INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

SYSTEMATIC REVIEW

OPEN ACCESS
Received: 19-01-2023
Accepted: 04-03-2023
Published: 06-04-2023

Citation: Kalaiselvi K, Kasthuri M (2023) Refining the Accuracy of Chest X-Ray Image Classification Through Layer and Activation Function Optimization. Indian Journal of Science and Technology 16(13): 1030-1037. https://doi.org/10.17485/IJST/v16i13.138

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Refining the Accuracy of Chest X-Ray Image Classification Through Layer and Activation Function Optimization

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Abstract

Objective: The goal of this article is to provide the Convolutional Neural Network (CNN)-based algorithm carried out to a Chest X-Ray (CXR) dataset to classifies pneumonia. **Method:** This study explores reduced layers in architecture of Deep Learning Model (DLM). A framework for classifying Chest-X-Ray image dataset with Deep Learning Model (CXR-DLM) proposed to extract features and detect COVID-19. **Finding:** Deep learning-based models have an exceptional ability to offer an accurate and efficient system for COVID-19 investigations**.** However, deep learning models affect the classification of small dataset. CXR-DLM solve this problem by designing with all layers and reduced layers learned during the training phase. The 60% of the CXR images carried for training phase and the remaining 40% for testing phase respectively. The testing images achieve an accuracy 99.57%. CXR normal (1341 images) and Covid (3875 images) collected from Kaggle dataset. **Novelty:** The proposed work CXR-DLM support in the field of radiological imaging of COVID-19 reduces false positive and false negative errors in the detection and diagnosis of this disease. In this work determined exclusive chance to provide rapid, safe diagnostic services to patients then classification using CT images.

Keywords: Deep learning; Covid19; CXR images; CXRDLM

1 Introduction

The outbreak of COVID-19, many technology companies, governments, and institutes have originated an urgent announcement for researchers to implement Artificial Intelligence (AI) applications to support COVID-19 suppression [(1)] . In healthcare, a large amount of data is collected from medical sensors and devices such as X-ray machines, magnetic resonance imaging, computed tomography (CT), which can be analysed using artificial intelligence methods for early disease detection. Recently, the outbreak of COVID-19 disease claimed many deaths. Computer vision researchers are assisting doctors by applying deep learning techniques to medical images to diagnose COVID-19 patients. An entropy driven firefly algorithm for robust feature selection [(2)].

Recently, an artificial intelligence-based computer-aided diagnosis of COVID-19 using CT scans was coined, which has proven its effectiveness in terms of accuracy and computing time [3]. Deep rank based average pooling network for COVID-19 detection to avoid overfitting [4]. AI helps to fight COVID-19 at certain levels of demographic level (prediction of upcoming infection prediction), patient level (diagnose early-stage of COVID-19) [5]. Researchers have proposed many computational methods based on Deep learning techniques to resolve Chest X-ray images for COVID-19 [6–11]. Deep Convolutional Neural Networks (DCNNs) are one of the powerful deep learning architectures and have been used automatically in many real-world applications such as pattern recognition and image classification [12]. Squeeze Net Guided Extreme Learning Machine (SNELM) for COVID-19 Recognition, Sparse Non-negative Embedding Logical model used for CXR images. The SNELM model is based on logistic regression that incorporates a non-negative sparse feature of an image [13]. However, the application of deep learning techniques to categorize and detect novel COVID-19 in X-ray image is yet very restricted. In a recent study, deep learning techniques have shown promising results for solving radiological tasks by automatically exploring various medical images [14,15]. COVID-19 Classification from Chest X-Ray Images of Deep Explainable Artificial Intelligence the contrast enhancement and feature optimization techniques improve the accuracy [16].

Deep Bayesian Optimization and Fusion-Assisted Optimal Deep Features(D2BOF-COVIDNet) for COVID-19 classification using Chest X-ray and MRI Scans. This framework improved tree growth optimization for best feature selection [17]. Bayesian optimization is used in deep learning models to optimize hyperparameters that help train selected data better. High-level features are extracted from both models and fused through a novel slicing-based serial fusion. Grad-CAM visualization is performed on the final classification, resulting in the colored results . A Healthcare system for COVID19 classification using multi-type classical features selection focused on classical features that are fused using the proposed Max-Correlation maximization approach [18]. COVID19 classification using Chest X-Ray Images of the Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN-LSTM) and improved max value moth flame optimization is proposed contrast enhancement technique based on merging the output of local and global filters. CNN LSTM architecture trained it from scratch using deep transfer learning instead of freezing a few layers. Fusion technique is proposed for new features called Serial based Maximum Information. An improved moth flame optimization algorithm based on the maximum value and proposed for the selection of the best features [19].

An improved VGG19 Transfer Learning Deep Neural Network for strip steel surface flaw detection based on few samples and unbalanced datasets that shows generalization and good convergence. The detection accuracy of the improved VGG19 network in this work reached 97.8% [20]. The first and second building blocks include two layers, such as convolution and pooling layer. The third and fourth blocks have four convolution layers and one pooling layer. The last block consists of four convolution layers. The authors established an algorithm from scratch using Deep Convolutional Neural Networks [21]. The VGG19 model achieved 95.7% accuracy with no-pre-trained approach and 98.3% with the pre-trained COVID-Capsule network approach. Sensitivity measure obtained are not as high as the general accuracy [22]. The challenges of VGG19 model are improving the accuracy of CXR image classification with lesser layer in a block.

To overcome this challenge, CXR-DLM model presents an architecture for classifying the X-ray images. The modified VGG-19 architecture utilizes feature extraction and Adam's optimization for images in training phase. The training object obtained using proposed architecture is tested on a two-class testing dataset (Covid, Normal). Finally, comparisons between the existing and the proposed models are done effectively.

2 Methodology

The aim of this work is to develop and compare different CNN models for COVID-19 detection from chest X-ray (CXR) images using different layers and activation functions. The paper presents a four-step methodology that includes acquiring the dataset, pre-processing and labeling the images, training the CNN models using a new training strategy, and testing the classifiers to evaluate their performance. The proposed CXR-DLM model framework consists of image acquisition, pre-processing, training the CXR-DLM model, and testing the classifier. The success of the proposed method will depend on how well the different layers and activation functions are chosen and how well the model is trained.

Overall, this work could be valuable for improving the accuracy of COVID-19 detection from CXR images, which could be beneficial for healthcare professionals in making diagnoses and informing treatment decisions. The proposed method consists of four main steps: (a) dataset acquisition, (b)pre-processing and labelling, (c) Model training, and (d) Evaluation and validation measures. Figure 1 shows the framework of CXR-DLM model. This framework comprised of image acquisition, pre-processing, CXR-DLM training model and classifier(testing).

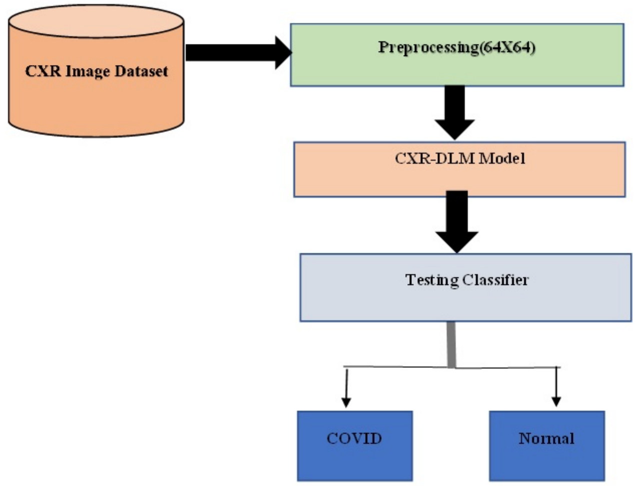

Fig 1. Framework of CXR-DLM model

2.1 Data acquisition

The dataset contains a set of covid and normal images that have been collected from the Kaggle website. The unique resolution of the image is amongst 1296X1200 and 1240X840 pixels.

2.2 Pre-processing and labelling

Pre-processing including data normalization, data augmentation, image resizing, image cropping and missing value imputation. The preprocessing technique can be used individually or in combination based on image resize and normalization performed on CXR image dataset. Image resizing crops the sub region of the image that preserves the spatial content of the image. Then the image is adjusted to increase the contrast of a low-contrast CXR images. Gray scale images have only one channel information representing the intensity equal pixel. In medical image applications gray scale image provide needful information than color image. Since color image distrait the results. All gray scale images are normalized to 64x64 pixel. This conversion doubles the number of parameters in the first convolution layer and also decreases the computation time.

2.3 CXR-DLM Model

The network architecture examined is presented in VGG-19 Figure 2 (a) and CXR-DLM Figure 2 (b). The parameters in VGG-19 model have one input layer,13convolution layers, 3 maxpolling layers 3 fully connected layers. The use of small 3X3 filters and max pooling layers helps to reduce the number of parameters and improve the performance of the network. In Table 1 represent CXR-DLM architecture. The parameters in CXR-DLM model have one input layer,12convolution layers, 4 maxpolling layers 3 fully connected layers. The convolution layer consists of 5 block of sizes 64,128,256,512,512 respectively. The max_pooling of kernel size 3X3 is adapted for convolution layer and SoftMax layer is employed for classifier. The number of layers in model implies to the depth of the model.

The multiple convolutions of different kernel size led to better features map for classification. In proposed CXR-DLM model a block of 128 size feature map is removed from the VGG-19 architecture and two dropout layer is added before the SoftMax layer. The dropout layer mask or nullifies the features. Its nullifiers some hidden features in hidden layers. In hidden layers, ReLU activation function activates the some of the features. In output layer soft max activation function is used to assign the probabilities to classify image as covid class or normal class.

2.4 Evaluation and validation measures

Various metrics can be used to estimate the efficiency of DL algorithms for image classification. These metrics include sensitivity, specificity, precision, F1 score, and accuracy. The most significant metric for evaluating a CNN model is accuracy, which expresses how similar the generated result is to the real-world value. Equation (1) defines the accuracy metric used to measure

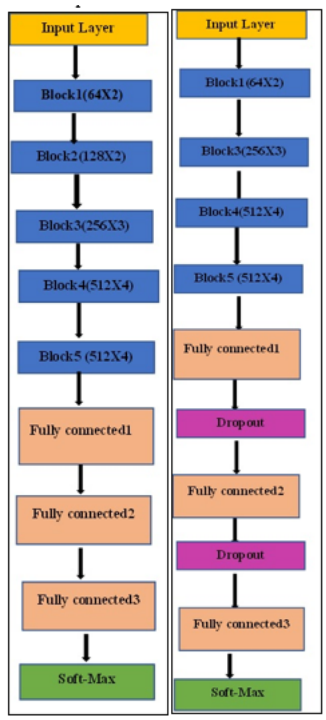

Fig 2. VGG-19 and CXR-DLM Architecture (Performance of CXR Image classification using proposed Model)

Table 1. Summary of the proposed CXR- DLM architecture for classification of COVID CXR images

Layers	Block	Type	Filters	Kernel size	Activation function
		INPUT	64	3X3	ReLU
1	Block1	Convolution2D	64	3X3	ReLU
2		Pooling (Max)	-	2X2	-
3		Convolution2D	256	3X3	ReLU
4	Block2	Convolution2D	256	3X3	ReLU
5		Convolution2D	256	3X3	ReLU
6		Pooling (Max)	-	2X2	-
7		Convolution2D	512	3X3	ReLU
8		Convolution2D	512	3X3	ReLU
9	Block3	Convolution2D	512	3X3	ReLU
10		Convolution2D	512	3X3	ReLU
11		Pooling (Max)	-	2X2	-
12		Convolution2D	512	3X3	ReLU
13		Convolution2D	512	3X3	ReLU
14	Block4	Convolution2D	512	3X3	ReLU
15		Convolution2D	512	3X3	ReLU
16		Pooling (Max)	-	2X2	-
17		Fully connected	4096	-	ReLU
18		Fully connected	4096	-	ReLU
19		Fully connected	1000	-	ReLU
		Dropout	50%	-	-
		Dropout	50%	-	-
		SoftMax	Probability	-	-

the efficiency of the CXR-DLM model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{1}$$

2.5 Dataset used

The CXR DLM proposed model was trained on a large dataset of CXR images for pneumonia. The images were gathered from Kaggle Database, one for each type of pneumonia COVID contain 3875 and Normal contains 1341 images [23].

3 Result and Discussion

The dataset was split into two sets to test and train set. The images are pre-processed and labelled. The performance of the established VGG-19 models and proposed CXR-DLM model are implemented using MATLAB programming. Figure 3 (a) and (b) represents a sample of covid and normal CXR images. For both the experiments, the batch size, learning rate, and number of epochs were set to 64, 0.0001, and (20,50) respectively. The CXR-DLM model is fully supervised trained and its parameters are optimized by minimizing the role of the binary entropy loss function and Adam optimization is used for learning.

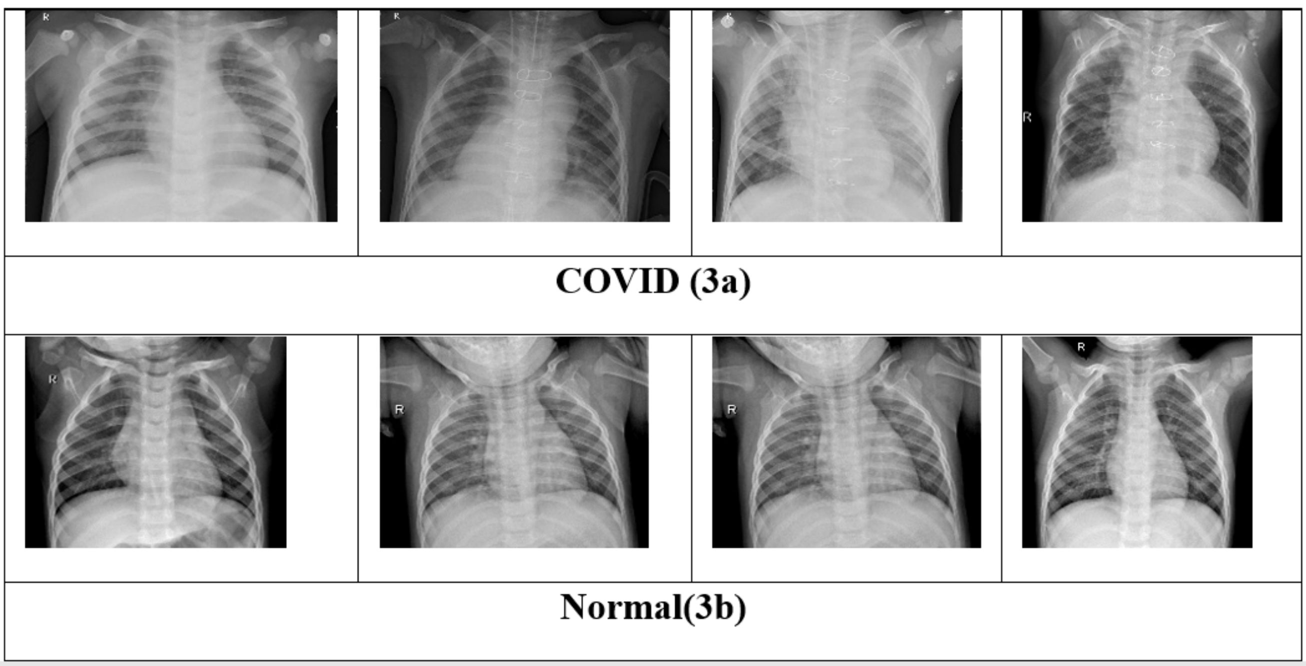

Fig 3. (a), (b) A sample of COVID and Normal images in Dataset

3.1 Comparison of the proposed method with pre-defined method

DL-based systems are now widely used to detect patients with a COVID-19 infection. Numerous studies have been conducted on this topic (Table 2). In binary classification, positive COVID-19 cases are typically distinguished from negative ones by chest X-rays due to their ready availability. Chest x-rays are widely used in health centres around the world during this pandemic. However, public COVID-19 imaging data is limited, and chest x-rays are constantly being augmented with public sources. Several previous studies used chest x-rays to distinguish individuals with COVID-19 infection, but with a limited number of images. To address the above issues, this study proposes a DL model called CXR-DLM to identify COVID-19 cases. In Table 2 represent the performance of CXR image classification and their training progress in Figures 4 and 5. The proposed model has achieved 99.56% accuracy in detecting COVID-19 cases from normal cases than VGG-19 model. Compared to results of existing study presented in Table 3 our VGG-19 model and the proposed model classifies covid and normal images with the higher accuracy.

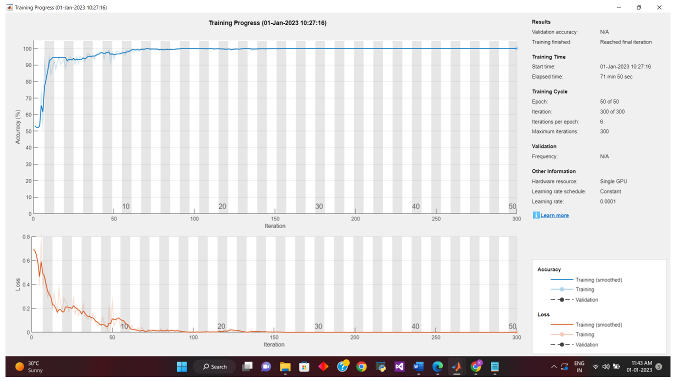

Fig 4. VGG-19,Training Progress of CNN Model

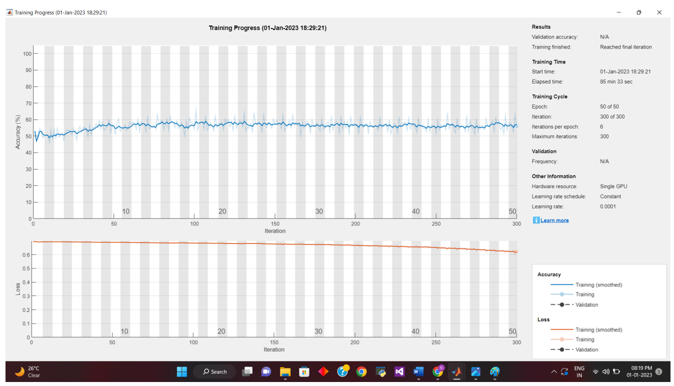

Fig 5. CXR-DLM,Training Progress of CNN Model

Table 2. Performance of CXR image classification

Model	Optimizer	Batch size	Learning Rate	Epoch	Accuracy	Sensitivity	Specificity	Precision	F1-Score
VGG-19	Adam	64	0.0001	50	0.993289	0.996774	0.983209	0.994208	0.995490
CXR-DLM	Adam	64	0.0001	50	0.995686	0.998065	0.988806	0.996137	0.997100

Table 3. Comparison of Proposed Model with Existing Study

Author	Method used	Samples	Accuracy (%)
Hamza et al., [24]	CNN-LSTM and fusion-optimization	Chest X-ray (Pneumonia-2599, COVID-19-1698, Tuberculosis-1538, Normal-1575)	98.50
Cao et al., [25]	BND-VGG-19	2778 Covid), 371 (Normal)	95.48
Sharma et al., [26]	Automatic Feature Extraction and Deep Learning based CNN Model	Chest X-ray images (4000,1000)	98.00
Our Model	CXR-DLM	3785(Covid), 1341 (Normal)	99.57

4 Conclusion

This article proposed a CXR-DLM model for chest X-ray images. A modified VGG19 architecture was used for feature extraction and classification of the input images. Adam algorithm is used to tune the hyperparameters of the modified VGG19. The proposed model was tested on a two-class dataset (Covid, Normal). Finally, comparisons were made between the existing and the proposed models. Extensive experimental results show that the proposed model outperforms competing COVID19 classification models with accuracy of 99.57% on 2086 test images. One of the limitations of this work was the data imbalance in the datasets used for training and testing. In general, a balanced dataset with an equal number of normal and COVID-19 X-rays variabilities modelling more suitable, and the developed model can provide better prediction accuracy. Furthermore, the classification algorithm finds it easier to learn from a balanced dataset.

The CXR-DLM architecture performance is dependent on the quality and size of the dataset used for training and testing. The potential drawbacks using deep learning for Xray image analysis and data availabilities, overfitting and limitation of images. Deep learning requires large amount of data may not be representative of all populations. This can be studied further.

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