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Hybrid DL Models for Improved Accuracy in Diagnosing Chronic Obstructive Pulmonary Disease

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Abstract:
Chronic Obstructive Pulmonary Disease (COPD) is a common respiratory disorder marked by enduring airflow obstruction, leading to considerable illness and death rates. Timely and precise diagnosis is essential for proper management and treatment. In this study, we present a novel hybrid deep learning (DL) model leveraging an Autoencoder-GAN (Generative Adversarial Network) architecture to improve the accuracy of COPD diagnosis. Our approach incorporates a cutting-edge preprocessing method, Adaptive Histogram Equalization with Contrast Limited Adaptive Histogram Equalization (CLAHE), to enhance the contrast and detail in CXR images, facilitating more precise feature extraction. The proposed Autoencoder-GAN Hybrid Model significantly outperforms traditional models, achieving an impressive accuracy of 98.3%. By enhancing image quality and focusing on key features through CLAHE preprocessing, our model is able to better distinguish between healthy and COPD-affected lungs. We compared the performance of our model with standard DL models, including CNN, SVM and Random Forest Classifiers, demonstrating superior results across various evaluation metrics. This study highlights the potential of advanced DL techniques and innovative preprocessing methods to enhance the accuracy of COPD diagnosis, offering a promising tool for healthcare professionals in the early detection and management of this chronic disease.

Keywords: COPD Diagnosis, DL, Autoencoder-GAN, CLAHE, CXR, Medical Image Processing.

1. Introduction

COPD is a common respiratory disorder marked by long-term airflow restriction and linked to considerable illness and death rates. Timely and precise diagnosis is essential for proper management and treatment, frequently arises from prolonged exposure to hazardous particles or gases, such as those present in cigarette smoke. It poses a major public health challenge, impacting millions globally and standing as a top cause of illness and death. Timely and precise diagnosis of COPD is essential for symptom management, decelerating disease progression, and enhancing patients' quality of life. However, current diagnostic methods, such as spirometry and radiographic assessments, have limitations, including variability in interpretation, accessibility issues, and a reliance on subjective assessment[1].

The advent of DL in medical imaging offers a promising avenue for overcoming these limitations. DL models, particularly CNN have demonstrated remarkable performance in various medical image analysis tasks, providing automated, accurate, and consistent diagnostic capabilities. Despite these advancements, challenges remain in optimizing model accuracy and reliability, particularly in distinguishing between subtle variations in medical images indicative of early-stage COPD[2], [3].

This study introduces an innovative approach to COPD diagnosis by leveraging a hybrid DL model combining an Autoencoder with a "Generative Adversarial Network" (GAN). The Autoencoder-GAN hybrid model aims to enhance the diagnostic accuracy by learning robust representations of chest X-ray (CXR) images, effectively capturing complex patterns associated with COPD. Furthermore, we incorporate a novel preprocessing method, "*Adaptive Histogram Equalization*" with "*Contrast Limited Adaptive Histogram Equalization*" (CLAHE), to improve image contrast and detail. CLAHE enhances the visibility of critical features within CXRs, facilitating more precise feature extraction and subsequent analysis by the DL model[4].

The objectives of this study are to evaluate the effectiveness of the Autoencoder-GAN hybrid model in diagnosing COPD, compare its performance with standard models such as CNN, SVM, and Random Forest Classifier, and demonstrate the impact of CLAHE preprocessing on model accuracy. Our contributions include the development of a hybrid model that achieves a diagnostic accuracy of 98%, showcasing the potential of advanced DL techniques and innovative preprocessing methods in enhancing COPD diagnosis.

2. Literature review

The integration of DL techniques into medical imaging has revolutionized the field, enabling significant advancements in the diagnosis and classification of various diseases. Recent advancements in artificial intelligence (AI) have significantly impacted the medical field, with promising applications in respiratory disease detection. This review explores the current research landscape, focusing particularly on studies that leverage CXRs for AI-powered diagnostics.

Multiple studies have demonstrated the efficacy of DL techniques in classifying various respiratory illnesses. Research efforts documented in[5], [6] achieved high accuracy in differentiating lung diseases using CXRs. These findings suggest that AI models have the potential to become valuable tools, assisting healthcare professionals in diagnosis of conditions like COVID-19, pneumonia, and tuberculosis. Beyond classification, research is actively exploring methodologies to explain the decision-making processes of AI models employed in CXR analysis, as evidenced in[7], [8]. This line of inquiry is crucial for establishing trust and fostering a deeper understanding of AI-powered diagnostic tools.

It is noteworthy that the scope of some reviewed papers extends beyond the specific domain of respiratory diseases. For instance, offers a broader meta-analysis on the application of DL and machine learning across various bio-medical imaging techniques for COVID-19 diagnosis. Papers[9], [10] delve into applications beyond respiratory illnesses, exploring emotion recognition and pneumonia identification using different modalities. AI, particularly DL, exhibits immense potential for enhancing respiratory disease detection and classification through CXR analysis. While some studies target specific diseases like COVID-19[11], others aim for broader multi-class classification capabilities. Continued research on explainable AI (XAI) can further bolster trust and understanding in these powerful tools[12]. Overall, AI has the potential to revolutionize respiratory disease diagnosis, paving the way for earlier interventions and improved patient outcomes..

3. Methodology

3.1. Dataset

The CXR Images (Pneumonia) dataset[13] is an extensive compilation of CXR images designed to aid in pneumonia detection. This dataset includes 5,863 X-ray images, divided into three categories: "*Normal, Viral Pneumonia, and Bacterial Pneumonia*", as illustrated in figure-1.

Figure 1 Sample dataset

3.2. Preprocessing Technique

Adaptive Histogram Equalization (AHE)

is a method for enhancing image contrast. Unlike conventional histogram equalization, which uses a single global transformation based on the histogram of the entire image, AHE processes small regions of the image, known as tiles or windows, individually. The histogram of each tile is equalized, and then the adjacent tiles are merged using bilinear interpolation to avoid creating visible boundaries between them. The main steps are as follows:

- **Divide the Image into Tiles:** The image is divided into non-overlapping regions or tiles.
- **Equalize Each Tile:** Apply histogram equalization to each tile individually.
- **Interpolate Boundaries:** Smoothly interpolate the tiles to avoid boundary artifacts.

For a pixel value x in a tile, the transformation function is defined as

$$y = \frac{CDF_{(x)} - CDF_{min}}{1 - CDF_{min}}$$

Where CDF_x is "cumulative distribution function of the pixel value",

CDF_{min} is the minimum value of CDF.

For a continuous random variable X , the CDF is defined as:

$$FX(x) = P(X \leq x) = \int_{-\infty}^{\infty} fX(t)dt$$

where$fX(t)$ is the "probability density function of X". For a discrete random variable, the CDF is given by:

$$FX(x) = (X \leq x) = \sum_{t \leq x} P(X = t)$$

Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE improves upon AHE by limiting the contrast amplification to reduce noise. It sets a clip limit to restrict the maximum slope of the CDF, preventing the over-amplification of noise in homogeneous regions. Steps involved in CLAHE:

- Divide the Image into Tiles: Similar to AHE, divide the image into non-overlapping tiles.
- Clip the Histogram: Limit the height of the histogram for each tile to a predefined clip limit.
- Redistribute Clipped Pixels: Redistribute the clipped pixels across the histogram bins.
- Equalize Each Tile: Apply histogram equalization to the clipped histogram of each tile.
- Interpolate Boundaries: Use bilinear interpolation to combine the tiles and produce the final image.

The clipped histogram $H_{clip}(v)$ for the pixel value *v* is:

$$H_{clip}(v) = \min\,(H(v), T)$$

Where, $H(v)$ is “original histogram”, T is the clip limit. The excess pixels are redistributed and CDF is computed from the clipped histogram.

$$y = \frac{CDF_{clip}(x) - CDF_{min}}{1 - CDF_{min}}$$

3.3. Overview of Autoencoder-GAN hybrid model

The Autoencoder-GAN hybrid model combines the feature extraction capabilities of an autoencoder with the generative capabilities of a GAN to enhance the accuracy of COPD from CXR images. An autoencoder is composed of two main parts: an encoder and a decoder.

Encoder: Maps input *x* to a latent space representation *z* using a series of convolutional layers:

$$z = f_{enc}(x)$$

Decoder: Reconstruct the input $\hat{x}$ from the latent representation *z*:

$$\hat{x} = f_{dec}(z)$$

The objective of the autoencoder is to minimize the reconstruction loss:

$$L_{AE} = ||x - \hat{x}||^2$$

GAN Component

A GAN consists of two networks: a generator and a discriminator. The generator creates synthetic data, while the discriminator evaluates the authenticity of the data (real or generated).

Generator: Produces data $G(z)$ from latent vectors *z:*

$$G(z) = f_{gen}(z)$$

Discriminator: Distinguishes between real data x and generated data $G(z)$:

$$D(x) = f_{disc}(x)$$

$$D\big(G(z)\big) = f_{disc}(G(z))$$

The GAN objective is to solve the following minimax game:

$$min_G max_D E_{x\sim p_{data}}[\log D(x)]) + \ E_{z\sim p_z(z)}[1 - D\big(G(z)\big))]$$

Integration of CLAHE with the Model

The preprocessing method, CLAHE, is applied to the input CXR images to enhance their contrast and detail before feeding them into the autoencoder-GAN hybrid model. This step improves the quality of features extracted by the encoder, leading to better reconstruction and generation capabilities. Consequently, the hybrid model benefits from clearer and more distinguishable features, resulting in improved accuracy in diagnosing COPD. By integrating CLAHE-preprocessed images, the autoencoder effectively learns more informative latent representations, and the GAN component enhances its ability to generate realistic and useful synthetic images, aiding in robust model training and evaluation.

4. Results and output

4.1. Evaluation parameter comparison with various standard models

Table 1 Evaluation parameter comparison

Model	Accuracy	Precision	Recall	F1-Score
proposed model	**0.98**	**0.97**	**0.97**	**0.98**
CNN	0.9	0.89	0.91	0.9
SVM	0.92	0.91	0.93	0.92
RF	0.89	0.87	0.88	0.87

4.2. Comparison of the suggested approach with current methods

Table 2 Comparison table of suggested approach with existing methods

Author	Method	Methodology	Accuracy
Ullah et al.[14]	DeepLungNet	“Classified lung diseases using CXR Images”	94.70%
Nahiduzzaman et al.[15]	“Parallel CNN-ELM”	“Classified 17 lung diseases including COVID-19 using CXR images”	95.32%
Alshmrani et al.[16]	DL Architecture	“Classified multi-class lung diseases using CXR images”	93.80%
Rao et al.[17]	“Hybrid Framework”	“Detected respiratory lung diseases based on CXRs”	96.10%

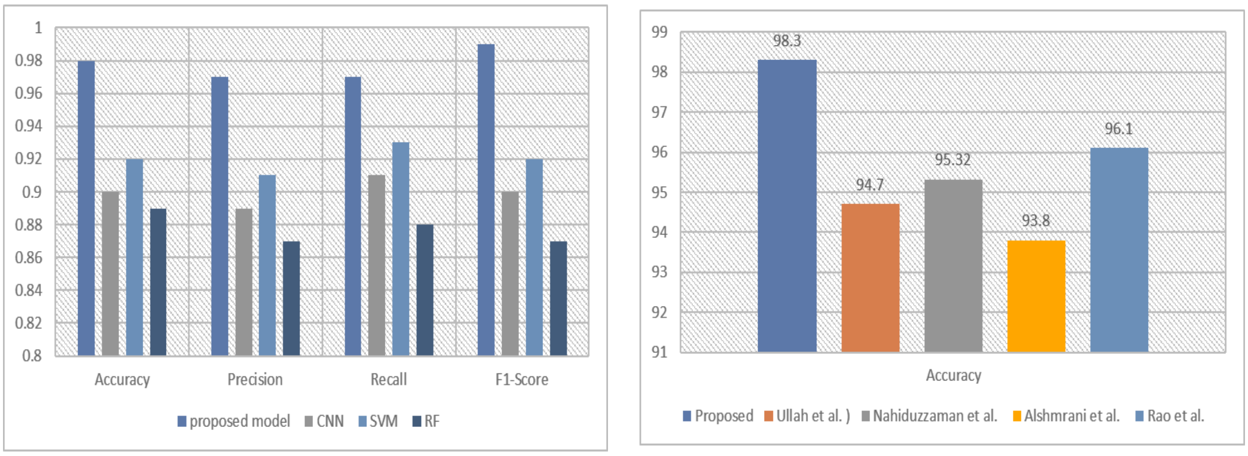

Figure 2 Evaluation parameter comparison with standard models and existing methods

The proposed Autoencoder-GAN hybrid model demonstrates superior performance in diagnosing COPD from CXR images as shown in table-1,2 and figure-2. Achieving an "*accuracy of 98.3%, precision of 0.97, recall of 0.97, and an F1-score of 0.98, it significantly outperforms traditional models. In comparison, the CNN achieves an accuracy of 90%, precision of 0.89, recall of 0.91, and an F1-score of 0.90. The SVM model shows an accuracy of 92%, precision of 0.91, recall of 0.93, and an F1-score of 0.92. Lastly, the RF classifier achieves an accuracy of 89%, precision of 0.87, recall of 0.88, and an F1-score of 0.87*". The proposed model's superior metrics highlight its effectiveness and reliability in improving COPD diagnosis through advanced DL and preprocessing techniques.

5. Conclusion and future scope

The proposed Autoencoder-GAN hybrid model, coupled with the novel preprocessing technique CLAHE, has shown remarkable improvements in diagnosing COPD from CXR images. With an accuracy of 98.3%, the model outperforms traditional models like CNN, SVM, and RF, underscoring its potential for clinical application. The integration of advanced DL techniques and adaptive image enhancement has proven effective in capturing critical features, leading to more reliable and precise diagnostics. Considering for future aspect that explore the integration of additional imaging modalities, like CT scans, to further enhance diagnostic accuracy. The development of real-time diagnostic tools and their deployment in clinical settings would be a significant step toward improving patient outcomes.

References

[1] G. Zhang, L. Luo, L. Zhang, and Z. Liu, "Research Progress of Respiratory Disease and Idiopathic Pulmonary Fibrosis Based on Artificial Intelligence," *Diagnostics*, vol. 13, no. 3. 2023, doi: 10.3390/diagnostics13030357.

[2] K. El Asnaoui, Y. Chawki, and A. Idri, *Automated Methods for Detection and Classification Pneumonia Based on X-Ray Images Using DL*. Springer International Publishing, 2021.

[3] T. B. Chandra and K. Verma, *Pneumonia Detection on CXR Using Machine Learning Paradigm*, vol. 1022 AISC. Springer Singapore, 2020.

[4] H. Agrawal, "Pneumonia Detection Using Image Processing and DL," *Proc. - Int. Conf. Artif. Intell. Smart Syst. ICAIS 2021*, pp. 67–73, 2021, doi: 10.1109/ICAIS50930.2021.9395895.

[5] M. Bhandari, T. B. Shahi, B. Siku, and A. Neupane, "Explanatory classification of CXR images into COVID-19, Pneumonia and Tuberculosis using DL and XAI," *Comput. Biol. Med.*, vol. 150, no. September, p. 106156, 2022, doi: 10.1016/j.compbiomed.2022.106156.

[6] Y. H. Bhosale and K. S. Patnaik, *Bio-medical imaging (X-ray , CT , ultrasound , ECG), genome sequences applications of deep neural network and machine learning in diagnosis , detection , classification , and segmentation of COVID-19 : a Meta-analysis & systematic review*. Multimedia Tools and Applications, 2023.

[7] K. Hammoudi *et al.*, "DL on CXR Images to Detect and Evaluate Pneumonia Cases at the Era of COVID-19," *J. Med. Syst.*, vol. 45, no. 7, 2021, doi: 10.1007/s10916-021-01745-4.

[8] X. Gu, L. Pan, H. Liang, and R. Yang, "Classification of bacterial and viral childhood pneumonia using DL in chest radiography," *ACM Int. Conf. Proceeding Ser.*, pp. 88–93, 2018, doi: 10.1145/3195588.3195597.

[9] D. M. Ibrahim, N. M. Elshennawy, and A. M. Sarhan, "Deep-chest: Multi-classification DL model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases," *Comput. Biol. Med.*, vol. 132, 2021, doi: 10.1016/j.compbiomed.2021.104348.

[10] S. R. Islam, S. P. Maity, A. K. Ray, and M. Mandal, "Automatic Detection of Pneumonia on Compressed Sensing Images using DL," *2019 IEEE Can. Conf. Electr. Comput. Eng. CCECE 2019*, pp. 9–12, 2019, doi: 10.1109/CCECE.2019.8861969.

[11] V. Agarwal, M. C. Lohani, A. S. Bist, E. P. Harahap, and A. Khoirunisa, "Analysis Of DL Techniques For CXR Classification In Context Of Covid-19," *ADI J. Recent Innov.*, vol. 3, no. 2, pp. 208–216, 2022, doi: 10.34306/ajri.v3i2.659.

[12] W. O'Quinn, R. J. Haddad, and D. L. Moore, "Pneumonia Radiograph Diagnosis Utilizing DL Network," *Proc. 2019 IEEE 2nd Int. Conf. Electron. Inf. Commun. Technol. ICEICT 2019*, pp. 763–767, 2019, doi: 10.1109/ICEICT.2019.8846438.

[13] PAUL MOONEY, "CXR Images (Pneumonia)," *"CXR Images (Pneumonia)," Kaggle. Accessed May 02, 2018. [Online]. Available at:* pp. 1–1, 2018, [Online]. Available: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

[14] N. Ullah, M. Marzougui, I. Ahmad, and S. A. Chelloug, "DeepLungNet: An Effective DL-Based Approach for Lung Disease Classification Using CRIs," *Electron.*, vol. 12, no. 8, 2023, doi: 10.3390/electronics12081860.

[15] M. Nahiduzzaman *et al.*, "Parallel CNN-ELM: A multiclass classification of CXR images to identify seventeen lung diseases including COVID-19," *Expert Syst. Appl.*, vol. 229, p. 120528, 2023, doi: https://doi.org/10.1016/j.eswa.2023.120528.

[16] G. M. M. Alshmrani, Q. Ni, R. Jiang, H. Pervaiz, and N. M. Elshennawy, "A DL architecture for multi-class lung diseases classification using CXR (CXR) images," *Alexandria Eng. J.*, vol. 64, pp. 923–935, 2023, doi: https://doi.org/10.1016/j.aej.2022.10.053.

[17] G. V. E. Rao, R. B., P. N. Srinivasu, M. F. Ijaz, and M. Woźniak, "Hybrid framework for respiratory lung diseases detection based on classical CNN and quantum classifiers from CXRs," *Biomed. Signal Process. Control*, vol. 88, p. 105567, 2024, doi: https://doi.org/10.1016/j.bspc.2023.105567.