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A Review on Deep Learning Based Automated Pneumonia Detection Using X-ray Images

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Abstract

This paper provides a comprehensive literature survey on the application of various deep learning models for pneumonia detection using chest X-ray images. It reviews numerous studies that propose different architectures and techniques aimed at enhancing detection accuracy and efficiency. The survey covers the use of methods such as transfer learning and ensemble techniques to mitigate data scarcity and augment model performance. It also discusses the development of advanced algorithms for the precise identification and localization of pneumonia indications. Despite promising results, the survey acknowledges persisting challenges, including the need for high accuracy in medical testing and the limited availability of annotated medical images. This review underscores the transformative potential of deep learning in pneumonia detection and identifies areas for future research.

Keywords: Algorithm, Deep Learning, Performance, Pneumonia, Research, Survey, X-ray images.

1. INTRODUCTION

Pneumonia, a prevalent and potentially life-threatening respiratory infection, continues to pose a significant public health challenge worldwide. It is characterized by inflammation of the lung tissue, leading to symptoms such as fever, cough, and difficulty breathing. Prompt and accurate diagnosis of pneumonia is crucial for timely intervention and effective treatment, as delayed or incorrect diagnoses can result in severe complications and increased mortality rates.

The below figures show the x-ray image of pneumonia positive (Fig.1.1) and pneumonia negative (Normal) (Fig.1.2).

Fig.1.1 Pneumonia Positive

Fig.1.2 Pneumonia Negative (Normal)

In Fig.1.1, the characteristic signs of pneumonia are clearly visible. The image showcases opacities in the lungs, indicating areas of inflammation and infection. These opacities appear as white or hazy areas on the X-ray, contrasting with the clearer regions representing healthy lung tissue. Whereas the second image Fig.1.2 is clear and free from these opacities and clearly depicts that it is an x-ray of pneumonia negative (Normal) patient.

At the core of this effort is the recognition that prompt diagnosis profoundly influences outcomes for patients. Conventional pneumonia detection methods, particularly those relying on X-ray images, frequently necessitate thorough manual examination, causing delays in the initiation of treatment. The project aims to alter this scenario through the creation of an automated solution. Through the training of our CNN model to identify complex patterns signaling pneumonia in X-ray images, the goal is to accelerate the diagnostic process and furnish healthcare professionals with a dependable tool.

Amidst this healthcare challenge, the incorporation of advanced technologies, namely artificial intelligence and deep learning, has unveiled fresh possibilities for improving diagnostic precision and effectiveness. The emphasis of this project is on utilizing Convolutional Neural Networks (CNNs), a category of deep learning algorithms crafted for image recognition assignments, to autonomously identify pneumonia in chest X-ray images. Through the utilization of CNNs, the objective of this investigation is to create a refined and automated system with the capacity to recognize abnormalities associated with pneumonia in medical images.

2. Statistics Survey

The Fig.2.1 (Death rate from pneumonia,1990 – 2019) shows that represents the death rate from pneumonia per 100,000 people for four countries: India, Pakistan, American Samoa, and Australia, from 1990 to 2019.

The graph is sourced from the IHME Global Burden of Disease Study and is age-standardized. India and Pakistan have the highest death rates. However, while India's death rate has been decreasing over time, Pakistan's death rate has been increasing. American Samoa and Australia have lower death rates. American Samoa's death rate has been decreasing over time, while Australia's death rate has remained relatively stable.

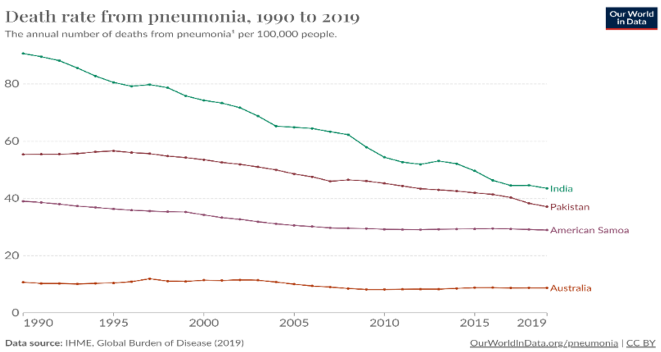

Fig.2.1 Death rate from pneumonia,1990 – 2019

This graph provides valuable insights into the impact of pneumonia in different countries and the effectiveness of their health care systems in dealing with this disease. It's important to note that numerous factors can influence these rates, including access to medical care, quality of healthcare, prevalence of risk factors like smoking and air pollution, and vaccination rates.

The Fig.2.2 (Deaths from pneumonia, by age, world,1990-2019) shows that represents the number of deaths from pneumonia in millions for different age groups: under 5, 5-14, 15-49, 50-69, and 70+, from 1990 to 2019.

The lines show a general decrease in deaths from pneumonia over time for all age groups. The highest number of deaths is in the 70+ age group, and the lowest is in the 5-14 age group. The graph notes that these are deaths from clinical pneumonia, which refers to a diagnosis based on symptoms.

This graph provides valuable insights into the impact of pneumonia in different age groups worldwide and the effectiveness of health care systems in dealing with this disease over time.

It's important to note that numerous factors can influence these rates, including access to medical care, quality of healthcare, prevalence of risk factors like smoking and air pollution, and vaccination rates.

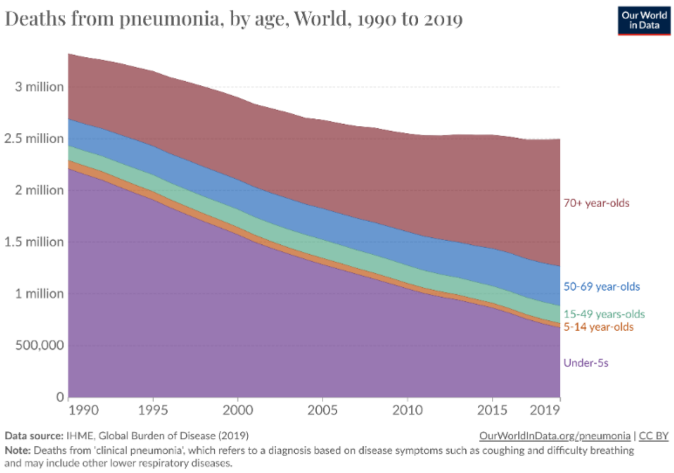

Fig.2.2 Deaths from pneumonia, by age, world,1990-2019

The table.1 shows the various x-rays image datasets from different open sources websites and its URL along with its size

Table.1 Dataset details

Dataset	Size	Website & URL
X-rays	5,856	Kaggle: https://www.kaggle.com/datasets/tolgadincer/labeled-chest-xray-images
X-rays	4,999	NIH Clinical Centre: - https://nihcc.app.box.com/v/ChestXray-NIHCC/file/219764235225
ChestX-ray14	112, 120	Deep lake: - https://datasets.activeloop.ai/docs/ml/datasets/nih-chest-x-ray-dataset/

3. METHODOLOGY

The methodology for developing a machine learning model for pneumonia detection from X-ray images

begins with the collection of a dataset composed of X-ray images, some of which are labeled as showing pneumonia. This dataset undergoes a process of data preprocessing, which may involve tasks such as resizing images, normalizing pixel values, and augmenting the data to increase its size and diversity.
Following preprocessing, a suitable machine learning algorithm is chosen. In the case of image classification tasks like pneumonia detection, Convolutional Neural Networks (CNNs) are commonly used. The chosen algorithm is then trained on a portion of the preprocessed dataset. During this training phase, the model learns to associate certain features in the X-ray images with the presence or absence of pneumonia.

The Fig.3.1 shows the proposed methodology.

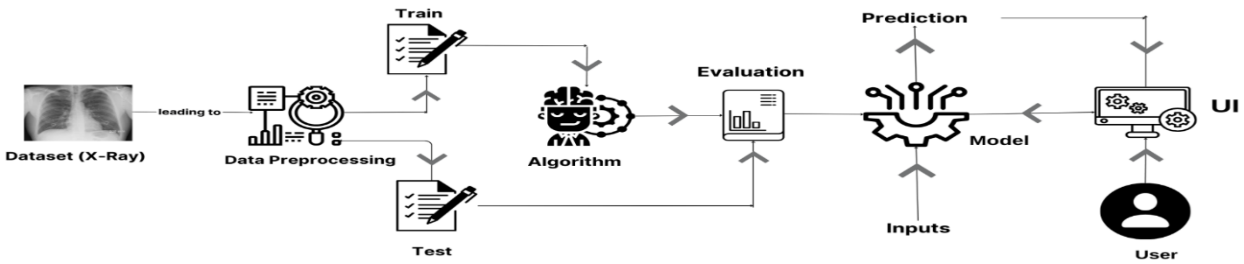

Fig.3.1 Proposed Methodology

After the model has been trained, it is tested on a different portion of the dataset that it hasn't seen during training. This testing phase provides an unbiased estimate of the model's performance. The model's predictions are then compared to the actual labels in a process known as evaluation. Common metrics used in this evaluation include accuracy, precision, recall, and the F1 score.
Once the model has been trained and evaluated, it is ready for use. Users can provide new, unlabeled X-ray images as inputs to the model, which processes these inputs and makes a prediction for each one, indicating whether it shows pneumonia or not. These predictions are then presented to the user through a user interface, allowing them to use these predictions to aid in diagnosis. This completes the general methodology for developing a machine learning model for pneumonia detection from X-ray images.

4. LITERATURE REVIEW

Sharma and Guleria [1] introduced a deep learning model incorporating NN with VGG16, which has exhibited outstanding efficacy in accurately predicting pneumonia from chest X-ray images, surpassing the performance of other models under consideration. Notably, the model demonstrated an accuracy of 92.15% for dataset 1 and 95.4% for dataset 2, marking the highest levels of accuracy among all the models examined in the study. Additionally, the proposed model outperformed alternative models in terms of precision, recall, and F1-score, highlighting its overall excellence in predicting pneumonia. A comprehensive comparative analysis of various models discussed in the literature consistently indicates that the NN with VGG16 model consistently achieves the highest accuracy and superior overall performance. Consequently, the suggested deep learning model stands out for its exceptional accuracy in predicting pneumonia from chest X-ray images compared to its counterparts in the literature.

V. Arun Kumar et al. [2] have introduced a framework designed for pneumonia detection in chest X-rays utilizing Convolutional Neural Networks (CNN). This framework leverages the capabilities of deep learning to autonomously identify and extract relevant features from chest X-ray images. To enhance the model's robustness and adaptability to variations in image quality and positioning, an extensive dataset consisting of annotated chest X-rays, including both pneumonia-positive and pneumonia-negative cases, is employed. The model undergoes preprocessing techniques aimed at standardizing images and reducing noise. The training process involves a transfer learning approach, utilizing a pre-trained model with weights derived from a large-scale dataset. Future directions for this research involve diversifying the dataset by incorporating a variety of chest X-ray images, integrating explainable AI techniques, exploring multi-modal strategies, optimizing the model for real-time processing, and enhancing the overall effectiveness and applicability of the pneumonia detection system in real-world clinical scenarios.

Ortiz-Toro et al. [4] conducted an extensive investigation to assess the efficacy of three textural image characterization techniques—radiomics, fractal dimension, and superpixel-based histon—in identifying pneumonia in chest X-ray images. The study employed two open-access image datasets, one centered on pediatric images and the other associated with COVID-19 cases. Using three machine learning algorithms (KNN, SVM, and RF), the researchers developed classification models. The findings highlighted that models utilizing superpixel-based histon and fractal dimension exhibited superior performance, demonstrating increased accuracy and F-score in comparison to radiomics. Notably, the study emphasized the positive impact of balanced training sets on model performance, showcasing improved outcomes with well-balanced datasets. However, the optimization of hyperparameters had either minimal or adverse effects on model performance. The study's limitations included potential biases in datasets and demographic information, along with variations in radiological and anatomical characteristics between pediatric and general population images. Furthermore, the research underscored the potential of textural image characterization methods for pneumonia detection in chest X-ray images, with superpixel-based histon and fractal dimension emerging as the most promising approaches. These results emphasize the significance of dataset balance while highlighting the limited impact of hyperparameter optimization on model efficacy.

Hwang et al. [5] suggested an assessment of a deep learning-based computer-aided detection (CAD) system designed to identify COVID-19 and associated pneumonia in chest X-rays (CXRs). The investigation involves a comparative analysis of the CAD system's performance with that of both thoracic radiologists and non-radiologist physicians. The primary focus is on understanding how the CAD system influences interpretative abilities and inter-reader agreement among physicians engaged in the analysis of CXRs. By employing statistical analyses and conducting subgroup examinations, the research aims to evaluate the CAD system's efficacy in detecting pneumonia across patients with diverse clinical and radiologic presentations. Additionally, the paper outlines the conceptualization and data curation process of the study, providing insights into the methodology employed to assess both the CAD system and the performances of the readers. In conclusion, the study suggests that the CAD system demonstrates performance levels comparable to thoracic radiologists and has the potential to enhance the capabilities of non-radiologist physicians in identifying COVID-19 and associated pneumonia on CXRs.

Kundu and colleagues [6] introduced an ensemble framework aimed at improving the performance of base convolutional neural network (CNN) learners in the classification of pneumonia.Utilizing a weighted average ensemble technique, the framework assigns weights to classifiers based on four evaluation metrics: precision, recall, F1-score, and area under the curve (AUC). The assessment involved conducting evaluations on two publicly available chest X-ray datasets, specifically the Kermany dataset and the RSNA Pneumonia Detection Challenge dataset. This process was executed within a five-fold cross-validation setting. The results indicate that the proposed method outperforms state-of-the-art techniques, establishing its practical utility. The study incorporates the utilization of gradient-weighted class activation maps (GradCAM) to visualize distinctive regions in X-ray images. Additionally, it compares the proposed ensemble method with other methodologies in the literature, demonstrating superior performance. The research findings hold significant implications for enhancing the accuracy and efficiency of pneumonia diagnosis, particularly in regions with limited medical resources. In conclusion, the research article presents a comprehensive approach to pneumonia detection in chest X-ray images, with the proposed ensemble method showing considerable promise for precise and reliable diagnosis.

Bhatt & Shah [7] reveals various strategies for enhancing the accuracy and precision of a model. The document suggests addressing the challenges of overfitting and insufficient data by acquiring a more diverse dataset encompassing various geographical locations, age groups, and ethnicities. This expanded and varied dataset is instrumental in enabling the model to discern general patterns more effectively, thereby mitigating the risk of overfitting. Furthermore, the literature emphasizes the potential improvement in model architecture by fine-tuning the threshold value for the sigmoid classifier. This adjustment aims to strike a balance between precision and recall, aligning with the specific requirements of the task. Notably, the literature suggests selecting a threshold value that maximizes the recall, prioritizing its significance in the context of pneumonia detection.

Liu and colleagues [8] introduced an inventive method, referred to as Multi-Branch Fusion Auxiliary Learning (MBFAL) to categorize samples of normal, COVID-19, other viral pneumonia, and bacterial pneumonia using chest X-ray (CXR) images. This approach incorporates a dual-branch network structure, where the primary task branch is dedicated to identifying the four categories, and the auxiliary task branch focuses on distinguishing between various pneumonia types, including COVID-19, other viral pneumonia, and bacterial pneumonia. The overarching objective of the MBFAL method is to enhance the recognition of diverse pneumonia types while optimizing its capacity to differentiate between normal and abnormal images. Experimental outcomes reveal that the method achieves high precision and recall rates for each pneumonia type, indicating its potential as an effective tool for the rapid and accurate screening of pneumonia from CXR images. This thorough literature survey provides a comprehensive understanding of the proposed MBFAL method and its efficacy.

Ukwuoma, C. et.al [9] utilized pre-trained models, namely DenseNet201, Xception,VGG16, Google Net, InceptionResNetV2, and EfficientNetB7, for the purpose of deep feature extraction. These models were chosen due to their proficiency in extracting rich features from chest X-ray images, a critical factor for precise pneumonia identification. An extensive evaluation of these pre-trained models was conducted within the study to ascertain their effectiveness in deep feature extraction for the proposed hybrid deep learning framework. This comprehensive literature survey provides an in-depth understanding of the selected pre-trained models, their capabilities, and their contribution to the proposed framework.

Jain and colleagues [10] underwent assessment using various training and testing ratios, specifically 80:20, 70:30, and 60:40. The experimental outcomes highlighted that the 80:20 training and testing ratio yielded the most promising results. In this configuration, the Convolutional Neural Network (CNN) model showcased its optimal performance, reporting a training accuracy of 89% and a validation accuracy of 93%. Despite a slightly lower performance compared to the Xception model, which demonstrated minimal loss, the CNN model exhibited robust capabilities. Additionally, the Xception architecture outperformed other models by achieving a validation accuracy of 94% in the 80:20 ratio. The experimental results underscored the efficiency of the Xception model, suggesting its potential for further improvement through additional integrations. The study revealed that the performance of the proposed model varied across different training and testing ratios, with the 80:20 ratio yielding the most favorable outcomes. This comprehensive literature survey enhances our understanding of the proposed model's performance evaluation and its effectiveness under diverse training and testing conditions.

Verma, D., Bose et.al [11] the chest X-ray images underwent a series of pre-processing steps to enhance the accuracy of the framework. Various data pre-processing and augmentation techniques were utilized to enhance the image quality and improve the model's precision during the training phase. These techniques encompassed the removal of low-quality or unreadable scans, artificial enhancement of the radiographs' size and quality, and the application of data augmentation methods such as rescaling, rotation, translation, shearing, and zooming. These procedures addressed factors like varying angles, heights, widths, and distances of the images, thereby boosting the system's accuracy. Moreover, the dataset was subjected to learning rate variation and annealing methods to adapt the small dataset to the model. The model was trained over 100 epochs and 2000 iterations, with 30% of the dataset set aside for the validation process. The model was tested on four classes: Tuberculosis (TB), Bacterial Pneumonia, Viral Pneumonia, and normal lung, using over 100 images for each class. The resulting confusion matrix showcased the effectiveness of the pre-processing and augmentation techniques in enhancing the framework's accuracy. This detailed literature survey provides an in-depth understanding of the pre-processing and augmentation techniques used in the study and their contribution to improving the accuracy of the proposed framework.

Sri Kavya, N. et.al [12] provides valuable insights into the use of deep learning for medical diagnosis and underscores the significance of leveraging CXR images for efficient and accurate detection of COVID-19 and pneumonia. The accuracy of the VGG16 model for detecting pneumonia from chest X-ray images is reported to be 89.34% in the study. This indicates that the VGG16 model achieved an average accuracy of 89.34% in diagnosing pneumonia cases from the chest X-ray images. The performance metrics for the VGG16 model in detecting pneumonia are as follows: Recall: 89%, Precision: 89%, F1-score: 89%. These metrics indicate the VGG16 model's ability to accurately identify pneumonia cases from chest X-ray images, with a balanced consideration of both false positives and false negatives.

5. Discussions

The comparative analysis of the works studied through the literature survey is as shown in table 2

Table.2 Comparative Analysis

Paper details	Methods employed	Dataset	Accuracy
Sharma & Guleria [1]	NN with VGG16	X-rays (5,856)	92.15%
V Arun Kumar et.al [2]	CNN	X-rays	91%
Çallı et.al [3]	CNNs & Transfer learning	ChestX-ray14, Chex pert, and MIMIC-CXR	89%
Ortiz-Toro [4]	KNN, SVM & RF	X-rays (5,856)	92%
Hwang, E.J [5]	CAD	172 Chest X-rays	83.8%
Kundu, R [6]	CAD & CNN	X-rays (5,856)	98%
Bhatt, H [7]	CNN	X-rays (5,863)	84%
Liu, J [8]	MBFL	X-rays (21,057)	96%

Ukwuoma,.C [9]	CNN	15000 Chest X-rays	95%
Jain, D.K [10]	CNN	X-rays (4,062)	90%
Verma, D [11]	RCNN	5,232 Chest X-rays	90%
Sri Kavya, N [12]	CNN	X-rays (15,153)	91.39%

6. CONCLUSION

This paper emphasizes the transformative potential of deep learning in pneumonia detection and identifies areas for future research. The comprehensive literature survey reviews various deep learning models and techniques for pneumonia detection, highlighting their promising results and persisting challenges. The survey underscores the importance of accurate diagnosis in medical testing and the limited availability of annotated medical images. Overall, the paper provides valuable insights into the application of deep learning models for pneumonia detection and sets the stage for further advancements in this critical area of healthcare.

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