSNT51715.2021.9509616.

[15] G. S. Tang, L. S. Chow, M. I. Solihin, N. Ramli, N. F. Gowdh, and K. Rahmat, "Detection of COVID-19 using deep convolutional neural network on chest x-ray (CXR) images," *2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, ON, Canada, 2021, pp. 1-6, doi: 10.1109/CCECE53047.2021.9569064.

[16] A. Shelke, M. Inamdar, V. Shah, A. Tiwari, A. Hussain, T. Chafekar, and N. Mehendale, "Chest x-ray classification using deep learning for automated COVID-19 screening," *SN Computer Science*, vol. *2*, no. 4, 2021, https://doi.org/10.1007/s42979-021-00695-5.

[17] W. Wang, W. Huang, X. Wang, P. Zhang, and N. Zhang, "A COVID-19 CXR image recognition method based on MSA-DDCovidNet," *IET Image Process*, vol. 16, pp. 2101-2113, 2022, https://doi.org/10.1049/ipr2.12474.

[18] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014, arXiv:1409.1556.

[19] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, and A. Rabinovich, "Going deeper withconvolutions," *Proceedings of the 2015 IEEE Conference on ComputerVision and Pattern Recognition (CVPR)*, pp. 1–9, 2015.

[20] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

[21] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

[22] F. N., Iandola, S. Han, M.W. Moskewicz, K. Ashraf, W.J. Dally, K. Keutzer, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size," 2016, arXiv preprint arXiv:1602.07360.

[23] A.G. Howard, M. Zhu, B. Chen, "Mobilenets: efficient convolutional neural networks for mobile vision applications." 2017, arXiv preprint arXiv:1704.04861.

[24] X. Zhang, X. Zhou, M. Lin, and J. Sun, "ShuffleNet: an extremely efficient convolutional neural network for mobile devices," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, 2018, pp. 6848-6856, doi: 10.1109/CVPR.2018.00716.

[25] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: inverted residuals and linear bottlenecks," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, 2018, pp. 4510-4520, doi: 10.1109/CVPR.2018.00474.

[26] N. Ma, X. Zhang, H.T. Zheng, and J. Sun, "ShuffleNet V2: practical guidelines for efficient CNN architecture design," *Proceedings of 2018 European Conference on Computer Vision (ECCV)*, 2018.