Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

Deep LIFT incorporated Deep Learning Framework for Classification of Novel Coronavirus (COVID-19) using Computed Tomography scan Images

Kiran H. Patil[1], Dr. M. Nirupama Bhat[2]
[1,2].CSE Dept
VFSTR Deemed to be University
Vadlamudi, Guntur (A.P.), India [1]patilk2008@gmail.com
Corresponding Author:
drmnb_cse@vignan.ac.in

Cite this paper: Kiran H. Patil, M. Nirupama Bhat (2024) Deep LIFT incorporated Deep Learning Framework for Classification of Novel Coronavirus (COVID-19) using Computed Tomography scan Images. *Frontiers in Health Informatics, 13* (3), 6282-6299

Abstract:
The world was devastated by the Coronavirus disease (COVID-19) since 2019 and its variant pandemic. It is very important and crucial to detect coronavirus infected patients as early as possible. Researchers have proposed many neural based learning based methodologies based on Computed Axial Tomography scan (CAT scan) figures and X-ray figures to assist healthcare expert. In this paper, we have proposed classification of Covid-19 disease from CAT study figures using hybridization of deep shift invariant based pretrained models and features generated by DeepLIFT (Neural based learning Important Features) technique. DeepLIFT assigns contribution scores based on the difference between each neuron's activation and its "reference activation." At first, picture preprocessing is done by resizing, normalization and then, features are extracted by hybridization of pre-trained deep models and DeepLIFT technique. Finally, images are classified into two categories, normal and Covid-19. Experiments are carried out on two standard COVID-19 CAT scan datasets and results show that the proposed hybridization technique gives better result than conventional one. Average accuracy of 95.4%, precision of 98.93%, recall of 95.96%, specificity of 80.12% and F1 score of 97.42 is achieved.

Keywords: *Covid-19, CAT scan figures, deep learning, convolutional network of neurons (CNN), Deep LIFT*

1. Introduction:

Millions of deaths and thousands of fatalities globally have been attributed to the virulent and contagious novel coronavirus, or COVID-19. This ailment was first identified in Wuhan, China, in December 2019, and is caused by the SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) virus family. On March 11, 2020, WHO proclaimed the Covid-19 outbreak to be a pandemic since it had begun to spread rapidly.Covid-19 infected patient get various common symptoms such as fever, cough, cold, sore throat etc. It also has some uncommon gastrointestinal symptoms like diarrhea, nausea, vomiting or abdominal pain. In serious cases, symptoms are difficulty in breathing or shortness of breath and pneumonia [1].
Currently, any patient having above symptoms is Corona positive or can be known by a test called rRT-PCR test (real time Reverse Transcription Polymerase Chain Reaction) among the different tests. But this test also has few limitations like low sensitivity, repeatability and false negative result due to rapid mutation of SARS-

CoV-2 [2]. In such cases, diagnosis can be assisted by analyzing chest X - ray figures or CAT study (Computed Tomography) figures. It has been proved by the research articles published by different researchers in Radiology and Medical Imaging journals that chest X- ray and chest scan figures are helpful in detecting Covid-19. CAT scan figures have high specificity and sensitivity to detect Covid-19 and it also contains Ground Glass Opacities (GGOs), consolidations which can be easily detectable by neural based learning methods [3, 8]. Radiology based imaging approaches gives fast result, higher sensitivity and True Positive rates in comparison with laboratory tests as they are costly too [10]. Moreover, disease infection can be recognized in early stages so that patient can be cured early by avoiding serious damages.

Artificial Intelligence, Machine Learning and Deep Learning based techniques have enormous applications in medical and healthcare practices including radiology and other medical figure analysis. Also, high quality freely available medical figure datasets provides great help to develop new applications and to do further research in any specific field. Novel neural based learning algorithms helps in automatic diagnosis of disease and management by accurately identifying, analyzing and classifying different patterns and features in medical figures.

The main objective of this proposed work is to develop a neural based learning model using several pre-trained models and use of transfer learning to detect novel coronavirus (COVID-19) disease from chest CAT scan pictures to achieve better accuracy. AlexNet, GoogleNet, ResNet50 and VGG19 models are used for this purpose. Then DeepLIFT technique is incorporated with ResNet50 and VGG19 models which give adequate rise in accuracy as well as all performance measures.

The rest of the paper is organized as follows: Survey of related literature articles is given in Section 2. Section 3 elaborates on methodology applied with different techniques in detail. Experimental results gives description of datasets used in this study and obtained results are discussed in the form of tables and graphs in Section 4. Finally, Section 5 describes conclusion and further scope of research.

2. Related Work:

T. R. Ornob et al [21] developed a system called CovidExpert using combination of triplet Siamese network and few shot learning. This framework classifies input CAT scan pictures into three classes like, normal, COVID-19 and CAP (Community-Acquired Pneumonia). They used dataset created by Maftouni et al [26] which is the largest dataset formed by combining seven different COVID-19 open datasets. It contains 2618 CAP pictures, 7593 COVID-19 pictures and 6893 normal CAT scan pictures. This proposed model accomplished 98.719% of overall accuracy, 99.36% of specificity, sensitivity of 96.72% and 99.99.9% of ROC score. M. Afif et al [22] proposed a system for lesions segmentation for prediction of COVID-19 using CAT pictures. Proposed system uses context aggregation NN which is a encoder-decoder type of architecture. It consists of three modules, namely context fuse module (CFM), attention mix module (AMM) and residual convolutional module (RCM). System detects two main regions from CT Pictures related to.COVID-19, ground glass opacity and consolidation area. They have used COVID-x-CT dataset for experimentation and achieved 96.72% of accuracy.

A. Smadi et al [23] developed an intelligent application called SEL-COVIDNET for diagnosing COVID-19 from X-ray and CAT pictures. This system is build using transfer learning and nine various pre-trained models like DenseNet121, InceptionNetV3, and VGG19 etc. and gives multi-class classification output. Experiments are carried out on three various X-ray datasets and SARS-CoV-2 CAT dataset. Extremely compact shift invariant model with multi-scale feature learning (MFL) blocks was created by Joshi et al. [24]. Composed of many MFL blocks, the MFL-Net effectively combines multiple convolutional layers with residual connections and 3x3 filters. As a result, the block is able to extract and retain multi-scale information at different levels. Two distinct datasets are used for experimentation; the COVID-CT dataset yielded an accuracy of 93.59%, while the SARS-CoV-2 CAT research dataset produced an accuracy of 98.79%. By combining deep features with the Parameter Free BAT (PF-BAT) optimized Fuzzy K-nearest neighbor (PF-FKNN) classifier, T. Kaur et al. [25] created an expert model. The MobileNetv2 model extracts features, and FKNN training comes after transfer learning. Additionally, the PF-BAT approach is used to fine-tune the FKNN hyperparameters. Accuracy rate of 99.38% is attained on the SARS-CoV-2 CAT research dataset. The literature review summary is displayed by **Table 1**. P. Silva et al. used scan figures to identify Covid-19 [4] in which they devised a voting-based strategy employing an effective neural based learning algorithm. With this method, groups of figures from a single patient are identified in a voting system and evaluated on the two largest scan datasets. They also provided cross-dataset analysis which shows generalization of neural based learning models is not that much robust where data comes from different distributions as accuracy drops from87.68% to 56.16% using best evaluation scenario.

Table 1: Summary of Literature Review

Authors	**Technique/Model**	**Dataset**	**Classification**	**Accuracy (%)**
Ornob et al [21]	Triplet Siamese Network	Combined dataset by Maftouni et al	Multi-class (3 classes)	98.719 Overall
Afif et al [22]	Context Agreegation NN with 3 modules	COVID-x-CT	Binary	96.72
Smadi et al [23]	SEL-COVIDNET (Based on 7 pre-trained models)	3 X-ray Datasets, SARS-CoV-2 CAT	Multi-class (3 classes)	98.52 (3 classes) 99.77 (2classes)
Joshi et al [24]	MFL-Net (shift invariant model with Multi-scale Feature Learning blocks)	COVID-CT SARS-CoV-2 CAT	Binary	93.59 98.79
Kaur et al [25]	Optimising Parameter Free BAT, PF-FKNN, or fuzzy K-nearest neighbour, classifier	SARS-CoV-2 CAT	Binary	99.38
Silva et al [4]	EfficientCovidNet with voting-based approach	SARS-CoV-2 CAT COVID-CT	Binary	97.38 86
Zhao et al [5]	Random, Bit-S and Bit-M (using ResNet-v2)	COVIDx CT-2A	Binary	97.9, 98.8, 99.2
Mishra et al [6]	Decision fusion model (based on 5 pre-trained models)	COVID-CT	Binary	88.34
Rohila et al [7]	ReCov-101 (using ResNet-101)	MosMedData (4 classes)	Binary	94.9 Overall
Shah et al [8]	CTnet-10 model and VGG-19 (using 5 pre-trained models)	COVID-CT	Binary	82.1 and 94.5

Perumal [9]	5 Neural based learning models and 5 machine learning methods	Multisource data assimilation	Multi-class (3 classes)	96.69
Mostafiz et al [10]	Hybridization of deep shift invariant model and DWT optimized features	COVID-19 chest X-ray (2 scenarios)	2-class and 4-class	99.45 and 98.48

W. Zhao et al [5] used transfer learning technique for testing Covid-19 disease using figures and developed model was pre-trained on ImageNet21k for generalization. The proposed model also tests the importance of initialization of various hyperparameters on the results and gives 99.2% accuracy for testing Covid-19 cases. A. K. Mishra et al [6] used different Deep CNN based techniques for finding Covid-19 from chest figures. They have proposed decision fusion based technique which combines results from multiple individual models to produce a final prediction and achieves above 86% results across all performance measures.

ReCOV-101 is a model that V. S. Rohila et al [7] proposed for identifying different levels of Covid-19 contagious disease using complete chest figures. This model is based on the residual network (ResNet-101) and transfer learning, where scan figures were preprocessed using segmentation and interpolation. Accuracy of 94.9% was achieved by this proposed model. With an accuracy of 82.1%, V. Shah et al. [8] created the CTnet-10 model for the identification of Covid-19 illness using scan figure. They have evaluated performance of number of pre-trained models, such as VGG-16, VGG-19, DenseNet-169, ResNet-50, and Inception V3. The highest accuracy was observed for VGG-19, which was 94.52% overall. In order to classify Covid-19 from scan figure, V. Perumal et al. [9] used a variety of pre-trained neural based learning models and machine learning methods for feature extraction and classification resp. They found AlexNet+SVM model with superior result amongst all with 96.69% of accuracy. R. Mostafiz et al [10] proposed an approach using chest X-ray figures to detect the infection. They have combined deep convolutional Network of neurons approach along with DWT features for feature extraction and bagging technique of random forest classifier for classification.

3. Methodology:

The suggested technique detects Covid-19 from chest CAT pictures using a neural based learning approach. Covid-19 and regular scans are the two types of pictures that the system accepts as input. System has to identify whether given scan figure is of Covid positive or negative patient. The block diagram of system workflow is given in fig. 2. Two dimensional neural based learning framework using transfer learning is developed which takes CAT pictures as an input. Transfer learning allows previously trained model on a large dataset to be reused for a similar kind of different task or problem. In the first step, figure preprocessing tasks are applied such as resizing and normalization. Second step is of feature extraction using AlexNet, GoogleNet, ResNet50 and VGG19 pre-trained models as backbone and same models along with DeepLIFT algorithm for better results. In the third and last step, pictures are classified into two classes.

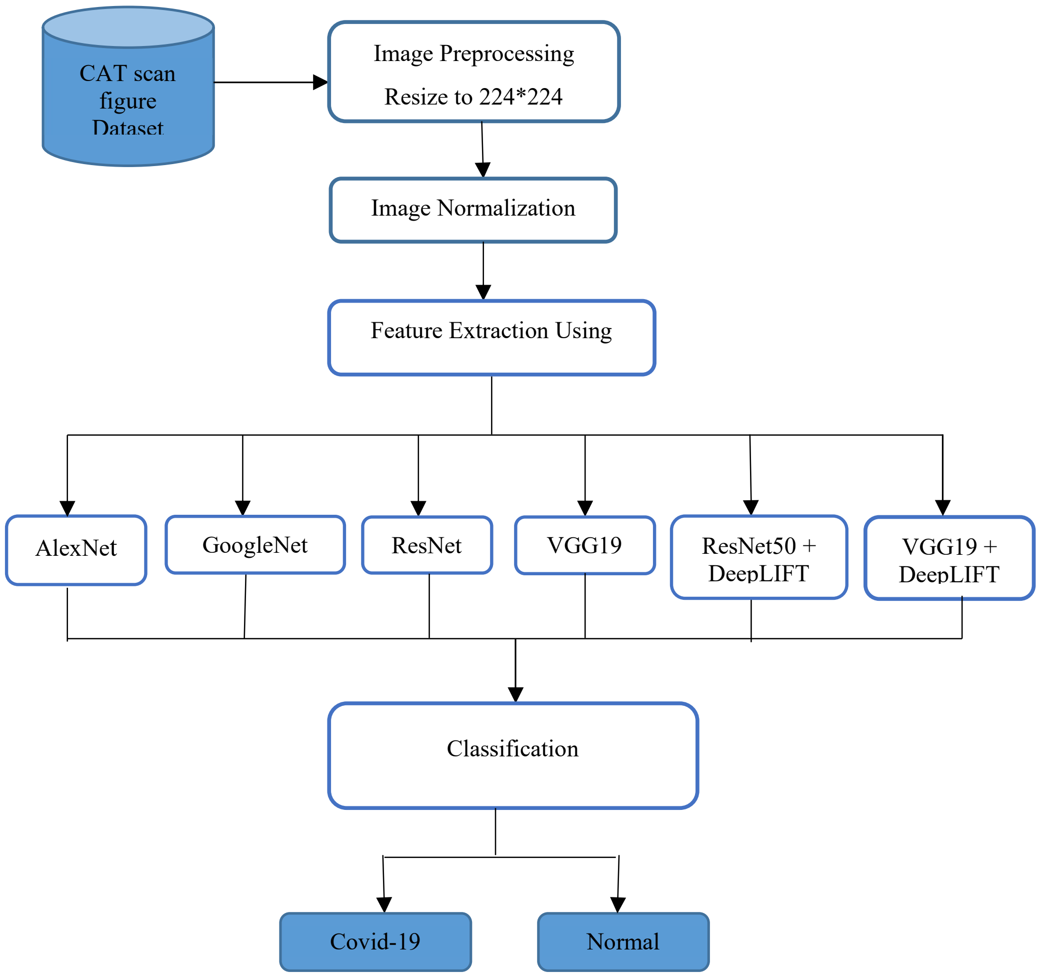


Fig.1 Block diagram of system workflow

1) Data Pre-processing:

In this step, figure is resized to 224 * 224 * 3 as needed in neural based learning training part and then intensity normalization is applied in the range of [0-1] that means each pixel value is divided by the highest range of intensity, 255. Normalization helps to remove the noise or to increase the contrast which assists in better feature extraction. Then dataset is divided into training and testing categories in 60:40 ratios.

2) Feature Extraction:

Pre-trained CNN models such as AlexNet, GoogleNet, ResNet50 and VGG19 are used as a backbone for feature extraction. These shift invariant models consist of sequence of convolution and pooling layers blocks. Generally, bottom and mid-level layers describes general features, so by replacing top layers according to problem; one can achieve required output with higher accuracy. In the proposed work, we have used AlexNet, GoogleNet, ResNet50 and VGG19 models for feature extraction and classification independently and along with DLIF technique. Higher accuracy can be achieved by using this technique, which is proved by the results.

2.1 ResNet50:

A pre-trained ResNet50 deep network of neurons model is used for feature extraction in figure classification task. It is a variant of Residual Network which is a classic network of neurons used for different tasks in computer vision [14]. Five stages make up the ResNet50 model, and each stage has an identity block and a convolution block. There are three convolution layers in each convolution and identity block, for a total of 48 convolution layers, plus 1 maxpool and 1 average pool layer, for a total of 50 layers. Resized and normalized figure is given as an input to this model.

2.2 VGG19:

Convolutional Network of neurons, often known as ConvNet, is a type of artificial Network of neurons that is the basis for VGG16. Karen Simonyan and Andrew Zisserman [17] from the Visual Geometry Group at the Department of Engineering Science at Oxford presented it in 2014 Picture Net challenge. It is most popularly used for object detection and figure classification also easily adaptable with transfer learning. VGG19 has 16 convolutional layers, with addition of 3 completely connected layers and 5 pooling layers. The first two FC layers each have four thousand ninety six neurons to recognize thousand figure classes, while the third FC layer has thousand neurons. When classifying thousand figures into thousand distinct categories, VGG19 achieves 92.7% classification accuracy.

For fine-tuning these models, all activations were flattened and last 2 fully connected layers (FC) were removed. Then 2 FC layers are added with 4096 neurons with ReLU activation. Finally, two nodes in the sigmoid layer received activations from the second dense layer. The categorical cross-entropy loss function and an Adam optimizer with a learning rate of 0.001 were used to compile the model. The model was trained on a batch size of 32, and EarlyStopping was employed to prevent the overfitting.

2.3 AlexNet:

The first deep convolutional neural network, AlexNet, achieved an accuracy of eighty seven percentages to win the renowned ImageNet challenge in 2012 and decreased the top five errors from twenty six to fifteen percentage. With additional filters per layer and stacked convolutional layers, this network has a deeper architecture. Three FC (Fully Connected) layers with ReLU activation and five convolutional (CONV) layers make up this structure. There are sixty two million trainable parameters in AlexNet overall. To lessen the issue of overfitting during the training phase, dropout layers are used. Ilya Sutskever, Alex Krizhevsky, and Geoffrey Hinton created it.

2.4 GoogleNet:

It is the winner of ILSVRC i.e. ImageNet challenge in 2014. It consists of Inception modules which contains skip connections in the network forming a mini module. These modules are repeated throughout the network. GoogleNet uses nine of these inception modules and average pooling layers in place of all fully linked layers. To solve the overfitting problem, GoogleNet proposed an idea of having multiple sizes filters operating on the same level. Due to this network becomes wider rather than deeper. GoogleNet architecture is 22 layers deep (with 27 pooling layers) and achieved top-5 error rate of 6.67 %. It also reduced number of parameters from 60 million to 4 million as in AlexNet.

2.5 Incorporating DeepLIFT (or DLIF)Technique:

DeepLIFT means Deep Learning Important FeaTures is a novel technique to assign importance score to the inputs for a given output. It is an interpretability/explainability method capable of analyzing network's decision making behavior. DeepLIFT evaluates the difference between an output and a "reference" output (Δt) in terms of the input's deviation from the reference input (Δx_i). Here this 'reference' input contains some 'neutral' or default value, selected according to appropriate for the given problem [Shrikumar et al, 15]. Unlike other gradient-based algorithms, DeepLIFT can communicate a significant signal even in cases when the gradient is zero by using a difference-from-reference, which prevents artifacts caused by gradient discontinuities. Secondly, by potentially accounting for the effects of positive and negative contributions independently at nonlinearities, DeepLIFT can detect dependencies that other approaches miss.

DeepLIFT scores are calculated using backpropagation algorithm. Hence, after a prediction has been made, score can be computed efficiently in a single backward pass. It overcomes the thresholding and saturation problem. It simply examines the neural network's feature selection process and discovers neurons, weights that significantly impacted the creation of the output. DeepLIFT uses the difference between the input and some "reference" input to explain the difference between the output and some "reference" output. The "reference" input is a default or "neutral" input selected based on what makes sense for the given situation.

Formally, let's represent some target output neuron of interest by t, and some neurons in an intermediate layer or collection of layers that are required and sufficient to compute t can be represented as $x_1, x_2, ..., x_n$. Let t_0 stand for t's reference activation. The difference-from-reference, or $\Delta t = t - t_0$, is how we define the quantity Δt. Contribution scores are assigned by following equation 1 –

$$\sum_{i=1}^{n} C_{\Delta x_i \Delta t} = \Delta t \tag{1}$$

Above mentioned equation is referred as summation-to-delta property. More motivation is added by the fact that the output of a deferential neuron is locally linear in its inputs. Even if $\partial t/\partial xi$ is zero, $C_{\Delta xi\Delta t}$ can still be non-zero. Because a neuron can signal important information even in the region when its gradient is zero, as shown in Fig. 2 DeepLIFT is able to address a basic constraint of gradients. Fig. 3 illustrates another problem with gradients that DeepLIFT addresses: their discontinuous character, which results in abrupt jumps in the significance score over very small changes in the input. In contrast, as the difference-from-reference is continuous, bias terms-induced discontinuities can be avoided by DeepLIFT.

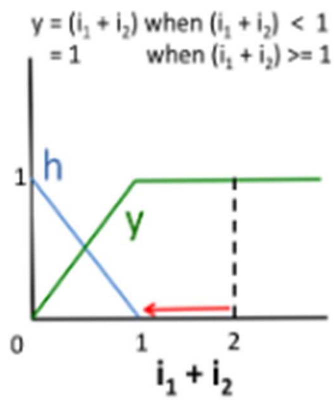


Fig. 2: Gradient based approach

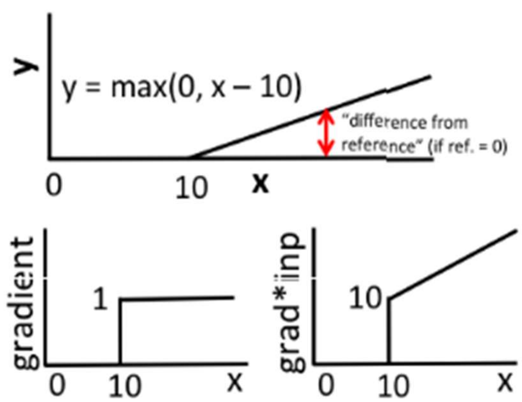


Fig. 3: Discontinuous gradients can produce misleading importance score

At x = 10, gradient and gradient×input discontinue; at this point, gradient×input gives x a contribution of 10 + α and the bias term a contribution of −10 (where α is a small positive number). When x is less than 10, the bias term and contributions on x are both zero. The contribution score increases continuously when one deviates from the reference, as indicated by the red arrow in the above figure.

Contribution score, $C_{\Delta xi\Delta t}$ is calculated by 4 ways as follows:

1) Summation-to-delta property: $\sum^{n}_{i=1} C_{\Delta xi\Delta t} = \Delta t$.
2) Chain rule for multipliers: Multiplier $m_{\Delta x\Delta t}$is the contribution of Δx to Δt divided by Δx.

$$m_{\Delta x\Delta t} = \frac{C_{\Delta x\Delta t}}{\Delta x} \quad (2)$$

Consider, $x_1,\ldots, x_n$ are input layers neurons, $y_1,\ldots, y_n$ are hidden layer neurons and t is some target output neuron then multipliers of any neuron for a given target neuron can be easily calculated by using backpropagation with the help of following formula:

$$m_{\Delta xi\Delta t}=\sum m_{\Delta xi\Delta yj} m_{\Delta yj\Delta t} \quad (3)$$

3) The Linear Rule: It is applied to convolutional and dense layers (excluding non-linearities)
4) The Rescale Rule: This rule applies to non-linear transformations that take a single input such as ReLU, tanh or sigmoid. It can be applied to convolutional layer or input pixels. It resolves both saturation and thresholding problem.
5) The RevealCancel Rule: This rule applies to non-linear function like MaxPool and overcomes both thresholding and saturation problem. It can be applied to FC layers to get better result.

Mathematical implementation is given in the original paper [Shrikumar et al, 15].

Steps of DeepLIFT Algorithm:

1) **Train a Model**: First, we need to train a neural based learning model for picture classification i.e. various pre-trained models suitable for the task.
2) **Implement DeepLIFT**: After model training, DeepLIFT algorithm can be implemented to analyze the contributions of different pixels or features in the input Picture to the model's predictions. There are libraries and frameworks available that provide implementations of DeepLIFT, such as DeepExplainer in the captum library for PyTorch.
3) **Apply DeepLIFT to Pictures**: Input pictures are passed through the DeepLIFT implementation along with the trained model. This will generate attribution scores indicating the importance of each pixel or feature in the Picture for the model's predictions.
4) **Interpretation:** Relevance scores provided by DeepLIFT are analyzed to gain insights into how the model makes predictions. This can help identify regions of the Picture that are most indicative of COVID-19 infection, potentially aiding radiologists in their diagnostic process.
5) **Validation and Improvement**: Validate the model's performance on a separate test dataset and iteratively refine the model architecture and training process based on insights gained from the interpretation step.

4. Experimental Results and Discussion:

A. Datasets:

Two datasets are used for experimentation which are publicly available as online repository for research and study purpose. Contributors and developers of these datasets have collected these CAT pictures from different hospitals, journal articles and other research papers.

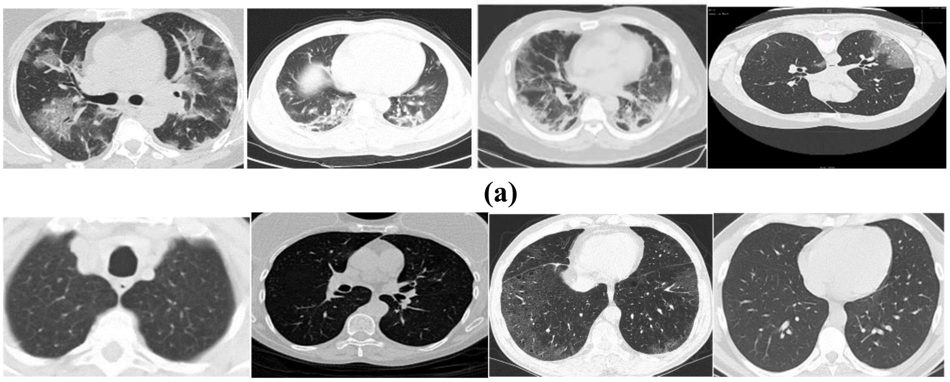
1) COVID-Dataset by GitHub:

This dataset includes 397 non-Covid scans in addition to 361 pictures from 216 patients that have clinical observations from Covid-19. These photos were gathered from Covid-19-related articles published in journals like the Lancet, JAMA, NEJM, BioRxiv and medRxiv. This dataset is developed by Yang et al [13] and open-sourced on GitHub.

2) SARS-CoV-2 scan dataset by Kaggle:

It consists of 2482 scans in total, 1252 of which are of patients who tested positive for Covid-19 and 1230 of which are of healthy individuals. This data was collected from real patients in hospitals from Sao Paulo, Brazil. This dataset is available at, www.kaggle.com/plameneduardo/sarscov2-scan-dataset and contributed by Eduardo Soares and Plamen Angelov [11].

Following are the examples of scan figures of COVID-19 positive and negative patients receptively, from above datasets:



(a)

(b)

Fig. 4: Sample figures from datasets: (a) COVID-19 positive patients, (b) COVID-19 negative patients

Dataset distribution and Train, test set split ratio:

Table 3 shows the total number of normal and COVID-19 Pictures in both datasets. Training and testing ratio is taken as 80:20 for experimentation. Table 4 shows the corresponding pictures per category accordingly.

Table 2: Dataset distribution

Sr. No	Dataset	Normal Pictures	COVID-19 Pictures	Total Pictures
1	**SARS-Cov-2 CAT study**	1230	1251	2481
2	**COVID-CT**	397	361	758

Table 3: Train test split ratio

Sr. No	Dataset	Training Set (80%)	Test set (20%)
1	**SARS-Cov-2 CAT study**	1984	497
2	**COVID-CT**	606	152

Hyperparameters Tuning:

Adamax optimization algorithm is used which is an extension of Adam algorithm of gradient descent optimization. Following table 4 shows different parameters with their initial values:

Table 4: Initialization of hyperparameters

neter	**l value**
_size (batch size for training)	
s (number of all epochs in training)	
ce (number of epochs to wait to adjust learning rate if monitored value does not improve)	
patience (number of epochs to wait before stopping training if monitored value does not improve)	
hold (if train accuracy is<threshold adjust monitor accuracy, else monitor validation loss)	
(factor to reduce lr by)	

1) Learning Rate:

A learning rate scheduler was employed to control the increase in validation accuracy throughout training in order to minimize fluctuations. Initially, learning rate is set to 0.001. When training accuracy did not improve for patience number of epochs, learning rate is reduced by following equation 4 –

$$\text{Learning Rate} = \text{Initial LR} * 0.5 \qquad (4)$$

2) Optimizer's step:

Train and test steps are defined using following equations 5 and 6:

$$\text{train\_steps} = \text{tr\_length} \,//\, \text{train\_batch\_size} \qquad (5)$$

$$\text{test\_steps} = \text{ts\_length} \,//\, \text{test\_batch\_size} \qquad (6)$$

B. Results and Discussion:

All the experiments are carried out in Google Colab GPU environment which is freely accessible. Each of the pre-trained models like AlexNet, GoogleNet, Resnet50 and VGG19 are implemented in Python3 Keras Library with TensorFlow as backend. The purpose of this study is to detect whether person is Covid positive or negative accurately. The performance evaluation of this model is measured using Learning curves and following metrics:

1) **Accuracy:** It determines the ratio of accurately anticipated observations to all observations as shown by eq.7:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \qquad (7)$$

2) **Precision:** It gives the ratio of correctly identified as positive out of all predicted as positive patients.

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (8)$$

3) **Recall:** It gives the fraction of correctly identified as positive out of all positive patients and given by the formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

4) **Specificity:** It is the ratio of how much were correctly identified as negative to the actual negative patients.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{10}$$

5) **F1-score (or F-measure):** It is a measure of performance of model's classification ability and calculated as actually the harmonic mean of precision and recall as follows:

$$\text{F1 - score} = \frac{2^* \text{(precision*recall)}}{\text{precision + recall}} \tag{11}$$

Where, TP = True Positive
FP = False Positive
TN = True Negative
FN = False Negative

Six feature extraction techniques, first four by using AlexNet, GoogleNet, Resnet50 and VGG19 Neural based learning models and last two by using ResNet50 and VGG19models incorporated with DeepLIFT algorithm are applied on two different datasets. Following tables 5 and 6 shows the result of model's performance using various evaluation metrics such as accuracy, precision, recall, specificity and F1 score for both the datasets respectively.

The pre-trained models, namely AlexNet, GoogleNet, ResNet50, VGG19, ResNet50+DeepLIFT and VGG19+DeepLIFT are analyzed for classification of scan figures in Covid19 positive or negative patients.

It is clearly seen that using DeepLIFT algorithm, all the metrics got improved results. Resnet50 model got 93.2% accuracy which is improved to 96.03 after using DeepLIFT for dataset 1. VGG19 model gives 91.8% for dataset 1 which is drastically increased to 94.98% after using DeepLIFT technique.

For dataset 2 with 2481 figures, ResNet50 model achieves 93.5% and that of VGG19 model has 92% of accuracy which then improved to 95.72% and 95% after incorporating DeepLIFT technique. Overall, AlexNet got fewer score and Resnet50 model along with DeepLIFT model achieves highest accuracy of 96.03%. Precision is almost achieved more than 99% and also improvement in recall, specificity and F1 score using proposed technique. It means that proposed models have correctly identified a positive patient as Covid-19 pos… y for this type of classification as wrong classification may lead to c… his may cause further more spread of the disease in society.

Table 5: Evaluation metrics for Dataset 1

Sr. No	Technique	Accuracy	Precision	Recall	Specificity	F1 score
1	AlexNet	70	84.15	84.55	63.07	84.34
2	GoogleNet	93	98.58	95.87	66.67	97.20
3	ResNet50	93.2	97.18	93.11	71.83	95.10
4	VGG19	91.8	97.08	94.06	67.74	95.54
5	**ResNet50+ DeepLIFT**	**96.03**	**99.29**	**96.55**	**83.33**	**97.90**
6	**VGG19+ DeepLIFT**	**94.98**	**98.03**	**95.36**	**70.83**	**96.68**

Table 6: Evaluation metrics for Dataset 2

Sr No	Technique	Accuracy	Precision	Recall	Specificity	F1 score
1	AlexNet	70	76.20	86.76	32.79	81.14
2	GoogleNet	91.97	94.82	96.53	39.69	95.66
3	ResNet50	93.5	98.43	94.58	78.26	96.46
4	VGG19	92	97.65	93.84	64.48	95.70
5	**ResNet50+DeepLift**	**95.72**	**99.048**	**96.43**	**79.24**	**97.71**
6	**VGG19+DeepLift**	**95**	**99.36**	**95.52**	**87.09**	**97.40**

Table7 shows the comparison of proposed models with other developed models available in literature. As compared to other different models our proposed technique gives quite good results in terms of accuracy.

Learning Curves:

Learning curves for model loss after every epoch and accuracy graph for training and validation dataset are depicted in the below figures. A line plot of learning (y-axis) over experience (x-axis) is called a learning curve. Model loss and accuracy graphs shows how the model is being optimized and model performance respectively. Learning curve in fig.5 shows that model has high validation loss initially and decreases gradually upon adding more training examples. There are two peaks in validation loss but at the end validation loss comes closer to training loss which indicates a good fit model. Training loss decreases and gradually flattens at the end. Training and validation accuracies are very much close to each other, it means that it is a good fit model.

Table 7: Comparison with other methods

Author	**Model/Technique**	**No. of sample figures**	**Accuracy (%)**
P. Silva et al [4]	EfficientNet-B3	2481	87.68
A. K. Mishra et al [6]	Decision fusion by majority voting	758	88
Joshi et al [24]	MFL-Net	758 2481	93.59 98.79
Shah et al [8]	CTnet model	758	82.1
Proposed Methods	**Resnet50+DeepLIFT**	**758**	**96.03**
		2481	**95.72**
	VGG19+DeepLIFT	**758**	**94.98**
		2481	**95**

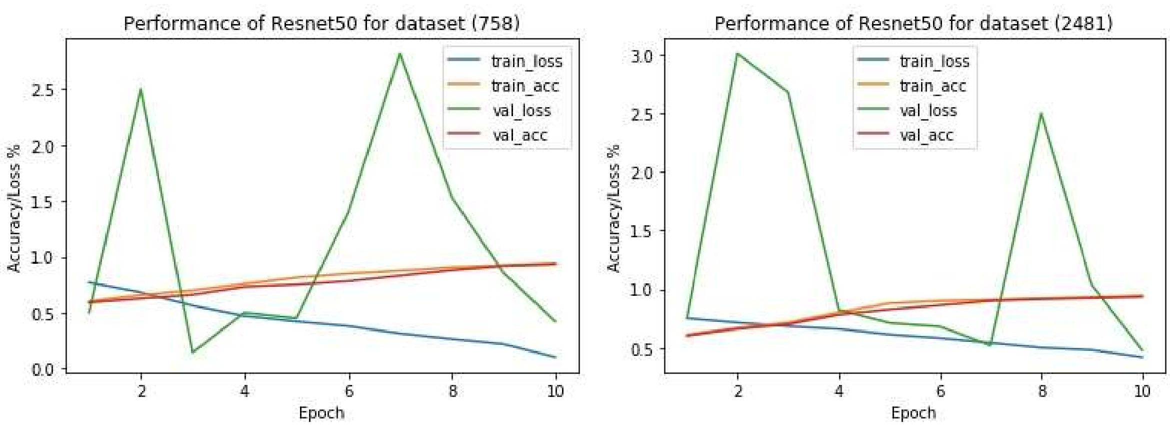


Fig.5 Learning curve for Resnet50 for dataset1 and dataset2

Learning curve of accuracy for VGG19 in fig. 6 shows that both training and validation accuracies are close to each other for both datasets which indicates a good-fit model. Model loss graph for training and validation, little differs from each other for dataset 1 which indicates that dataset size should be large enough. Generally DeepLIFT algorithm works better for large datasets. In case of dataset 2, both loss curves goes parallel at the end is satisfactory.

Using DeepLIFT algorithm:

Following fig.7 shows that both loss and accuracy curves are quite parallel to each other for both the datasets which indicates a good fit model.

Frontiers in Health Informatics
ISSN-Online: 2676-7104
2024; Vol 13: Issue 3

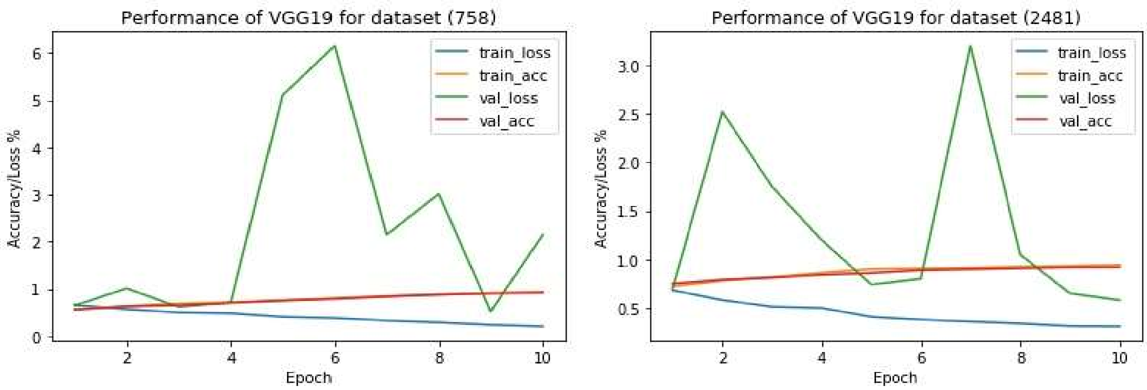


Fig.6: Learning curve for VGG19 for dataset1 and dataset2

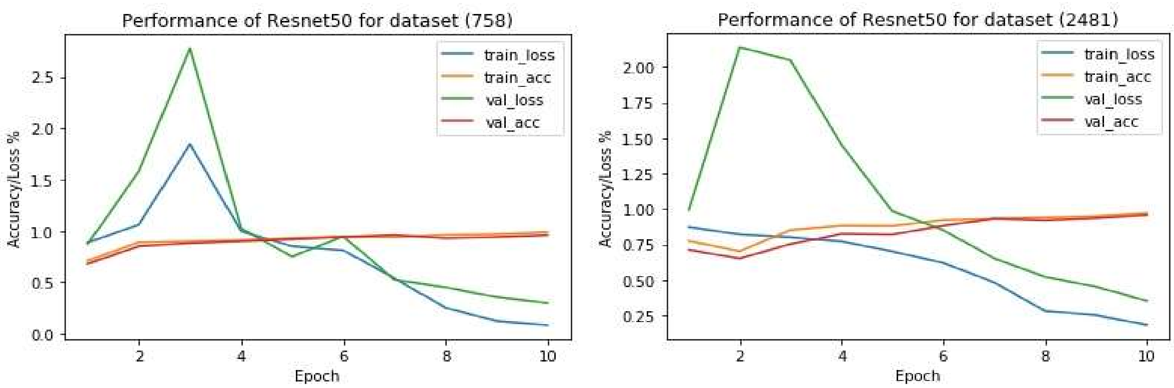


Fig.7: Learning curve for DeepLIFT+Resnet50 for dataset1 and dataset2

But in fig. 8 for dataset 1 using VGG19 model, training and validation curves differ from each other comparative to dataset 2. It means the same thing as mentioned as above that dataset size should be large enough.

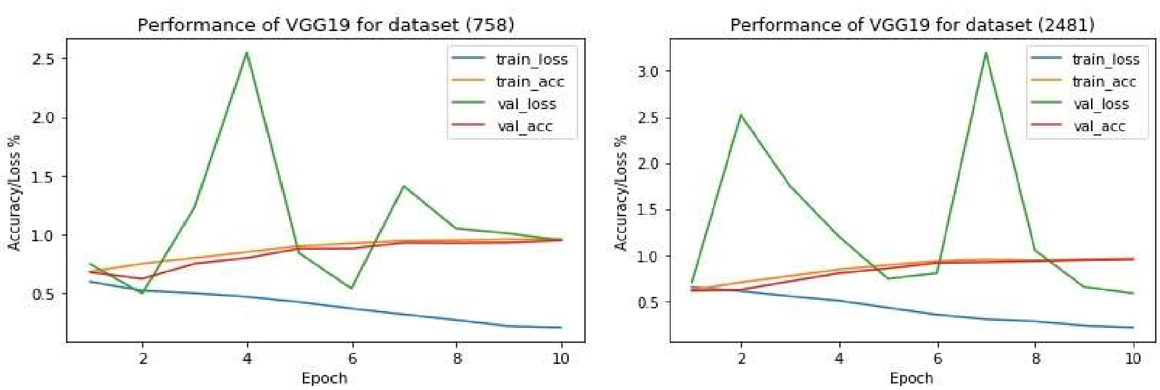


Fig. 8: Learning curve for DeepLIFT+VGG19 for dataset1 and dataset2

5. Conclusion:

In the proposed work, we have applied six techniques for evaluation of CAT pictures for COVID-19 detection, first four using pre-trained neural based learning models like AlexNet, GoogleNet, ResNet50 andVGG19 and last two by combining the models with DeepLIFT features. Former technique yields better result in experimental evaluation and gives accuracy of 96.03% and 94.98% respectively than first one. On two distinct, sizable datasets with varied numbers of Covid and non-Covid photos, experiments are conducted. This proves the importance of Deep learning based techniques in medical imaging field. It will also facilitate radiologists and doctors for better understanding of different aspects of Covid-19 disease.

In future, these techniques can be applied on real time clinical data to assist physicians for screening and detection of Covid-19 patients for early prognosis and diagnosis. Still there is a need of very large scan figures data repository because larger the dataset, DL based techniques gives better the result. Also, accuracy can be further improved by hybridization of current technique with some other features or exploring the proposed techniques. Furthermore, Picture retrieval system can be developed in combination with classification to build CBMIR system [19, 20].

Statements and Declarations:

Competing Interests and Funding:

The authors have no conflict of interests to declare that are relevant to this article. Also, the authors did not receive any funding, grants or other support from any organization for submitted work.

Financial Interests:

The authors certify that they have no financial interest in the subject matter or materials discussed in this manuscript.

References:

[1] Tanu S (2020) A Review of Coronavirus Disease-2019 (COVID-19)Indian J Pediatr. Apr;87(4):281-286. https://doi.org/10.1007/s12098-020-03263-6

[2] Jeffrey K, Brent L, Jonathan C, Brett E, Loren K (2020) Essentials for Radiologists on COVID-19: An update – Radiology Scientific Expert Panel. Radiology: 296(2):E113-E114,https://doi.org/10.1148/radiol.2020200527

[3] Tao A, Zhenlu Y, Hongyan H, et al (2020) Correlation of Chest and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases. Radiology vol. 296:E32-E40. https://doi.org/10.1148/radiol.2020200642

[4] Pedro S, Eduardo L, Guilherme S, et al (2020) COVID-19 detectionin figures with deep learning: A voting-based scheme and cross-datasets analysis.Informatics in Medicine Unlocked 20 100427. https://doi.org/10.1016/j.imu.2020.100427

[5] Wentao Z, Wei. J, Xinguo Q (2021)Neural based learning for COVID-19 detection based on figures. Scientific ReportsNature, 11:14353, https://doi.org/10.1038/s41598-021-93832-2

[6] ArnabKumar M, Sujit Kumar D, Pinki R, Sivaji. B (2020)Identifying COVID19 from Chest Figures: A Deep Convolutional Network of neuronss Based Approach.Hindawi, https://doi.org/10.1155/2020/8843664

[7] Varan Singh R, Nitin G, Amit K, Deepak Kumar S (2021) Neural based learning assisted COVID-19 detection using full -scans.Internet of Things 14:100377, Elsevier, https://doi.org/10.1016/j.iot.2021.100377

[8] Vruddhi S, Rinkal K, et al (2021) Diagnosis of COVID-19 using scanfigures and neural based learning techniques. Emergency Radiology 28:497–505,.https://doi.org/10.1007/s10140-020-01886-y

[9] Varalakshmi P, Vasumathi N, Sakthi J. S. R (2021) Prediction of COVID-19 with Computed Tomography Figures using Hybrid Learning Techniques. Hindawi, Disease Markers, Volume 2021, Article ID 5522729, https://doi.org/10.1155/2021/5522729

[10] Rafid M, Mohammad S. U. et al (2020) Cov-19 detection in chest X-ray through random forest classifier using a hybridization of deep CNN and DWT optimized features. Journal of King Saud University – Computer and Information Sciences, Sciencedirect. https://doi.org/10.1016/j.jksuci.2020.12.010

[11] Walid El-Shafai, Abd El-Samie, Fathi E (2020) Extensive COVID-19 X-Ray and Chest Figures Dataset. Mendeley Data, V3, https://doi:117632/8h65ywd2jr.3

[12] [dataset] Eduardo S, Plamen A, et al (2020) SARS-CoV-2 CT-scan dataset: A large dataset of real patients scans for SARS-CoV-2 identification.medRxiv.https://doi.org/10.1101/2020.04.24.20078584

[13] Xingyi Y, Xuehai H, et al (2020) COVID- Dataset: A CAT scans dataset about COVID-19. arXiv:2003.13865v3 [cs.LG], https://doi.org/10.48550/arXiv.2003.13865

[14] Kaiming H, Xiangyu Z, Shaoqing R, JianS (2015) Deep Residual Learning for Figure Recognition.arXiv:1512.03385 [cs.CV], https://doi.org/10.48550/arXiv.1512.03385

[15] Avanthi S, Peyton G, Anshul K (2019) Learning Important Features Through Propagating Activation Differences.arXiv:1704.02685v2 [cs.CV], https://doi.org/10.48550/arXiv.1704.02685

[16] Leo B (2001) Random Forests.Machine Learning, 45, 5–32

[17] Karen S, Andrew Z (2015) Very Deep Convolutional Networks for LargeFigure Recognition.arXiv:1409.1556 [cs.CV],https://doi.org/10.48550/arXiv.1409.1556

[18] Hussein K, Ali Hussein, Ali Chehab (2021) AI-Based Figure Processing for COVID-19 Detection in Chest scan Figures. Frontiers in Communications and Networks, Vol. 2, Article 645040,https://doi.org/10.3389/frcmn.2021.645040

[19] Maher A, Supreethi K.P. (2021) COVID-19 Diagnostic System Using Medical Figure Classification and Retrieval: A Novel Method for Picture Analysis. The British Computer Society, https://doi.org/10.1093/comjnl/bxab051

[20] Saeed M, Mehdi A. et al (2021) Integration of CNN, CBMIR, and Visualization Techniques for Diagnosis and Quantification of Covid-19 Disease. IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 25, NO. 6, 1873-1880, https://doi.org/10.1109/JBHI.2021.3067333

[21] Tareque R O, Gourab R, Enamul H (2023) CovidExpert: A Triplet Siamese Network of neurons framework for the detection of COVID-19. Informatics in Medicine Unlocked 37, 101156, https://doi.org/10.1016/j.imu.2022.101156

[22] Mouna A, Riadh A, Yahia S, Mohamed A (2023)Deep learning-based technique for lesions segmentation in CAT studyPictures for COVID-19 prediction. Multimedia Tools and Applications, Springer https://doi.org/10.1007/s11042-023-14941-w

[23] Ahmad A S, Ahed A, Ahmad MAS, Sultan A (2022) SEL-COVIDNET: An intelligent application for the diagnosis of COVID-19 from chest X-rays and CAT studys. Informatics in Medicine Unlocked 37, 101059, https://doi.org/10.1016/j.imu.2022.101059

[24] Amogh M J, Deepak R N (2022) MFL-Net: An Efficient Lightweight Multi-Scale Feature Learning CNN for COVID-19 Diagnosis From CT Pictures. IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 11, pp. 5355-5363, https://doi.org/10.1109/JBHI.2022.3196489

[25] Taranjit K, Tapan. K G, Bijaya KP (2021) Automated Diagnosis of COVID-19 Using Deep Features and Parameter Free BAT Optimization. IEEE Journal of Translational Engineering in Health and Medicine, vol. 9, pp. 1-9,Art no. 1800209, https://doi.org/10.1109/JTEHM.2021.3077142

[26] Maftouni M, Law ACC, Shen B, Grado ZJK, Zhou Y, Yazdi NA. (2021). A robust ensemble-neural based learning model for COVID-19 diagnosis based on an integrated CAT study pictures database. IIE annual conference. Proceedings, vols. 632–37. Institute of Industrial; Systems Engineers (IISE)