Available online @ https://jjem.jnnce.ac.in
https: www.doi.org/10.37314/JJEM.SP0262
Indexed in International Scientific Indiexing (ISI)
Impact factor: 1.395 for 2021-22
Published on: 08 December 2024

AI for Healthcare: Pneumonia Detection with Convolutional Neural Networks (CNNs)

Priyanka M[1] & Santhosh SG[2]
[1]Student, [2] Associate Professor, Dept of MCA, JNNCE,
Shivamoga-577201, Karnataka, India.
priyankamahesh1350@gmail.com, santhoshsgrao@jnnce.ac.in

Abstract

Artificial intelligence has significantly impacted various industries, particularly with the expansion of the data set available. Its principal function is to improve decision-making processes by delivering more accurate, fast, and dependable judgments. AI has been widely applied in medicine recently, especially in areas that depend on diagnostic techniques that process vast amounts of digital pictures and biomedical imaging modalities. Applying machine learning to analyze photographs used in medicine have notably improved reporting accuracy and consistency. This study specifically focuses by utilizing machine learning techniques to analyze chest X-ray images, aiming to support diagnostic decisions through enhanced decision-making processes.
keywords: *CNN (Convolutional Neural Network), Pneumonia, X-ray, Python, Deep Learning.*

1. Introduction

Pneumonia remains a major global health concern, contributing to high rates of morbidity and mortality worldwide, particularly in vulnerable populations such as children and the elderly. An accurate and timely diagnosis is crucial for the successful treatment of pneumonia and the improvement of patient outcomes. Traditional diagnosis methods often rely on the visual evaluation of chest X-ray images by medical professionals, which can be time-consuming and subjective. Artificial intelligence (AI) has revolutionized medical image processing, particularly with Convolutional Neural Network application (CNNs). CNNs are useful for tasks like determining pneumonia from chest X-ray pictures since they are excellent at spotting intricate patterns and features in images. Developing an automated method that enhances pneumonia detection is the aim of this research. CNNs are excellent at identifying complex patterns and characteristics in images, which makes them helpful for jobs like diagnosing pneumonia from chest X-ray scans. The objective of this research is to develop an automated technique that improves pneumonia detection. In this research, CNNs are utilized to evaluate chest X-ray images for the presence of pneumonia. Python programming serves for both model building and implementation. Additionally, to automating and expediting the diagnosis process, the project aims to give medical practitioners a dependable tool that could improve clinical decision-making and patient outcomes. This study aims to explore and demonstrate the revolutionary effect of artificial intelligence (AI) on healthcare, with a focus on medical imaging and diagnostics.

2. Literature review

The foundational work by E. Sayed et al. on computer-aided diagnosis through MRI exemplifies the integration of advanced algorithms for medical imaging analysis [2]. Their survey and proposed algorithm provide a comprehensive background for understanding the evolution of diagnostic techniques using machine learning, specifically in detecting brain tumors.

Research by D.K. Das et al. and M. Poostc`hi et al. explores machine learning approaches for Detecting malaria through microscopic images [3, 4]. These studies utilize image processing and machine learning methods to classify and detect malaria parasites, setting a precedent for similar approaches in pneumonia detection. The use of light microscopy images in these studies parallels the utilization of chest X-rays for pneumonia diagnosis.

N.E. Ross et al. developed automated image processing methods for diagnosing and classifying malaria, emphasizing the role of automation in medical diagnostics [5]. Their approach involves the use of thin blood smear images, which is conceptually similar to analyzing chest radiographs for pneumonia.

A.S. Razavian et al. and A. Krizhevsky et al. demonstrated the potential of CNNs in image recognition tasks [6, 9]. Razavian et al. showcased CNN features as a strong baseline for recognition tasks, while Krizhevsky et al.'s work on ImageNet classification with deep CNNs highlighted the effective use of deep learning models in handling large-scale image datasets. These foundational studies underpin the use of CNNs for pneumonia detection from chest X-ray images.

R.H. Abiyev and M.K.S. Ma'aitah specifically applied deep CNNs for chest diseases detection, providing a direct correlation to pneumonia detection [8]. Their work in the Journal of Healthcare Engineering outlines the architecture and performance of CNNs in identifying various chest diseases, including pneumonia.

M. Cicero et al. focused on training and validating deep CNNs for the detection and classification of abnormalities in frontal chest radiographs [10]. Their findings on the efficacy of CNNs in recognizing patterns and anomalies in medical images provide insightful viewpoints on developing robust pneumonia detection models.

D. Demner-Fushman et al. discussed the preparation of radiology examination datasets for distribution and retrieval, which is crucial for training and validating CNN models in pneumonia detection [11]. Proper dataset curation ensures the accessibility of high-quality training data, which is crucial for creating precise diagnostic models.

Chu et al. and A. Shrestha and A. Mahmood provided best practices for fine-tuning visual classifiers and reviewed deep learning algorithms and architectures, respectively [12, 14]. These reviews offer guidance on optimizing CNN models for particular tasks, likepneumonia detection and highlight recent advancements in deep learning techniques.

The book by I. Goodfellow, Y. Bengio, and A. Courville serves as an authoritative resource on deep learning, detailing various architectures and their applications [15]. This comprehensive text provides theoretical underpinnings and practical insights essential for developing CNN-based pneumonia detection systems.

3. Methodology of Proposed Model

CNN models were built from the ground up and trained on X-ray images of the chest. The dataset was acquired from Kaggle. Tensor flow and the Keras Neural Library were used to run the models. The project's dataset consists of 5215 training images, 623 test photographs, and 17 validated photographs. Data augmentations were used to obtain good results from the database. The models in the study were trained with a variable number of CLs. Each model was trained using 20 epochs.

3.1 Convolutional layer:

CNN's Convolution Layer serves as its foundation. The convolutional method has been built by applying mathematics to blend two functions. In convolutional neural network models, the input photo usually goes into matrix form. The input matrix is used to apply a convolution filter, which multiplies each element by itself while maintaining the sum. In the era of monochrome photos, 3 × 3 filters are meant to function as 2D feature maps. When the input photo is treated as a 3D matrix, where the red-green-blue shade speaks for the third area, 3D convolutions are carried out. Numerous feature sensors are used together with the input matrix, which ultimately forms the convolutional layer, to construct a layer of feature mapping. The ReLU activation function is all that remains of the corrected linear function. When the supplied input is positive and is a non-linear function, the ReLu function returns 1. When the supplied input is negative, it returns 0. These types of activation functions are usually used in convolutional neural networks since they aid with disappearing gradient problems and layer non-linearity.

3.2 Pool Layer:

CL comes after the pool layer. The maximum pool layer is the swimming layer that is being utilized.

Max-pool is used to down sample photos by reducing their dimensionality and difficulty. The other two kinds of layers that can be applied in the pooling layer are general pooling and overlapping pooling. In this project, max-pooling is used. Max pooling is employed in the pooling layer because it facilitates the identification of crucial details in photographs. The input photos are fed to the flatten layer once they've made it through the convolution and pool layers. Roman, wherein these rules have been established. As you can see here, a 9-point text is the intended format. Kindly reserve the use of sans-serif or non-proportional fonts for unique applications, like text that needs to be separated from source code. If the Times Roman font isn't available, consider the Computer Modern Roman font. Use the Times font on a Macintosh. Justified margins are preferable to ragged ones. The Lower layer reduces the operating difficulties of insertion photos and straightens them vertically. The result of the flattening layer travels to the dense layer, which comes after the flattening layer. The dense layer will have multiple layers; each branching in the first layer of a dense layer has an attachment to each branching in the second layer. Each layer in the dense layer extracts a characteristic, and the network generates an estimate based on this. This entire process is referred to as forward propagation. Following the evaluation of the cost estimation, back propagation takes place. Until the network reaches its peak performance, back propagation happens repeatedly. A technique called dropout was used in the project. The disappear gradient problem is addressed and overfitting is lessened via the dropout method. The dropout technique serves as an inspiration for each somatic cell as they create their unique characterization of the injected data. In the tutoring method, attachments between somatic cells are divided into successive layers by an irregular approach.

3.4 Proposed system

The development of this system reduces the need for manual labor and substitutes computerization for any manual labor performed by a physician or medical assistant. Using the CNN model, the proposed method asks the computer to predict if the patient's X-ray is pneumonic or normal. Those who test positive for pneumonia are the only ones who are advised to visit the doctor in person; using this technique will make it easier to identify patients who have pneumonia from those who do not. This method will reduce the amount of medical support required, and an X-ray from a patient who is not dealing with pneumonia can be utilized in place of a face-to-face consultation with the doctor to get manual clarification on pneumonia.

5.Implementation

Expanding the execution concept makes sense because observing the task would earn you a credential. The project work would be successfully and methodically finished thanks to the execution concept. Fixing the project's timeline, mentoring and training the service providers, and allocating all roles and responsibilities to the project's participants are all beneficial.

5.1 Workflow

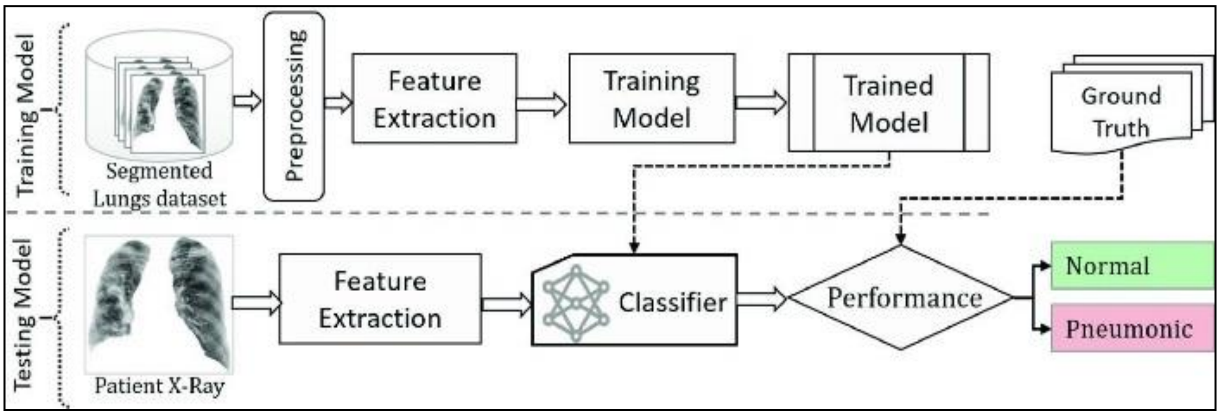

Fig 5.1: Training and evaluating the model image which explains the function extraction to classify and the suggested reuse.

5.2 Outcome

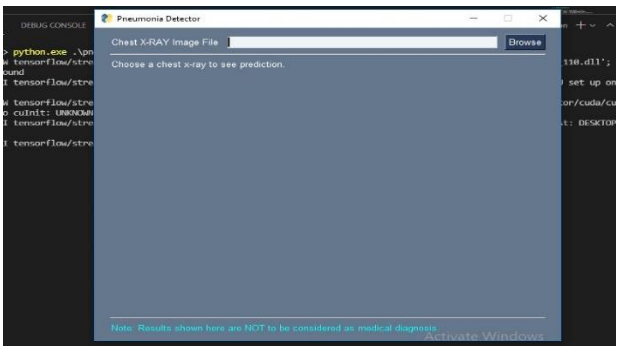

Fig 5.2.1: X-ray Upload
Main page for uploading the chest X-ray images

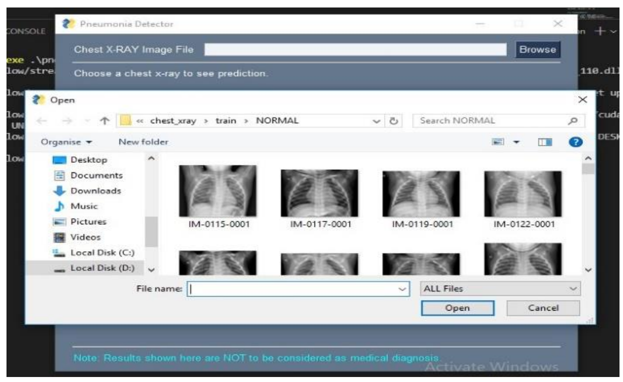

Fig 5.2.2: locating and choosing the radiograph image for the chest.

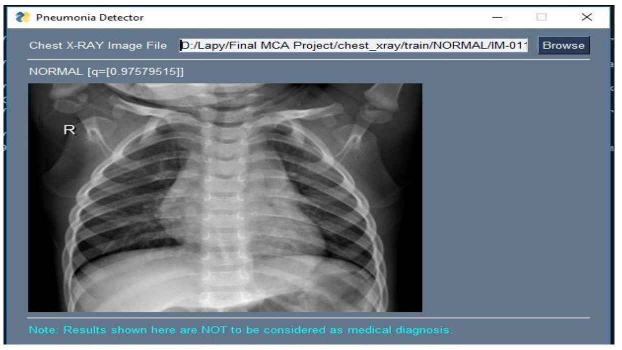

Fig 5.2.3: Output Prediction 1

Normal is the condition, defined by the prediction's accuracy.

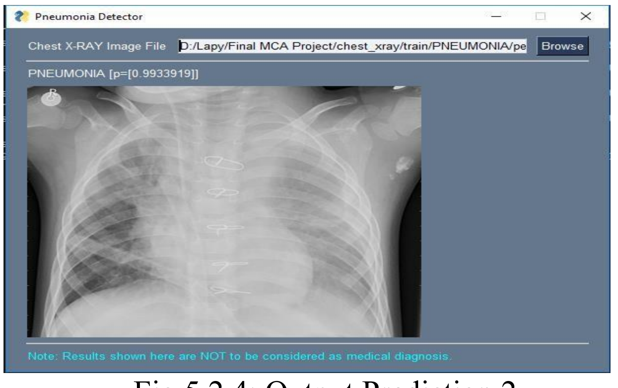

Fig 5.2.4: Output Prediction 2

Pneumonia is the condition, defined by the prediction's accuracy.

5.2 Software evaluation

Testing will aid in the revelation of faults. The process of trying to find every possible flaw or issue with a work product is called testing. Testing enables you to evaluate how well a component, assembly, subassembly, and/or final product perform. Different test kinds exist. Every test type aims to test a particular combination of conditions. Pneumonia is a lung illness that results in the rupture and filling of the lungs' air sacs with fluid. It can cause chills, a mucusy cough, fever, and difficulty breathing.

The Project uses a percentage to predict whether a lung X-ray will show pneumonia or not the percentage range is represented by the notation 0.000 to 0.100. (Or, in other words, 0% to 100%) The values with and without pneumonia are separated by a 0.5 center line.

6. Conclusion

In order to identify pneumonia, this project uses computer graphics to experiment with deep learning functions. Convolutional Neural Networks emerged as a result of scientists' desire to create a machine that could mimic human neurons, which is how the concept of a neural network was first introduced. This project was developed using this methodology. The unaffected chest radiograph database and the pneumonia disease that is afflicted are obtained. We gave an example of how to extract pneumonic and non-pneumonic information from a set of X-ray pictures. Only seven of the project's twenty epochs have been finished due to the dropout feature, which saves time and memory while resulting in the desired outcomes.

7. References

1. P. Rui, K. Kang, National Ambulatory Medical Care Survey: 2018 Emergency Department Summary Tables.

2. E. Sayed, et. al, Computer-aided Diagnosis of Human Brain Tumor though MRI: A Survey and a new algorithm, Expert System with Applications (41): 2014.

3. D.K. Das, M. Ghosh, M. Pal, A.K. Maiti, and C. Chakraborty, Machine learning approach for automated screening of malaria parasite using light microscopic images, Micron 45, 97106, 2013.

4. M. Poostchi, K. Silamut, R. Maude, S. Jaeger, and G. Thoma, Image analysis and machine learning for detecting malaria, Translational Research, 2018.

5. N.E. Ross, C.J. Pritchard, D.M. Rubin, and A.G. Duse, Automated image processing method for the diagnosis and classification of malaria on thin blood smears, Medical and Biological Engineering and Computing 44, 5, 427436, 2006.

6. A.S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, CNN features off-the-shelf: an astounding baseline for recognition, In Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 806813, 2014.

7. Fafi, Kusworo and Catur, Breast Tumor Detection using Haar-Like Feature Method on Ultrasonography (USG) Imaging, International Journal of Innovative Research in Advanced Engineering, Volume V, 154157. doi://10.26562/IJIRAE.2018.MYAE10082 classifiers to new domains, in Proceedings European.

8. Abiyev R. H., Ma'aitah M. K. S., Deep Convolutional Neural Networks for Chest Diseases Detection, Journal of Healthcare Engineering,2018.

9. A. Krizhevsky, I. Sutskever, & G.E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, Neural Information Processing Systems, 25.10.1145/3065386, 2012.

10. M. Cicero, A. Bilbily, E. Colak, T. Dowdell, B. Gra, K. Perapaladas, and J. Barfett, Training and Validating a Deep Convolutional Neutral Network for Computer-Aided Detection and Classification of Abnormalities on Frontal Chest Radiographs, Investigative Radiology 52(5) 281- 287, 2017.

11. D. Demner-Fushman, M.D. Kohli, M.B. Rosenman, S.E. Shooshan, L. Rodriguez, S. Antani, G.R. Thoma, and C.J. McDonald, preparing a collection of radiology examinations for distribution and retrieval, J Am Med Inform Assoc, 2016 Mar;23(2):304-10. Doi: 10.1093/jamia/ocv080. Epub 2015 Jul 1.

12. Chu, V. Madhavan, O. Beijbom, J. Hoffman, and T. Darrell, Best practices for fine- tuning visual classifiers to new domains, in Proceedings European Conference on Computer Vision, pp. 435–442, Oct. 2016.

13. Sharif Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, CNN features off-the-shelf: An astounding baseline for recognition, in Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 806–813, Sep. 2014.

14. A. Shrestha and A. Mahmood, Review of Deep Learning Algorithms and Architectures, in IEEE Access, vol. 7, pp. 53040-53065, 2019, DOI: 10.1109/ACCESS.2019.2912200.

15. I. Goodfellow, Y. Bengio, and A. Courville, Deep learning, in Adaptive Computation and Machine Learning. Cambridge, MA, USA: MIT Press, p. 775, 2016.

16. Santhosh.S.G. G, "Python Conventional neural network towards pneumonia detection", International journal of Engineering Science and Technology, Vol.7, Issue 2, ISSN No.2455-2143, Pages 294-297, 2022.