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"AN IMPROVED MODEL FOR PNEUMONIA DETECTION USING CONVOCATIONAL NEURAL NETWORK"

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Abstract:

Pneumonia continues to be a significant global health concern, necessitating precise and timely detection for effective treatment. In this research, we introduce an innovative algorithm for pneumonia detection utilizing Convolutional Neural Networks (CNNs). Our model integrates a Faster R-CNN architecture with Feature Pyramid Network (FPN) and a Conv-Dilated Net framework, harnessing the deep learning capabilities of CNNs for robust feature extraction and hierarchical representation learning. This integrated approach enables accurate localization and classification of pneumonia lesions in chest X-ray images. The algorithm commences with preprocessing steps aimed at enhancing image quality and normalizing features. Subsequently, convolutional, and max-pooling layers, activated by Rectified Linear Unit (ReLU) functions, are applied to extract features. These feature maps are then fed into dense layers, culminating in an output neuron activated by a sigmoid function for binary classification. To address overfitting, data augmentation techniques are employed during model training, ensuring generalizability to unseen data. Experimental results showcase the effectiveness of the proposed algorithm in accurately detecting pneumonia, achieving high sensitivity and specificity rates. The automation of the diagnosis process through deep learning facilitates prompt and reliable assessment, enabling timely intervention and improving patient outcomes. Future research endeavours will concentrate on refining and validating the model across diverse patient demographics and healthcare environments, with the ultimate objective of integrating it as a valuable clinical tool for pneumonia detection and management.

Keywords: Pneumonia, Convolutional Neural Network (CNN), Max Pooling, Sigmoid Function, Rectified Linear Unit (ReLU), Data Augmentation, Deep Learning.

Introduction:

One of the most severe infections, Pneumonia kills nearly a million people each year in preventable deaths, according to a recent WHO estimate. According to World Health Organization Pneumonia causes 15% of all deaths in children under the age of five. According to data from 2017, there were about 8,08,694 kids. It affects over 450 million people worldwide on an annual basis. It was the fourth most frequent cause of death in 2016. The danger of Pneumonia is very high and increasing daily in nations with rapid population expansion. X-rays are the main diagnostic tool used to pinpoint Pneumonia because the sickness can be brought on by a variety of bacteria and viruses. It could be difficult to spot Pneumonia in its early stages while analysing the different chest X-rays. Since the advent of technology, the healthcare sector has experienced significant growth. Thought to be helpful, chest X-rays can make it challenging to diagnose Pneumonia since it can be confused for heart failure or a variety of other types of lung cancer.

The main problem is developing an efficient algorithm to assess a patient's chest X-ray to identify if he has pneumonia or not. The algorithm must be incredibly accurate because people's lives are on the line. Convocational Neural Network is one of the most well-liked deep learning neural networks. The convolutional neural network (CNN), which comprises many layers in addition to the max pooling layer, is one of the most well-known deep learning neural networks. The layers support automatic X-ray image recognition. The Rectified Linear Unit, or ReLU layer, which contributes to improving nonlinearity, is also present. It is a structure made to efficiently handle both 2D and 3D images. It is proposed that the fixed network of the trial-and-error system shares some similarities. The paper looks for patterns in patients and categorises them as having or not having pneumonia.

Related Work:

The study of machine learning (ML) methods for detecting thoracic disorders has recently attracted attention in the field of research for medical picture categorization. A approach for diagnosing pulmonary tuberculosis was put up by Lakhani and Sundaram in 2017 [12] and was modelled after the design of the two separate DCNNs Alex Net and Google Net. Deep learning techniques were used in the classification of lung nodules, which Huang et al. [13] advocated as a method primarily for identifying lung cancer.

Islam et al. [14] proposed the performance of several Convolutional Neural Network (CNN) variations for abnormality identification in chest X-rays using the openly accessible OpenI dataset [15]. A larger dataset of frontal chest X-rays was made available by Wang et al. (2017) [16] for the better study of machine learning in chest screening. The COVID-19 Pneumonia outbreak, which first surfaced at the end of 2019, continues to put all of humanity in danger.

The ability to promptly diagnose new crown Pneumonia has also become extremely important in light of the new crown Pneumonia infection rate's rapid growth. New crown diagnosis is aided by deep learning.

Numerous approaches have been suggested via scientific research. COVID-Net, a deep convolutional neural network design specifically suited for the detection of COVID-19 instances from chest X-ray (CXR) pictures, was proposed by Wang and Wong in 2020 [20].

Covid AID: COVID-19 AI Detector, a cutting-edge deep neural network-based model to prioritise patients for the right tests, was proposed by Mangal et al. [21].

Methodology

The processing of data. A dataset on the identification and localisation of Pneumonia in chest X-rays was published by the Radiological Society of North America (RSNA) [b20] in 2018 [13]. The collection includes radiologist-annotated chest X-ray pictures from the National Institutes of Health (National 2 Computational and Mathematical Methods in Medicine Institutes of Health) [10]. On the Kaggle website, you can get more information about the Kaggle Pneumonia detection dataset [9]. The Kaggle Pneumonia data used in this experiment includes information on 6684 cases, only 6012 Pneumonia images (which account for 22.03 percent), 8851 normal images (which account for 31.19 percent), and 1821 images (which account for 44.77 percent), which are images that are abnormal or lack turbidity in the lungs.

The CNN Model consists of feed-ahead networks with convolutional, pooling, flattening, and absolutely linked layers that use the appropriate activation functions. Layer of convolution. It serves as the foundation for CNNs. Convolution is an outdated mathematical technique for combining two functions [17]. The entry image is first transformed into a matrix inside the CNN Model. The enter matrix that slides over it is given a convolution filter, which plays around with element-clever multiplication and stores the sum. Thus, a feature map is produced. Once photos have been converted to black and white, the 30 30 filter is typically used to create 2D feature maps. When the input image is represented as a three-dimensional matrix anywhere the RGB colour represents the third dimension, convolutions are finished in three dimensions. The entry matrix is used to run a number of function detectors to create a layer of feature maps, which then makes up the convolutional layer.

The algorithms CNN Classifier worked within side the CNN classifiers are defined in Figs. one and 2. Figure 3 suggests the flow diagram of the schema of research. the number of epochs for all of the classifier fashions bestowed all through this paper become mounted at twenty as soon as education and trying out many CNN fashions over the path of research. Classifier fashions educated for a variety of quantity of epochs have confirmed over fitting. many optimizers perform had been conjointly educated and studied. Adam optimizer feature become finalized to be used for all classifiers after it gave the first-rate results. Initially, a trustworthy classifier version with convolutional layer of photograph length set to 64 * 64, 30 function maps and the usage of ReLU activation carry out become educated. surely related dense layer with 128 perceptron become utilized. second one classifier version become educated with a new convolutional layer of 64 function maps for better function extraction. the amount of perceptron in dense layer become conjointly doubled to 256 layer so higher learning is probably achieved. The 0.33 version become educated for three convolutional layers with 128 function maps in 0.33 convolutional layer for a variety of cautious function extraction

Proposed Model:

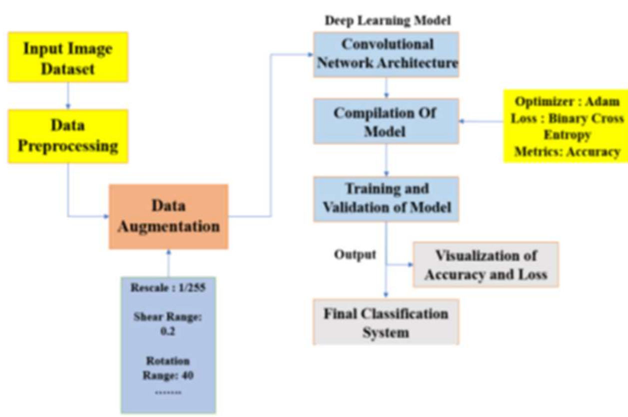

Figure 1 Proposed Model for Pneumonia Analysis

Result and Epoch Values:

```
Set: train, normal images: 234, pneumonia images: 390
Set: val, normal images: 8, pneumonia images: 8
Set: test, normal images: 71, pneumonia images: 96
Found 624 images belonging to 2 classes.
Found 167 images belonging to 2 classes.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:118: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version
Epoch 1/10
19/19 [==============================] - 89s 5s/step - loss: 1.1589 - accuracy: 0.5693 - val_loss: 0.6844 - val_accuracy: 0.5688 - lr: 0.0010
Epoch 2/10
19/19 [==============================] - 41s 2s/step - loss: 0.6689 - accuracy: 0.6250 - val_loss: 0.7005 - val_accuracy: 0.4938 - lr: 0.0010
Epoch 3/10
19/19 [==============================] - 42s 2s/step - loss: 0.6465 - accuracy: 0.6098 - val_loss: 0.6322 - val_accuracy: 0.5625 - lr: 0.0010
Epoch 4/10
19/19 [==============================] - ETA: 0s - loss: 0.5984 - accuracy: 0.6990
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.0003000000142492354.
19/19 [==============================] - 43s 2s/step - loss: 0.5984 - accuracy: 0.6990 - val_loss: 0.4786 - val_accuracy: 0.8375 - lr: 0.0010
Epoch 5/10
19/19 [==============================] - 43s 2s/step - loss: 0.4975 - accuracy: 0.7618 - val_loss: 0.4038 - val_accuracy: 0.8625 - lr: 3.0000e-04
Epoch 6/10
19/19 [==============================] - ETA: 0s - loss: 0.4065 - accuracy: 0.8277
Epoch 6: ReduceLROnPlateau reducing learning rate to 9.000000427477062e-05.
19/19 [==============================] - 43s 2s/step - loss: 0.4065 - accuracy: 0.8277 - val_loss: 0.3380 - val_accuracy: 0.8625 - lr: 3.0000e-04
Epoch 7/10
19/19 [==============================] - 45s 2s/step - loss: 0.3517 - accuracy: 0.8480 - val_loss: 0.2996 - val_accuracy: 0.8625 - lr: 9.0000e-05
Epoch 8/10
 7/19 [=========>....................] - ETA: 22s - loss: 0.3101 - accuracy: 0.8798
```

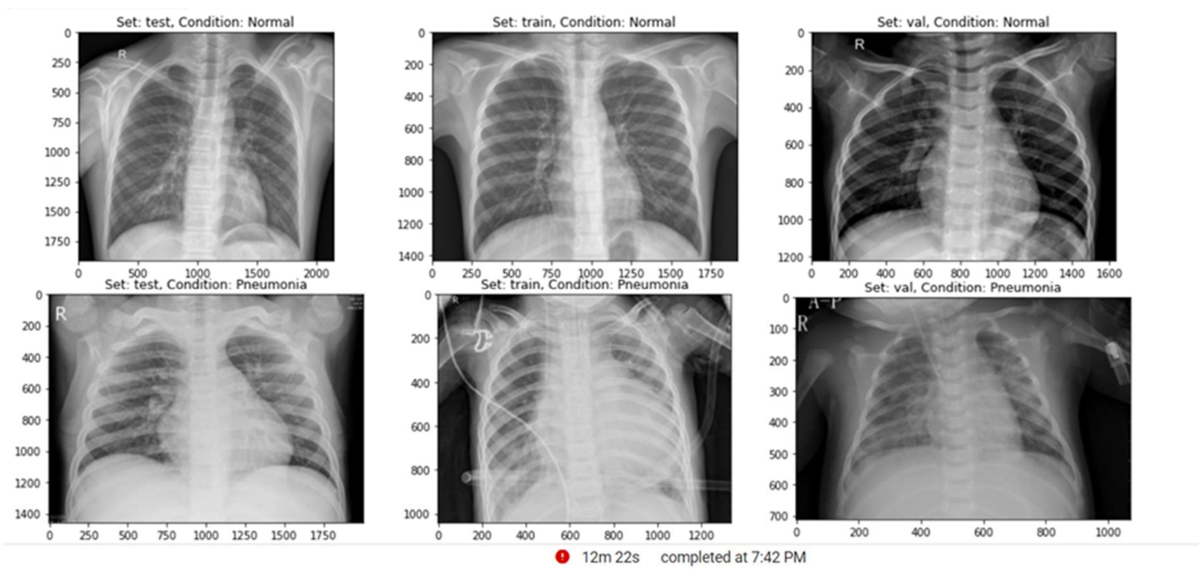

Figure 2 Condition analysis for Normal or Pneumonia

Conclusion:

Therefore, it is terminated that the Deep Learning Model on top of classifies the chest X-rays for Respiratory disorder identification in an exceedingly very correct manner. The loss of the model is reduced whereas coaching and therefore the accuracy at the same time will increase through every epoch stages so as to yield distinct results for classifying the respiratory disorder affected and non-affected on individuals. The information augmentation and pre-processing stages make it possible for CNN and Deep Neural Network to perform without being subject to overfitting, ensuring that the results obtained can always remain consistent. However, we have achieved 91% Accuracy with improved CNN Model. The projected model accurately predicts whether or not a particular sample of Chest X-ray has Pneumonia or is normal with a reduced variety of convolutional layers. This is frequently quite helpful in the medical sector for patients early and accurate detection of respiratory disorders. Early diagnosis is crucial for preserving a person's life since it ensures that the patient will receive prompt, efficient care.

References:

[1] Acharya A. K, Satapathy R. A Deep Learning Based Approach towards the Automatic Diagnosis of Pneumonia from Chest Radio-Graphs. Biomed Pharmacol J 2020; 13(1). Available from: ht tps://bit .ly/2vYHz8V

[2] Chandra T.B., Verma K. (2020) Pneumonia Detection on Chest X-Ray Using Machine Learning Paradigm. In: Chaudhuri B., Nakagawa M., Khanna P., Kumar S. (eds) Proceedings of 3rd International Conference on Computer Vision and Image Processing. Advances in Intelligent Systems and Computing, vol 1022. Springer, Singapore

[3] Saul, CanJozef, Deniz Yagmur Urey and Can Doruk Taktakoglu.(2019). Early Diagnosis of Pneumonia with Deep Learning. ArXiv abs/1904.00937

[4] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detect ion Using CNN based Feature Extract ion," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.

[5] Garima Verma, Shiva Prakash (February 2020). Pneumonia Classification using Deep Learning in Healthcare. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-4.

[6] Stephen, Okeke & Sain, Mangal & Maduh, Uchenna & Jeong, Doun. (2019). An Efficient Deep Learning Approach to Pneumonia Classificat ion in Healthcare. Journal of Healthcare Engineering. 2019. 1-7. 10.1155/2019/4180949.

[7] Shorten, C., Khoshgoftaar, T.M. A survey on Image Data Augmentation for Deep Learning. J Big Data 6, 60 (2019). https://doi.org/10.1186/s40537-019- 0197-0.

[8] A. Mikołajczyk and M. Grochowski, "Dat a augment at ion for improving deep learning in image classification problem," 2018 International Interdisciplinary PhD Workshop (IIP hDW), Swinoujście,2018,pp.117 -12

[9] O'Shea, Keiron & Nash, Ryan. (2015). An Introduction to Convolutional Neural Networks. ArXiv eprints. https://www.researchgate.net/publication/285164623_An_Introduct ion_to_Convolutional_Neural_Networks

[10] S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), Antalya, 2017, pp. 1-6, doi: 10.1109/ICEngTechnol.2017.8308186.

[11] Yamashita, R., Nishio, M., Do, R.K.G. et al. Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611– 629 (2018). ht tps://doi.org/10.1007/s13244-018-0639-9

[12] Agarap, Abien Fred. (2018). Deep Learning using Rectified Linear Units (ReLU).

[13] Rahman, T.; Chowdhury, M.E.H.; Khandakar, A.; Islam, K.R.; Islam, K.F.; Mahbub, Z.B.; Kadir, M.A.; Kashem, S. Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detect ion Using Chest X-ray. Appl. Sci. 2020, 10, 3233

[14] A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classificat ion with deep convolut ional neural networks. In Advances in Neural Informat ion Processing Systems 25, pages 1106–1114, 2012.

[15] J. Dean, G. Corrado, R. Monga, K. Chen, M. Devin, M. Mao, M. Ranzato, A. Senior, P. Tucker, K. Yang, Q. V. Le, and A. Y. Ng. Large scale dist ributed deep networks. In P. Bart let t , F. Pereira, C. Burges, L. Bot tou, and K. Weinberger, editors, NIPS, pages 1232– 1240. 2012

[16] A. G. Howard. Some improvements on deep convolutional neural network based image classificat ion. CoRR, abs/1312.5402, 2013

[17] D. Erhan, C. Szegedy, A. Toshev, and D. Anguelov. Scalable object detect ion using deep neural networks. In CVPR, 2014.

[18] Manoharan, S., & P onraj, N. (2019),"Precision Improvement And Delay Reduct ion In Surgical Telerobotics", Journal of Artificial Int elligence, 1(01), 28-36.

[19] Manoharan, Samuel. "Patient Diet Recommendat ion System Using K Clique and Deep learning Classifiers." Journal of Artificial Intelligence 2, no. 02 (2020): 121-130.

[20] Tharwat, Alaa. (2018). Classification Assessment Methods: a detailed tutorial. 10.1016/j.aci.2018.08.003