Pneumonia Detection Using CNN based Feature Extraction

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***Abstract*—Humans can contract pneumonia, a potentially fatal bacterial disease that primarily affects one or both lungs and is brought on by the bacteria Streptococcus pneumoniae. According to the World Health Organization (WHO), pneumonia accounts for one in three deaths in India. Radiotherapists with specialized training are needed to assess chest X-rays used to diagnose pneumonia. Therefore, creating an automated approach to identify pneumonia would be helpful in order to treat the illness as soon as possible, especially in isolated regions. Convolutional Neural Networks (CNNs) have received a lot of interest for illness categorization as a result of the effectiveness of deep learning algorithms in the analysis of medical pictures. Furthermore, pre-trained CNN models' characteristics, which they acquired from large-scale datasets, are very helpful for image classification tasks.In this study, we evaluate the performance of pre-trained CNN models that are used as feature-extractors and then go on to use various classifiers to classify abnormal and normal chest X-rays. We identify the best CNN model for the job analytically. The statistical results show that the use of pretrained CNN models in conjunction with supervised classifier algorithms can be very helpful in the analysis of chest X-ray pictures, particularly in the diagnosis of pneumonia.**

Keywords*—DensetNet, Deep Convolutional Neural Networks, SVM, Transfer Learning, Random Forest, Naive Bayes, K-nearest neighbors, Feature extraction.

I. Introduction

Computer Aided Designs (CAD) has emerged as the principal machine learning study area in recent years. It has already been demonstrated that the current CAD systems help the medical field, particularly with lung nodules, mammography, and breast cancer detection. Important aspects are important in the process of applying Machine Learning (ML) techniques to medical photos. Because of this, the majority of earlier algorithms relied on manually created features to create CAD systems using image analysis [1, 2, 3]. But the manually designed features, whose capabilities varied depending on the work, were unable to provide many useful functions. Convolutional neural networks (CNNs), in particular, have demonstrated their inherent capacity to extract valuable features in image classification tasks when employed as Deep Learning (DL) models [4,24]. The feature extraction procedure necessitates the use of transfer learning techniques, in which CNN models that have already been trained on massive datasets like ImageNet are trained on generic characteristics that are then applied to the necessary job. Pre-trained CNN models, such as AlexNet [5], VGGNet [6], Xception [7], ResNet [8], and DenseNet [9], are readily available and greatly facilitate the process of extracting key features.

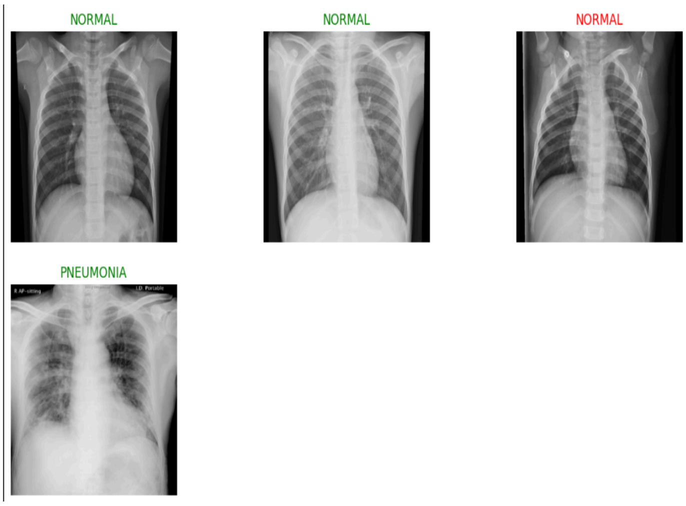


Fig. 1. An example of Normal CXR (right) and an example of a Pneumonia CXR (left) from ChestX-ray14 dataset. The pathology in the left CXR cannot be easily distinguished from the right CXR.

In addition to being primarily utilized to detect lung nodules, chest screening subroutines can also be used to diagnose other conditions including pneumonia, cardiomegaly, effusion, etc. Among these, pneumonia is a contagious and fatal illness that affects millions of individuals, mostly those over 65 with chronic conditions like diabetes or asthma [11]. Chest X-rays are thought to be the most efficient way to identify the amount and location of the infected zone in the lungs during the diagnosis process of pneumonia. Nonetheless, radiotherapists do not take their time reviewing chest radiographs. Pneumonia can appear foggy on chest X-ray pictures and be mistaken for other conditions. Evaluation of the chest X-ray in particular when a patient has pneumonia can be deceiving because pneumonia can mimic a number of other conditions, such as lung scarring, congestive heart failure, etc. This is the primary cause of the X-ray pictures in the dataset's incorrect classification. Consequently, the work is difficult, and the Creating an algorithm to identify thoracic illnesses such as pneumonia would also make clinical settings more accessible in isolated locations. In order to distinguish between pathological and normal chest X-rays, we assessed the performance of several variations of pre-trained CNN models, which were then followed by several classifiers. The following are the study's major contributions: In order to propose the ideal classifier in the same classification field, (a) a comparative analytical study comparative analytical study of various pre-trained CNN models as feature-extractors for analyzing chest X-rays is conducted; (b) these models are presented with different classifiers; and (c) the best pre-trained CNN model is evaluated by hyperparameter-tuning the best-analyzed classifier to further improve performance. This paper's structure is explained as follows:

A summary of relevant research in the same topic is provided in Section 2. A summary of every feature pertinent to the dataset used is provided in Section 3. The applicable approach, which has been broken down into several stages, is described in Section 4. The experimental setup for the tests conducted on several iterations of pre-trained CNN models is shown in Section 5, along with the outcomes of using various classifiers. Results and discussions regarding the final AUC-scores obtained are presented in Section 6.

II. Related Work

The study of machine learning (ML) methods for thoracic disease detection has drawn more attention recently in the field of medical image categorization research. A technique for identifying pulmonary tuberculosis was presented by Lakhani and Sundaram (2017) [12], based on the architecture of two distinct CNNs, AlexNet and GoogleNet. The Huang et al. [13] pulmonary nodule classification system, which is primarily used to diagnose lung cancer, also incorporated deep learning techniques. Islam et al. [14] recommended utilizing the publicly available OpenI dataset [15] to evaluate the performance of various CNN variations for abnormality identification in chest X-rays. A larger dataset of frontal chest X-rays was released by Wang et al. (2017) [16] to facilitate a better investigation of machine learning in chest screening.

In order to detect pneumonia at a level higher than radiologists, Pranav Rajpurkar, Jeremy Irvin, et al. (2017) [17] recently investigated this dataset. They called their model ChexNet, which employs DenseNet-121 layer architecture for detecting all 14 diseases from a large number of 112,200 images available in the dataset. Using the same dataset, Benjamin Antin et al. (2017) [18] developed a logistic regression model for pneumonia detection, which was modeled after the CheXNet[17] model. Using cascading convolutional networks, Pulkit Kumar and Monika Grewal (2017) [19] offered their study for multilabel categorization of thoracic illnesses. A convolutional network model for disease diagnosis and localization was recently proposed by Zhe Li (2018) [20].

III. Dataset Description

The Kaggle website is the source of our dataset. The dataset used in the investigation is divided into two categories: normal and pneumonia. The tools used - google collab, Libraries used - numpy, panda, scipy

IV. METHODOLOGY OF PROPOSED MODEL

The implemented methodology is described in detail in this section. Figure 2 describes the proposed "Densely Connected Convolutional Neural Network" (DenseNet-169) pneumonia detection method. There are three distinct stages in the design of the suggested model: preprocessing, feature extraction, and classification.

A. The Pre-Processing Stage

Reducing the computational complexity of the model, which is likely to rise if the input consists of images, is the main objective of utilizing convolutional neural networks in the majority of image classification jobs. The initial three-channel photos were downsized from 1024 x 1024 pixels to 224 x 224 pixels in order to expedite processing and lessen computational burden. These resized photos have been subjected to every additional approach.

B. The Feature-Extraction Stage

Despite using many variations of pre-trained CNN models to extract the features, the statistical findings suggested that DenseNet-169 was the best model for the feature extraction phase. Consequently, the explanation of the DenseNet-169 model architecture and its role in feature extraction are covered in this step.

1) *DenseNet-169's architecture: Due to the unique types of convolutional and pooling layers, deep convolutional networks, or CNNs, have emerged as the most effective frameworks for image recognition. However, as the network deepens, the input data or gradient that formerly passed through the majority of the layers disappears by the time the last layer is reached. DenseNets solve the gradient vanishing issue by directly connecting all of the layers with equal feature sizes. The main reason for employing DenseNet architecture as a feature extractor is the ability to extract more generic characteristics from deeper network layers. 169-layer Densely Connected Convolutional Neural Network that has been pre-trained* The feature extraction procedure has been carried out using (DenseNet-169). The form of this model that we employed in this investigation was trained using the extensive publicly available ImageNet dataset, and it was first proposed by Huang et al. (2016) [9].Three transition layers, four dense blocks, one convolution and pooling layer at the start make up the DenseNet-169 architecture. The last layer, or the categorization layer, is present after these layers. The first convolutional layer uses stride 2 to construct 7×7 convolutions, and then it uses stride 2 to perform a 3×3 max pooling.

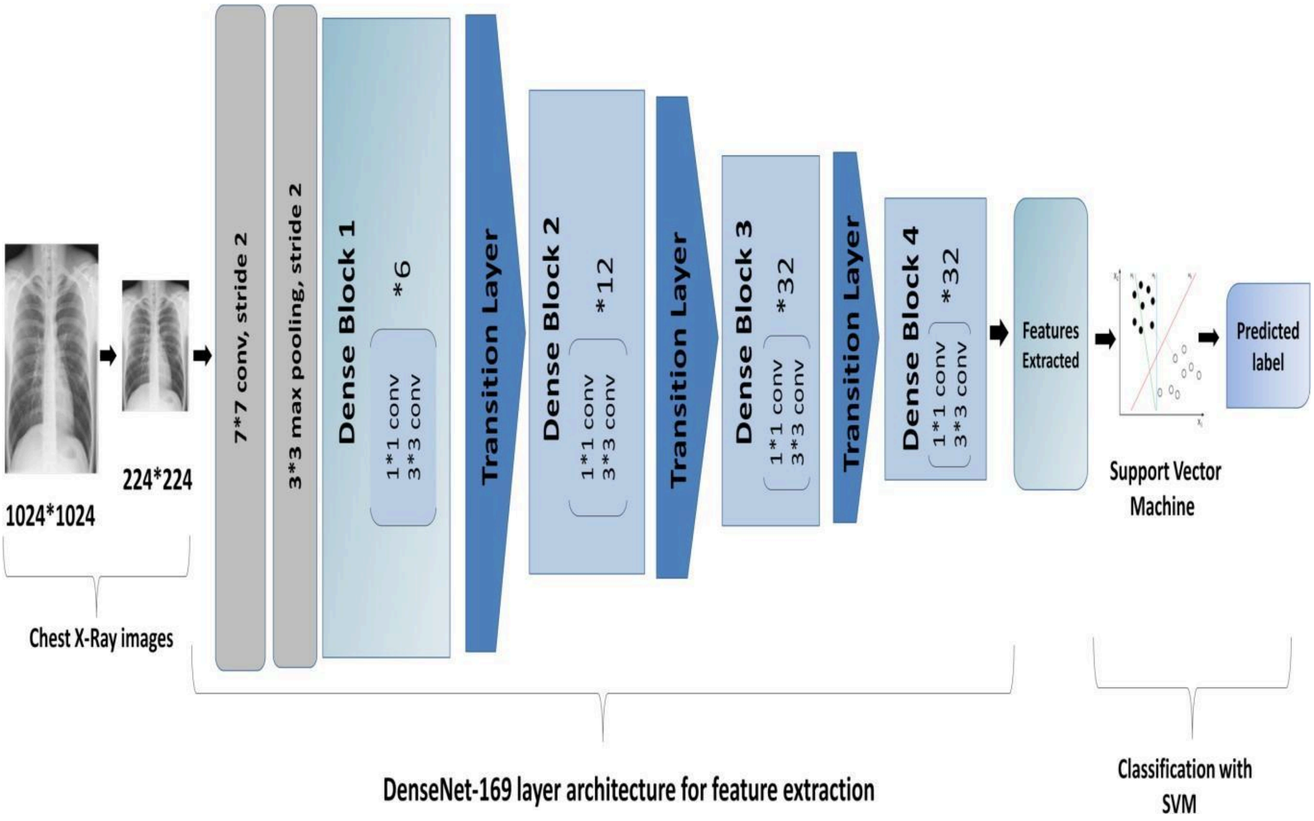


Fig. 2. Represents a flow diagram of our methodology applied.

The network then consists of three sets, each consisting of a transition layer and a dense block after it.

Direct connections between any layer and any other layer in the network are used to provide DenseNets with the dense connectivity that Huang et al. [9] suggested. The gradient flow throughout the network is improved since the lth layer of the network receives the feature-maps of every layer that came before it. Convolutional neural networks primarily aim to sample feature map sizes down, so the DenseNets architecture is divided into multiple densely connected dense blocks mentioned above. This requires concatenating the feature maps of the preceding layers, which cannot be done unless all the feature maps are of the same sizes.Transition layers are the layers that lie in between these thick blocks.

The network's transition layers are comprised of a 1×1 convolutional layer, a batch normalization layer, and a 2×2 average pooling layer with a stride of 2.

As previously said, there are four dense blocks, with two convolution layers in each. The first layer is one × one in size, while the second is three × three. Six, Twelve, 32, and 32 are the sizes of each of the four dense blocks in the DenseNet169 architecture that were pretrained on ImageNet. The last layer, the classification layer, sits next to it. It completes the global average pooling of 7x7. After that, there is a final fully-connected layer using "softmax" as the activation.

2) Extraction of Features: With the exception of the final classification layer, all network layers can be processed using the feature extraction method from the model described in this section 4.2.1. Upon obtaining the final feature representation, a 50176×1 dimension vector was parsed and subsequently used as an input for various classifiers.

C. The Classification Stage

Various classifiers, including Random Forest and Support Vector Machine, were employed for the classification job following feature extraction. However, it was discovered that using Support Vector Machine as the problem's classifier produced the greatest results. Therefore, to achieve better outcomes, features taken from DenseNet-169 were combined with an SVM classifier in the best recommended model. The following is a description of the kernel and parameters used with SVM: Let us consider a training data set of (x1,y1), (x2,y2) (xn,yn) that needs to be divided into two classes: the label class is represented by yi ε (0,1), and the feature vector is represented by xi ε Fd. When used for binary classification, a support vector machine may identify the optimal hyperplane—that is, the hyperplane with the largest margin between the classes—for the training data that is shown above and can separate the data points belonging to the different classes. The choice of kernel and parameters has a major impact on SVM performance. The Gaussian "radial basis function" kernel (rbf) was employed [13]. The RBF kernel's gamma and C parameters have a significant impact on SVM performance. The gamma parameter, whose bigger value indicates "close," and whose smaller value implies "far," is used intuitively to specify the amount of influence that a single training sample should have.

V. Limitations

Although the results were overwhelming, there were still some limitations in our model which we believe are vital to keep in consideration. The first biggest limitation is that there is no history of the associated patient considered in our evaluation model. Secondly, only frontal chest X-rays were used but it has been shown that lateral view chest X-rays are also helpful in diagnosis [22]. Thirdly, since the model exercises a lot of convolutional layers, the model need very high computational power otherwise it'll eat up a lot of time in computations.

VII. Experimental Setup

This section deals with the description of several experiments performed in order to propose the optimal model toward the Pneumonia detection problem.

A. Feature-Extractor and Classifier

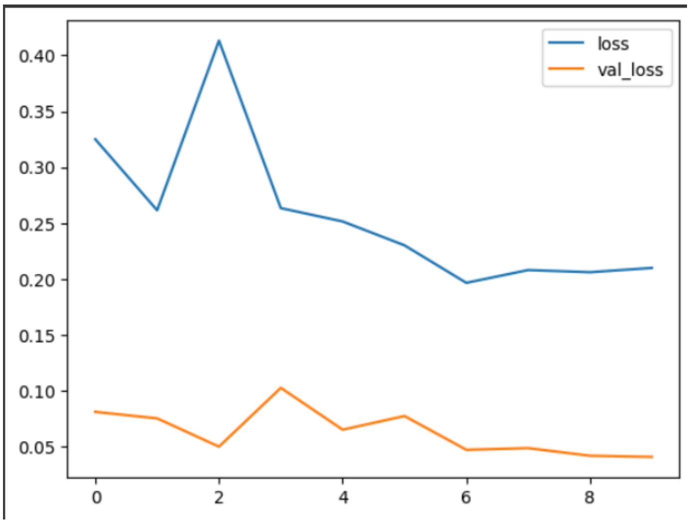
For pre-trained CNN models including Xception [7], VGG16 [6], VGG-19 [6], ResNet-50 [8], DenseNet-121 [9] and DenseNet-169 [9], we evaluated their performance followed by different classifiers including Random Forest, K-nearest neighbors, Naive Bayes and Support Vector Machine(SVM). Table-1 lists the performance of all these models in the procedure of classifying abnormal and normal chest X-Rays. It was observed that ResNet-50 CNN model of depth 168 followed by SVM classifier outperformed all the other prerained CNN models attaining an AUC score of 0.7749. We observed that DenseNets also accomplished results near ResNet50 achieving an AUC of 0.75(approx). Table-2 shows the results obtained by DenseNet-121 and DenseNet-169. Statistical results demonstrated the use of ResNet-50 and DenseNets (DenseNet-121 and DenseNet-169) as the optimal pre-trained CNN models for the feature-extraction stage and use of SVM (with rbf kernel) as the classifier for the classification stage. Figure 3 shows the performance of ResNet50 and DenseNets (DenseNet-121 and DenseNet-169) along with different classifiers and demonstrates SVM classifier as the optimal one to accomplish higher AUC scores along with all three pretrained CNN models. In the process of evaluating the optimal CNN model, it was also noted that VGGNets (VGG16 and VGG19) accomplishes the lowest scores among all the pretrained models employed.

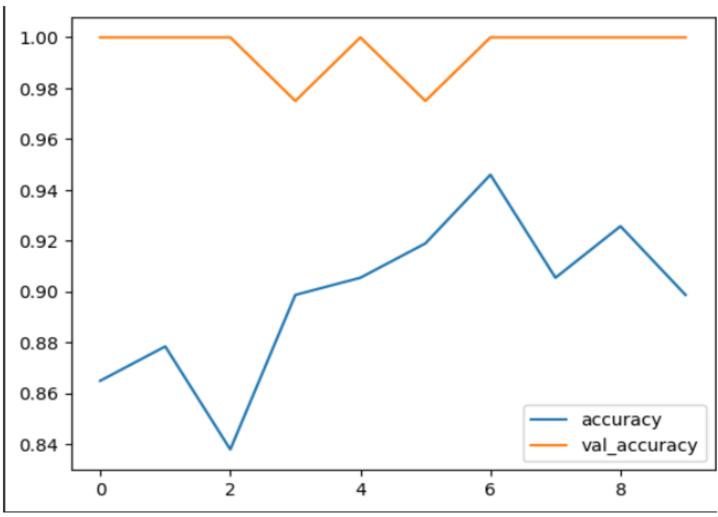
B. Optimal Hyperparameters Optimization

To further improve the performance of models, we performed hyper-parameter tuning with SVM classifier (rbf kernel in each case). We observed that the process highly affected the statistical results with an accomplishment of most prominent AUC score till now. We performed around 350 combinations of C and gamma individually with each preferred CNN model to achieve better results. But a majority of tuned hyper-parameter values showed no substantial improvement in the performance. Table-3, Table- 4 and Table-5 lists only the important combinations of C and

VI. Conclusion

This paper discusses the critical need for qualified radiologists in the diagnosis of thoracic illnesses, especially in settings where access to specialists is limited. The project aims to enhance the medical capabilities of these regions by facilitating the early detection of pneumonia and preventing adverse outcomes. Prior research has not focused much on pneumonia detection in the dataset under discussion. Following a comprehensive analysis of multiple pretrained CNN models and classifiers, DenseNet-169 and SVM were selected for feature extraction and classification. The performance of the model was much improved by adjusting the hyperparameters. The work's objective is to identify dominant models and classifiers for next studies in this field, which may lead to better pneumonia identification methods.





References

[1] Dev Kumar Das, Madhumala Ghosh, Mallika Pal, Asok K Maiti, and Chandan Chakraborty. 2013. Machine learning approach for automated screening of malaria parasite using light microscopic images. Micron 45 (2013), 97106.

[2] MahdiehPoostchi,KamolratSilamut,RichardMaude,StefanJaeger,and George Thoma. 2018. Image analysis and machine learning for detecting malaria. Translational Research (2018).

[3] Nicholas E Ross, Charles J Pritchard, David M Rubin, and Adriano G Duse. 2006. Automated image processing method for the diagnosis and classification of malaria on thin blood smears. Medical and Biological Engineering and Computing 44, 5 (2006), 427436.

[4] Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. 2014. CNN features off-the-shelf: an astounding baseline for recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition workshops. 806813.

[5] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems. 10971105.

[6] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

[7] F Chollet. 2016. Xception: deep learning with separable convolutions. arXiv Prepr. arXiv1610 2357 (2016).

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 770778.

[9] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. 2017. Densely Connected Convolutional Networks.. In CVPR, Vol. 1. 3.

[10] Heba Mohsen, El-Sayed A El-Dahshan, El-Sayed M El-Horbaty, and AbdelBadeeh M Salem. 2017. Classification using deep learning neural networks for brain tumors. Future Computing and Informatics Journal (2017).

[11] CDC URL: https://www.cdc.gov/features/pneumonia/index.html

[12] Paras Lakhani and Baskaran Sundaram. 2017. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology 284, 2 (2017), 574582

[13] Kai-Lung Hua, Che-Hao Hsu, Shintami Chusnul Hidayati, Wen-Huang Cheng, and Yu-Jen Chen. 2015. Computer-aided classification of lung nodules on computed tomography images via deep learning technique. OncoTargets and therapy 8 (2015).

[14] Mohammad Tariqul Islam, Md Abdul Aowal, Ahmed Tahseen Minhaz, and Khalid Ashraf. 2017. Abnormality detection and localization in chest x-rays using deep convolutional neural networks. arXiv preprint arXiv:1705.09850 (2017).

[15] 2016. Openi Dataset :. (2016). https://openi.nlm.nih.gov

[16] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M Summers. 2017. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on. IEEE, 34623471.

[17] Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, and others. 2017. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225 (2017).

[18] Benjamin Antin, Joshua Kravitz, and Emil Martayan. 2017. Detecting Pneumonia in Chest X-Rays with Supervised Learning. (2017).

[19] Pulkit Kumar, Monika Grewal, and Muktabh Mayank Srivastava. 2018. Boosted cascaded convnets for multilabel classification of thoracic diseases in chest radiographs. In International Conference Image Analysis and Recognition. Springer, 546552.

[20] Zhe Li, Chong Wang, Mei Han, Yuan Xue, Wei Wei, Li-Jia Li, and F Li. 2017. Thoracic disease identification and localization with limited supervision. arXiv preprint arXiv:1711.06373 (2017).

[21] 2018. Kaggle URL :. (2018). https://www.kaggle.com/nih-chestxrays/data

[22] Suhail Raoof, David Feigin, Arthur Sung, Sabiha Raoof, Lavanya Irugulpati, and Edward C Rosenow III. 2012. Interpretation of plain chest roentgenogram. Chest 141, 2 (2012), 545558.

[23] Nijhawan R, Das J, Balasubramanian R. A Hybrid CNN+ Random Forest Approach to Delineate Debris Covered Glaciers Using Deep Features. Journal of the Indian Society of Remote Sensing. 2018:1-9.

[24] Nijhawan, Rahul, Rose Verma, Shashank Bhushan, Rajat Dua, and Ankush Mittal. ”An Integrated Deep Learning Framework Approach for Nail Disease Identification.” In Signal-Image Technology and InternetBased Systems (SITIS), 2017 13th International Conference on, pp. 197202. IEEE, 2017.

[25] Nijhawan R, Rishi M, Tiwari A, Dua R. A Novel Deep Learning Framework Approach for Natural Calamities Detection. InInformation and Communication Technology for Competitive Strategies 2019 (pp. 561-569). Springer, Singapore.

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