Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences
ISSN：1674-2974 | CN 43-1061 / N

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

VISUALIZATION OF CHEST X-RAY IMAGES WITH LIME EXPLANATION FOR COVID-19 AND PNEUMONIA CLASSIFICATION

SHYLAJA P
Research Scholar, Department of Computer Science, Central University of Kerala, Kasaragod, India. Email: shylup2002@gmail.com, ORCID: https://orcid.org/0000-0003-2115-2962

Dr. JAYASUDHA J S *
Professor, Department of Computer Science, Central University of Kerala, Kasaragod, India.
*Corresponding Author Email: jayasudhajs@cukerala.ac.in,
ORCID: https://orcid.org/0000-0002-3044-6885

Abstract

COVID-19 disease has taken several millions of lives since December 2019. Pneumonia is a lung infection disease killed many in previous years. Research has been going on for the early detection of COVID-19 and Pneumonia from both CXR (Chest X-ray) and CT (Computed Tomography) images. This paper presents a Deep Neural Network implementation using LIME for three class classifications COVID-19, Pneumonia and Normal. The dataset is taken from Mendeley which contains 5228 chest X-ray images that are categorized into three groups such as COVID-19 (1626 images), PNEUMONIA (1800 images) and Normal (1802 images). Manual examination of Chest X-ray images is time-consuming and complex. LIME technology is useful for interpreting a black box Machine Learning model. It explains every individual prediction. LIME contributes to quality interpretation in the research area. Many researchers have developed models using deep learning techniques but they lack the explanation about the interpretation of the result and they got less accuracy compared to our proposed model. Our proposed model got 98.76% accuracy for the standard dataset of 5228 CXR images which outperforms the state-of-the-art models.

Keywords: *Chest X-ray, COVID-19, Deep Learning, Explainable Artificial Intelligence, LIME.*

1. INTRODUCTION

Since December 2019, COVID-19 had been spread all over the world and already lost millions of lives in a little span of time. In addition to that, some others got damage on respiratory systems also. Pneumonia is caused by microbes and infects lungs affecting serious breathing problems. Timely detection of CIVID-19 and pneumonia helps to expert treatments thus saving life and other serious aftereffects. Research has been going on to the early detection of COVID-19 and pneumonia. RT-PCR test was using for the detection of COVID-19 in the starting stage [1]. Also CT-scans were used for the detection of chest related diseases. Generation of CT-scans is costly, has low specificity property and the radiation causes other serious problems too. Diminishing the radiation intensity slows down the clarity of CT-scan images. So it is not the good option to adopt. Generation of chest x-ray images is comparatively safer and cheaper. This work uses chest x-ray images for the early detection of COVID-19, PNEUMONIA from the chest x-ray images [2, 3]. Advancement in Machine Learning algorithms, especially in Deep Learning reveals the hidden medical information [6].

The second session explains the properties of LIME. Comprehensive literature review has been done in session 3. Session 4 details the materials and evaluation metrics used in our model. Statistical

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

Analyses and Discussion are done in sessions 5 and 6 respectively, and finally session 7 makes conclusion.

2. PROPERTIES OF LIME

LIME (Local Interpretable Model-agnostic Explanations) generate local prediction explanations based on the analysis of inputs rather than a global explanation. It is a blackbox model, hiding the background details or internal workings of the model. It generates synthetic data points by perturbing the inputted original data. It highlights the superpixels of the image input data [4].

The class, Lime ImageExplainer explains the prediction details of an image classification model. It perturbes the image and analyzes how changes affect the final prediction and which are the most relevant parts of that prediction. It highlights the boundaries of segments making it more visible for prediction and interpretation [5].

Lime Explainer focuses on the relevant part of the image that leads to the model's diagnosis which highlights the influential super pixels. The framework first divides the image into super pixels clustered the similar pixels. They are then perturbed to create a new version of images. LIME fits the local interpretable model locally on the perturbed images to highlight the most relevant feature in the prediction [20.21].

Steps of LIME contain:

Step1: Initialization

Setting up of LIME explainer with appropriate configuration is the essential step for very model using LIME as explainer.

Step2: Super pixel Segmentation

Segmenting the image into super pixels for simplification purpose is done in this step.

Step3: Perturbation and Sampling

Creating perturbed images by modifying super pixels is done in this step.

Step4: Weighting Perturbations

Assigning weights to perturbed images based on the original image similarity.

Step5: Generating Linear Model

Fitting a simpler model to an appropriate complex model depends on the similarity of both images in a local area.

Step6: Generating Explanation

Produces interpretable explanations based on fitted models. It highlights important areas by setting boundaries.

3. LITERATURE REVIEW

Bhatt et.al. [6] demonstrated an ensemble model to indicate the presence of pneumonia in a set of CXR images with an accuracy of 84.12%. Since they used less data for their work, they found overfitting in their model.

Kumar et.al. [7] developed a two-class classification model for the detection of COIVD and non-COVID pneumonia using visualization techniques. They draw boundaries on infected images. Their work,

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

namely RYOLO v4 tiny detector that consists of both CT scan and CXR dataset implementation. They claimed an average precision value of 88.18%.

Hariri et.al. [8] Implemented a four class classification of chest X-ray images of Healthy, COVID-19, viral pneumonia and bacterial pneumonia with an accuracy of 89.89%. Cuing Convolutional Neural Network.

Sharma et.al. [9] took two CXR datasets for pneumonia classification. They got 92.15% accuracy for VGG16 model for the first dataset and 95.4% for the second dataset (of 6436 images).

Constantinou et.al. [3] proposed a Deep Learning Neural Network to detect COVID-19 from CXR images. They used ResNet50, ResNet101, DenseNet121, DenseNet169 and InseptionV3 using Transfer Learning and got highest accuracy of 96% on ResNet101.

Duong et.al. [10] tried EfficientNet and MixNet for the datasets of chest X-ray and Lung Computer Tomography images aiming to detect COVID-19 from various types of images. CXR datasets contains 15,000 and 17,905 images and LCT datasets contain 2,482 and 411,528 images respectively for the four datasets and claiming accuracy larger than 95% for all datasets.

Wang et.al. [11] developed PneuNet, a vision transformer based deep neural network algorithm for pneumonia diagnosis from chest X-ray images. They got 94.96% accuracy for the three class problem classification.

De Jesus Silva et.al. [12] compared three algorithms namely, DenseNet169, VGG16 and Xception for classifying COVID-19 and non-COVID from CT scan images. The dataset contains 2477 CT images and got high accuracy of 97.7% for the ensemble model.

Mittal et.al. [13] tried ResNet-101, ResNet152, InceptionResNetV2, DenseNet201, and EfficientNetV2L Convolution Neural Network in Chest X-ray images and got the best accuracy of 98.6% for the ResNet-101 for the two class classification for normal pneumonia and COVID pneumonia for the self-preprocessed dataset.

Alshahrni et.al [14] proposed a deep-learning algorithm to detect COVID-19. A Dense-CNN model categorizes the COVID and non-COVID patients, and the accuracy of their work is 98.062%.

Celik et.al. [15] proposed a deep learning based algorithm, CovidDWNet for the detection of COVID-19, Lung Opacity, Normal and Virul pneumonia from CT and CXR images. It used Feature Reuse Residual Block and Depthwise Dilated Convolutions units.with 96.81% accuracy.

Huy et.al. [16] proposed CBAMWDnet for tuberculosis detection in CXR images. They combined Convovutional Block Attension Module and Wide Dense Net and claiming best for capturing spatial and contextual information in images and have an accuracy of 98.80%.

Wu et.al. [17] used deep learning method for capturing COVID-19 from CAP using a method of Maximum intensity Projection from CT scan images. The dataset contains 333CT scan images and validated for 3581 CT scan images.

Kilicarslan et. al. [18] developed a system for detecting pneumonia using a newly proposed activation function Superior Exponential (SupEx). They conducted experiments using the datasets of MNIST and CIFER-10.
Ying et. al. [19] introduced a framework for noisy chest x-ray images and proposed a noisy recovery algorithm using a method of Subset Label Iterative Propogation and Replacement.

ISSN：1674-2974 | CN 43-1061 / N

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

Table 1: Literature Review

Authors	Models used	Classification type	Dataset details	Accuracy achieved
Bhatt et. al. [6]	Ensemble CNN	Pneumonia detection	Chest X-ray images(CXR)	84.12%
Kumar et. al. [7]	RYOLO v4-tiny	COVID-19 vs non-COVID Pneumonia	Computed Tomography(CT) and CXR images	88.18%
Hariri et. al. [8]	Convolutional Neural Network(CNN)	Healthy, COVID-19, Viral and Bacterial Pneumonia classification	CXR images	89.89%
Sharma et. al. [9]	VGG-16	Pneumonia Classification	Two datasets of CXR	92.15%(First Dataset) and95.4(Second Dataset)
Constantinou et. al. [3]	ResNet50, ResNet101, DenseNet121, DenseNet169, InseptionV3	COVID-19 detection	CXR and LungCT	96% (ResNet101)
Duong et. al. [10]	EfficientNet, MixNet	COVID-19 detection	CXR and LungCT	>95% in all datasets
Wang et. al. [11]	PneuNet (Vision Transformer)	COVID-19 and Pneumonia	CXR images	94.96%
De Jesus Silva et. al. [12]	DenseNet169, VGG16, Xception	COVID-19 vs non-COVID19	CT scans(2477 images)	97.7%(Xception)
Mittal et. al. [13]	ResNet101, ResNet152, InseptionResNet v2, DenseNet201, EfficientNet V2L	Normal, Pneumonia and COVID Pneumonia classification	CXR images(Self-Preprocessed Dataset)	98.6% (ResNet101)
Alshahrni et. al. [14]	Dense-CNN	COVID-19 detection	CXR images	98.06%
Celik et. al. [15]	CovidDWNet	COVID-19, LungOpacity, Normal, Viral Pneumonia	CT and CXR images	96.81%
Huy et. al. [16]	CBAMWDnet	Tuberculosis detection(Binary classification)	CXR images	98.8%
Wu et. al. [17]	Capsule Network with maximum intensity projection	COVID-19	CT scan image	Not specified
Kilicarslan et. al. [18]	SupEx Activation Function in CNn	Pneumonia detection	MNIST, CIFAR-10	Not specified
Ying et. al. [19]	Subset Label Iterative Propagation and Replacement	Binary(COVID-19 classification with noisy label)	CXR images	Not Specified

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

4. MATERIALS AND EVALUATION METRICS

It is found that the performance of the model depends on the dataset and number of epochs. Public X-ray dataset of 5228 chest X-ray images was selected for implementation and for the evaluation of three-class classification performance. The samples are divided into three categories namely COVID-19, Normal and PNEUMONIA. Normalization and resizing to 224 x 224 was done in google collaboratory. It is then randomly splitted to 80:20 training set and testing set respectively. As visualization result is very important for the medical officers to detect disease, we did visualization in this work using LIME. Deeplearning and LIME is used in the work for better interpretation. Accuracy is the prevalent metric of classification which is the proportion of current classification to the total samples. Accuracy is the key metric used for statistical classification.

5. STATISTICAL ANALYSES

Quality of dataset is most important in diagnosing the disease. We took public dataset from mendeley [22]. The dataset consists of 5228 chest X-ray images containing 3 classes: COVID-19, Pneumonia and Normal images. Images are PNG format with a resolution of 256 x 256 pixels and this dataset was sited in many medical imaging deep learning algorithms.

The 256 x 256 sized images are resized into 224 x 224 inorder to reduce memory unitization using python language and executed in Collaboratory. Label Binerizer preprocessing tool is used for converting our categorical labels into binary encoded format. We took VGG16 as base model and after avoiding classification layer of the VGG16 model of ImageNet, we added custom layers for the classification task. Before adding a custom layer, we freeze all the layers in the base model. Then created custom layers for our new classification task. The custom layer consists of a flattened layer followed by three dense layers.

First two dense layer uses 'relu' activation function and the inputs are 1024 and 512 respectively. The final dense layer classifies the images into three classes. So it uses 3 as a parameter and the activation function for the final dense layer is 'softmax'. Combined the original model with the new layers. We enabled the stratified sampling to make the training and testing data more representative of the whole dataset. The model was compiled with an Adam optimizer with a learning rate of 0.0001. The loss function used in this model is categorical cross-entropy since our input belongs to multiple classes. This loss function compares the predicted probability distribution from the softmax with the actual distribution and penalizes it.

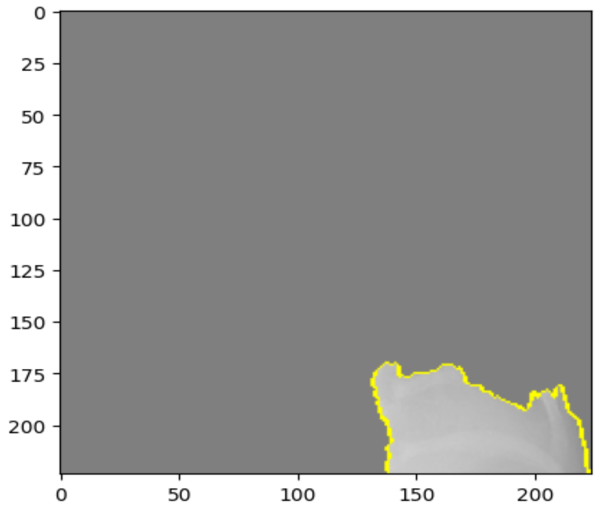
The dataset was randomly split into 80% for training and the remaining 20% for testing purposes and the random_state value used in this model is 42. The training process is done with 50 epochs for the chest X-ray dataset.

Heatmap representation of LIME (Lime-0.2.0.1) is used for local explanation. The color map of Red-Blue (RdBu) specifies the positive and negative contributions, showing how different colors correspond to different levels of importance of each superpixel for the model prediction. In our work, 1000 perturbed samples are used for the local interpretation model. If more samples are used, it provides better approximation. Our model got the accuracy of 98.76% which is more than the state-of-the-art method. This local model makes deep learning model more transparent.

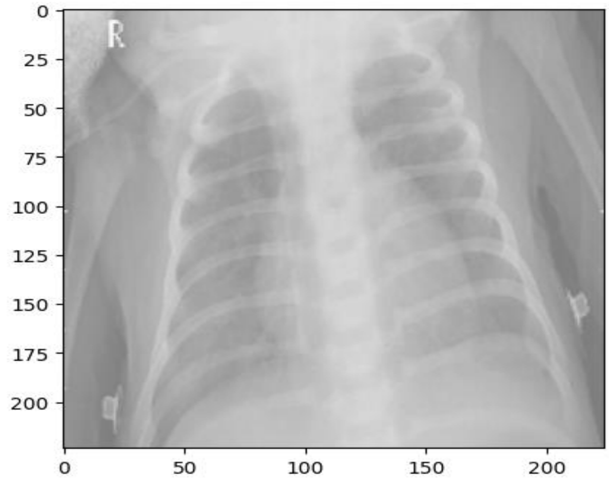
Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences
ISSN：1674-2974 | CN 43-1061 / N

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

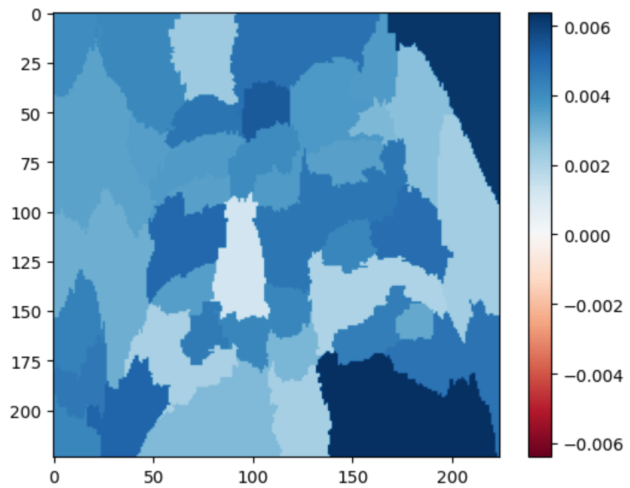
(a) Boundary marking after hiding other details of the image



(b) Chest X-ray image of Pneumonia patient



(c) Mapping of super pixel



Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences
ISSN : 1674-2974 | CN 43-1061 / N

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

(d) Most significant feature marked with boundary

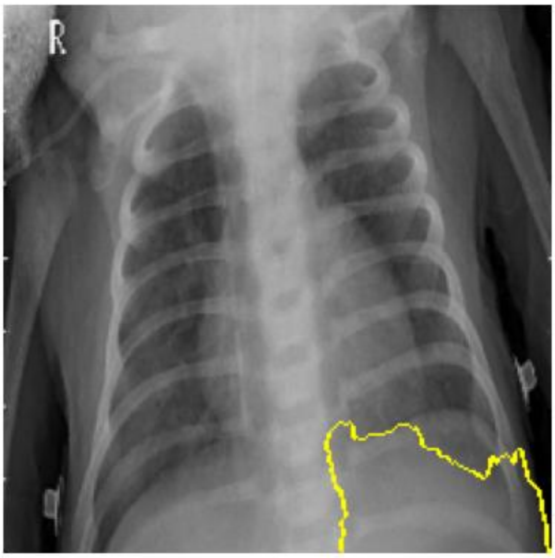


Figure 1: (a) Boundary marking after hiding other details (b) Chest X-ray image of Pneumonia patient (c) Mapped each explanation weight to the corresponding super pixel (d) Most significant feature is marked with boundary.

The figures highlight super pixels that positively contribute to the model's prediction by hiding the weakly contributing features and by suitably marking the boundaries. This visualization helps medical officers to focus and reasoning. Table 1represent the summary of the proposed model. It includes the layer type, output shape of each layer and the parameters handled in each layer. Moreover it contains total parameters consisting trainable, non-trainable and optimizer parameters and the memory utilized in Mega Bytes.

Table 1: Summary of the proposed model

Layer Type	Output Shape	Param
input_layer	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808

ISSN：1674-2974 | CN 43-1061 / N

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 1024)	25,691,136
dense_1 (Dense)	(None, 512)	524,800
dense_2 (Dense)	(None, 3)	1,539
Total params:	40932163 (156.14 MB)	
Trainable params	26217475 (100.01 MB)	
Non-trainable params:	14714688 (56.13 MB)	

6. DISCUSSION

Many researchers used [3, 6-9, 11, 13-16, 19] CXR (chest X-ray images) for their study highlighing the suitability of disease detection detection of CXR dataset. They used Deep Learning algorithms for their implementation like ResNet, CNN and Vision Transformer for classification purpose. Few researchers [6-9, 11, 13, 15] concentrated on Pneumonia detection, whether as a standalone condition or with COVID-19 detection. Some of the most popular work are based on binary classifications [3, 6-7, 10, 12, 14, 17] to detet a disease from healthy condition and few researchers [3, 7, 10-12, 14, 19] focused their research on COVID-19 detection from dataset.

Bhatt et.al. [6] and Sharma et.al. [9] Proposed their work by taking dataset of CXR images for Pneumonia detection whereas Constantinuo et.al. [3] and Kumar et.al. [7] experimented both CXR and CT datasets. Compared to other studies, [13] put forward a self-preprocessed dataset. Comparing to the accuracy from different authors, it varies from 84.12% to 98.8% (for Tuberculosis detection), depending on the dataset size, pre-processing technique, and the performance of the model. Hariri et.al. [8] and Celik et.al. [15] experimented with multi-class classifications for the Healthy, COVID-19, Viral, and Bacterial Pneumonia categories and others for Lung Opacity, COVID-19, and Normal Viral Pneumonia respectively. Wang et.al. [11] used a complex, recent Vision Transformer for their study. Huy et.al. [16] targeted their study on tuberculosis detection using CBAMWDnet. Wu et.al. [17] and Kilicarslan et.al. [18] did not specify accuracy in their study results making it difficult to compare their results with others. Mittal et.al [13] got maximum accuracy of 98.6% among the state-of-the-art methods. The limitation is that they used a self-preprocessed dataset. In our model, we used a standard dataset of Chest X-ray images with 5228 images and the proposed model got 98.76% accuracy, the results obtained when comparing the existing models are given in Table 2.

Table 2: Accuracy of the state-of-the-art and proposed methods

Authors	Models used	Dataset details	Accuracy achieved
Kumar et. al. [7]	RYOLO v4-tiny	Computed Tomography(CT) and CXR images	88.18%
Hariri et. al. [8]	Convolutional Neural Network(CNN)	CXR images	89.89%
Wang et. al. [11]	PneuNet (Vision Transformer)	CXR images	94.96%
De Jesus Silva et. al. [12]	DenseNet169, VGG16, Xception	CT scans(2477 images)	97.7% (Xception)
Mittal et. al. [13]	ResNet101, ResNet152, InseptionResNet v2, DenseNet201, EfficientNet V2L	CXR images(Self-Preprocessed Dataset)	98.6% (ResNet101)
Proposed Method		**CXR standard dataset**	**98.76%**

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

7. CONCLUSION

A new model for classifying COVID-19, Pneumonia and Normal images from a public dataset is proposed in this paper. The dataset contains a total of 5228 chest X-ray images categorized into COVID, Pneumonia, and Normal. We have got the model accuracy of 98.76%. Early detection of diseases prevents the severity and mortality in COVID-19 and pneumonia cases may be severe after some time. The proposed model diagnoses COVID-19 and Pneumonia more accurately than the state-of-the-art methods. In addition to the previous algorithms, it implements visualization of the most relevant area using LIME making the model more transparent and interpretable.

References

1) Huy, Vo Trong Quang, and Chih-Min Lin. "An improved densenet deep neural network model for tuberculosis detection using chest x-ray images." IEEE Access 11 (2023): 42839-42849.
2) Haghanifar, Arman, et al. "Covid-cxnet: Detecting covid-19 in frontal chest x-ray images using deep learning." Multimedia tools and applications 81.21 (2022): 30615-30645.
3) Constantinou, Marios, et al. "COVID-19 classification on chest X-ray images using deep learning methods." International Journal of Environmental Research and Public Health 20.3 (2023): 2035.
4) Slack, Dylan, et al. "Fooling lime and shap: Adversarial attacks on post hoc explanation methods." Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society. 2020.
5) Garreau, Damien, and Ulrike Luxburg. "Explaining the explainer: A first theoretical analysis of LIME." International conference on artificial intelligence and statistics. PMLR, 2020.
6) Bhatt, Harsh, and Manan Shah. "A Convolutional Neural Network ensemble model for Pneumonia Detection using chest X-ray images." Healthcare Analytics 3 (2023): 100176.
7) Kumar, Akhil. "RYOLO v4-tiny: A deep learning based detector for detection of COVID and Non-COVID Pneumonia in CT scans and X-RAY images." Optik 268 (2022): 169786.
8) Hariri, Muhab, and Ercan Avşar. "COVID-19 and pneumonia diagnosis from chest X-ray images using convolutional neural networks." Network Modeling Analysis in Health Informatics and Bioinformatics 12.1 (2023): 17.
9) Sharma, Shagun, and Kalpna Guleria. "A deep learning-based model for detecting pneumonia from chest X-ray images using VGG-16 and neural networks." Procedia Computer Science 218 (2023): 357-366.
10) Duong, Linh T., et al. "Automatic detection of COVID-19 from chest X-ray and lung computed tomography images using deep neural networks and transfer learning." Applied Soft Computing 132 (2023): 109851.
11) Wang, Tianmu, et al. "PneuNet: deep learning for COVID-19 pneumonia diagnosis on chest X-ray image analysis using Vision Transformer." Medical & Biological Engineering & Computing 61.6 (2023): 1395-1408.
12) De Jesus Silva, Lúcio Flávio, Omar Andres Carmona Cortes, and João Otávio Bandeira Diniz. "A novel ensemble CNN model for COVID-19 classification in computerized tomography scans." Results in Control and Optimization 11 (2023): 100215.
13) Mittal, Vasu, and Akhil Kumar. "COVINet: A hybrid model for classification of COVID and non-COVID pneumonia in CT and X-Ray imagery." International Journal of Cognitive Computing in Engineering 4 (2023): 149-159.
14) Alshahrni, Mohammad M., et al. "An intelligent deep convolutional network based COVID-19 detection from chest X-rays." Alexandria Engineering Journal 64 (2023): 399-417.
15) Celik, Gaffari. "Detection of Covid-19 and other pneumonia cases from CT and X-ray chest images using deep learning based on feature reuse residual block and depthwise dilated convolutions neural network." Applied Soft Computing 133 (2023): 109906.

DOI: 10.5281/zenodo.13810519
Vol: 61 | Issue: 09 | 2024

16) Huy, Vo Trong Quang, and Chih-Min Lin. "An improved densenet deep neural network model for tuberculosis detection using chest x-ray images." IEEE Access 11 (2023): 42839-42849.

17) Wu, Yanan, et al. "Classification of COVID-19 from community-acquired pneumonia: Boosting the performance with capsule network and maximum intensity projection image of CT scans." Computers in Biology and Medicine 154 (2023): 106567.

18) Kiliçarslan, Serhat, et al. "Detection and classification of pneumonia using novel Superior Exponential (SupEx) activation function in convolutional neural networks." Expert Systems with Applications 217 (2023): 119503.

19) Ying, Xiaoqing, Hao Liu, and Rong Huang. "COVID-19 chest X-ray image classification in the presence of noisy labels." Displays 77 (2023): 102370.

20) Zandehshahvar, Mohammadreza, et al. "Toward understanding COVID-19 pneumonia: A deep-learning-based approach for severity analysis and monitoring the disease." Scientific Reports 11.1 (2021): 11112.

21) Park, Sangjoon, et al. "Vision transformer for covid-19 cxr diagnosis using chest x-ray feature corpus." arXiv preprint arXiv: 2103.07055 (2021).

22) https://data.mendeley.com/datasets/dvntn9yhd2/1