

## A TRANSFER LEARNING APPROACH FOR PNEUMONIA DETECTION IN CT SCANS WITH SMOTE-BASED DATA BALANCING

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DOI: <https://doi.org/10.5281/zenodo.18374713>

**Keywords**

CNN, AlexNet, SMOTE, Deep Learning, data augmentation, CT scan, pneumonia

**Article History**

Received: 01 December 2025

Accepted: 11 January 2026

Published: 26 January 2026

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**Abstract**

This research on using technology for critical health applications, specifically in detecting pneumonia through medical imaging, is truly impressive. This study focuses on the application of the deep learning Convolutional Neural Network (CNN) AlexNet model to classify lung Computed Tomography (CT) scan images and distinguish between normal and pneumonia-indicative conditions. This model is known for its simplicity and effectiveness in capturing intricate features from images. It has achieved remarkable performance on various benchmark datasets. In this research, comprehensive preprocessing techniques, including pixel rescaling and data augmentation, were implemented, along with addressing data imbalance using the Synthetic Minority Over-Sampling Technique (SMOTE). The findings are remarkable, with the developed AlexNet model achieving an impressive **validation accuracy rate of 96.04% and 97.38%** in classifying lung CT scans without and with SMOTE, respectively. The accuracy of this research is better compared to previous published research work. This highlights the potential of the AlexNet model as a reliable tool for pneumonia detection, leading to more efficient and accurate early diagnosis and timely treatment.

**INTRODUCTION**

The researcher or scientist embarks on a comprehensive exploration of the significance of human health and its intricate relationship with the pervasive respiratory infection known as pneumonia [1]. To provide a solid foundation for our study, we begin by defining the concept of human health, encompassing physical, mental, and social well-being. Building upon this understanding, we delve into the multifaceted nature of pneumonia, examining its causes, symptoms, and potential complications [2].

Moving forward, scientists shift their focus to the broader context of public health issues, with a particular emphasis on pneumonia as a major concern [3]. They analyze the current state of public health, identifying the key challenges and obstacles faced in effectively addressing pneumonia and other related diseases [4]. In this section, we also propose potential solutions and strategies for mitigating the impact of pneumonia on public health.

Recognizing the crucial role of nutrition in maintaining optimal human health, scientists dedicate a section to exploring the intricate relationship between nutrition and pneumonia prevention [5]. He delves into the specific nutrients and dietary factors that play a significant role in bolstering the immune system and reducing the susceptibility to respiratory infections, including pneumonia [6].

Moreover, scientists delve into the realm of physical activity and its profound impact on human health and pneumonia prevention. He highlights the numerous benefits of regular exercise, ranging from enhancing respiratory function and strengthening the immune system to reducing the risk of pneumonia and other respiratory ailments [7].

Expanding our perspective to encompass mental well-being, he investigates the intricate connection between mental health and human health, particularly in the context of pneumonia [8]. We explore the potential psychological factors that may influence the susceptibility to pneumonia and the overall prognosis of the disease. Additionally, he discusses the importance of addressing mental health concerns as an integral part of comprehensive pneumonia prevention and management strategies.

Recognizing the significance of special occasions in our lives, scientists dedicate a section to exploring the challenges and opportunities associated with maintaining human health and preventing pneumonia during these unique events [9]. He provides practical recommendations and guidelines to ensure that individuals can enjoy these occasions while prioritizing their health and minimizing the risk of pneumonia transmission.

Finally, drawing upon the insights gained throughout this research, he concludes by presenting future recommendations for improving human health and combating pneumonia. Scientists have highlighted the importance of continued research, innovation, and collaboration in developing more effective prevention strategies, diagnostic tools, and treatment options to mitigate the burden of pneumonia on individuals and communities [10].

Patients with SARS-CoV-2 pneumonia have ICU stays and mechanical ventilation that are more than twice as long as those of patients with respiratory failure complicating pneumonia caused by other pathogens and patients with other causes of acute respiratory distress syndrome (ARDS) [11]. Some researchers hypothesized that the extended ICU length of stay (LOS) among patients with SARS-CoV-2 pneumonia is attributable to multiple organ dysfunction based on analysis of peripheral blood samples from patients with severe vs mild COVID-19.

Patients suffering from pneumonia and respiratory failure due to other causes. At the time of study enrollment and anytime pneumonia was clinically suspected during their incubation, all patients had a bronchoalveolar lavage (BAL) sample in conjunction with complete microbiological diagnoses. BAL fluid investigations were used to guide antibiotic therapy by clinicians as part of routine clinical care [12].

Pneumonia is a severe illness of the lower respiratory system that mostly affects the lungs. The alveoli are microscopically filled with exudative fluid (pus), which impairs breathing and gas exchange in the lungs. Cough, fever, trouble breathing, lower chest wall in drawing, and hypoxia are all clinical symptoms of acute respiratory distress in young children. Bacteria and viruses are the most prevalent etiological agents (for example, *Streptococcus pneumoniae*, *Haemophilus influenzae*, and respiratory syncytial virus) [13].

Complement fragments (C4, C5) have been reported to be elevated in individuals with coronavirus illness 2019 (COVID-19). Furthermore, various investigations have found that incomplete complement fragments are increased in CAP patients. These findings suggested that the complement system may play a role in the evolution of CAP. However, the relationship between the complement system and severity remained unknown. Furthermore, the precise involvement of the complement system in CAP was unknown. As a result, the primary goal of this cross-sectional study was to examine the relationship between serum complement level and

the severity of CAP [14]. Furthermore, the effect of complement inhibition on the inflammatory response was investigated. Experiments were conducted *in vitro*. Vitamin D deficiency significantly raises the risk of pneumonia in children under the age of five. Single-nucleotide polymorphisms (SNPs) in genes connected to the VDR have also been linked to vulnerability to respiratory syncytial virus infection, according to research. Few trials in which vitamin D supplements were given to children with pneumonia indicated a reduction in recurrent pneumonia [15].

A large randomized controlled trial (RCT) published in 2023 found that hydrocortisone treatment in the intensive care unit (ICU) could result in a lower risk of 28-day mortality than placebo treatment [16]. To address this debate, we conducted an updated systematic review and meta-analysis of randomized controlled trials (RCTs) to assess the clinical effectiveness and safety of adjunctive corticosteroid therapy in patients with sCAP. We omitted studies that (1) focused on patients with septic shock; (2) presented data from post-hoc analysis; (3) were only published as conference posters, case series, case reports, or single-arm studies; (4) did not report outcomes of interest; or (5) were pharmacokinetic research.

Due to significant advancements in medical image processing through the use of deep learning, particularly through applying transfer learning techniques, diagnoses are now often more accurate when it comes to complicated visual processes [23] and [24]. Examples of previously reported work involving convolutional neural networks and transfer learning methods can be found within a wide variety of areas, including the intelligent sorting of waste [25], the protection of crops [26], diagnosing both fungal and skin diseases [23] and [24], and identifying cancers through CT scans [27]. These studies have repeatedly demonstrated how effective these types of neural networks have been when it comes to extracting features as well as classifying them. In addition, the imbalance of data was noted to create an often challenging environment for those working with datasets from the real world. As such, there exists a strong need for intelligent

means of both managing and learning from unbalanced datasets [28] and [29]. Drawing from these previous studies, this study develops a method that uses transfer learning methods for the purpose of identifying pneumonia in someone based off of their CT scan image; additionally, it will use data balancing via SMOTE to enhance model generalizability, as well as increase model sensitivity with respect to the minority class.

Recently, increased applications of nontraditional methods to identify pneumonia use the principles and algorithms of ML, including but not limited to SVMs, RFs, and K-NN, which understand how to recognize pneumonia by learning from identifying patterns in medical images [17]. Unfortunately, the applications of these traditional classifiers are heavily dependent on features that have been created manually and do not effectively represent the significant diversity and complexity of the anatomical structure of lung CT scans. Additionally, traditional classifiers may have reduced performance due to the differences in the quality of images, noise, and subtle manifestations of pneumonia present in the CT imagery [18]. Traditional ML classifiers are also challenged by imbalanced classes, which require quite a bit of manual feature engineering to consistently achieve a high level of reliability and accuracy. All of the issues noted above indicate the need for a more advanced approach to developing ML classification models by using the principles of deep learning. For example, CNNs automatically learn and create more elaborate structures and feature representations to enhance ML performance in medical image classification.

The objective of this study is to develop a deep learning-based approach to classify lung CT scans as either 'normal' or 'pneumonia' based on a previously established approach to medical image analysis. Although many previous studies focused on converting qualitative criteria to quantitative criteria to enhance the capability to identify lesions, the work presented in this paper focuses on the implementation and use of a Convolutional Neural Network (CNN) that employs an AlexNet architecture (a modified version of AlexNet specifically designed for image classification) to detect pneumonia quickly and

accurately from lung CT images. To improve the overall performance of this model, numerous preprocessing techniques have been performed, including pixel resizing, data augmentation, and application of the Synthetic Minority Over-Sampling Technique (SMOTE) to create balance among classes. The goal of this study is to develop an AI-based classifier that will enhance the speed and accuracy of pneumonia diagnosis, thereby enabling clinicians to make timely and accurate decisions regarding patient treatment, while also providing a tool for faster and more efficient healthcare delivery.

#### Related Work:

The world has faced pneumonia as a significant health issue across countries and populations. The WHO suggests that it is one of the leading causes of death among children younger than 5 years of age [19]. Traditional limited methods of diagnosing pneumonia include using chest x-rays, clinical examinations, and microbiology tests to determine whether an individual has pneumonia. However, these methods have limitations because how a physician interprets the X-ray image can differ from the opinion of another physician, and the time-consuming process of conducting and interpreting these tests requires specially trained personnel. Because of this, the use of AI and, especially, deep learning has grown in popularity to automate the process of identifying pneumonia using medical imaging techniques [20].

Computer-Assisted Diagnosis (CAD) systems have addressed issues associated with using CAD for identifying abnormalities present within a medical image. Initially, CAD systems were constructed manually based on various algorithms—similar rules for identifying patterns and abnormalities within medical imaging based on images generated by utilizing different methodologies (e.g., Pixar's 3d Animation Software). In general, many early CAD systems were more limited by their ability to accurately recognize patterns due to the human skill required to define the rules [21].

With the introduction of machine learning (ML), CAD systems were able to be enhanced in the manner in which algorithms could be trained using large quantities of data rather than being

constrained by human-written rule sets. Algorithms used by CAD to determine how to classify pneumonia as well as other diseases, such as lung cancer, include support vector machines (SVM), random foresting (RF), and k-nearest neighbor (KNN) methods. The characteristics of the medical images used to train these algorithms include measures derived from X-rays and computed tomography (CT) images, including intensity values, organ shape, and relationships between key landmarks[18].

Sousa et al. (2019) evaluated the accuracy of a machine learning algorithm based on random forest as a decision power tool and achieved approximately 85% accuracy in classifying pneumonia using publicly available chest X-ray datasets. Although these machine learning algorithms achieved some level of accuracy, many variables still exist that ultimately determine the usefulness of each algorithm as a CAD decision-making tool.

Not only is there a rapid growth in the use of deep learning (DL) models for the identification of pneumonia in chest X-ray images, but also for other parts of the world as well, as it is quickly gathering momentum as a viable technology in the field of computer vision. With the development of Convolutional Neural Networks (CNNs), one of the primary applications of CNNs is to eliminate the need for complex manual feature-extraction methods by automatically searching for high-dimensional feature sets in chest X-ray images and to generate spatial hierarchies of feature arrangements in space [22].

An example of the evolution of deep learning technologies is the work of Rajpurkar et al., who developed the CheXNet DL model with 121 DenseNet layers related to the ChestX-ray14 dataset. In detecting pneumonia on chest X-ray images, the performance of CheXNet was superior. This clearly demonstrates the viability of applying DL methods within the clinical environment to gain more accurate and therefore improved outcomes.

Kermany et al. (2018) created a deep learning (DL) CNN model to identify the type of pneumonia (normal pneumonia, bacterial pneumonia, and Aspirational pneumonia) to help in diagnosis

from pediatric chest radiography in the clinical setting. The model achieved over 92% accuracy in identifying between types of pneumonia.

Transfer learning has gained popularity in the medical imaging space due to the need for large amounts of data to train deep learning models. Pre-trained models such as AlexNet, VGG16, ResNet, and InceptionV3 can be fine-tuned; therefore, by using medical images from the respective domain, that reduces the time needed to train these models can be reduced, and their performance can be increased with small amounts of training data.

Chouhan et al. (2020) found that using AlexNet to classify patients with pneumonia based on chest X-ray images led to classifications with an accuracy greater than 95%. Liang and Zheng (2020) achieved an accuracy of 96.2% with ResNet50 using transfer learning. Data augmentation techniques (e.g., flipping, rotating, zooming, and changing the contrast) are used in conjunction with transfer learning techniques to improve the robustness of most models by overcoming any potential data class imbalance created by the collection of the training dataset. Pneumonia datasets present a challenge with class imbalance; there are more normal images compared to pneumonia images. To overcome this problem, we have made an approach, Synthetic

Minority Over-Sampling Techniques (SMOTE), that may be used to generate synthetic pneumonia samples.

#### Methodology:

This section provides the research methodology for the image classification of lung CT scans using a machine learning approach to identify pneumonia in the lungs. Our proposed framework provides a method for classifying CT scan images into either normal or pneumonia-infected lungs by utilizing the power of Convolutional Neural Networks (CNNs), namely the AlexNet architecture, combined with techniques for data preprocessing, augmentation, and class balancing.

#### Data Collection.

The dataset used for this research consisted of labelled (normal vs pneumonia-infected) CT scan images that were procured from publicly available medical imaging repositories. The two classes of images (normal vs pneumonia-infected) were acquired under varying clinical conditions and thus included variability in terms of image resolution and noise level. The entire dataset was meticulously reviewed and evaluated for quality and relevance.

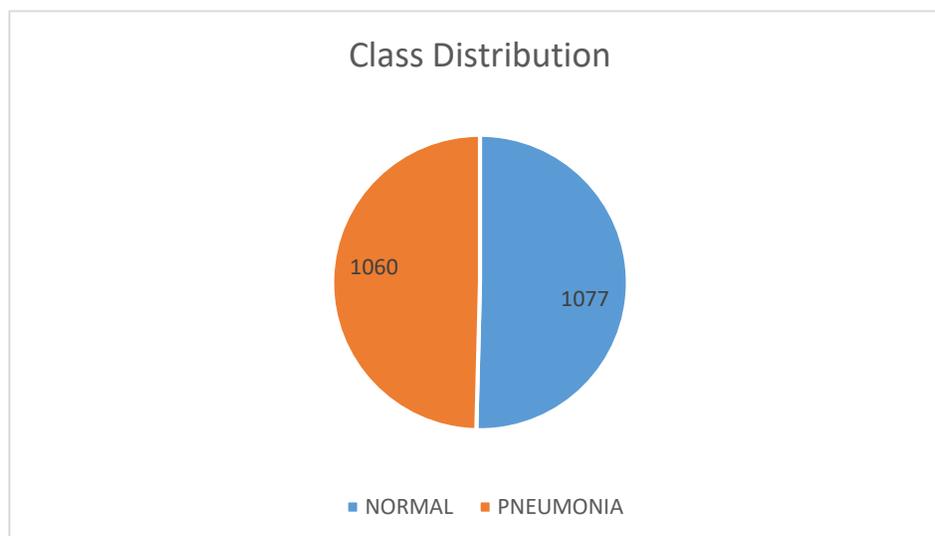


Figure 1: Data Distribution

### Images Processing

As part of building an effective Convolutional Neural Network (CNN), it is essential to have excellent execution of preprocessing procedures. There are three essential preprocessing methods for the images:

- **Resize All Images:** All images should be resized so that their input dimension matches that of AlexNet (227x227 pixels).
- **Normalize All Images:** The colour values in each pixel will be normalised to range from 0 to 1. Normalised values will decrease the cycle time of the learning process and create a more uniform model.
- **Remove Noise from Images:** There are multiple means by which the images can be filtered and enhanced to eliminate noise.

### Data Augmentation

Data augmentation is one of the most effective ways to improve how well a neural network will perform. Data augmentation involves creating new training examples by applying several different types of transformations (e.g., image flipping, rotation, and image scaling) to existing training samples. In this study, a large number of different transformation types were applied to build up the augmented dataset, resulting in an augmented dataset that has approximately 5 times the number of training samples as the original dataset.

### Model workflow:

Developing a pneumonia detection model involves collecting raw lung CT scan images to serve as the primary input for the system. The airway images need to go through a preprocessing process that improves the quality of the images, making them suitable for deep learning. Preprocessing involves resizing all images to the same dimensions required by AlexNet, normalizing the pixel intensities of the images so that all images have similar contrast levels, removing noise or artifacts that may affect the extraction of features, and using data, including

rotation, flipping, and scaling, to expand the dataset and build a more robust model when completed. After preprocessing is complete, the dataset is divided into two parts (75% will be used for training and 25% will be reserved for testing), ensuring the model is only tested with previously unseen images. Because medical imaging datasets usually have an imbalance in class representation, the Synthetic Minority Oversampling Technique (SMOTE) can be used to create synthetic minority samples to give the classifier the ability to learn equally well from the normal and pneumonia classes.

After the dataset has been prepared, you will have access to the AlexNet architecture in its original state, or modified by adding layers to represent the individual added structural features of different types of lung CT Scanning. As soon as you have imported AlexNet's architecture into your application, you will begin to continually train your model on the dataset that was created, repeating the iterative process of adjusting the weights in the neural network until a maximum reduction in error is attained. Throughout this cyclical training procedure, three different measurements will be monitored and measured to determine how well the model has learned to perform correctly: accuracy, validation loss, and stability of classification. If any of these metrics are not met during the course of your training, you will proceed to train your model by running additional epochs, as well as possibly adding hyperparameter tuning to improve model learning quality. The model will continue to be trained until it either meets or exceeds the expected performance levels, at which time it is considered a fully trained classifier. The last step in developing a trained model will be comparing the trained model with the validation/test data set to determine its capability of generalizing the information learned. Once the trained model has been validated, it will be valid for use as a Computer-Aided Diagnosis (CAD) System that will produce classifications.

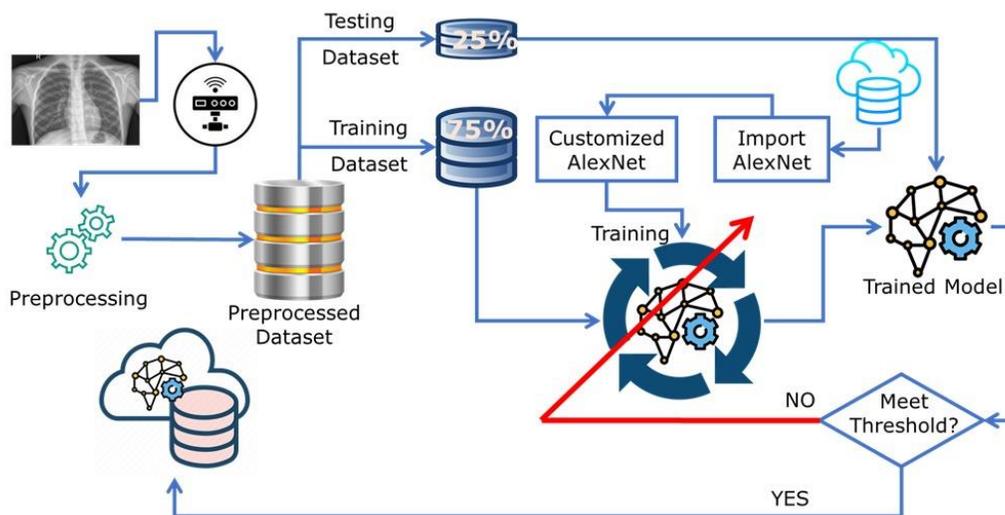


Figure 2: Proposed Model

Performance Metrics:

$$\text{Accuracy} = \frac{\tau_p + \tau_v}{N}$$

$$\text{Miss rate} = \frac{\mathcal{F}_\rho + \mathcal{F}_v}{N}$$

$$\text{Sensitivity} = \frac{\tau_p}{(\tau_p + \mathcal{F}_v)}$$

$$\text{Specificity} = \frac{\tau_v}{(\tau_v + \mathcal{F}_\rho)}$$

$$\text{Precision} = \frac{\tau_p}{(\tau_p + \mathcal{F}_\rho)}$$

$$\text{NPV} = \frac{\tau_p}{(\tau_p + \mathcal{F}_\rho)}$$

$$\text{FPR} = \frac{\mathcal{F}_\rho}{(\tau_v + \mathcal{F}_\rho)}$$

$$\text{FDR} = \frac{\mathcal{F}_\rho}{(\mathcal{F}_\rho + \tau_p)}$$

$$\text{F1 - Score} = \frac{2 * \text{TPR} * \text{PPV}}{\text{TPR} + \text{PPV}}$$

Confusion Matrix:

		Predicted		Total
		NORMAL	PNEUMONIA	
Actual	NORMAL	$\tau_p = 1045$	$\mathcal{F}_v = 24$	1069
	PNEUMONIA	$\mathcal{F}_p = 32$	$\tau_v = 1036$	1068
Total		1077	1060	N = 2137

Actual	N: 2137	Predicted	
		NORMAL	PNEUMONIA
	NORMAL	1045	24
PNEUMONIA	32	1036	

Accuracy:97.37%

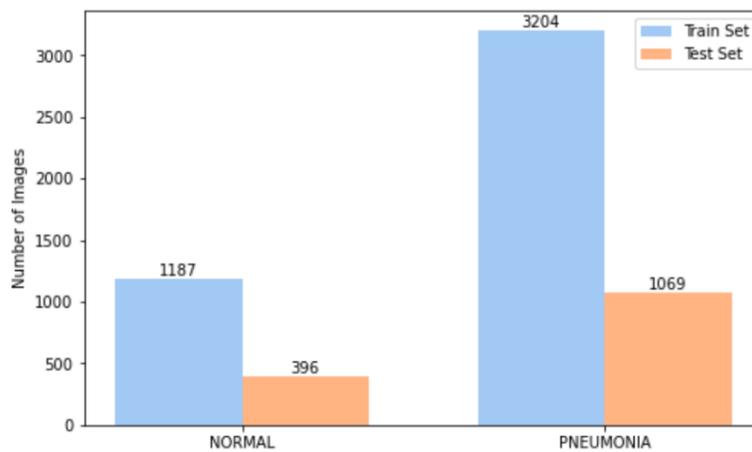


Figure 1: Split SMOTE dataset 75% for training and 25% for validation using Stratify sampling

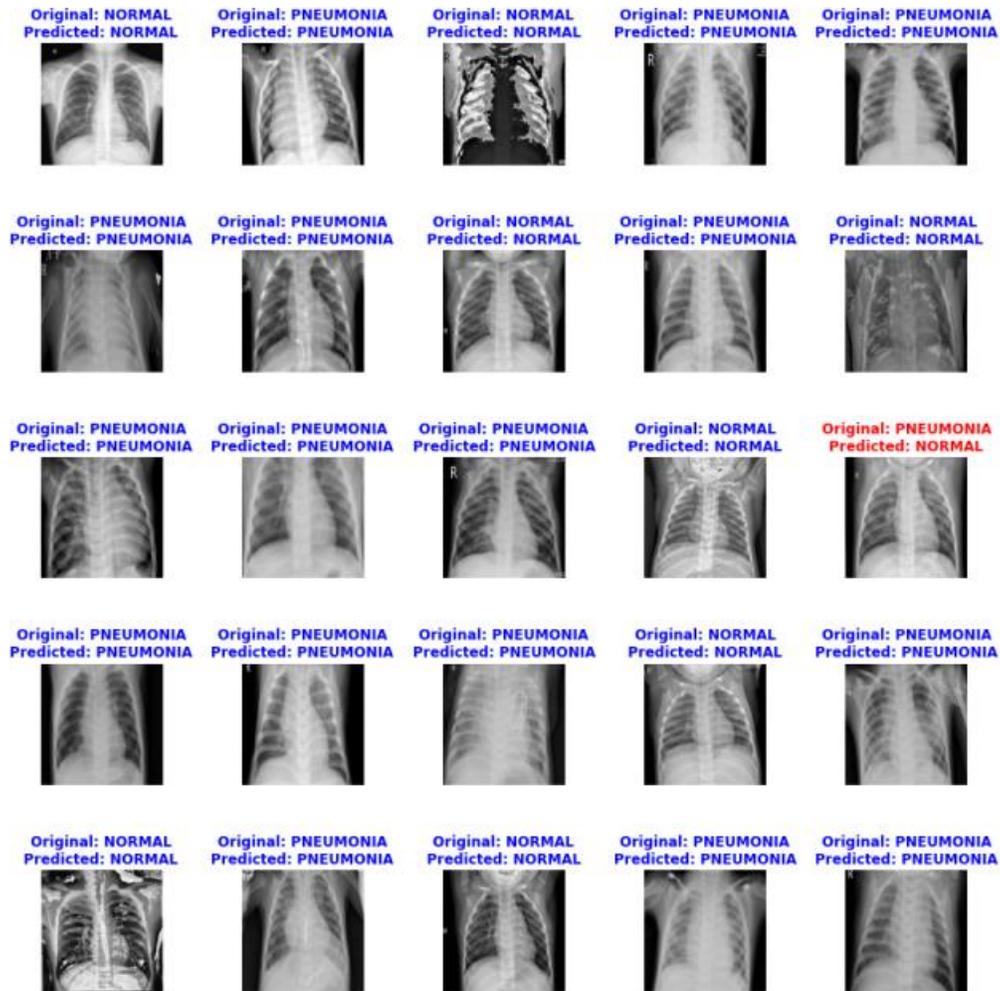


Figure 4: Actual and Predicted results by the trained Model

Without Data Augmentation

Confusion Matrix:

		Predicted		Total
		NORMAL	PNEUMONIA	
Actual	NORMAL	$\tau_p = 368$	$\mathcal{F}_v = 28$	396
	PNEUMONIA	$\mathcal{F}_p = 30$	$\tau_v = 1038$	1068
Total		398	1066	N = 1464

Accuracy:96.03%

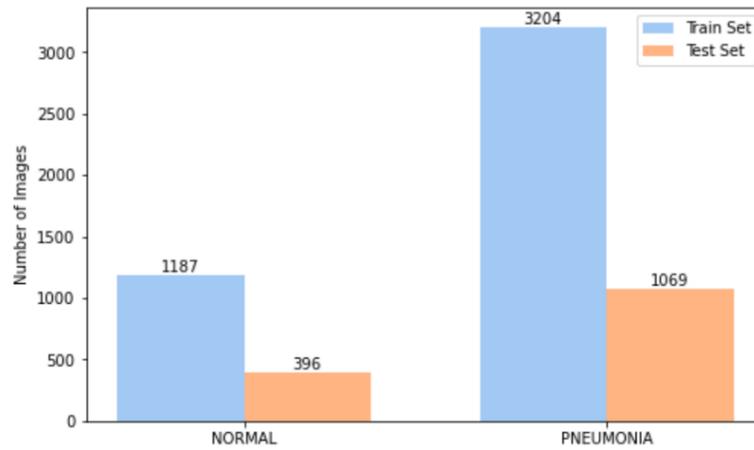


Figure 1: Split an imbalanced dataset 75% for training and 25% for validation using Stratified sampling

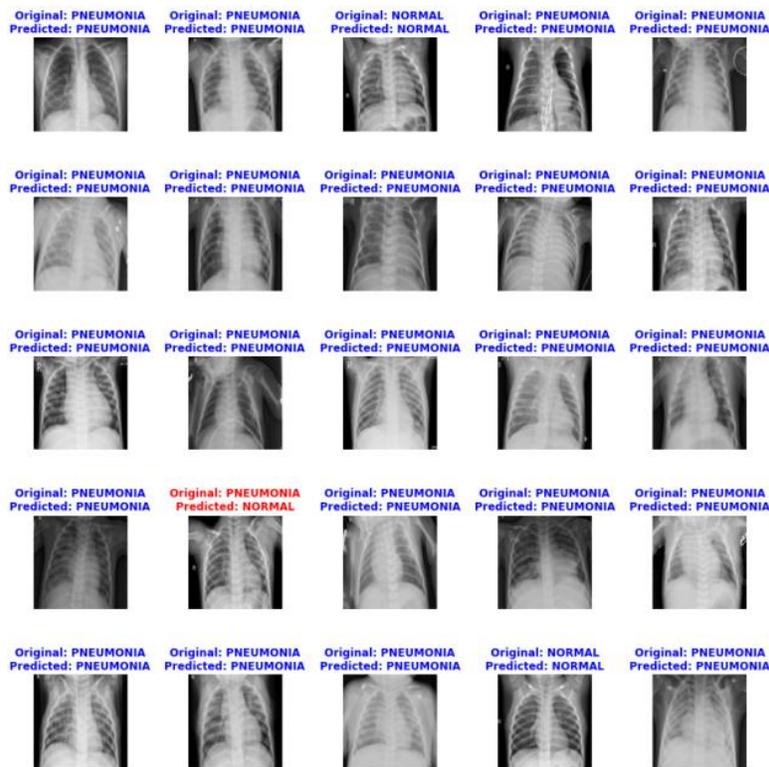
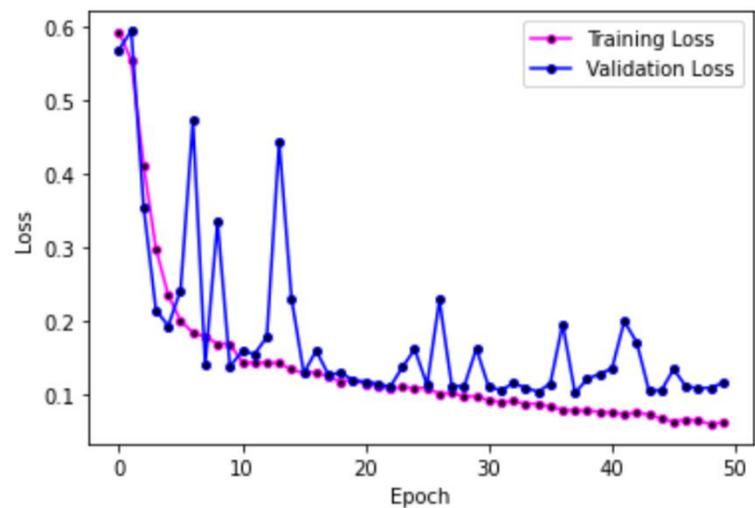
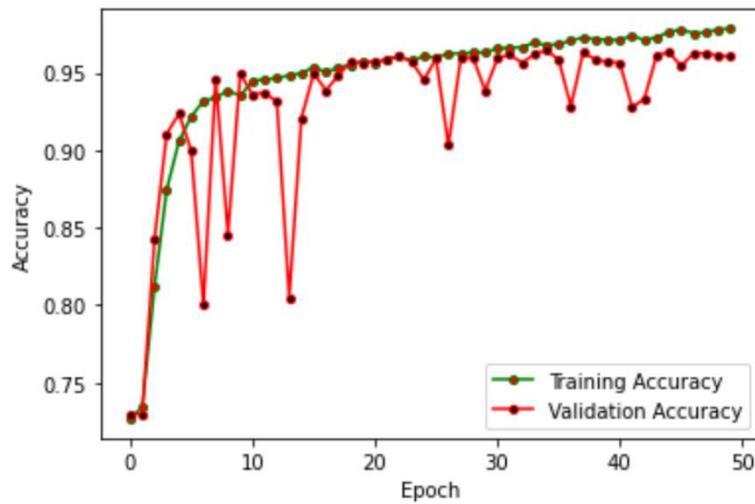


Fig 4: Actual and Predicted results by the trained Model



Without SMOTE

Results	Accuracy	Miss Rate	Sensitivity	Specificity	Precision	NPV	FPR	FDR	F1-Score
Validation	0.9604	0.0396	0.9293	0.9719	0.9246	0.9737	0.02809	0.07538	0.9270
	96.04%	3.96%	92.93%	97.19%	92.46%	97.37%	2.81%	7.54%	92.70%

With SMOTE

Results	Accuracy	Miss Rate	Sensitivity	Specificity	Precision	NPV	FPR	FDR	F1-Score
Validation	0.9738	0.0262	0.9775	0.9700	0.9703	0.9774	0.02996	0.02971	0.9739
	97.38%	2.62%	97.75%	97.00%	97.03%	97.74%	3.00%	2.97%	97.39%

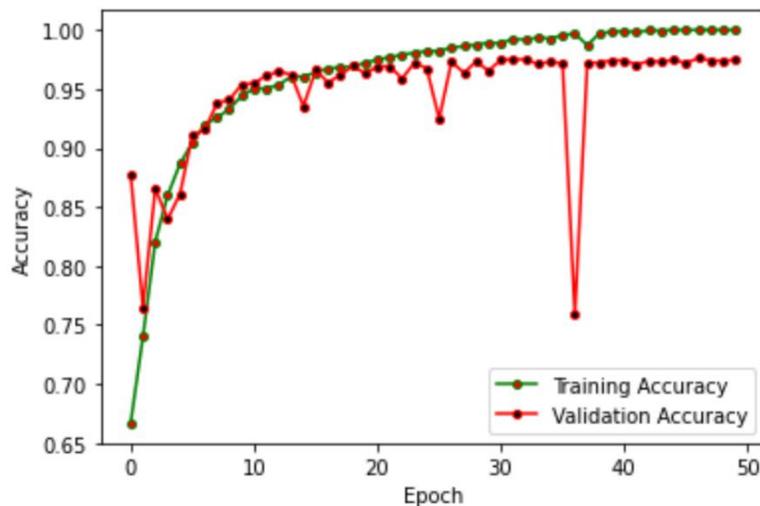


Figure 2: Accuracy graph of training and validation

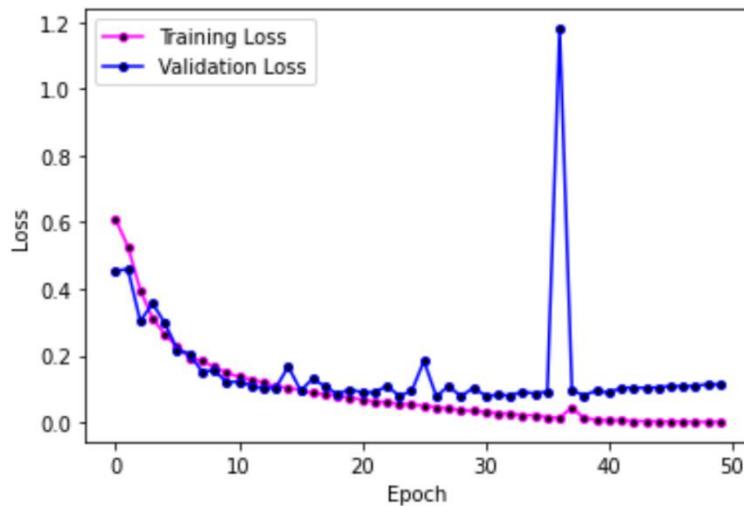


Figure 3: Loss graph of training and validation

### Conclusion:

Utilizing the deep learning Convolutional Neural Network (CNN) **AlexNet model**, the results of this research show that **pneumonia** can be detected in lung CT scan images. Comprehensive preprocessing methods, including pixel rescaling, data augmentation, and **Synthetic Minority Over-Sampling Technique (SMOTE)** for balancing the dataset, have improved the classification performance of the model. **Using the model without SMOTE** resulted in a validation accuracy of **96.04%**, and using the **model with SMOTE** gave a validation accuracy of **97.38%**, both of which are substantially higher than any of the

previous studies. These results demonstrate the ability of the **AlexNet model** to detect key characteristics of medical images and thus demonstrate the potential for the use of this model to provide accurate and timely diagnoses of pneumonia. Ultimately, these results can help develop a **computer-assisted diagnostic (CAD) system** that can allow doctors to detect pneumonia in patients earlier, thus improving patient care.

## References

- [1] J. Verma et al., "Exploring Pneumonia: Understanding its Epidemiology, Deciphering Pathogenic Complexities, and Developing Advanced Diagnostic and Therapeutic Approaches," *Curr. Respir. Med. Rev.*, 2025.
- [2] T. Schramme, "Health as Complete Well-Being: The WHO Definition and Beyond," *Public Health Ethics*, vol. 16, Jul. 2023, doi: 10.1093/phe/phad017.
- [3] S. H. Podolsky, "The changing fate of pneumonia as a public health concern in 20th-century America and beyond," *Am. J. Public Health*, vol. 95, no. 12, pp. 2144-2154, 2005.
- [4] C. J. Gill et al., "Bottlenecks, barriers, and solutions: results from multicountry consultations focused on reduction of childhood pneumonia and diarrhoea deaths," *Lancet*, vol. 381, no. 9876, pp. 1487-1498, 2013.
- [5] F. Shokirova and U. Khatamov, "EXPLORING THE LANDSCAPE OF NUTRITIONOLOGY: ITS INTEGRAL ROLE IN HEALTH PROMOTION AND DISEASE PREVENTION," *Mod. Sci. Res.*, vol. 2, no. 10, pp. 625-631, 2023.
- [6] C. Govers, P. C. Calder, H. F. J. Savelkoul, R. Albers, and R. J. J. van Neerven, "Ingestion, immunity, and infection: nutrition and viral respiratory tract infections," *Front. Immunol.*, vol. 13, p. 841532, 2022.
- [7] A. A. Mohamed and M. Alawna, "Role of increasing the aerobic capacity on improving the function of immune and respiratory systems in patients with coronavirus (COVID-19): A review," *Diabetes Metab. Syndr. Clin. Res. Rev.*, vol. 14, no. 4, pp. 489-496, 2020.
- [8] J. Liao, J. Hong, L. Miao, X. Shen, and C. Xie, "A retrospective analysis of mental well-being, nutritional status, and comorbidity burden in elderly patients with community-acquired pneumonia," *BMC Public Health*, vol. 25, no. 1, p. 667, 2025.
- [9] N. A. of Sciences et al., "Microbiomes of the built environment: a research agenda for indoor microbiology, human health, and buildings," 2017.
- [10] I. Martin-Loeches, L. F. Reyes, and A. Rodriguez, "Severe community-acquired pneumonia (sCAP): advances in management and future directions," *Thorax*, 2025.
- [11] L. B. Laguna et al., "Dysphagia and mechanical ventilation in SARS-CoV-2 pneumonia: It's real," *Clin. Nutr.*, vol. 41, no. 12, pp. 2927-2933, 2022.
- [12] J. C. P. Gomes et al., "Impact of BAL in the management of pneumonia with treatment failure: positivity of BAL culture under antibiotic therapy," *Chest*, vol. 118, no. 6, pp. 1739-1746, 2000.
- [13] S. McChlery, G. Ramage, and J. Bagg, "Respiratory tract infections and pneumonia," *Periodontol.* 2000, vol. 49, no. 1, p. 151, 2008.
- [14] D. C. Mastellos et al., "Complement C3 vs C5 inhibition in severe COVID-19: Early clinical findings reveal differential biological efficacy," *Clin. Immunol.*, vol. 220, p. 108598, 2020.
- [15] D. Roth, A. Jones, C. Prosser, J. Robinson, and S. Vohra, "Vitamin D Receptor Polymorphisms and the Risk of Acute Lower Respiratory Tract Infection in Early Childhood," *J. Infect. Dis.*, vol. 197, pp. 676-680, Apr. 2008, doi: 10.1086/527488.
- [16] D. C. Angus, "Effect of hydrocortisone on mortality in patients with severe community-acquired pneumonia: the REMAP-CAP corticosteroid domain randomized clinical trial," *Intensive Care Med.*, vol. 51, no. 4, pp. 665-680, 2025.
- [17] A. Kheirdoust et al., "Evaluation of Machine Learning Methods Developed for Prediction and Diagnosis of Pneumonia: A Systematic Review," *Heal. Sci. Reports*, vol. 8, Nov. 2025, doi: 10.1002/hsr2.71446.

- [18] D. Li, "Attention-enhanced architecture for improved pneumonia detection in chest X-ray images." *BMC Med. Imaging*, vol. 24, no. 1, p. 6, Jan. 2024, doi: 10.1186/s12880-023-01177-1.
- [19] A. Schuchat and S. F. Dowell, "Pneumonia in children in the developing world: new challenges, new solutions." *Semin. Pediatr. Infect. Dis.*, vol. 15, no. 3, pp. 181-189, Jul. 2004, doi: 10.1053/j.spid.2004.05.010.
- [20] H. Melbye, B. Straume, U. Aasebø, and J. Brox, "The diagnosis of adult pneumonia in general practice: the diagnostic value of history, physical examination and some blood tests," *Scand. J. Prim. Health Care*, vol. 6, no. 2, pp. 111-117, 1988.
- [21] K. Doi, "Computer-aided diagnosis in medical imaging: historical review, current status and future potential." *Comput. Med. Imaging Graph. Off. J. Comput. Med. Imaging Soc.*, vol. 31, no. 4-5, pp. 198-211, 2007, doi: 10.1016/j.compmedimag.2007.02.002.
- [22] C. Chen, N. Isa, and X. Liu, "A review of convolutional neural network-based methods for medical image classification," *Comput. Biol. Med.*, vol. 185, p. 109507, Dec. 2024, doi: 10.1016/j.compbimed.2024.109507.
- [23] G. Ahmad, F. M. Aleem, T. Alyas, Q. Abbas, W. Nawaz, T. M. Ghazal, and A. Aziz, "Intelligent waste sorting for urban sustainability using deep learning," *Scientific Reports*, vol. 15, no. 1, Art. no. 27078, 2025.
- [24] G. Ahmad, A. Khan, M. Sajjad, A. Saddiqa, M. M. Naveed, and Z. Riaz, "Transfer learning-based smart crop protection system for animal detection and deterrence," *Spectrum of Engineering Sciences*, pp. 899-810, 2025.
- [25] T. Alyas, K. Alissa, A. S. Mohammad, S. Asif, T. Faiz, and G. Ahmed, "Innovative fungal disease diagnosis system using convolutional neural network," *Computers, Materials & Continua*, vol. 73, no. 3, 2022.
- [26] G. Ahmad, M. Saleem, J. A. Malik, W. A. Bukhari, M. I. Kashif, and H. Salahuddin, "Mobile application for skin disease classification using CNN with user privacy," *Journal of Computing & Biomedical Informatics*, 2024.
- [27] M. Sajjad, U. A. Butt, A. Ahmad, S. B. Hameed, G. Ahmad, J. C. Vargas, and A. Aziz, "AI-driven approach for early prostate cancer detection and diagnosis," *Spectrum of Engineering Sciences*, pp. 1141-1151, 2024.
- [28] S. Abbas, M. A. Khan, A. Ata, G. Ahmad, A. Saeed, and N. Anwar, "Multi user detection using fuzzy logic empowered adaptive back propagation neural network," *Neural Network World*, vol. 29, no. 6, pp. 381-401, 2019.
- [29] J. A. M. Gulzar Ahmad and M. Saleem, "Analysis of convolutional neural network for image classification," *Journal of Computing & Biomedical Informatics*, vol. 8, no. 1, 2024.