A Review of deep learning models for pneumonia identification via chest X-rays

[1] Ms. Sneha M. Deshmukh, [2] Mr. Gaurav A. Gaikwad

[1] P.G. Student , [2] Assistant Engineer
[1] Dept of Computer Engineering
[1] Gokhale Education Society's, R.H. Sapat College of Engineering,
Nashik, Maharashtra, India

Abstract : People of all ages can get pneumonia, which can be a very serious illness. Bacteria, fungus, and viruses are just a few of the things that can cause it. Chest x-rays are the most common way to tell if someone has pneumonia. This paper describes several new research studies on X-ray images of pneumonia. These studies use Vision Transformers, a new way to use RetinaNet, CP_DeepNet, and EfficientNetV2L. They are meant for people who are just starting to learn about AI and how it can be used to find pneumonia. We will also offer recommendations for future research on AI-based pneumonia detection utilizing deep learning techniques**.**

***IndexTerms* - AI detection, pneumonia, X-ray, machine learning, CNN, EfficientNet, and healthcare AI.**

I. INTRODUCTION

Pneumonia makes one or both of the lungs swell up, which is called inflammation. Pneumonia is a major global public health problem because it affects children all over the world and adults with pneumonia are often hospitalized. Pneumonia is thought to be the most common cause of death in children under five years old around the world. It kills about 1.8 million children each year, or about 16% of all deaths in that age group. Each year, about 1 million adults get pneumonia, and about 50,000 adults die from it.

Radiologists are having a harder time finding and classifying lung diseases using chest X-ray images because radiology currently depends on people to read X-ray images. For this reason, most research has been on automatic ways to find lung disease. Deep learning is one of the most important areas of research in AI. Deep learning has become a field of study that gives modern computer scientists new chances to make new applications based on it.

Pneumonia is a serious respiratory infection that mostly affects the lung alveoli, which are the small air sacs in the lungs. The main job of the alveoli is to move gases (oxygen and carbon dioxide) between the blood and the air in the lungs. The attached diagram shows that pneumonia can show up in both systemic (fever, headache, chest pain, etc.) and respiratory (coughing with phlegm, pale skin, etc.) ways. The symptoms displayed are due to an invasion by microorganisms and the immune system's reaction to the infection, both of which lead to lower oxygen saturation levels and a decline in lung function.The diagram shows the clinical diagnostic process, which shows how doctors use clinical data from the patient's interview and physical exam to figure out if pneumonia is likely present. A chest X-ray is used to confirm that pneumonia is present and to see how bad the disease is getting once it has been determined that pneumonia may be present. It is important to focus on early clinical evaluation and diagnosis of pneumonia so that the patient can get treatment right away and not get complications from pneumonia. This is especially important for older adults and young children, who are more likely to get serious complications from pneumonia.

This diagram gives a short clinical overview of pneumonia by connecting the pathology of lung disease, the symptoms of lung disease, and the clinical assessment of pneumonia. This strongly suggests that we need to come up with automated and accurate ways to find pneumonia using advanced deep learning techniques.

An illustration comparing the chest X-ray images of both healthy and pneumonia - affected individuals. The healthy individual has a chest X-ray that shows clear lung fields with uniform intensity throughout and well-defined structures, which means there is nothing blocking the airflow into the lungs. However, in the chest X-ray of the individual with pneumonia, areas of opacities and localized consolidations, marked with arrows, are seen. These areas are due to fluid and/or pus that has built up in the airspaces of the lungs. This is indicative of pneumonia, as well as signs of inflammation and decreased aeration of the lungs. The visual differences between the healthy vs. pneumonia- affected lungs provide evidence of the usefulness of chest X-rays for diagnosing conditions, such as pneumonia, and encourage the use of automated deep learning-based techniques for accurately identifying pneumonia..

II. REVIEW OF DEEP LEARNING ALGORITHMS.

For pneumonia detection

A. Automated Lung Disease Detection Using the EfficientNetV2L Model

Ali M et al. presented a new approach to automatic detection of pneumonia in chest images through a novel deep learning framework using the EfficientNetV2L model [1]. The EfficientNetV2L model is an advanced deep learning architecture that uses large quantities of X-ray images to train and learn the major visual identifiers of pneumonia and achieve very high performance and accuracy when used to identify cases of pneumonia from chest X-ray images. In addition, efficient automated detection of pneumonia will significantly assist physicians in diagnosing pneumonia faster and with greater accuracy thereby improving the quality of patient care. Based on continued development of this technology, the implementation of efficient pneumonia detection algorithms will result in improved respiratory medicine practices as well as improved accuracy of diagnosing pneumonia: An automatic diagnostic tool is a significant advancement in both technology and healthcare. In the assessment processes, the authors' proposed EfficientNetV2L model outperformed all of the comparators, including CNN (convolutional neural network), EfficientNetV2, VGG16, ResNet50, and InceptionResNetV2.

This is because of the hyperparameter tuning. The model gave an excellent performance when it was tested on the test dataset. The accuracy of the model is 94.02%, 94.40%, while the recall is 97.24%, and the F1 score is 95.80%. The hyperparameter tuning helped in improving the classification accuracy of the model. This is because it not only gives accurate results but also very consistent results in terms of accuracy and recall. The performance of the EfficientNet V2L model is exceptional. This is a clear demonstration of its scalability and efficiency in solving complex classification problems.

The authors also discuss how important it is to investigate a variety of different preprocessing techniques and configurations of convolutional neural networks as part of the deep learning process; however, they provide no specific details about how these techniques were implemented or what results were obtained from them. Furthermore, although there is a reference to using data augmentation techniques to increase the size of a data set, there is no actual implementation of them or any evaluation of the results of a data set before and after augmentation.

B. Vision Transformers

Pneumonia is a debilitating global disease that affects people of all ages and should be diagnosed and treated as soon as possible to avoid complications and improve clinical outcomes. By developing and implementing efficient tests for pneumonia detection, we can help reduce mortality, increase the effectiveness of healthcare and help alleviate the burden of diseases that have plagued mankind for centuries. The need for advanced medical technologies is underscored by the need for rapid detection of pneumonia. Chest X-ray is one of the most frequently used imaging modalities in the diagnosis of pneumonia. In this paper, we present an innovative vision-transformer (ViT) architecture based engine for pneumonia detection based on chest X-rays, which was applied to publicly available datasets from Kaggle.

The proposed method is based on a Visual Transformer (ViT) model that utilizes a Self-Attention processing method in the transformer architecture to derive spatial relationships and global context from chest X-ray images. The results from the experiments conducted using the proposed Vision Transformer architecture indicate that it accurately detects pneumonia in chest X-ray images with much greater accuracy (97.61% accuracy, 95% sensitivity and 98% specificity).

C. Model on based RetinaNet

Gabruseva T's Research Team Developed a Deep Learning Based Computational Methods to Automatically Detect Pneumonia. Many Techniques Were Combined to Create an Effective Deep Learning Method to Detect Pneumonia, Including Using Single Detector, Deep Convolutional Neural Network (DCNN), Data Augmentation and Multitask Learning. The Method Work has Been Applied To The Radiological Society's Pneumonia Detection Challenge and The Results Were one of the Highest Overall Scores. This Research Method is a Powerful Method to Improve Early Pneumonia Diagnosis by Improving the Diagnosis Efficiency and Effectiveness. The Model Developed by Gabruseva and his Team Uses An SSD RetinaNet and An SE-ResNext101 Encoder, Which Was Previously Trained On ImageNet [3].

The performance of the model was evaluated across multiple intersection ratio (IoU) thresholds with the mean average precision (mAP). The selection of threshold values was from 0.40 to 0.75, with an increment value of 0.05. If a predicted target has an intersection ratio to the actual target on the ground of greater than 0.4, then this is considered a hit. The variations in mAP are influenced by the number of rounds of training and the threshold for non-maximum suppression (NMS). The predicted bounding box for both the training and test sets was expanded to 87.50% of its original size in order to accommodate the differences in labeling programs utilized to label the images in the training set versus those used to label the images in the test set. The results from this ablation analysis support the assertion that the model can be improved through the implementation of the proposed method.

D. CP_DeepNet

For many years, the COVID-19 pandemic has been a significant cause of death due to its symptoms, which are usually associated with common flu-like ailments such as fever and cough. In addition to presenting a severe public health threat worldwide due to these similarities in symptomology to flu, COVID-19 will create a continued and ongoing opportunity for China as they manage the current outbreak and its associated risk. People of all ages are vulnerable to the COVID-19 virus, but older individuals with suppressed immune systems have an increased level of vulnerability. Although real-time polymerase chain reaction (RT-PCR) tests are currently the most frequently used method to diagnose coronaviruses, they are expensive, time-consuming, and subject to false negative results. Therefore, there is an urgent need for a low-cost, rapid, and reliable method to diagnose COVID-19. Chest X-ray images are commonly used to diagnose a variety of respiratory illnesses, including infections of the lung, dyspnea syndrome, neoplasms of the lung, and gas build-up within lung caverns.

Using the chest X-ray datasets for the identification of COVID-19 and Pneumonia, the authors have proposed CP_DeepNet which is a newly developed deep learning model based on pre-trained models using SqueezeNet. The performance of the CP_DeepNet classification was evaluated using three additional convolutional layer blocks and methods of data augmentations were utilized to increase the number of images created and overcome overfitting. The suggested model was evaluated using the dataset of COVID-19 radiography [4].

The performance of the CP_DeepNet model in classifying both COVID-19 and normal class with binary classification yielded 99.32% accuracy, 100% accuracy, 99% recall, 99.2% specificity, 99.78% area under the curve (AUC), and 99.49% F1 scores. The model also yielded the following results: 99.62% accuracy, 99.79% accuracy, 99.52% recall, 99.69% specificity, 99.62% AUC, and 99.72% F1 scores when classifying COVID-19, Pneumonia, and normal human participants.

3.1Population and Sample

KSE-100 index is an index of 100 companies selected from 580 companies on the basis of sector leading and market capitalization. It represents almost 80% weight of the total market capitalization of KSE. It reflects different sector company's performance and productivity. It is the performance indicator or benchmark of all listed companies of KSE. So it can be regarded as universe of the study.Non-financial firms listed at KSE-100 Index (74 companies according to the page of KSE visited on 20.5.2015) are treated as universe of the study and the study have selected sample from these companies.

The study comprised of non-financial companies listed at KSE-100 Index and 30 actively traded companies are selected on the bases of market capitalization.And 2015 is taken as base year for KSE-100 index.

III. COMPARITIVELY ANALYSIS OF DIFFERENT METHODOLOGY

Table 1 Comparitive Analysis Of Different Methodology

Paper Author	System Name	Dataset	Prediction Auccuracy	Limitations
S. A. Aljawarneh and R. Al-Quraan (2023)[5]	Enhanced CNN Model	Chest X-ray images	92.4 %	X-ray only; generalizability unclear
A. Khan, M. U. Akram, and S. Nazir (2023)[6]	CNN Ensemble with ROI	Chest X-ray images	61–62% (mAP	Ensemble complexity; higher compute
S. Sharma and K. Guleria (2023)[7]	VGG-16 + NN	Chest X-ray dataset	92.15 % accuracy	Potential overfitting; data split bias
C. Asswin et al. (2023)[8]	Channel Attention Deep CNN	Pediatric chest X-ray	96.15 %	Age-group specificity
R. Chiwariro and J. B. Wosowei (2023)[9]	Comparative TL CNNs	Chest X-ray images	88%	Benchmark limited to selected CNNs
M. Shaikh et al. (2023)[10]	MDEV Ensemble	CXR images	95.31%	Computationally intensive
J. A. Prakash et al. (2023)[11]	Stacked Ensemble CNNs	Pediatric CXR	96.2%	Pediatric-only evaluation
A. H. Rangkuti et al. (2023)[12]	Image-Clarity-Aided DL	Chest X-ray images	92.87%	Focus on clarity; limited architecture details
H. Bhatt and M. Shah (2023)[13]	CNN Ensemble	Chest X-ray dataset	97.4%	High compute cost; latency
S. Sharma and K. Guleria (2023)[14]	Systematic Literature Review	Multiple datasets (review)	(Review paper – no new accuracy, but cites models in 85–98% range)	No new model; heterogeneous reporting
S. Singh et al. (2023)[15]	Deep Attention Network	Chest X-ray images	96.85%	Potential sensitivity to class imbalance

X. Xue et al. (2023)[16]	Ensemble for COVID-19 & Pneumonia	CT scans and X-ray datasets	98.7%	Modality heterogeneity; dataset shift

IV. CONLCUSION

With the ongoing development of deep learning, there has been a dramatic increase in the number of research papers focused on the use of deep learning for the identification and diagnosis of pneumonia. Overall, while there has been some improvement in identifying pneumonia, the application of deep learning for the diagnosis of pneumonia continues to be lacking due to the complexity of diagnosing medical diseases. At this stage of technological development (the current technology is immature), the medical community has a considerable amount of experience, and therefore must also confirm or verify the results of the techniques used for the diagnosis of pneumonia; hence, it is highly likely that many medical doctors will still rely on their years of training and experience and ultimately be responsible for deciding whether the pneumonia diagnosis is correct or incorrect. Many researchers have only examined the images of the lungs to provide a diagnosis of pneumonia because there are many different types of pneumonia (e.g. lobar pneumonia, bronchopneumonia, and interstitial pneumonia). Therefore, based on the results of this study and the knowledge gained from clinical practice, the following recommendations for future research are suggested:
Multimodal data fusion: The use of multimodal data from other sources (e.g. X-ray, CT, and clinical data) could enhance the accuracy and precision of pneumonia detection.

Reinforcement learning and transfer learning: Transfer learning could aid models in generalizing to new domains and overcoming the difficulties of limited data and unequal data distributions. Reinforcement learning can continually improve and adapt the model to different pneumonia detection challenges by interacting with the environment.
Deep learning models can be made more interpretable, for example, by visualizing the model's attention mechanisms or using interpretive deep learning model structure. Other technologies such as encrypting patient data through state encryption, federated learning and other data privacy technologies can increase the amount of information used for model training and preserve patient privacy.

With clinician workloads decreasing through the use of deep learning models combined with automated screening systems; and therefore, efficiency and accuracy in detecting pneumonia can increase.

REFERENCES

[1]. M. Ali, M. Shahroz, U. Akram, et al., "Pneumonia detection using chest radiographs with a novel EfficientNetV2L model," IEEE Access, vol. 12, pp. xxx–xxx, 2024.

[2]. S. Singh, M. Kumar, A. Kumar, et al., "Efficient pneumonia detection using vision transformers on chest X-rays," Scientific Reports, vol. 14, Art. no. 2487, 2024, doi: 10.1038/s41598-024-52703-2..

[3]. Gabruseva T, Poplavskiy D, Kalinin A. Deep learning for automatic pneumonia detection[C]//Proceedings of the IEEE/ CVF conference on computer vision and pattern recognition workshops. 2020: 350-351.

[4]. Mehmood M H, Hassan F, Rahman A U, et al. CP_DeepNet: a novel automated system for COVID-19 and pneumonia detection through lung X-rays[J]. Multimedia Tools and Applications, 2024: 1-18.

[5]. S. A. Aljawarneh and R. Al-Quraan, ''Pneumonia detection using enhanced convolutional neural network model on chest X-ray images,'' Big Data, Apr. 2023.

[6]. A. Khan, M. U. Akram, and S. Nazir, "Automated grading of chest X-ray images for viral pneumonia with convolutional neural networks ensemble and region of interest localization," PLoS ONE, vol. 18, no. 1, Jan. 2023, Art. no. e0280352.

[7]. S. Sharma and K. Guleria, ''A deep learning based model for the detection of pneumonia from chest X-ray images usingVGG-16 and neural networks,'' Proc. Comput. Sci., vol. 218, pp. 357–366, Jan. 2023.

[8]. C. Asswin, K. S. Kumar, A. Dora, V. Ravi, V. Sowmya, E. Gopalakrishnan, and K. Soman, ''Transfer learning approach for pediatric pneumonia diagnosis using channel attention deep CNN architectures,'' Eng. Appl. Artif. Intell., vol. 123, Aug. 2023, Art. no. 106416.

[9]. R. Chiwariro and J. B. Wosowei, "Comparative analysis of deep learning convolutional neural networks based on transfer learning for pneumonia detection," International Journal of Research in Applied Science and Engineering Technology, vol. 11, no. 1, pp. 1161–1170, Jan. 2023.

[10]. M. Shaikh, I. F. Siddiqui, Q. Arain, J. Koo, M. A. Unar, and N. M. F. Qureshi, "MDEV model: A novel ensemble-based transfer learning approach for pneumonia classification using CXR images," Computer Systems Science and Engineering, vol. 46, no. 1, pp. 287–302, 2023.

[11]. J. A. Prakash, C. Asswin, V. Ravi, V. Sowmya, and K. Soman, "Pediatric pneumonia diagnosis using stacked ensemble learning on multi-model deep CNN architectures," Multimedia Tools and Applications, vol. 82, no. 14, pp. 21311–21351, Jun. 2023.

[12]. A. H. Rangkuti, R. Y. Mogot, and V. J. Kusuma, ''A recognizing technique specific disease on a chest X-ray with support for image clarity and deep learning,'' Int. J. Intell. Syst. Appl. Eng., vol. 11, no. 3, pp. 176–183, 2023.

[13]. H. Bhatt and M. Shah, ‘‘A convolutional neural network ensemble model for pneumonia detection using chest X-ray images,’’ Healthcare Analytics, vol. 3, Nov. 2023, Art. no. 100176.

[14]. S. Sharma and K. Guleria, ‘‘A systematic literature review on deep learning approaches for pneumonia detection using chest X-ray images,’’ Multimedia Tools Appl., vol. 83, no. 8, pp. 24101–24151, Aug. 2023.

[15]. S. Singh, S. S. Rawat, M. Gupta, B. K. Tripathi, F. Alanzi, A. Majumdar, P. Khuwuthyakorn, and O. Thinnukool, ‘‘Deep attention network for pneumonia detection using chest X-ray images,’’ Comput., Mater. Continua, vol. 74, no. 1, pp. 1673–1691, 2023.

[16]. X. Xue, S. Chinnaperumal, G. M. Abdulsahib, R. R. Manyam, R. Marappan, S. K. Raju, and O. I. Khalaf, ‘‘Design and analysis of a deep learning ensemble framework model for the detection of COVID- 19 and pneumonia using large-scale CT scan and X-ray image datasets,’’ Bioengineering, vol. 10, no. 3, p. 363, Mar. 2023.