PNEUMONIA DETECTION USING DEEP LEARNING

Ms Ashna Satheesh

BCA Student

PG Department of CA & AI

Saintgits College Of Applied Sciences, Kottayam, Kerala

ashnasatheesh15@gmail.com

7025537084

Ms Darsana Rajesh

BCA Student

PG Department of CA & AI

Saintgits College Of Applied Sciences, Kottayam, Kerala

darsanarajesh648@gmail.com

8590470618

Ms Krishnanjali J

BCA Student

PG Department of CA & AI

Saintgits College Of Applied Sciences, Kottayam, Kerala

krishnanjalij28@gmail.com

9539516327

Ms Sruthika R

BCA Student

PG Department of CA & AI

Saintgits College Of Applied Sciences, Kottayam, Kerala

shruthikareghu@gmail.com

6282519468

Dr Meenu Suresh

Assistant Professor

PG Department of CA & AI

Saintgits College Of Applied Sciences, Kottayam, Kerala

meenu@saintgits.org

Abstract:

This paper introduces an advanced deep learning approach for pneumonia detection using convolutional neural networks (CNNs). Trained on a large dataset of annotated chest X-ray images, our model leverages transfer learning and addresses class imbalance through data augmentation and weighted loss functions. Visualization techniques, including Grad-CAM, enhance interpretability, aiding clinicians in understanding the model's focus. Evaluation on a benchmark dataset demonstrates superior sensitivity and specificity compared to traditional methods. Our findings highlight the model's robustness across diverse demographics, emphasizing its potential for early diagnosis and improved patient outcomes. The study underscores the transformative impact of deep learning on pneumonia diagnosis, providing a valuable tool for efficient and accurate healthcare practices.

Keywords: Pneumonia detection, Deep Learning, Convolutional neural networks(CNNs), Transfer learning, Robustness, Grad-CAM, Diagnostic radiology, Specificity.

I. INTRODUCTION

Pneumonia remains a pervasive global health challenge, demanding swift and precise diagnostic methodologies for effective patient management. Traditional diagnostic approaches often face limitations in accuracy and timeliness, necessitating innovative solutions to augment the capabilities of healthcare professionals. In response to this critical need, our research on the application of deep learning techniques, specifically convolutional neural networks (CNNs), for pneumonia detection through the analysis of chest X-ray images.The advent of deep learning has ushered in a new era in medical image analysis, offering unprecedented potential to revolutionize the field of diagnostic radiology. Convolutional neural networks, in particular, have exhibited remarkable proficiency in discerning intricate patterns and subtle features within medical images. Leveraging these advancements, our study proposes a state-of-the-art methodology that amalgamates advanced image processing and machine learning algorithms. This integration aims to increase the accuracy and efficiency of pneumonia diagnosis, providing a robust and reliable tool for healthcare practitioners.In this test, we delve into the intricacies of our deep learning framework, meticulously trained on a substantial dataset of annotated chest X-ray images. The model's ability to discern nuanced patterns indicative of pneumonia presence is optimized through transfer learning from pre-trained architectures. To mitigate challenges posed by class imbalance inherent in diagnostic image datasets, we employ sophisticated strategies such as data augmentation and weighted loss functions, ensuring the model's resilience in diverse clinical scenarios.Furthermore, the interpretability of deep learning framework is a pivotical aspect often overlooked in medical diagnostics. Our research emphasizes the importance of providing clinicians with insights into the decision-making process. To this end, we employ visualization techniques, including Grad-CAM, to elucidate the regions of interest in X-ray images, fostering a deeper understanding of the model's diagnostic focus.As we proceed, this paper will present the comprehensive evaluation of our proposed approach on a benchmark dataset, showcasing its superior performance compared to traditional diagnostic methods. The study will not only highlight the model's sensitivity and specificity but also explore its robustness across varied patient demographics, affirming its potential applicability in real-world clinical settings.Our research contributes to the ongoing paradigm shift in pneumonia diagnosis through the fusion of deep learning and medical imaging. The transformative impact of this work extends beyond technological innovation, aiming to provide clinicians with a reliable and interpretable tool for accurate pneumonia detection, ultimately improving patient outcomes in the realm of respiratory health.

II. LITERATURE REVIEW

The recent emergence of deep learning has transformed medical imaging analysis, particularly in the realm of pneumonia detection. Convolutional neural networks (CNNs), a cornerstone of deep learning, have showcased impressive abilities to discern subtle patterns and features within medical images, often outperforming human experts in specific diagnostic tasks. This shift toward automated image analysis presents vast potential for enhancing diagnostic precision, mitigating interpretation inconsistencies, and streamlining patient care pathways.

The paper "Deep Learning for Automatic Pneumonia Detection by Tatiana Gabruseva" [1] presents a deep learning approach for automatic pneumonia detection, addressing its status as a major global cause of death, especially among young children. Current detection methods based on chest X-ray examinations by specialists are time-consuming and prone to disagreements. The proposed computational method utilizes deep convolutional neural networks, single-shot detectors, and squeeze-and-extinction mechanisms to automatically identify pneumonia areas. The approach showed promising results in the Radiological Society of North America Pneumonia Detection Challenge, achieving top performance.

The thesis by Alaa M. A. Barhoom and Prof. Dr. Samy S. Abu Naser [2] from Al-Azhar University focuses on using deep learning for pneumonia detection and classification using X-ray imaging. Deep learning, a subset of machine learning, enables computers to analyze data inputs and output values within a specific range. The aim is to develop an effective method for pneumonia detection based on X-rays to aid chest doctors in making accurate decisions. The thesis includes designing and implementing a model with deep learning algorithms and testing it on various chest X-ray images, with results discussed in detail. Deep learning, mostly used in driverless cars and consumer devices, is gaining attention in artificial intelligence and medical imaging.

The paper "Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network "by Luka Racic, Tomo Popovic [13] discusses the rising use of artificial intelligence (AI) in medicine, particularly in analyzing chest X-ray images for pneumonia diagnosis using machine learning algorithms like deep learning. It highlights AI's role in supporting faster and more accurate decision-making processes. The research focuses on classifying X-ray images into pneumonia-related changes or not. It also mentions the emergence of fields like Machine Learning (ML) and Deep Learning (DL) and concludes with AI's significant advancements, such as Google's AlphaGo beating world champion Gary Kasparov in chess in 2016. Overall, AI facilitates better decision-making in medicine, especially in analyzing biological image formats.

The paper "Pneumonia Detection Using CNN based Feature Extraction" [16] discusses the importance of detecting pneumonia, a life-threatening infectious disease primarily caused by Streptococcus pneumoniae, which is a significant cause of mortality in India. Developing an automatic detection system for pneumonia is crucial, especially in remote areas lacking access to expert radiologists. Convolutional Neural Networks (CNNs) are highlighted as effective tools for disease classification, particularly in analyzing chest X-ray images. Pre-trained CNN models facilitate feature extraction and classification, enhancing the accuracy of pneumonia detection. The study underscores the potential of autonomous systems using CNN-based feature extraction to aid in prompt diagnosis and treatment of pneumonia.

The study conducted by Thawsifur Rahman on "Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray" [14] aims to detect bacterial and viral pneumonia using digital chest X-ray images. They employ four pre-trained deep Convolutional Neural Networks (CNNs) for transfer learning: AlexNet, ResNet18, DenseNet201, and SqueezeNet. With a dataset of 5247 chest X-ray images, including germ cases that contain bacteria, virus and normal cases, the study achieves impressive accuracy rates. Specifically, they report 98% correctness for normal vs. pneumonia images, 95% for bacterial vs. viral pneumonia images, and 93.3% for distinguishing viral, bacterial, and normal pneumonia. These findings offer potential for enhancing pneumonia diagnosis by radiologists and facilitating rapid airport screening of pneumonia patients, crucial for early and accurate treatment.

The paper "A Deep Feature Learning Model for Pneumonia Detection Applying a Combination of mRMR Feature Selection and Machine Learning Models" by M. Togaçar ,B. Ergen b, Z. Cömert [15] applied deep learning models and image augmentation techniques to discover pneumonia in chest X-ray images. Researchers combined features extracted from CNN models and reduced them using the mRMR feature selection method. They achieved optimal results with various classifiers, using lung X-ray images for diagnosis. For each deep model,the number of deep features was decreased from 1000 to 100 which gives a total of 300 deep features as result. The study found that deep features provided robust pneumonia detection, and the mRMR method effectively reduced feature set dimensionality.

III. METHODOLOGY

Three sections make up the approach of the work, data pre-processing, balancing the imbalanced classifiers and model descriptions.

Dataset Description

A well-known Machine Learning wearhouse for sharing and assessing datasets, Kaggle, provided the dataset used in this study to assess students' ability to adapt to online learning. Kaggle provides a wide range of datasets that have been contributed by individuals, organizations, and scholars who operate in various sectors. The dataset employed must be consistent with the goals and parameters of our investigation. Researchers thoroughly evaluated the dataset's dependability and quality. This assessment comprises reviewing the dataset for correctness, completeness, and relevance in order to ensure that it meets the need of our learning.

Figure 1 : Loss & Accuracy of VGG16

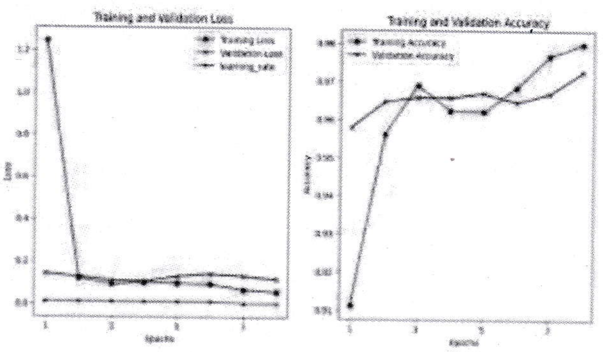


Figure 2: Confusion matrix of VGG16

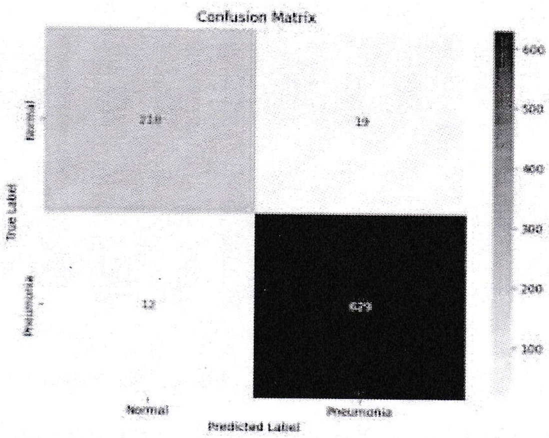


Figure3: Loss & Accuracy of Xception Model

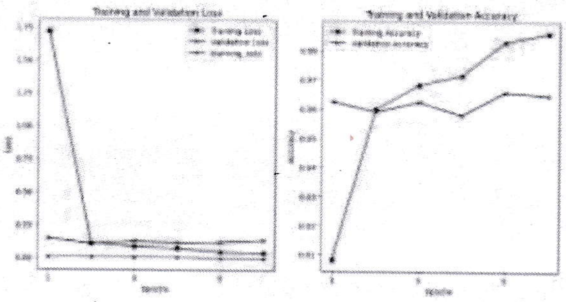


Figure 4: Confusion Matrix for Xception model.

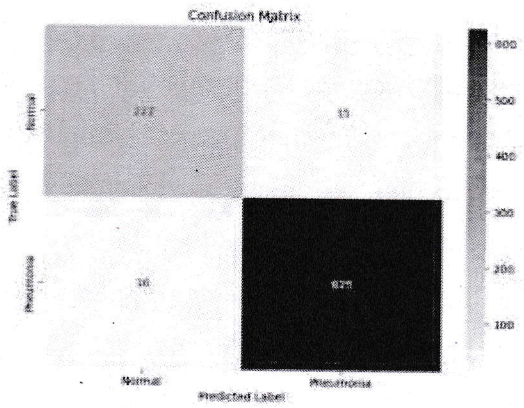


Figure 5: Normal Chest X-Ray

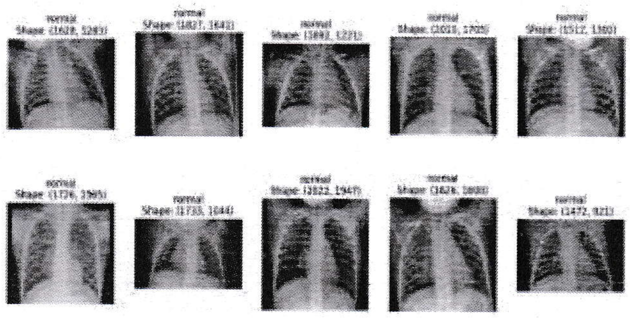
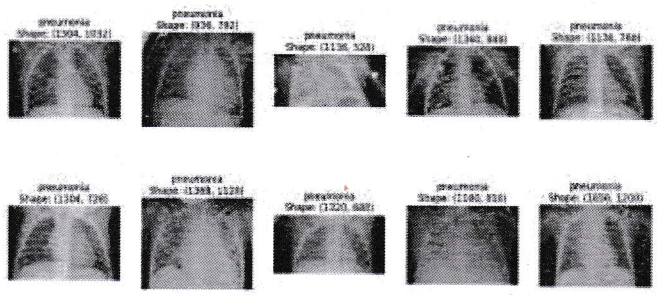


Figure 6: X-Ray detected with pneumonia



The dataset includes both normal chest X-rays and X-rays detected with pneumonia. Figure 5 shows the normal chest X-Rays and Figure 6 shows X-Rays detected with pneumonia

A. *Data Preprocessing*

In this study before the analysis, cleaning, transforming, and organizing the data to ensure its quality and suitability for the research objective has been completed. Through meticulous data preprocessing, including collection, cleaning, augmentation, normalization, and class balancing, the project seeks to ensure the quality and suitability of the dataset for training robust CNN models, ultimately facilitating timely and accurate pneumonia diagnosis.

B. *Description of Models*

This study explores various machine learning and deep learning methodologies for pneumonia detection. The algorithms and techniques investigated include CNN + Data Augmentation (color jitter),CNN + Data Augmentation (Color jitter + Layers Augmentation),CNN (batch normalization & padding + color jitter),VGG16,Xception Model.

These strategies each offer a unique way to handle and examine medical imaging data in order to identify pneumonia. The study compares the performance and effectiveness of these methodologies in accurately identifying pneumonia cases from chest X-rays or CT scans.

1. ***CNN + Data Augmentation (color jitter)***

Convolutional Neural Networks (CNNs) are more resilient and more generalizable in computer vision applications when used with data augmentation methods such as color jittering.CNNs automatically learn spatial hierarchies of features from images, making them effective in tasks like image recognition and object detection. Data augmentation diversifies the learning dataset by applying transformations, reducing overfitting, and improving generalization. Color jittering randomly adjusts image colors, making the model more resilient to variations in lighting and color distribution. This combination improves model performance in real-world scenarios where object appearance may vary due to environmental factors..

2.CNN + Data Augmentation (Color jitter + Layers Augmentation)

Convolutional Neural Networks (CNNs) perform much better in computer vision tasks when combined with data augmentation methods like layer augmentation and color jittering. This combination also improves model robustness. CNNs excel at processing visual data by extracting hierarchical features. Data augmentation, including color jittering, diversifies training data to improve generalization. Layer augmentation enhances model complexity by adding or modifying layers. Color jittering introduces variability in color distributions, making models more resilient to changes in lighting and color. Layer augmentation increases model capacity and adaptability. Together, these techniques create versatile models capable of handling diverse data and real-world scenarios effectively.

3. CNN (batch normalization & padding + color jitter)

Combining Convolutional Neural Networks (CNNs) with techniques such as batch normalization, padding, and color jittering significantly improves model performance in computer vision tasks. CNNs process visual data effectively, extracting hierarchical features crucial for tasks like image classification and object detection. Batch normalization stabilizes training by normalizing layer activations. Padding preserves spatial dimensions during convolutional operations, preventing information loss at image borders. Color jittering introduces variability in color distributions during training, enhancing the model's robustness to changes in lighting and color. Together, these techniques create more stable, robust, and adaptable models capable of handling diverse data distributions and real-world scenarios effectively.

4.VGG16

VGG16 is a widely-used convolutional neural network architecture known for its simplicity and effectiveness in image recognition tasks. Developed by the Visual Geometry Group at the

University of Oxford, it comprises 16 layers, including 13 convolutional and 3 fully connected layers. VGG16 employs 3x3 filters with ReLU activation functions, followed by max-pooling layers for downsampling. With approximately 138 million parameters, it achieved remarkable performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. VGG16 serves as a base model for transfer learning and continues to be influential in various computer vision applications.

5. Xception Model

Google created Xception, a convolutional neural network architecture, as an expansion of the Inception model.. It replaces standard convolutional layers with depthwise separable convolutions, leading to improved efficiency and performance. Depthwise separable convolutions consist of depthwise and pointwise convolutions, reducing parameters and computational complexity while maintaining or improving model accuracy. Xception is well-suited for various computer vision tasks, including image classification, object detection, and segmentation. Its efficiency and effectiveness make it a valuable tool for both research and practical applications in the area of deep learning.

I. RESULT AND DISCUSSION

The effectiveness of models can be evaluated using a variety of metrics. Precision, Recall, F1 score,Support and Accuracy are the most important characteristics used to assess a model's performance. The value of the confusion matrix which is generated during the testing of the model is considered to calculate the score of the precision, recall, F1- Score, and accuracy.

The performance metrics of various machine learning models utilized in this study are displayed on TABLE 1, encompassing a diverse array of methodologies. The models examined include VGG16, and the Xception Model. The evaluation metrics, such as accuracy, precision, recall, and F1 Score, provide valuable insights into the efficacy of each approach in pneumonia detection from chest X-ray or CT scan images. The study enhances understanding of deep learning architectures in medical imaging, aiding healthcare professionals in making informed decisions regarding pneumonia diagnosis and treatment.

Model	Class Name	Precision	Recall	FI Score	Support
VGG16	Normal	0.95	0.92	0.93	237
	Pneumonia	0.97	0.98	0.98	641
	Accuracy			0.96	878
	Macro avg	0.96	0.95	0.95	878
	Weighted avg	0.96	0.96	0.96	878
Xception	Normal	0.93	0.94	0.93	237
	Pneumonia	0.98	0.98	0.98	641
	Accuracy			0.96	878
	Macro avg	0.95	0.96	0.96	878
	Weighted avg	0.96	0.96	0.96	878

TABLE1: Results of Deep Learning Prototypes

II. FUTURE SCOPE

The paper introduces an advanced deep learning method for pneumonia detection using CNNs. Trained on a large dataset, the model addresses class imbalance and uses visualization techniques for interpretability. It shows superior performance compared to traditional methods. Future directions include refining the model, integrating it into clinical workflows, and expanding its scope for longitudinal monitoring and prognostication.

III. REFERENCES

[1] Tatiana Gabruseva,Dmytro Poplavskiy,Alexandr Kalinin "Deep Learning for Automatic Pneumonia Detection",2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW),pp.350-351

[2] Alaa M. A. Barhoom and Prof. Dr. Samy S. Abu Naser "Diagnosis of Pneumonia Using Deep Learning",International Journal of Academic Engineering Research (IJAER) 6 (2):48-68 (2022)

[3] Chouhan, V.; Singh, S.K.; Khamparia, A.; Gupta, N.; Tiwari, P.; Moreira, C.; Damasevicius, R.; De Albuquerque, V.H.C. A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images. Appl. Sci. 2020, 10, 559.

[4] Mohammad Tariqul Islam, Md Abdul Aowal, Ahmed Tahseen Minhaz, and Khalid Ashraf. 2017. Abnormality detection and localization in chest x-rays using deep convolutional neural networks. arXiv preprint arXiv:1705.09850 (2017).

[5] Sirazitdinov, I.; Kholiavchenko, M.; Mustafaev, T.; Yixuan, Y.; Kuleev, R.; Ibragimov, B. Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database. Comput. Electr. Eng. 2019, 78, 388–399.

[6] D. Kermany, K. Zhang, M. Goldbaum, "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification", Mendeley Data, v2, 2018. Accessed July 2020. [Online]

[7] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770–778.

[8] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, et al., Chexnet: radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv:1711.05225.

[9] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan, A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conf. on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp 1-7.

[10] Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, and An drewY.Ng. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv:1711.05225v1, 2017.

[11] O. Stephen, M. Sain, U. J. Maduh and D.-U. Jeong, "An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare," Journal of HealthCare Engineering, vol. 2019, 2019.

[12] Benjamin Antin, Joshua Kravitz, and Emil Martayan. 2017. Detecting Pneumonia in Chest X-Rays with Supervised Learning. (2017).

[13] Luka Račić; Tomo Popović; Stevan čakić; Stevan Šandi, Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network, 2021 25th International Conference on Information Technology (IT). 10.1109/IT51528.2021.9390137

[14] Saad Kashem, Amith Khandakar, Tawsifur Rahman: Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray 10.3390/app10093233

[15] M. Toğaçar, B. Ergen, Z. Cömert, F. Özyurt: A Deep Feature Learning Model for Pneumonia Detection Applying a Combination of mRMR Feature Selection and Machine Learning Models 10.1016/j.irbm.2019.10.006

[16] DimpyVarshni; KartikThakral; LuckyAgarwal; RahulNijhawan; Ankush Mittal, Pneumonia Detection Using CNN based Feature Extraction, 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT).10.1109/ICECCT.2019.8869364