

Automatic Detection of Lung Ailments using Deep Convolutional Neural Networks

Dr.S.Rajeswari¹, Sathya.B², Shabbna.K³, Srinithi.S⁴, Tejaswini.S⁵

Associate Professor - Department of Electronics and Communication Engineering, Saranathan College of Engineering, Trichy, Tamil Nadu¹

UG - Department of Electronics and Communication Engineering, Saranathan College of Engineering, Trichy, Tamil Nadu^{2,3,4,5}

Abstract- Diagnosis is a critical preventive step in Coronavirus research which has similar manifestations with other types of pneumonia and lung cancer. X-rays play an important role in that direction. However, processing chest X-ray images and using them to accurately diagnose lung ailments is a computationally expensive task. Machine Learning techniques have the potential to overcome this challenge. This study proposed a CNN model to automatically detect COVID-19, pneumonia and lung cancer patients from digital chest x-ray images using deep convolution of neural networks. Here we use X-ray images which is pre-processed and given as input to the pre-trained model. In this model, the feature extraction process takes place in both convolutional and pooling layers. The classification process occurs in fully connected layer. The proposed model InceptionV3 performs with an accuracy of 88% and a precision of 92%. This model gives the F1-score of 88.0.

Keywords- Covid-19, Pneumonia, Lung Cancer, Chest X-ray, CNN, Deep Transfer Learning, Lung Ailments detection.

I. INTRODUCTION

Lung diseases^[1] range from mild and self-limiting, such as the common cold, influenza, and pharyngitis to life-threatening diseases such as pneumonia, pulmonary embolism, tuberculosis, acute asthma, lung cancer,^[2] and severe acute respiratory syndromes, such as COVID-19^[3]. The coronavirus disease pandemic emerged in Wuhan, China in December 2019 and became a serious public health problem worldwide^{[4][5]}. Until now, no specific drug or vaccine has been found against COVID-19. COVID-19 causes lighter symptoms in about 99% of cases, according to early data, while the rest is severe or critical^[6]. Nowadays the world is struggling with the COVID-19 epidemic. Deaths from pneumonia developing due to the SARS-CoV-2 virus are increasing day by day. Pneumonia is an acute respiratory infection that affects the lungs. It can be caused by a virus, bacteria, fungi or other germs. Patients with pneumonia could have the symptoms like cough that produces phlegm or sometimes blood, fever, shortness of breath or difficulty breathing, chills or shaking, fatigue, sweating and chest or muscle pain^[7]. Lung cancer, also known as lung carcinoma, since about 98–99% of all lung cancers are carcinomas, is a malignant lung tumor characterized by uncontrolled cell growth in tissues of the lung. Many of the symptoms of lung cancer (poor appetite, weight loss, fever, fatigue) are not specific^[8]. Cancer develops after genetic damage to DNA and epigenetic changes. Those changes affect the cell's normal functions, including cell proliferation, programmed cell death (apoptosis), and DNA repair. As more damage accumulates, the risk for cancer increases. Cancer screening plays an important role in preventive care because it is most treatable when caught in the early stages.

Although both low dose computed tomography (LDCT) and computed tomography (CT) scans provide greater medical information than normal chest x-rays. This study explores the use of chest x-rays with a computer-aided diagnosis (CAD) system to improve lung diseases diagnostic performance. The convolutional neural network (CNN) is proven to be very effective in image recognition and classification tasks. The development of CNNs starts from, LeNet, AlexNet, ZFNet, VGG, Inception, ResNet, Inception-ResNet, Xception, DenseNet, and NASNet. In our study we use inception v3 model to detect the lung ailments. InceptionV3 is a kind of convolutional neural network model, in which 48 layers network trained on the ImageNet dataset. ImageNet is an image database with more than 14 million images belonging to more than 20 thousand categories created for image recognition competitions^[9]. The model consists of numerous convolution and maximum pooling steps. In the last stage, it contains a fully connected neural network^[10].

II. RELATED WORKS

Studies diagnosed with COVID-19 using chest X-rays have binary or multiple classifications. Some studies use raw data while others have feature extraction process. The number of data used in studies also varies. Among the studies, the most preferred method is convolutional neural network (CNN).

Apostolopoulos and Bessiana used a common pneumonia, COVID-19-induced pneumonia, and an evolutionary neural network for healthy differentiation on automatic detection of COVID-19. In particular, the procedure called transfer learning has been adopted. With transfer learning, the detection of various abnormalities in small medical image datasets is an achievable goal, often with remarkable results [11].

Based on chest X-ray images, Zhang et al. aimed to develop a deep learning-based model that can detect COVID-19 with high sensitivity, providing fast and reliable scanning [12].

Khan et al. classified the chest X-ray images from normal, bacterial and viral pneumonia cases using the Xception architecture to detect COVID-19 infection [13].

Hashemi et.al. (2013) his aim has to improve the efficiency of the lung cancer diagnosis system, with the help of proposing a region growing segmentation method to segment CT scan lung images. First of all, for noise removing linear-filtering and contrast enhancement technique was used as pre-processing step, to prepare the image for segmentation. After that for differentiating among malignant, benign and advance lung nodules, the cancer recognition was presented by fuzzy inference system. The authors also compare the diagnosis performance of the proposed method with the artificial neural network [14].

Chaudhary et.al. (2012) aim has to get more accurate results using the various enhancement and segmentation techniques. The image processing procedures that is, image pre-processing; segmentation and feature extraction were done. In image enhancement, image are compared with Gabor filter, auto enhancement and fast Fourier transform techniques. In the segmentation stage the Watershed and thresholding segmentation were used and comparison has been made [15].

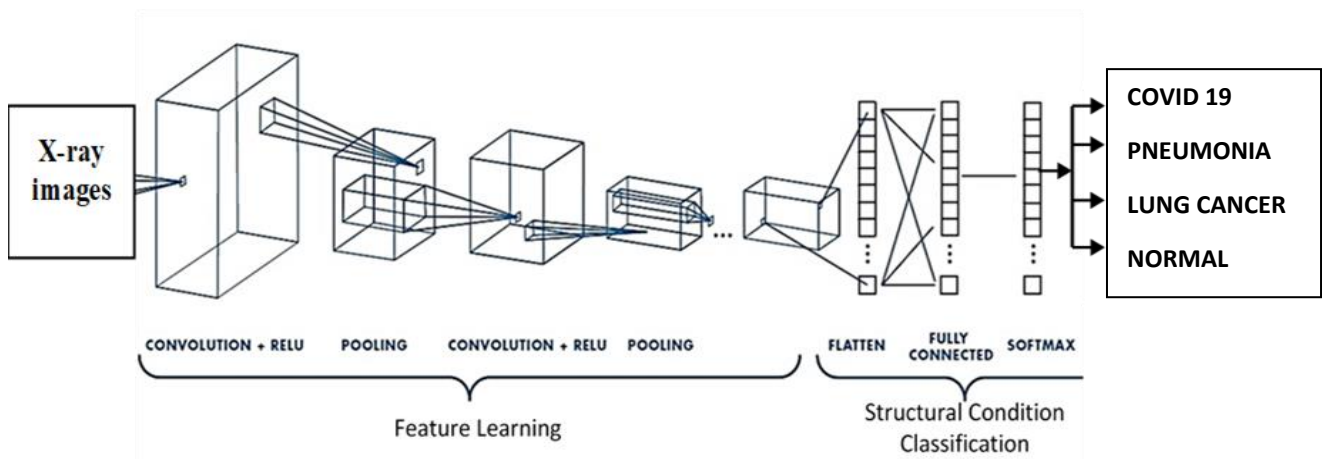


Fig.1. Workflow diagram of the proposed CNN model for detection of lung ailments

III. PROPOSED CNN MODEL

A. Dataset

1) In this study, chest X-ray images of 460 COVID-19 patients have been obtained from the open source GitHub repository shared by Dr. Joseph Cohen et al [16]. This repository is consisting chest X-ray / computed tomography (CT) images of mainly patients with acute respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia, severe acute respiratory syndrome (SARS). 540 normal (healthy) chest X-ray images were selected from “ChestX-ray8” database [17]. In addition, 100 pneumonia chest X-ray images were used from Kaggle repository called “Chest X-Ray Images (Pneumonia)” [18].

2) JSRT Dataset [19]: This public dataset from JSRT (Japanese Society of Radiological Technology) consists of 247 frontal chest x-ray images; 154 of which have lung nodules (100 malignant cases, 54 benign cases) and 93 are images without lung nodules. All images have a pixel size of 2048 x 2048.

Totally we have used 188 images for lung ailment detection.

B. Data preparation

Data preparation was applied to all images, consisting of the following:

First all the images are converted into 224 x 224 pixels. Then the image augmentation technique is done as it is a great way to expand the size of your dataset. Image Augmentation techniques with Keras undergoes Image Data Generator such as Rotations, Shifts, Flips, Brightness, Zoom.

The whole dataset were randomly split into two categories: 75% for training and 25% for testing.

C. CNN Model

A convolutional neural network (CNN) is a class of deep neural networks used in image recognition problems^[20]. Coming to how CNN works, the images given as input must be recognized by computers and converted into a format that can be processed. For this reason, images are first converted to matrix format. The system determines which image belongs to which label based on the differences in images and therefore in matrices. It learns the effects of these differences on the label during the training phase and then makes predictions for new images using them. CNN consists of three different layers that are a convolutional layer, pooling layer, and fully connected layer to perform these operations effectively. The feature extraction process takes place in both convolutional and pooling layers. On the other hand, the classification process occurs in fully connected layer. These layers are examined sequentially in the following.

Convolutional layer is the base layer of CNN. It is responsible for determining the features of the pattern. In this layer, the input image is passed through a filter. The values resulting from filtering consist of the feature map. This layer applies some kernels that slide through the pattern to extract low- and high-level features in the pattern^[21]. The kernel is a 3x3 or 5x5 shaped matrix to be transformed with the input pattern matrix. Stride parameter is the number of steps tuned for shifting over input matrix. The second layer after the convolutional layer is the pooling layer. Pooling layer is usually applied to the created feature maps for reducing the number of feature maps and network parameters by applying mathematical computation. In this study, we used max pooling which selects only the maximum value and global average pooling layer that is only used before the fully connected layer, reducing data to a single dimension^[22]. Fully connected layer is the last and most important layer of CNN. This layer functions like a multi-layer perceptron. Rectified Linear Unit (ReLU) activation function is commonly used on fully connected layer, while Softmax activation function is used to predict output images in the last layer of fully connected layer.

D. Loss and Optimizer

The two transfer learning methods involve imbalanced binary classification datasets. To counteract this problem, the following weighted binary classification loss was used:

$$L(X, y) = -\omega^+ \cdot y \log p(Y = 1|X) \\ -\omega^- \cdot (1 - y) \log p(Y = 0|X),$$

where X is the image and y is the real label of the image which is labeled 0 for covid case, 1 for pneumonia, 2 for normal, 3 for lung cancer, $p(Y = i|X)$ is the predicted probability of having label i. Whereas ω is the weight applied on the loss to make the training process more efficient. The Adam (adaptive moment estimation) optimizer^[23] was used in this work with the standard parameter setting, i.e. $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The initial learning rate was 0.001, decreasing by a factor of 10 when validation loss plateaued.

IV. RESULTS AND ANALYSIS

The proposed model is trained for 100 epochs. All the training images are resized to 224x224 pixels. Moreover, to avoid overfitting of the model data augmentation is used which undergoes Image Data Generator such as Rotations, Shifts, Flips, Brightness, and Zoom. Then InceptionV3 model is trained and tested with the same dataset. The training and validation accuracy with corresponding epochs for the model is plotted in Fig.2

The training and validation loss with corresponding epochs for the model is plotted in Fig.3

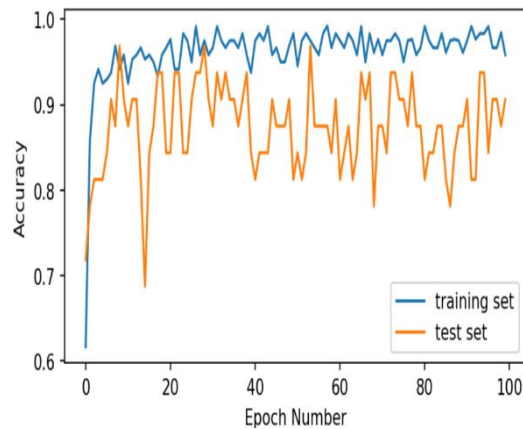


Fig.2. Training and Validation accuracy graph

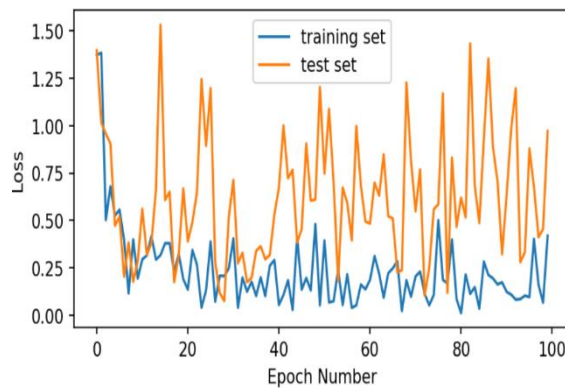


Fig.3. Training and Validation loss graph

5 criteria were used for the performances of deep transfer learning models. These are:

$$\text{Accuracy} = \frac{\text{TN}+\text{TP}}{\text{TN}+\text{TP}+\text{FN}+\text{FP}} \dots\dots\dots (1)$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \dots\dots\dots (2)$$

$$\text{Specificity} = \text{TN} / (\text{TN}+\text{FP}) \dots\dots\dots (3)$$

$$\text{Precision} = \text{TP} / (\text{TP}+\text{FP}) \dots\dots\dots (4)$$

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \dots\dots (5)$$

TP, FP, TN and FN given in Equation (1) – (5) represent the number of True Positive, False Positive, True Negative and False Negative, respectively. For given a test dataset and model, TP is the proportion of positive (Lung Ailments) that are correctly labeled as COVID-19, Pneumonia and lung cancer by the model; FP is the proportion of negative (normal) that are mislabeled as positive (Lung Ailments); TN is the proportion of negative (normal) that are correctly labeled as normal and FN is the proportion of positive (Lung Ailments) that are mislabeled as negative (normal) by the model.

TABLE I PERFORMANCE METRICS OF THE INCEPTIONV3 MODEL

Accuracy %	Precision %	Recall %	F1-score
88	92	88	88

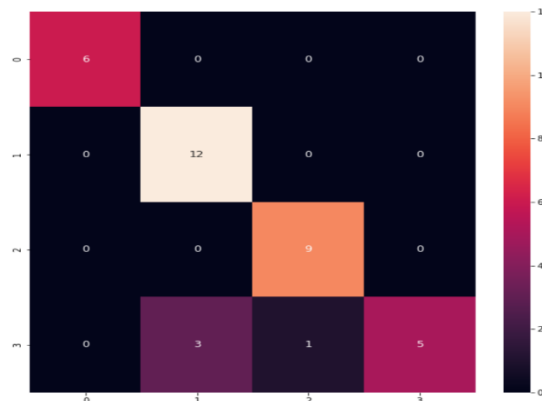


Fig.4. Confusion matrix

The confusion matrix of Inception V3 are presented in Fig 4. The diagonal square of the matrix represents the TP case of pneumonia, normal, covid and lung cancer respectively.

V. CONCLUSION

To conclude, the performance of convolutional neural network in detecting lung ailments from chest x-ray images was done. In this study, we proposed a deep transfer learning based approach using Chest X-ray images obtained from normal, COVID-19, pneumonia and lung cancer patients. To perform the process, InceptionV3, a CNN based model is proposed in this paper for detecting Lung ailments from patient's chest X-rays. The process involve training the model several times to learn about the image step-by-step, which in this case, starts from the use of images in the ImageNet dataset and then testing the image. The dataset consists of 188 images in which 75% for training and 25% for testing the image. This model performed with accuracy and precision of 88% and 92%. In future work we implemented the new part of deep learning algorithm for classification of lung ailment system and identify the stages of lung ailments. Data augmentation could be additionally performed by randomly adding Gaussian Noise and cropping the image. The idea of an Attention-Guided Convolutional Neural Network (AG-CNN) can also be used to crop the nodule part from the full image and use its real size to identify malignancy. Furthermore, cooperation with doctors and radiologists can help to identify the performance of predicted results.

REFERENCES

- [1] "Lung diseases". MeSH.nlm.nih.gov. Retrieved 14 August 2019.
- [2] Sengupta N, Sahidullah M, Saha G (August 2016). "Lung sound classification using cepstral-based statistical features". *Computers in Biology and Medicine*. 75 (1): 118–29.
- [3] "COVID-19 and vascular disease". *EBioMedicine*. 58: 102966. August 2020.
- [4] Roosa K, Lee Y, Luo R, Kirpich A, Rothenberg R, Hyman JM, and et al. Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. *Infectious Disease Modelling*, 5:256-263, 2020.
- [5] Yan L, Zhang H-T, Xiao Y, Wang M, Sun C, Liang J, and et al. Prediction of criticality in patients with severe COVID-19 infection using three clinical features: a machine learning based prognostic model with clinical data in Wuhan. *medRxiv* 2020.02.27.20028027, 2020.
- [6] McKeever A. Here's what coronavirus does to the body. *National Geographic*, 2020.
- [7] Ashby B, Turkington C (2007). *The encyclopedia of infectious diseases* (3rd ed.). New York: Facts on File. p. 242. ISBN 978-0-8160-6397-0. Retrieved 21 April 2011.
- [8] Lu C, Onn A, Vaporciyan AA, et al. (2017). "Chapter 84: Cancer of the Lung". *Holland-Frei Cancer Medicine* (9th ed.). Wiley Blackwell. ISBN 9781119000846.
- [9] Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, and et al. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision*, 115:211-252, 2015.
- [10] Ahn JM, Kim S, Ahn KS, Cho SH, Lee KB, and Kim US. A deep learning model for the detection of both advanced and early glaucoma using fundus photography. *PloS ONE*, 13(11):e0207982, 2018.
- [11] Apostolopoulos ID, and Mpesiana TA. Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine*, 43:635-640, 2020.
- [12] Zhang J, Xie Y, Li Y, Shen C, and Xia Y. COVID-19 Screening on Chest X-ray Images Using Deep Learning based Anomaly Detection. *arXiv:2003.12338v1*, 2020.
- [13] Khan AI, Shah JL, and Bhat MM. Coronet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*, 196:105581, 2020.

- [14] Hashemi, A., Pilevar, A. H., & Rafeh, R. (2013). Mass Detection in Lung CT Images Using Region Growing Segmentation and Decision Making Based on Fuzzy Inference System and Artificial Neural Network. *International Journal of Image, Graphics and Signal Processing (IJIGSP)*, 5(6), 16.
- [15] Chaudhary, A., & Singh, S. S. (2012, September). Lung cancer detection on CT images by using image processing. In *Computing Sciences (ICCS), 2012 International Conference on* (pp. 142- 146). IEEE.
- [16] Cohen JP, Morrison P, and Dao L. COVID-19 Image Data Collection. arXiv:2003.11597, 2020.
- [17] Wang X, Peng Y, Lu L, Lu Z, Bagheri M, and Summers RM. ChestX-Ray8: HospitalScale Chest X-Ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, pp. 3462-3471, 2017.
- [18] Mooney P. Chest X-ray Images (Pneumonia). *Kaggle Repository*, 2018.
- [19] J. Shiraishi, S. Katsuragawa, J. Ikezoe, T. Matsumoto, T. Kobayashi, K.- I. Komatsu, M. Matsui, H. Fujita, Y. Kodera, and K. Doi, "Development of a digital image database for chest radiographs with and without a lung nodule: Receiver operating characteristic analysis of radiologists' detection of pulmonary nodules," vol. 174, pp. 71–4, 02 2000.
- [20] Jmour N, Zayen S, and Abdelkrim A. Convolutional neural networks for image classification. *International Conference on Advanced Systems and Electric Technologies (IC_ASET)*, Hammamet, Tunisia, pp. 397-402, 2018.
- [21] LeCun Y, Bengio Y, and Hinton G. Deep learning. *Nature*, 521:436-444, 2015.
- [22] Srivastava N, Hinton G, Krizhevsky A, Sutskever I, and Salakhutdinov R. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research*, 15:1929-1958, 2014.
- [23] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," vol. abs/1412.6980, 2014.