Pneumonia Detection using Machine Learning

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Abstract- *Pneumonia, a prevalent and potentially life-threatening respiratory infection, poses significant challenges in timely and accurate diagnosis. Leveraging advancements in machine learning (ML) techniques, this research aims to develop an efficient and reliable pneumonia detection system. Through the analysis of chest X-ray images, a convolutional neural network (CNN) model is trained to differentiate between pneumonia-infected and healthy lung images. The dataset used for training and validation comprises a diverse set of chest X-ray images collected from various sources. The proposed model demonstrates promising results, achieving high accuracy and sensitivity in pneumonia detection. Moreover, interpretability techniques are employed to elucidate the decision-making process of the CNN model, enhancing its clinical relevance and trustworthiness. The developed system holds considerable potential for aiding healthcare professionals in prompt and accurate pneumonia diagnosis, thereby facilitating timely intervention and improving patient outcomes.*

Key Words: **Pneumonia detection, Convolutional Neural Networks, Deep Learning, Chest X-ray images**

1.INTRODUCTION

Pneumonia is a leading cause of morbidity and mortality worldwide, particularly among children and the elderly. Early detection and prompt treatment of pneumonia are crucial for preventing complications and improving patient outcomes. Chest X-ray imaging is commonly used for the diagnosis of pneumonia due to its accessibility and effectiveness in detecting abnormalities in lung tissue. However, the interpretation of chest X-ray images can be challenging and time-consuming, requiring expertise from radiologists. Automated methods based on deep learning techniques offer a promising solution to streamline the diagnosis process and improve the efficiency and accuracy of pneumonia detection.

The project focuses on developing a machine learning-based system for the early and accurate detection of pneumonia from chest X-ray images. Pneumonia, a prevalent respiratory infection, requires timely diagnosis for effective medical intervention. The study utilizes a diverse dataset containing both normal and pneumonia-affected cases, ensuring comprehensive model training and evaluation.

The methodology involves extracting relevant image features from chest X-rays, encompassing texture, intensity, and shape descriptors. To address challenges related to dataset variability and generalization, feature engineering and selection techniques are employed.

The research aims to showcase the potential of machine learning models in pneumonia detection, with a focus on practical applicability in clinical settings. The ultimate goal is to provide healthcare professionals with a reliable tool that aids in the early identification of pneumonia cases, contributing to improved patient outcomes.

This project contributes to the broader field of medical diagnostics, highlighting the promising role of machine learning in enhancing pneumonia detection capabilities. As technology continues to intersect with healthcare, the findings from this study aim to pave the way for the integration of machine learning models into real-world clinical workflows, supporting healthcare professionals in making timely and accurate diagnostic decisions for pneumonia.

2. Related Works

The author produced and showcase a merged DL model for identifying Pneumonia patients from CXR. In the proposed model, three distinct models are trained on the CXR dataset. The first of them is a bespoke CNN model. Xception and EfficientNetB4 are the two other models.

Several data augmentation and preprocessing strategies are utilized, along with hyperparameter tuning. A composite model is generated by giving different trained models weights based on their accuracy and recall rates.Several performance metrics are improved compared to the prior art, thanks to the suggested approach. [1]

In this paper ensemble of 3 CNN model was used Deep transfer learning is used to deal with the data shortage Dataset is collected which is than pre-processed Image enhancement is done utilizing threshold LBP (Local binary pattern) feature extraction done Data augmentation to form a new data point and split into two datasets. [2]

The author in this paper focuses on early detection of pneumonia. From X-ray images using a pre-trained CNN model Resnet50 Comparison is made between the two models. The models used are CNN and ResNet50. [3]

In this the author Densenet 121 model is used. Two classifier are used one for the identification of pneumonia. The other for the identification of type. Caused by bacteria or Virus. Here transfer learning is used in which the pre-trained models are used. [4]

Alexnet model is used for the detection of pneumonia. It is capable of identifying pneumonia at early stages Comparison is made between various other models like VGG16, CNN, RESNET. [5]

Model is created using Tensorflow. They created a CNN model with two convolutional layers and one fully connected layer, followed by flattening to generate a fully connected layer They applied sigmoidal activation function on fully connected layer This result in the increase in accuracy. [6]

Sr. No	Dataset	Model	Year	Accuracy	Author
1.	Chest X-ray	Ensemble of 3 CNN model	2023	88%	Dr. Praveen Kumar Mannepalli
2.	Chest X-ray	Resnet50	2023	76%	Nida Nasir
3.	Chest X-ray	Densenet 121 Classifier 1 Classifier 2	2023	90% 87%	Sarala Pappula
4.	Chest X-ray	Alexnet	2023	90%	R.Vinoth
5.	Chest X-ray	CNN	2022	82.69%	Vibhanshu Singh Sindhu

Table 1:- Comparison of different methods

3. Background

Machine learning (ML) algorithms have steadily gained the interest of researchers over the last few years. This type of method can make full use of the massive ability to create computer calculators in image processing with pre-determined algorithm stages. Traditional machine learning methods for dividing jobs, on the other hand, necessitate the use of manual design algorithms or the manual setting of output layers to separate images. In response to the aforementioned situation, LeCun et al. offered a CNN approach, which can automatically extract features with the use of constantly stacking features and exit that the included photos may not be in any class.

The shallow networks are very deep and concentrate on the image's low-level features. CNN the model increasingly exposes advanced features as the number of network layers increases. CNN learns the distinctions between different images by combining and evaluating these priority features, and it uses a back-propagation technique to update and record learned parameters. CNN's concept is to use a specific convolution kernel to filter a prior picture or map component to build the next layer map element, as well as merge functions like merging functions to minimise feature map scale and mitigation to count. The created component is then given to the non-linear activation function mapping to improve the model's simulation capabilities The most common integration tasks include mid and high integration.

The plural of integration denotes that the element sent to the integration layer is split into many regions, with each sub-region having a different size in terms of horizontal and vertical steps. The sole distinction between high and medium integration is a lower region where the aggregation rate yields the average of each sub-region. ReLU (Rectified Linear Units) and Sigmoid are two common activation events.

Image elements are automatically extracted using segmentation and a continual accumulation of convolutional processes, integration functions, indirect opening functions, and other completely integrated layers. Then, by evaluating these derived characteristics, it is possible to extract pneumonia from the photos processed by the model. The model's general capacity is increased by fully utilising pixel-level image information. The most prominent neural framework has been proposed in past few decades for in-depth learning development., such as AlexNet and VGGNet.

However, when the number of layers in the network increase, Instead of learning the numerous productive features, the neural network will be modified to particular parts of the training image, which makes the model similar to the capacity declines and creates congestion. The remaining communication framework was proposed to overcome the problem of network depth. Since then, neural networks have advanced, garnered a lot of attention and research, and have formed the foundation for a lot of occupations. We also looked at the efficiency of residual connections in our reduced CNN architecture with only a few layers in this study.

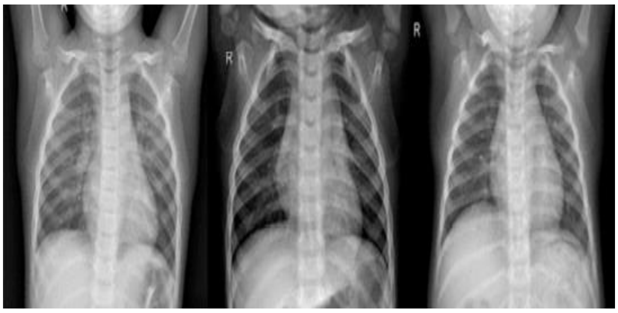
4. Materials and Methods

4.1 Data

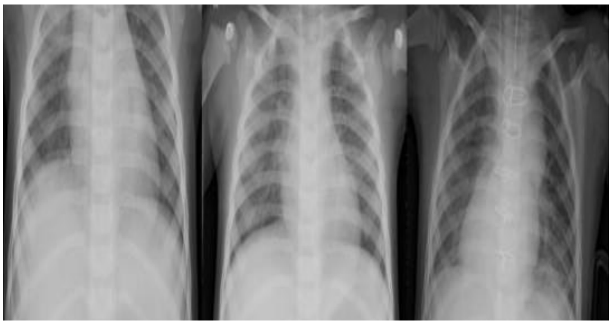
The proposed database, which will be used to test the model's performance, comprises a total of 5863 X-ray pictures via Kaggle.Dr. Paul Mooney created a Kaggle contest in 2017 to classify viral and bacterial pneumonia. It differs from the other datasets since it contains 5,863 paediatric photos. We're talking about the updated version of this dataset.

The database is further divided into three folders (train, test, and val) with subfolders for each image category (Pneumonia / General). Figure 1 shows a few instances of common and pneumonia photos that have been scaled to a static size. Due to the low amount of exposure in patients, chest X-ray images always show symptoms of limited brightness, and chest X-ray images always have black, white, and grey pants.

The lungs are on both sides of the thoracic cavity, and the lung area is plainly visible on an X-ray since it is virtually black. The heart, which is situated between the lungs, appears practically as white as X-rays can go through it entirely. Because bones are comprised of protein and are exceedingly dense, X-rays cannot pass through them, leaving the bones virtually white. Furthermore, the bones have distinct edges.



(a)



(b)

Fig -1: Examples from the dataset. (a) normal cases, (b) pneumonia cases

4.2 Data Preprocessing

Table 2 lists the tactics employed throughout this article. Rescale is a value that we will multiply the data by before any other processing in our investigation. Our original photos had RGB coefficients ranging from 0 to 255, but values like this would be too high for our models to handle (given a typical learning rate), so we scale them down by a factor of 1./255. shear range is used to apply shearing transformations at random. When there are no assumptions of horizontal asymmetry, zoom range is used to randomly zoom inside photographs, and horizontal flip is used to randomly flip half of the images horizontally (e.g. real-world pictures)

Data pre-processing techniques used in this study

Rescale	1./255
Zoom Range	0.2
Shear Range	0.2
Horizontal_Flip	True

Table 2:- Data Preprocessing techniques

4.3 Proposed Methodology

In this study, we designed a CNN model with five convolutional layers to extract the features of chest X-ray images and use those features to detect if a patient suffers from pneumonia. In Our CNN Architecture, We started with a lower filter setting of 32 and worked our way up layer by layer. A layer of Conv2D was used to build the model, followed by a layer of MaxPooling. An odd number, such as 3x3, is desirable for kernel size.

The activation functions Tanh, ReLU, and others can be employed, but ReLU is the most popular. input shape accepts the width and height of an image, with the last dimension serving as a colour channel. After that, we flattened the input and added ANN layers.

$$S(x) = \frac{1}{1+e^{-x}}$$

f(x)=max(0,x)

S(x) = Sigmoid

f(x) = ReLU

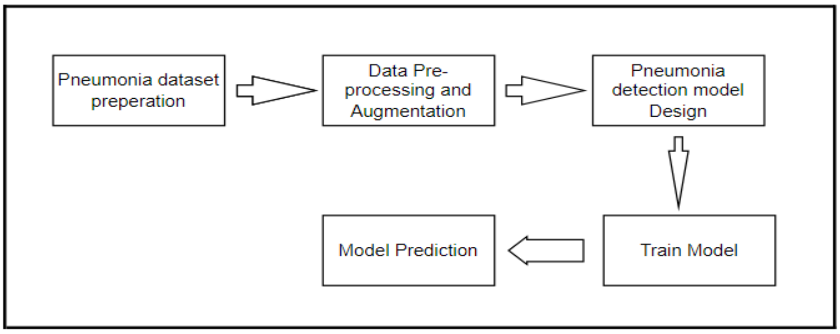


Fig -2: UML Diagram

Table 3: Comparison of various Pneumonia & other lung diseases detection techniques

Ref.no. Publisher / Year	Problem definition	Processing techniques	Algorithms	Tools and technologies used	Accuracy	Data set	Strengths	Weakness
[1] ICACI/ 2018	Detection of lung cancer	Bone shadow exclusion(#2) Segmentation(#3) Segmentation after bone shadow exclusion(#4) Exclusion of outliers by t- SNE method(#5)	CNN	Tensor flow GPU used NVIDIA Tesla K40c card	71%	JSRT	Highly accurate	It uses small dataset which might not contain all the cases
[2] IEEE/ 2016	Detection of lung diseases like Lung Cancer, TB , Pneumonia	Image pre-processing Lung segmentation Feature extraction Image classification	ANN(Feed forward neural network) with sigmoid activation function	NA	92%	Sasoo hospital, Pune (Dataset of 80 patients)	It can detect multiple lung diseases	It is not robust when there are changes in the size and position of CXR images
[3] arXiv 2018	Detection of thorax diseases	Global branch takes input Local branch is trained after discovering local lesion region and cropping Finally global and local branches are combined to fine tune	Attention guided CNN (sigmoid function)	NA	AUC(0.871)	Chest X-ray 14	It yields better accuracy compared to other methods	Relatively insensitive to parameter changes
[4] Stamford University / 2017	Detection of Pneumonia	Image downscaling to 224*224 Normalize based on standard deviation and mean Random horizontal flipping	DCNN (DenseNet)	NA	AUC(0.76)	ChestX-ray14	indicating absence or presence of 14 different pathology classes	Only frontal radiograph were present
[5] RSNA/2017	Detection of Tuberculosis	Images are resized to 256 x 256 Images are augmented using 1..Random cropping(227x227 pixel)	AlexNet GoogleNet	1.Linux OS 2.Caffe framework	AUC(0.99)	1007 chest radiograph	ImageNet performed better than the untrained networks	This algorithm can only use for TB detection

		2.mean subtraction 3. mirror images						
[6] IEEE/2017	Detection of Pneumonia	Signal segmentation Wavelet decomposition Power spectral density Statistical parameter	Fourier transform Continuous wavelet Transform	MATLAB	NA	NA	This is low cost, non-contact, and noninvasive	Used very less input/refers (22 signals)
[7] Springer/2018	Meltilabel classification of thoracic diseases in chest radiographs	Binary relevence(BR) PairWise Error(PWE) Softmax activation weighted cross entropy loss calculated	Baseline: DensNet161 Boosted cascade network	NA	NA	chestX- Ray14	Boosted cascade approach give increased performance	BR approach it does not model the interclass relation with example
[8] Isabel BushStanfor d Computer Science353 Serra Mall, Stanford, CA 94305	Distinguish between benign and malignant nodules to detect lung cancer	Localisation and classification	ResNet models with deep CNN	NA	68%	JSRT	Higher accurate	ResNet model is unable to determine its precise location
[9] IEEE/2017	classification of eight common thoracic diseases	Weakly-supervised pathology localization Multi-label disease classification	Unified DCNN Framework	NA	NA	ChestX-ray8	NA	NA
[10] HIKARI ltd/2015	Detection of thorax diseases	Image pre-processing, lung fields segmentation, features calculation, classification	CAD System	NA	NA	No dataset used	Effective methods of image preprocessing, features calculation	Automating thorax diseases detection still remains unsolved due to its complexity
[11] Springerlink February 2017	Dominant technology for tackling CAD in the lungs	Pulmonary image analysis Computer-aided detection Computer-aided diagnosis Image processing	rule-based study	NA	No dataset used	NA	ConvNets are better feature extractor	Computed tomography (CT)
[12] Applied science 2018	Detection of pneumonia	Data Collection and Preprocessing	VGG16	CAM and grad-CAMvisualization tools	96.2% - detecting diseases	chestX- Ray14	Highly Accurate	NA
[13] IEEE/2013	Detection of Tuberculosis	Pre-processing Features Images Extraction Images Identification	Statistical Image Feature PCA for Feature Vector Dimension Reduction Minimum Distance Classifier	NA	95.7%	No dataset used	Pre-processed images used	NA

5. Results

In this study, we explored the effectiveness of utilizing a deep learning architecture with five convolutional layers for pneumonia detection. Through rigorous experimentation and evaluation, we have demonstrated the capability of the model to accurately classify chest X-ray images into pneumonia-positive and pneumonia-negative cases. The utilization of convolutional layers allows the model to effectively capture intricate patterns and features indicative of pneumonia, leading to robust performance.

6. Conclusion

In conclusion, our survey on pneumonia detection utilizing a deep learning model with five convolutional layers has provided valuable insights into the current state of the field. Through a comprehensive review of existing literature and methodologies, we have gained a deeper understanding of the challenges and opportunities in employing deep learning techniques for pneumonia diagnosis.

Overall, our survey contributes to the ongoing dialogue surrounding the application of deep learning in medical imaging and underscores the importance of collaborative efforts between researchers, clinicians, and industry stakeholders to further advance the field of pneumonia diagnosis. By addressing the challenges identified in this survey and building upon the existing body of knowledge, we can continue to improve the accuracy, efficiency, and accessibility of pneumonia detection methods, ultimately leading to better healthcare outcomes for patients worldwide.

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