ORIGINAL ARTICLE

AI MODELS FOR ACCURATE BACTERIAL PNEUMONIA DIAGNOSIS IN CHEST X-RAY IMAGES

Akciğer Röntgeni Görüntülerinde Doğru Bakteriyel Pnömoni Teşhisi için Yapay Zeka Modelleri

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ABSTRACT

Objective: This study aims to contribute to this gap by evaluating the performance of various deep learning models, including a proposed Convolutional Neural Networks (CNN) model, ResNet50, and EfficientNetB0, for the detection of bacterial pneumonia from chest X-rays.
Material and Methods: This study investigates the use of artificial intelligence (AI) in detecting pneumonia from chest X-ray (CXR) images using deep learning techniques, specifically CNN, ResNet50, and EfficientNetB0.
Results: A created novel dataset consisting of 1228 images of bacterial pneumonia and 1228 images of non-pneumonia cases, is used for model training and evaluation. X-ray images obtained from Yozgat Bozok Medical Faculty are classified by a specialist physician and supplemented with additional images from a publicly available dataset to eliminate class imbalance. Three deep learning models are implemented and evaluated in terms of accuracy, precision, recall, and F1-score. All models achieved an accuracy of 97%, with high performance in detecting both pneumonia and non-pneumonia cases. The Proposed CNN model showed precision and recall values of 1.00 and 0.94 for non-pneumonia and 0.95 and 1.00 for pneumonia detection, respectively. EfficientNetB0 and ResNet50 demonstrated similar robust performance.
Conclusion: The results indicate that AI-based models can offer reliable and accurate pneumonia detection, supporting clinical decision-making processes and acting as a valuable second opinion for physicians. These findings highlight the potential of AI in enhancing diagnostic accuracy and efficiency, particularly in resource-limited healthcare settings. Further validation with larger datasets and clinical trials is necessary to confirm the generalizability of these models for widespread clinical use.

Keywords: *Deep Learning; Neural Networks; Pneumonia; Classification; Mass Chest X-Ray*

ÖZET

Amaç: Bu çalışma, akciğer röntgeninden bakteriyel pnömoninin saptanması için önerilen Evrişimsel Sinir Ağları (CNN) modeli ResNet50 ve EfficientNetB0 dahil olmak üzere çeşitli derin öğrenme modellerinin performansını değerlendirerek bu boşluğa katkıda bulunmayı amaçlamaktadır.
Gereç ve Yöntemler: Bu çalışma, özellikle CNN, ResNet50 ve EfficientNetB0 olmak üzere derin öğrenme tekniklerini kullanarak akciğer röntgeni görüntülerinden pnömoniyi tespit etmede yapay zekanın kullanımını araştırıyor.
Bulgular: Model eğitimi ve değerlendirmesi için 1228 bakteriyel pnömoni görüntüsü ve 1228 pnömoni olmayan vaka görüntüsünden oluşan oluşturulmuş yeni bir veri seti kullanıldı. Yozgat Bozok Tıp Fakültesi'nden alınan röntgen görüntüleri, uzman hekim tarafından sınıflandırılıp, sınıf dengesizliğini ortadan kaldırmak amacıyla kamuya açık bir veri setinden alınan ek görüntülerle desteklendi. Üç derin öğrenme modeli uygulandı ve doğruluk, kesinlik, geri çağırma ve F1 puanı açısından değerlendirildi. Tüm modeller hem pnömoni hem de pnömoni dışı vakaların tespitinde yüksek performansla %97'lik bir doğruluğa ulaştı. Önerilen CNN modeli, pnömoni dışı için sırasıyla 1,00 ve 0,94 ve pnömoni tespiti için 0,95 ve 1,00 hassasiyet ve geri çağırma değerleri gösterdi. EfficientNetB0 ve ResNet50 benzer güçlü performans sergiledi.
Sonuç: Sonuçlar, yapay zeka tabanlı modellerin güvenilir ve doğru pnömoni tespiti sunabileceğini, klinik karar verme süreçlerini destekleyebileceğini ve hekimler için değerli bir ikinci görüş olarak hareket edebileceğini gösteriyor. Bu bulgular, yapay zekanın özellikle kaynakların sınırlı olduğu sağlık hizmetlerinde teşhis doğruluğunu ve verimliliğini artırma potansiyelini vurgulamaktadır. Bu modellerin yaygın klinik kullanıma yönelik genelleştirilebilirliğini doğrulamak için daha büyük veri kümeleri ve klinik çalışmalarla daha fazla doğrulama yapılması gerekmektedir.

Anahtar Kelimeler: *Derin Öğrenme; Yapay Sinir Ağları; Pnömoni; Sınıflandırma; Akciğer Grafisi*

INTRODUCTION

Pneumonia is a fatal disease caused by the inflammation of the lung parenchyma (1). Bacteria, viruses, and less commonly fungi are the pathogenic microorganisms that cause lung inflammation. Pneumonia can cause fatal disease through a dysregulated inflammatory response and activated hypercoagulation (2). These pathological responses to infections have the potential to lead to multiple organ dysfunction syndrome (MODS) (3). As a result of these pathophysiological processes, pneumonia is a potentially fatal disease.

Globally, causes of death are categorized into communicable and non-communicable diseases (4). According to the World Health Organization (WHO), lower respiratory tract infections were the fifth leading cause of death in 2021. The same report also listed COVID-19 as the second leading cause of death. Fatal COVID-19 infections often lead to death due to severe sepsis, which is caused by lower respiratory tract infections (5). These findings underscore the importance of addressing lower respiratory tract infections as a leading cause of death, especially given that COVID-19, which is also a lower respiratory tract infection, was a major contributor to mortality during the pandemic. However, with the pandemic's decline, pneumonia and other lower respiratory tract infections remain critical causes of death worldwide.

Additionally, death in low-income countries presents crucial findings. Lower tract respiratory infections were reported to be 1st death cause (4). One more aspect to address is that lower tract respiratory infections are one of the communicable diseases. Preventing the transmission could have a key role in managing infections to reduce mortality.

The diagnosis of infection is the first and essential step in preventing transmission. Chest radiography plays a key role in diagnosing pneumonia, with the primary options being chest X-ray (CXR) and computed tomography (CT) scans (6). Although CT scans provide more detailed chest images, chest X-rays remain critical due to their accessibility and affordability. CXR is a widely used and common imaging modality for identifying pneumonia. It is important to note that lower respiratory tract infections are the leading cause of death in low-income countries, where access to CT scanning facilities is often limited. In these regions, CXR continues to be a crucial tool for early detection and diagnosis of pneumonia.

While many studies focus on the use of artificial intelligence (AI) for detecting COVID-19 pneumonia, fewer studies have explored AI-based approaches for detecting bacterial pneumonia (6–10). Khan et al propose a framework utilizing deep explainable artificial intelligence (XAI) techniques for the classification of COVID-19 from chest X-ray (CXR) images (7). The authors emphasize the importance of explainability in AI models for medical applications, aiming to make the decision-making process more transparent to clinicians. Kufel et al. submitted an overview of various AI techniques, particularly deep learning, that have been used to detect COVID-19-related changes in chest X-rays (8).

The authors discuss the performance, limitations, and potential of AI in the clinical setting, while also identifying the challenges such as data quality, model generalization, and the need for large, diverse datasets to train robust AI systems. Gupta et al. focused on using neural architecture search (NAS) to optimize deep learning models for pneumonia diagnosis from chest X-ray images (9). NAS is a technique for automating the design of neural network architectures, allowing for the discovery of more efficient and effective models for medical image classification.

This study aims to contribute to this gap by evaluating the performance of various deep learning models, including a proposed Convolutional Neural Network (CNN) model, ResNet50, and EfficientNetB0, for the detection of bacterial pneumonia from chest X-rays. We investigate the potential of AI to support clinicians in diagnosing pneumonia and enhancing the accuracy and efficiency of the diagnostic process. The findings from this study could provide valuable insights into improving AI-based diagnostic systems in clinical settings.

MATERIAL AND METHOD

This study was approved by the local ethics committee (Date:18.09.2024, approval number: 2024-GOKAEK-248_18.09.2024_147). This single-center retrospective study was conducted in a tertiary referral center. The chest X-ray (CXR) images of patients visiting internal medicine and pulmonology outpatient clinics were collected from the hospital's database. The CXR images were retrieved from the hospital system, ensuring that only anonymized data were used to maintain patient confidentiality.

The identification of pneumonia was performed by a physician, who provided manual annotations of the images based on clinical findings and radiological evaluation. In addition, AI-based software was used to assist in the detection of pneumonia. For the artificial intelligence technique, a deep learning approach was employed, using CNNs for image classification. The proposed CNN model was trained on the CXR dataset, with both pneumonia and non-pneumonia cases. The accuracy of the AI-based detection system in identifying pneumonia was evaluated by comparing the model's predictions against the physician's annotations. This approach aims to assess the potential of AI in supporting clinical decision-making processes, providing a second layer of diagnostic verification to ensure high detection accuracy in pneumonia diagnosis.

The original dataset consists of 106 images of Bacterial Pneumonia and 1,228 images of No_Pneumonia. To address class imbalance, additional Bacterial Pneumonia images from a publicly available dataset are incorporated into the original dataset (11). A specialist clinician carefully reviewed these images before inclusion to ensure data accuracy and quality.

Deep learning is a sophisticated subset of machine learning that leverages multiple layers of nonlinear computing to extract and transform intricate features from data. Unlike traditional machine learning models that rely on handcrafted feature engineering, deep learning algorithms autonomously learn hierarchical representations of data through an iterative process. Each successive layer in a deep learning architecture takes the output of the previous layer as input, allowing the model to progressively capture higher-level abstractions and gain a deeper understanding of complex patterns and relationships within the data (12).

Convolutional Neural Networks represent the most commonly used architecture in deep learning, particularly in the domain of image and video processing. CNNs consist of two main components and have gained widespread adoption due to their remarkable capabilities. In a CNN, the neurons in the initial layer are responsible for extracting features from the input data, while the subsequent layers combine these extracted features to form higher-level representations (13). The success of CNNs can be attributed to their hierarchical feature extraction capability, enabling them to effectively capture intricate patterns and structures in the data at various levels of abstraction.

EfficientNetB0 is a convolutional neural network model that balances accuracy and efficiency by employing a compound scaling approach, where depth, width, and resolution are systematically scaled. This architecture is part of the EfficientNet family, known for achieving state-of-the-art performance on various image classification benchmarks while maintaining computational efficiency. The foundation of EfficientNetB0 lies in its use of Mobile Inverted Bottleneck Convolution (MBConv) blocks and the Swish activation function, optimizing both speed and accuracy (14).

ResNet50, on the other hand, is a 50-layer deep convolutional neural network architecture that introduced the concept of residual learning. The residual blocks in ResNet50 address the problem of vanishing gradients, enabling the training of deeper networks by bypassing the direct mapping of inputs to outputs through shortcut connections. ResNet50 has been widely adopted in image processing tasks for its robustness and simplicity (15). Both architectures are frequently used in medical image analysis due to their pre-trained weights on large-scale datasets such as ImageNet, allowing for transfer learning to enhance performance in domain-specific tasks.

In this study, we propose a convolutional neural network architecture designed to effectively classify images into two categories. As outlined in Table 1, the model consists of several key layers that work together to extract hierarchical features from input images. The input image is first passed through a series of convolutional layers, each followed by batch normalization and spatial dropout, aimed at enhancing training stability and reducing overfitting.

Cross-validation techniques are commonly used in machine learning to evaluate and validate model performance (16). One frequently used method is 5-fold cross-validation, where the dataset is split into

Table 1. Architecture details of the proposed Convolutional Neural Networks (CNN)

Layer No	Layer Type	Output Shape	Number of Parameters
1	Input	(224, 224, 3)	0
2	Conv2D	(224, 224, 32)	896
3	BatchNormalization	(224, 224, 32)	128
4	SpatialDropout2D	(224, 224, 32)	0
5	MaxPooling2D	(112, 112, 32)	0
6	Conv2D	(112, 112, 64)	18,496
7	BatchNormalization	(112, 112, 64)	256
8	SpatialDropout2D	(112, 112, 64)	0
9	MaxPooling2D	(56, 56, 64)	0
10	Conv2D	(56, 56, 128)	73,856
11	BatchNormalization	(56, 56, 128)	512
12	MaxPooling2D	(28, 28, 128)	0
13	Conv2D	(28, 28, 256)	295,168
14	BatchNormalization	(28, 28, 256)	1,024
15	GlobalAveragePooling2D	(256)	0
16	Dense	(512)	131,584
17	Dropout	(512)	0
18	Dense (Output Layer)	(2)	1,026
• Trainable Parameters: 522,946 • Non-trainable Parameters: 0 • Total: 522,946			

five approximately equal-sized subsets or folds. In this approach, the model is trained using four of the folds and validated on the remaining fold. This process is repeated five times, each time with a different fold serving as the validation set. The performance metrics from each fold are then averaged to estimate the model's overall performance. 5-fold cross-validation helps reduce the risk of overfitting and provides a more reliable assessment of the model's ability to generalize to unseen data.

Evaluation metrics are crucial for assessing the performance of machine learning algorithms, especially in deep learning models. These metrics help determine how well a model generalizes to new, unseen data. Various evaluation criteria are available, and using multiple metrics provides a more comprehensive view of model performance, as a model might excel in one metric but underperform in another. Classification estimates rely on four key values: True Positive (TP) when a model correctly predicts the positive class, False Positive (FP) for incorrect positive predictions, True Negative (TN) for correct negative predictions, and False Negative (FN) for incorrect negative predictions (17,18).

Accuracy=(TN+TP)/(TN+TP+FN+FP)

Recall=TP/(TP+FN)

Precision=TP/(TP+FP)

F1-Score =2x (Precision x Recall)/(Precision+Recall)

RESULTS

This study analyzes three different models for pneumonia detection in chest X-ray images: a custom CNN, ResNet50, and EfficientNetB0. The models are trained and evaluated using a 5-fold cross-validation approach to ensure robust performance assessment. The dataset used includes images categorized into Bacterial Pneumonia and No Pneumonia, with the Bacterial Pneumonia class verified by expert clinicians before being added to the dataset. Various performance metrics are used to evaluate and compare the models, including accuracy, precision, recall, and F1 score. This section details the steps taken to prepare the dataset, train the models, and assess their effectiveness in classifying pneumonia from chest X-ray images. The experiments were conducted on a system with the following specifications: 32 GB of memory, Intel(R) Core i7 CPUs 12700F operating at 2.10 GHz, and an NVIDIA GeForce RTX 3090 TI graphics card. The system runs Windows 10 Pro, and the machine learning tasks are carried out using Python 3 in Jupyter Notebook. This configuration provided the necessary computational power for training and evaluating the deep learning models used in this study.

The classification reports and confusion matrix given in Table 2 for the 5-fold cross-validation of the three models—Proposed CNN, EfficientNetB0, and ResNet50—demonstrate the effectiveness of each model in detecting pneumonia from chest X-ray images. The accuracy for all three models is 0.97, indicating high performance across all folds.

• Proposed CNN: The model achieves an accuracy of 97%, with precision, recall, and F1-score of 0.97 for both classes (0: No Pneumonia, 1: Bacterial Pneumonia). The high recall and precision for class 1 (Bacterial Pneumonia) highlight its effectiveness in identifying pneumonia cases.

• EfficientNetB0: The performance is very similar to the Proposed CNN model, with an accuracy of 97%. Precision and recall are slightly lower for the "No Pneumonia" class (0) compared to the Proposed CNN model, but the overall F1-score remains consistent at 0.97 for both classes, indicating reliable classification performance.

• ResNet50: This model also shows an accuracy of 97%, with the precision, recall, and F1-scores all nearing 0.97. Precision and recall for both classes are slightly lower than the other two models but still exhibit a strong balance in performance across both classes.

The graph given in Figure 2 (a) illustrates the accuracy trends for each model over multiple epochs. All models show a steady increase in accuracy, stabilizing around 97% at the end of training, confirming the models' strong ability to generalize well to the test data.

Figure 2 (b) represents the models' loss over time during training. The loss values for all models decrease consistently, with EfficientNetB0 and ResNet50 showing slightly lower loss values toward the end, indicating efficient training. The CNN model demonstrated a strong performance during the training process, with a rapid decline in validation loss, particularly in the initial epochs. While the difference between validation loss and training loss is slightly more pronounced compared to the other models, this indicates that the model is effectively utilizing its learning capacity and adapting to the data across different epochs. The fluctuations observed in the validation loss suggest that the model is attempting to generalize over different features of the data during training. Additionally, the rapid decrease in validation loss at the beginning highlights the model's ability to quickly learn and adapt. Given

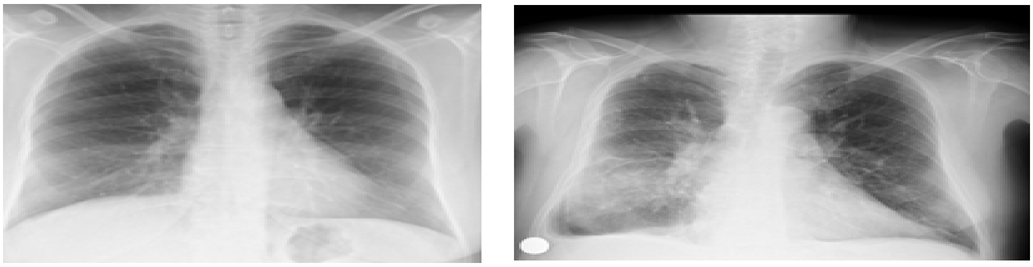

Figure 1. An example of dataset a) No_Pneumonia, b) Bacterial Pneumonia

Table 2. Classification reports and confusion matrix

Model	Accuracy	Precision (0)	Recall (0)	F1-score (0)	Precision (1)	Recall (1)	F1-score (1)	TN	FP	FN	TP
Proposed CNN	0.97	1.00	0.94	0.97	0.95	1.00	0.97	231	14	1	245
EfficientNetB0	0.97	1.00	0.94	0.97	0.94	1.00	0.97	237	8	5	241
ResNet50	0.97	0.98	0.97	0.97	0.97	0.98	0.97	230	15	1	245

CNN: convolutional neural networks

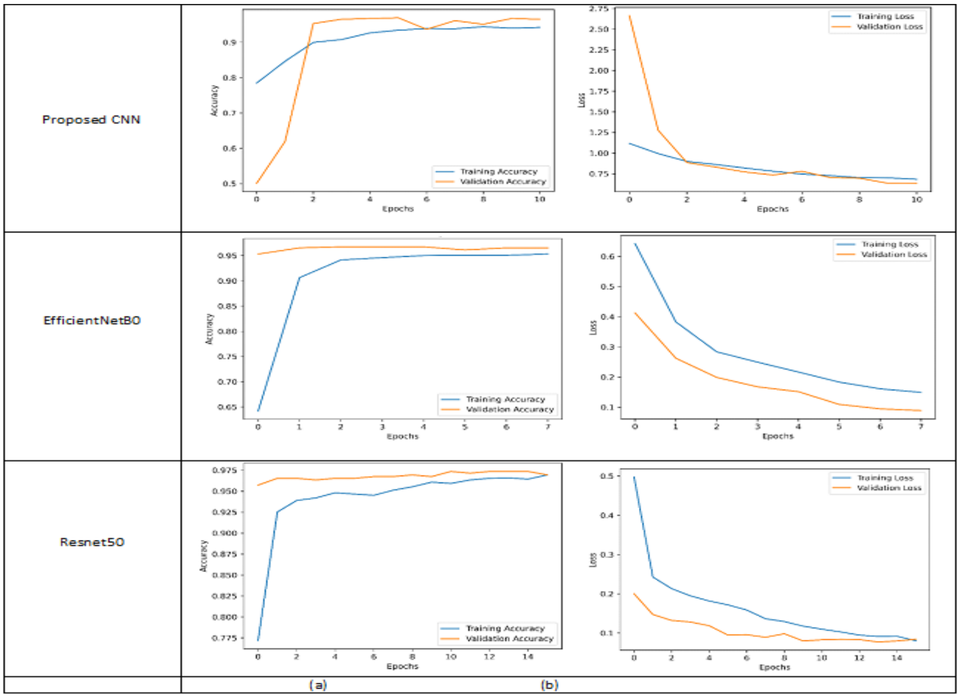

Figure 2. Accuracy and Loss graph of models

its simpler architecture compared to ResNet50 and EfficientNetB0, the CNN model stands out as a practical solution for scenarios where computational efficiency is critical. From an accuracy perspective, the CNN model also performs well, with validation accuracy quickly reaching around 95% and maintaining a trend similar to training accuracy. However, slight fluctuations in validation accuracy in later epochs indicate a moderate level of instability compared to the other models. On the other hand, ResNet50 and EfficientNetB0 achieve validation accuracies above 95%, offering both higher precision and stability. ResNet50, in particular, excels in both accuracy and loss reduction, while EfficientNetB0 closely follows with comparable performance. The CNN model delivers acceptable accuracy and loss performance with lower computational requirements, making it a viable option for applications where efficiency is a priority. However, for studies demanding the highest accuracy and stability, ResNet50 and EfficientNetB0 emerge as more robust choices.

The ROC curves given in Figure 3 demonstrate the trade-off between true positive rate and false positive rate. All models show a high area under the curve (AUC), suggesting excellent discriminative ability between the two classes.ResNet50 (AUC = 1.00): ResNet50 achieves a perfect AUC score of 1.00, indicating excellent classification capability with no compromise between sensitivity and specificity. This highlights ResNet50 as the most reliable model for this task. EfficientNetB0 (AUC = 0.98): With an AUC of 0.98, EfficientNetB0 also demonstrates high classification performance. While slightly below ResNet50, it remains an excellent choice with a strong balance of true positive and false positive rates. CNN (AUC = 0.97): The CNN model achieves an AUC of 0.97, showcasing robust performance. Though slightly behind the other two models, its results are still highly competitive, particularly given its simpler architecture. ResNet50 stands out with perfect AUC, making it the top-performing model. EfficientNetB0 and CNN also provide strong and reliable results, with CNN being a computationally lighter alternative for less resource-intensive scenarios.

The Grad-CAM visualizations shown in Figure 4 effectively illustrate the regions within the X-ray images that the model focuses on for its predictions. In the first image (a), the heatmap highlights concentrated activation around the lung regions, particularly in areas that may indicate abnormalities, suggesting the model is successfully identifying critical features. Similarly, the second image (b) shows widespread activation across the lungs, with notable focus near the ribcage and diaphragm, reflecting the model's effort to generalize its attention across the image. In the third image (Fold 2), the heatmap reveals precise activations in specific regions of the lungs, emphasizing potential abnormal areas and demonstrating the model's ability to narrow its focus to relevant features. Overall, these visualizations confirm that the model is attending to clinically significant regions, enhancing interpretability and reinforcing its reliability in decision-making.

DISCUSSION

This study aimed to evaluate the effectiveness of artificial intelligence (AI)-based systems, specifically convolutional neural networks (CNNs), in detecting pneumonia from chest X-ray (CXR) images. The study leveraged a dataset of 2,456 images, including both bacterial pneumonia and non-pneumonia cases, which were annotated by a physician and supplemented with additional images from a publicly available dataset. By utilizing deep learning approaches like CNN, ResNet50, and EfficientNetB0, we explored how these models could assist in pneumonia detection, particularly in a clinical decision-making context. The performance of all models—Proposed CNN, EfficientNetB0, and ResNet50—was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. All models achieved an impressive overall accuracy of 97%, with each demonstrating strong performance in both the detection of bacterial pneumonia and non-pneumonia cases. For example, the Proposed CNN model achieved a precision of 1.00 and recall of 0.94

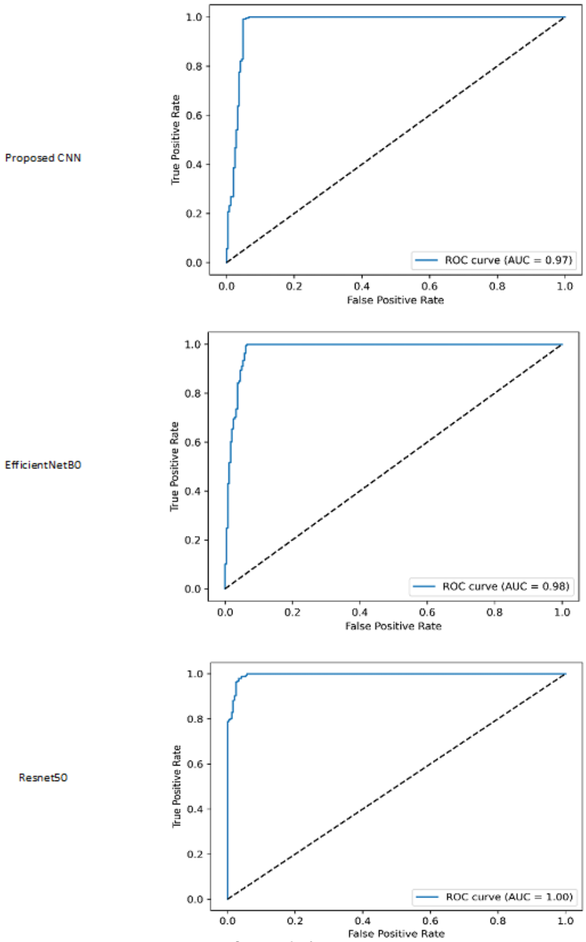

Figure 3. ROC curve of models

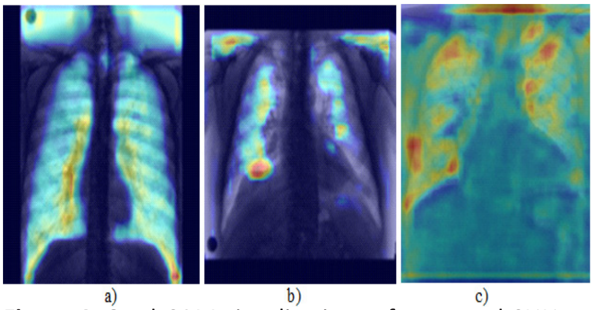

Figure 4. Grad-CAM visualizations of proposed CNN

for the non-pneumonia class, and a precision of 0.95 and recall of 1.00 for pneumonia detection. Similarly, EfficientNetB0 and ResNet50 showed slightly varied results, but their performance remained robust, with high F1 scores across both classes. These findings suggest that the proposed AI-based systems are capable of providing accurate pneumonia detection, even in the presence of class imbalance (where non-pneumonia cases are more numerous). The use of a multi-model comparison, including well-established architectures like ResNet50 and EfficientNetB0, allowed us to understand how different deep learning models perform in medical image classification tasks. All three models demonstrated high precision and recall, ensuring reliable identification of both pneumonia and non-pneumonia cases. Moreover, the use of AI systems can serve as a valuable tool for clinicians, offering an additional layer of diagnostic verification. While AI cannot replace the expertise of healthcare professionals, it can assist in reducing diagnostic errors and enhance the efficiency of the clinical workflow, especially in environments with limited access to radiology specialists.

CONCLUSION

In this study, we demonstrated that deep learning-based models, particularly CNN, EfficientNetB0, and ResNet50, are effective in the detection of pneumonia from chest X-ray images. The models provided high accuracy, precision, and recall, making them suitable candidates for supporting clinical decision-making in pneumonia diagnosis. The results of this study suggest that AI can enhance diagnostic capabilities, offering reliable and accurate second opinions in clinical settings. The integration of AI in medical image analysis holds significant potential for improving the accuracy and efficiency of diagnoses, particularly in under-resourced healthcare settings. However, further validation with larger datasets and clinical trials is necessary to confirm the robustness and generalizability of these models in real-world scenarios. Future work could also explore the integration of AI systems with other diagnostic tools to create comprehensive, multi-modal decision support systems.

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The authors declare that they have no conflict of interest to disclose.

REFERENCES

1. Irfan A, Adivishnu AL, Sze-To A, Dehkharghanian T, Rahnamayan S, Tizhoosh HR. Classifying Pneumonia among Chest X-Rays Using Transfer Learning. Annu Int Conf IEEE Eng Med Biol Soc. 2020;2020:2186-9.

2. Liufu R, Chen Y, Wan XX, Liu RT, Jiang W, Wang C, et al. Sepsis-induced Coagulopathy: The Different Prognosis in Severe Pneumonia and Bacteremia Infection Patients. Clin Appl Thromb Hemost. 2023;29:10760296231219249.

3. Robba C, Battaglini D, Pelosi P, Rocco PRM. Multiple organ dysfunction in SARS-CoV-2: MODS-CoV-2. Expert Rev Respir Med. 2020;14(9):865-8.

4. Msemburi W, Karlinsky A, Knutson V, Aleshin-Guendel S, Chatterji S, Wakefield J. The WHO estimates of excess mortality associated with the COVID-19 pandemic. Nature. 2023;613(7942):130-7.

5. Asselah T, Durantel D, Pasmant E, Lau G, Schinazi RF. COVID-19: Discovery, diagnostics and drug development. J Hepatol. 2021;74(1):168-84.

6. Salvatore C, Interlenghi M, Monti CB, Ippolito D, Capra D, Cozzi A, et al. Artificial Intelligence Applied to Chest X-ray for Differential Diagnosis of COVID-19 Pneumonia. Diagnostics (Basel). 2021;11(3):530.

7. Khan MA, Azhar M, Ibrar K, Alqahtani A, Alsubai S, Binbusayyis A, et al. COVID-19 Classification from Chest X-Ray Images: A Framework of Deep Explainable Artificial Intelligence. Comput Intell Neurosci. 2022;2022:4254631.

8. Kufel J, Bargieł K, Koźlik M, Czogalik Ł, Dudek P, Jaworski A, et al. Application of artificial intelligence in diagnosing COVID-19 disease symptoms on chest X-rays: A systematic review. Int J Med Sci. 2022;19(12):1743-52.

9. Gupta A, Sheth P, Xie P. Neural architecture search for pneumonia diagnosis from chest X-rays. Sci Rep. 2022;12(1):11309.

10. Anai S, Hisasue J, Takaki Y, Hara N. Deep Learning Models to Predict Fatal Pneumonia Using Chest X-Ray Images. Can Respir J. 2022;2022:8026580.

11. Kermany D, Zhang K, Goldbaum M. "Labeled optical coherence tomography (oct) and chest x-ray images for classification." Mendeley data 2.2 (2018): 651.

12. Deng L, Dong Y. "Deep learning: methods and applications." Foundations and trends® in signal processing 7.3–4 (2014): 197-387.

13. Kelleher JD. Deep learning. Vol. 1. Cambridge, Massachusetts: MIT press; 2019:159-84.

14. Tan M, Le Q. Efficientnet: Rethinking model scaling for convolutional neural networks. Proceedings of 36th International Conference on Machine Learning, PMLR 97. 2019:6105-14.

15. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016:770-8.

16. Sahin ME. "Image processing and machine learning-based bone fracture detection and classification using X-ray images." Int J Imag Syst Tech (2023);33:853-65.

17. Sahin ME. "Deep learning-based approach for detecting COVID-19 in chest X-rays." Bıomed Signal Proces (2022);78:103977.

18. Sahin ME, Ulutas H, Yüce E.. "A deep learning approach for detecting pneumonia in chest X-rays." Avrupa Bilim ve Teknoloji Dergisi (2021);28:562-7.