Predicting Diseases Using Chest X-Ray Medical Images

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***Abstract*— Pneumonia and Coronavirus are the key disease that has affected people rapidly in the last couple of years across the globe. Medical Practitioners confirm the diseases using chest X-ray medical images. Computed Radiology, Computer Aided Diagnosis has an edge over the traditional process as it helps to find the ailment at a primary stage, which saves lives at a growing scale day by day. To predict the chest diseases, deep learning methods are promising in predicting the type of chest disease with greater accuracy. In the proposed model to detect chest diseases, DenseNet, Image processing, and deep-learning classification techniques are used. The proposed methodology optimizes the output that includes the inclusion of augmentation layers, dataset filtering, etc., and results in achieving an accuracy of 95.96%.**

***Keywords*— DenseNet, X-ray Chest images, Disease Classification, Coronavirus, Pneumonia**

I. Introduction

Coronavirus and pneumonia belong to a large family of bacterial and viral infections that cause illnesses such as sickness or weakness, weight loss, fever, and night sweats. Symptoms include a worsening cough, fever, and shortness of breath. This infection leads to extreme acute respiratory syndrome, septic shock, multiple organ failure, and in other severe cases death. Early diagnosis is a critical factor for a successful treatment process. In Medical practice, X-ray reports of chests are diagnosed by radiologists for analyzing such diseases. Computer-Aided Diagnosis (CAD) assists radiologists in analyzing medical images (C. Suárez-Ortega et al., 2013[1]).

The CAD system displays an image of the general appearance and highlights areas of interest where the ailment can be found. Therefore, a significant goal of computer-aided diagnosis is to accurately detect disease by reducing the negative miss rate. Deep learning methods like Convolutional Neural Networks are used for CAD, after conducting a study of the various architecture of Machine Learning models of CNNs like ZFNet, VGG16, ResNet18, ResNet101, GoogLeNet, and DenseNet. Most researchers have concluded that DenseNet would be an optimal choice in making a CAD system (Y. Tan, et al., 2020[2]).

The accuracy of these CAD systems is limited by the selection of visual features used to represent radiographic images and the power of machine learning methods used to match new cases to positive or negative classes.

II. Proposed Model

The model used image preprocessing, and deep learning classification techniques to reliably detect pneumonia from chest radiographs. CNN has been used in several recent studies to analyze chest X-rays to detect lung diseases such as pneumonia and to make disease detection more accurate, The DenseNet-201 architecture, comprising of 201 convolutional layers, is used here which can negatively impact accuracy. DenseNet was designed to mitigate this problem by reducing the gap between input and output layers, thereby preserving information flow.

III. Related Work

Lung Cancer Detection and Classification with 3D-CNN suggests the use of a 3D-CNN can be a promising e approach for lung cancer detection and classification. The authors discuss the potential benefits of this approach, including the ability to accurately detect and classify lung cancer got an accuracy of 88% in their approach. 88% accuracy may conclude fatal risks to be used for clinical purposes (Alakwaa, Wafaa, et al., 2017[3]). Shelke, Ankita,[4] et al. developed a model to detect Covid-19, suggesting deep learning techniques for classifying chest x-ray images to be an effective approach for automated COVID-19 diagnosis, getting an accuracy of 98.9% using ResNet18, VGG16, and DenseNet 161(Shelke, Ankita, et al., 2021)Model trained by Z. Wan, Z. Yuxiang, et al[5]. was able to achieve high levels of accuracy in classifying cancer images as DenseNet model trained was optimized using RAdam algorithm and they have concluded

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that Auc-Roc (Area Under the Receiver Operating Characteristic curve) parameter of DenseNet-121 model gives 1.8% higher with a greater Accuracy score of near to 2% than VGG19 model. This ignited the paper's architecture to be based on DenseNet, In other domains unlike CAD, DenseNet is implemented for classification purposes like Botany, Face Detection, etc. (Z. Wan, et al., 2021).

While using transfer learning, the DenseNet has good efficiency over other CNN models, the accuracy came out to be 99% (B. Chellapandi, et al., 2021).[6]A face detection solution that works on a Dual Shot Face Detector (DSFD) network and applies modifications to enhance results while also getting low memory usage and inference is done by providing DenseNet as backbone along with focal loss function (A. Nandy, 2019) [7]. DenseNet is also been used for fruit disease classification YAN QI, et al.[8] proposes an algorithm that is used to improve the accuracy of fruit disease identification, particularly in the presence of fog or other environmental conditions that can affect image quality.

The authors claim that their proposed method achieves improved performance compared to other methods for fruit disease identification, and can be used in a range of applications (Y. Qi, et al. 2021). Applications and Implementation of DenseNet covers a range of topics like building an automatic image tagger (T. H. Tran, et al., 2019)[9] A method for classifying diseases in X-ray chest films using a DenseNet, a type of CNN was proposed as authors claim their proposed method is able to achieve high accuracy in disease classification and can be used in a variety of medical settings to assist with diagnosis and treatment planning (L. Bing-jin, et al, 2020)[10].

T. Rahman et al. [11], claim that their proposed method is able to achieve high accuracy in detecting tuberculosis and can be used in a variety of medical settings to assist with diagnosis and treatment planning (T. Rahman et al., 2020)[12]. A method proposed for detecting coronavirus-based ailments in CXR using an artificial neural network called a Deep Separable DenseNet. The method involves training the network on a dataset of X-ray images and using it to classify images as either positive (Q. Wang, et al,. 2021)[12]The use of deep learning algorithms, specifically DenseNet and SqueezeNet, to classify fetal brain MRI images as normal or abnormal. The performance of these algorithms was evaluated using various metrics, and it was found that DenseNet had a higher accuracy (98.7%) compared to SqueezeNet (96.3%). The paper likely discusses the use of these algorithms for the purpose of identifying abnormalities in the neurodevelopment of fetuses, with the goal of enabling earlier diagnosis and prevention of problems (P. S, et al, 2022)[13]

DenseNet was used to analyze CXR in detecting COVID-19. The available datasets for training these types of algorithms are insufficient, so the authors suggested a better approach by using domain extension transfer learning (DETL), which involves using a pre-trained deep CNN on a dataset consisting of X-rays of the chest. Initial results show optimized accuracy of 90.13% ± 0.14 (S. Basu, et al., 2020)[14]. The authors compared the performance of different convolutional neural network (CNN) architectures on various classification tasks. The results concluded the best-performing neural network architecture varied depending on the specific classification task. No single CNN architecture was found to be the best for all tasks. However, some architecture performed well across a range of tasks and may be a good choice for general-purpose classification (Y. Tan, et al.,. 2020)[15]. B. Yaman, et al[16] conducted a study that found that a DenseNet was equally promising as the ResNet and U-Net neural network models when used as the regularization prior in a deep learning-based Magnetic Resonance Imaging reconstruction. Additionally, the DenseNet architecture requires fewer parameters for training, thus reducing the likelihood of overfitting.

Studies above conclude the fact that using a dense layer on top of convolutional layers not only provides good accuracy but also optimizes the cost of computation while training a neural network thus it is justifiable to include a dense layer in the architecture of the model proposed in the paper, several optimizations can also be achieved while enhancing the dataset by applying data augmentation and both of the above composites a significant role in the model.

IV. Materials and Methods

A. Dataset

Chest X-ray images are helpful for the diagnosis of COVID-19 in earlier stages due to the widespread availability of X-ray machines and the ability to obtain images quickly. The dataset used in this study was sourced from Kaggle and GitHub and is considered by the University of Montreal's Ethics Committee (CERSES-20-058-D). The dataset includes images of patients who have tested to be diseased or are presumed to have infections of coronavirus, as well as other viral and bacterial pneumonia such as MERS, SARS, and ARDS. These images and data were consolidated from various sources, as well as indirectly from medical centers and medical professionals, and are made publicly available on a GitHub repository. Additionally, a separate pneumonia dataset was taken from Kaggle, which includes chest X-ray images of pediatric patients between the ages of one and five from Guangzhou, who underwent the imaging as part of their routine clinical care.

TABLE I. Dataset Composition

Dataset	Covid-19	Pneumonia	Normal	Total
Train	460	3418	1266	5144
Test	116	855	317	1288
Sum	576	4273	1583	6432

All images of the dataset were verified for authenticity before being sorted from the study of the CXR, so the photos could be used for the Artificial Intelligence system's training process, these were assessed by medical experts. A third reviewer additionally analyzed the assessment ensuring that any gradient inaccuracies were taken into account.
The dataset, which totals 6432 photos Fig. 1. is divided into two folders (train and test), each of which has three subfolders (COVID-19, PNEUMONIA, NORMAL). A total of 6432 x-ray pictures are included in the dataset; of these, 20% are utilized as test data, and the remaining 80% are used to train the model.

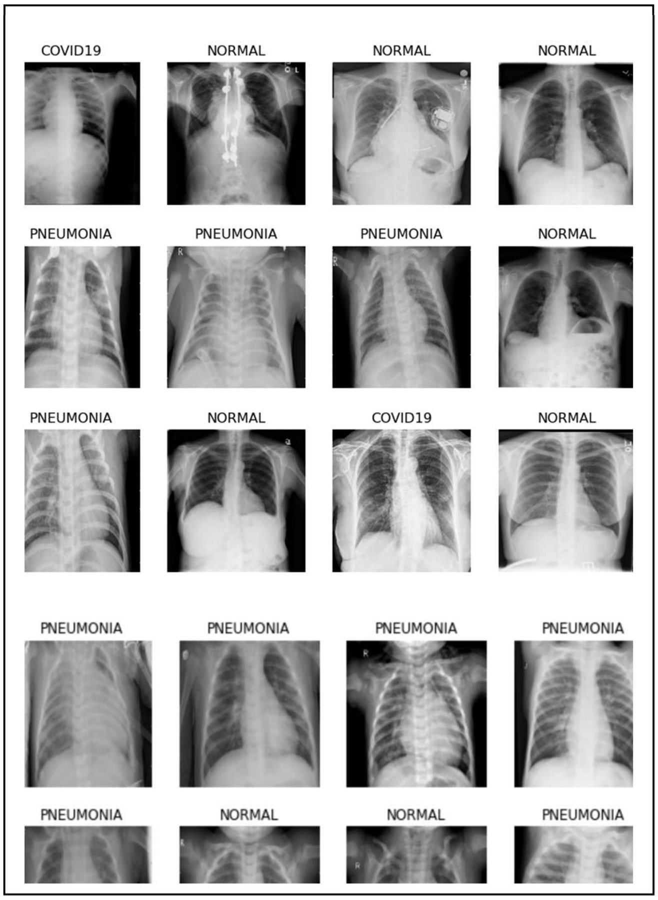

Fig. 1. CXR dataset sample consisting of both diseased and normal images

B. Methods

The methodology proposed in this paper consists of using CNN architecture of the DenseNet-201 model, proposed (Huang, G., et al, 2016)[17] and addresses the vanishing gradient problem of ResNet by introducing a new pattern that proposes layer-to-layer connectivity in a feed-forward approach. Here network utilizes all features learned so far to produce the output, and it also enables feature reuse.

The architecture has fewer trainable parameters which reduces the chances of overfitting and has been shown to perform well on image classification tasks and is widely used in different fields such as object detection, segmentation, and medical imaging. In the given architecture, the number of connections is calculated as L multiplied by L+1 divided by 2 (L(L+1)/2) where L is the number of layers in the network.

C. Flow of Data

CNN requires a wide range of data sets for training, one must also have the skillful and right knowledge to opt for the right model architecture for good convergence. In clinical practice, images in the dataset are usually not plentiful and with a greater cost of annotation if done by an expert. Transfer learning (TL) is a better alternative for fine-tuning CNNs by using a pre-trained model on a larger available tagged dataset of different categories when there is insufficient data. provide. This allows faster convergence while reducing the cost of computing during training.

To tackle the scarcity of data, X-ray images are augmented using data augmentation techniques. This paper uses the Keras library to process the same, ImageDataGenerator class is used to augment the images. The DenseNet 201 layer is applied to the augmented layers which trains the model on the processed images.

As mentioned in Fig. 2., the model undergoes classification of X-ray images.

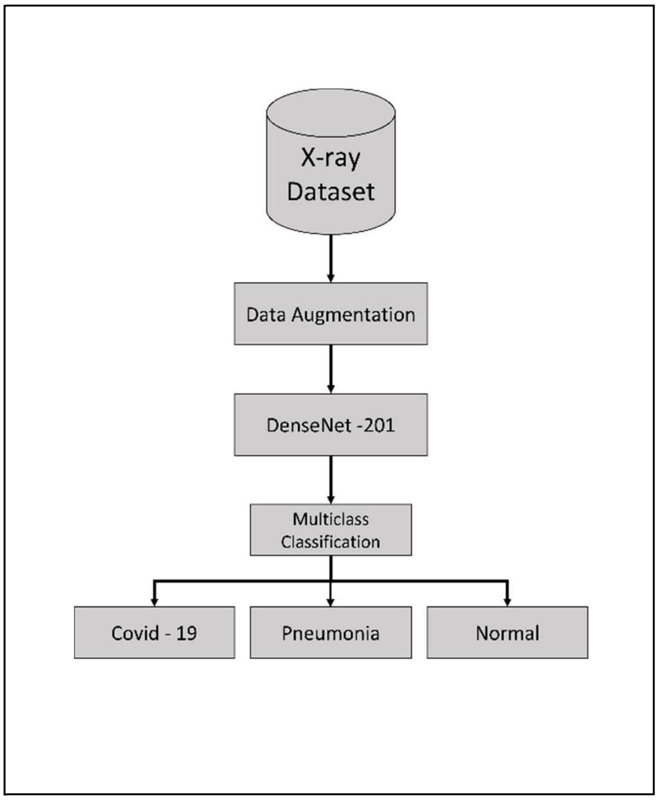

Fig. 2. Flowchart of the Proposed Model

V. Architecture of the Proposed Model

Initial CNN layers typically learn low-level features of images of most visual tasks. Later layers, on the other hand, learn higher-level functionality that specific to its application, As explained in Fig. 3. , the architecture of the proposed model is based on Densenet-201, which is working on 3 classes of the dataset Pneumonia, COVID-19, and Normal. On top of the base model Average pooling layer is applied as a way to summarize the information in a region of the input, as it has the effect of reducing the spatial dimensions of the input data while preserving important features.

Flattening operation is done afterward to convert the image data is transformed into a 1D array, and is ready to be used as an input in a fully connected neural network, followed by a Dense layer with relu activation followed by Dropout to reduce overfitting errors.

The prediction layer is the last layer of a neural network that is used for making predictions or classifications. This layer is used as our output layer, receives the output of the previous layers, and produces the final predictions of the network into three classes namely Pneumonia, COVID-19, and Normal images. The model has a total of 19,428,163 with 1,106,179 trainable parameters and 18,321,984 non-trainable parameters.

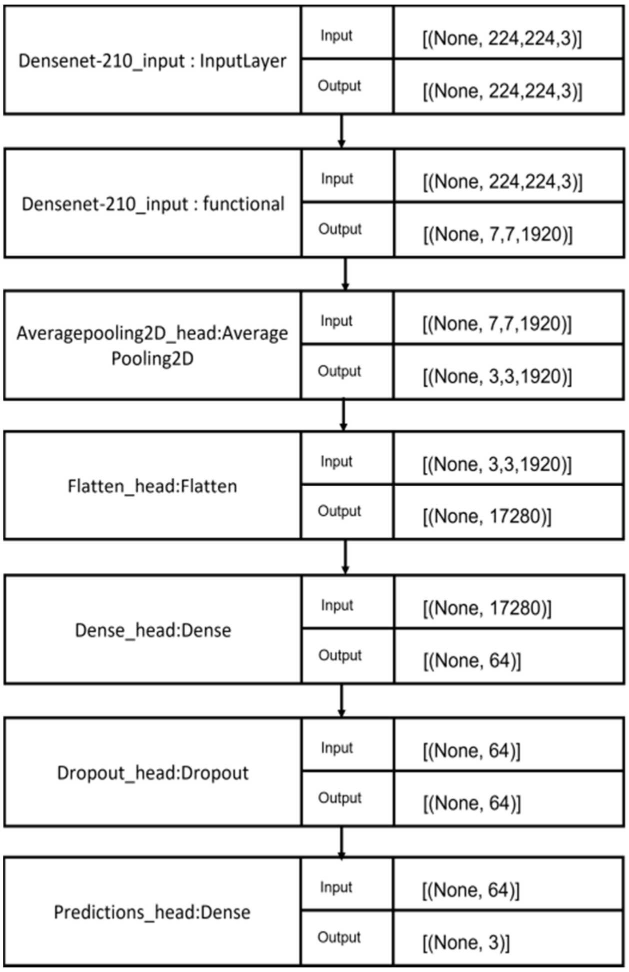

Fig. 3. Architecture of proposed model

The model proposed is trained with 5144 images of the three categories and the rest 1288 images are used for validation. We have done data augmentation using Image DataGenerator from Keras. The images are then provided as input to the DenseNet201 model. The model uses an Adam optimizer and a specified learning rate. Early stopping and changing the learning rate based on validation accuracy is also implemented on the model while running for 30 epochs.

VI. Results and Discussion

Further discussions have been made as mentioned in the above references, on how the optimal approach DenseNet can be for Computer Aided Diagnosis (CAD).

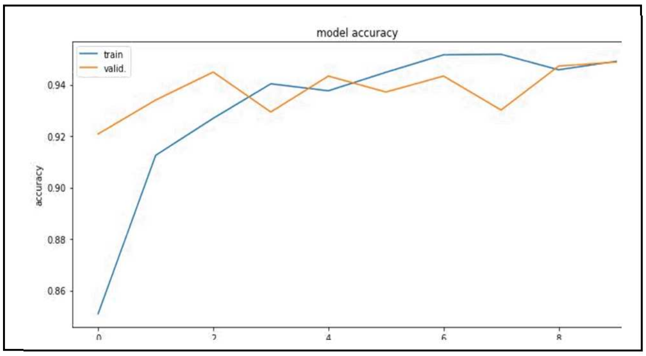

Fig. 4. Accuracy curve

Loss Curve (Fig. 5.) describes the loss per epoch in computing the accuracy of the model a negative slope in a loss graph is interpreted as a sound output, the loss occurred in the model for 10 epoch 0.423.

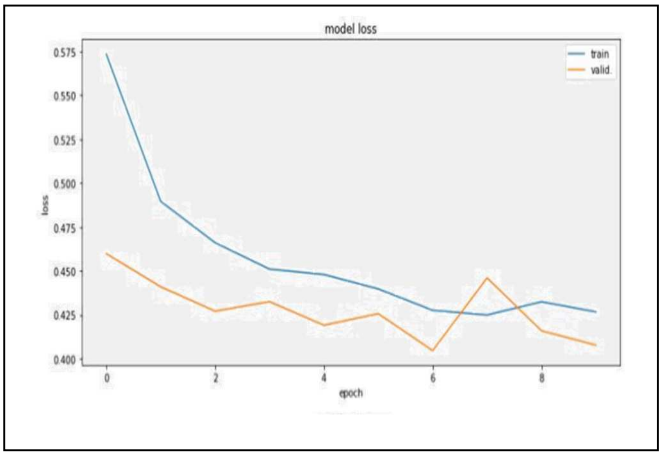

Fig. 5. Loss curve

The accuracy curve Fig. 4. in contrast to the loss curve is considered to show a forward and upward plot for the given model, The graph describes 95% training and validation accuracy for 10 epochs and is taken as a good result for the proposed model.

The accuracy curve exhibits a 'forward and upward plot, which means that as the model undergoes more training epochs, its accuracy steadily increases. This phenomenon applies to both the training and validation datasets, signifying that the model consistently improves its ability to make correct predictions.

Specifically, the mention of '95% training and validation accuracy for 10 epochs' implies that after just 10 rounds of training, the model achieves an impressive accuracy rate of 95% on both the data it was trained on and a separate validation dataset.

1) *Calculation of f1-score*

$Recall = \frac{Tp}{Tp+Fn}$ $\quad Precision = \frac{Tp}{Tp+Fp}$ $\quad F1 - Score = \frac{2*Recall*Precsion}{Recall+Precesion}$

here, [a] Tp is True positive, [b] FP is False negative and [c] Fn is false negative

	precision	recall	f1-score	support
0	0.99	0.96	0.97	116
1	0.89	0.91	0.9	317
2	0.96	0.96	0.96	855
accuracy			0.95	1288
macro avg	0.95	0.94	0.94	1288
weighted avg	0.95	0.95	0.95	1288

Fig. 6. F1 score analysis

In Figure 6 the diseases COVID-19 and pneumonia are represented by zero and two in the classification report and healthy is represented by one. the overall f1 score was found to be .95.

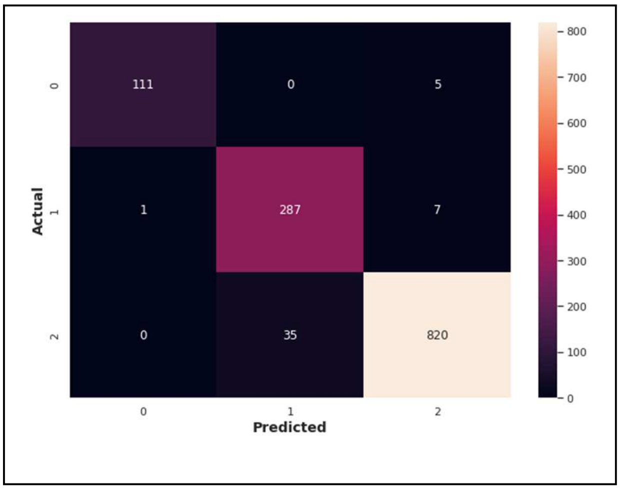

Fig. 7. Confusion Matrix

In Figure 7, the y-axis represents the true value and the x-axis represents the predicted value. The diagonal represents the correctly predicted images, for example in COVID-19, only 111 images are correctly classified.

VII. Conclusion

The proposed model provides an accuracy of 95.96 percent, for 30 epochs. Thus, the model is liable to be used as a CAD tool to assist radiologists in examining CXR of Pneumonia & COVID-19 under the supervision of medical professionals.

References

[1] C. Suárez-Ortega, et al "Using CAD systems and e-Learning in radiologists training," 2013 IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013), 2013, pp. 172-176, doi: 10.1109/HealthCom.2013.6720661.

[2] Y. Tan, et al Performance Comparison of Data Classification based on Modern Convolutional Neural Network Architectures," 2020 39th Chinese Control Conference (CCC), 2020, pp. 815-818, doi: 10.23919/CCC50068.2020.9189237.

[3] Alakwaa, Wafaa, et al. “Lung Cancer Detection and Classification With 3D Convolutional Neural Network (3D-CNN).” International Journal of Advanced Computer Science and Applications, vol. 8, no. 8, The Science and Information Organization, 2017. Crossref, https://doi.org/10.14569/ijacsa.2017.080853.

[4] Shelke, Ankita, et al. “Chest X-ray Classification Using Deep Learning for Automated COVID-19 Screening.” SN Computer Science, vol. 2, no. 4, Springer Science and Business Media LLC, May 2021. Crossref, https://doi.org/10.1007/s42979-021-00695-5.

[5] Z. Wan, et al "DenseNet model with RAdam optimization algorithm for cancer image classification," 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE), 2021, pp. 771-775, doi: 10.1109/ICCECE51280.2021.9342268.

[6] B. Chellapandi, et al "Comparison of Pre-Trained Models Using Transfer Learning for Detecting Plant Disease," 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 383-387, doi: 10.1109/ICCCIS51004.2021.9397098

[7] A. Nandy, "A Densenet Based Robust Face Detection Framework," 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), 2019, pp. 1840-1847, doi: 10.1109/ICCVW.2019.00229.

[8] Y. Qi, et al "Fruit Disease Identification Based on Improved Densenet Fusion Defogging Algorithm," 2021 18th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), 2021, pp. 313-317, doi: 10.1109/ICCWAMTIP53232.2021.9674088.

[9] T. H. Tran, et al "Building an Automatic Image Tagger with DenseNet and Transfer Learning," 2019 International Conference on Advanced Computing and Applications (ACOMP), 2019, pp. 34-41, doi: 10.1109/ACOMP.2019.00013.

[10] L. Bing-jin, et al "Research and Practice of X-ray Chest Film Disease Classification based on DenseNet," 2020 International Conference on Artificial Intelligence and Education (ICAIE), 2020, pp. 241-244, doi: 10.1109/ICAIE50891.2020.00063.

[11] T. Rahman et al., "Reliable Tuberculosis Detection Using Chest X-Ray With Deep Learning, Segmentation and Visualization," in IEEE Access, vol. 8, pp. 191586-191601, 2020, doi: 10.1109/ACCESS.2020.3031384.

[12] Q. Wang, et al, "X-ray Images Detection of COVID-19 Based on Deep wise Separable DenseNet," 2021 IEEE 6th International Conference on Signal and Image Processing (ICSIP), 2021, pp. 294-298, doi: 10.1109/ICSIP52628.2021.9688876

[13] P. S, et al "Performance Analysis of Squeezenet and Densenet on Fetal Brain MRI Dataset," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 1340-1344, doi: 10.1109/ICCMC53470.2022.9753874.

[14] S. Basu, et al "Deep Learning for Screening COVID-19 using Chest X-Ray Images," 2020 IEEE Symposium Series on Computational Intelligence (SSCI), 2020, pp. 2521-2527, doi: 10.1109/SSCI47803.2020.9308571.

[15] Y. Tan, Y. Li, H. Liu, W. Lu and X. Xiao, "Performance Comparison of Data Classification based on Modern Convolutional Neural Network Architectures," 2020 39th Chinese Control Conference (CCC), 2020, pp. 815-818, doi: 10.23919/CCC50068.2020.9189237.

[16] B. Yaman, S. A. Hossein Hosseini, S. Moeller and M. Akçakaya, "Comparison of Neural Network Architectures for Physics-Driven Deep Learning MRI Reconstruction," 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 2019, pp. 0155-0159, doi: 10.1109/IEMCON.2019.8936238.

[17] Huang, G., Liu, Z., & Weinberger, K.Q. (2016). Densely Connected Convolutional Networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2261-2269.