**DEEP-LEARNING-BASED-CNN ALGORITHMN DIAGNOSING DIVERSE LUNG DISEASES FROM CHEST X-RAY IMAGES**

**ABSTRACT**

The global public health concern of lung diseases is substantial—due to the rise in morbidity and mortality rates. The emergence of the COVID-19 pandemic in late 2019 has brought even greater urgency for early and accurate diagnosis and management of these diseases. Although chest X-rays play a crucial role in identifying and monitoring these conditions, accurately interpreting the images remains challenging—as the task relies on the expertise and experience of radiologists—making the process time-consuming for large datasets and susceptible to human error when detecting subtle signs of the diseases. Considering the issue, our paper presents a state-of-the-art deep-learning-based CNN algorithm that enables the development of an automated AI tool capable of accurately and independently identifying abnormalities and detecting specific lung diseases.

**Keywords:** Convolution Neural Network (CNN), Chest X-Ray (CXR), Deep-learning (DL), Densely Connected Convolutional Network (DenseNet)

**INTRODUCTION**

Lung diseases are medical conditions that affect the lungs and respiratory system. These conditions develop from various causes such as infections, genetic factors, or environmental factors like smoking, pollution, or chemical exposure. Lung diseases manifest in several types, from acute conditions like pneumonia and bronchitis to chronic conditions such as asthma, lung cancer, and COPD. These diseases often exhibit diverse symptoms, including coughing, shortness of breath, wheezing, chest pain, and fatigue [1], [2]. Consequently, lung diseases have become a substantial cause of morbidity and mortality globally, leading to millions of deaths annually—particularly in low and middle-income countries [3], [4].

The outbreak of the COVID-19 pandemic in late 2019 has emphasized the critical importance of diagnosing and managing lung conditions: not only to prevent infection in individuals with pre-existing lung diseases but also to reduce the risk of severe illness to those already infected [5], [6]. While chest X-rays are a fast, cost-effective, and non-invasive imaging tool that provides valuable and relevant information for diagnosing lung diseases, accurately interpreting the images remains challenging for subtle abnormalities or early-stage diseases. The process relies on the expertise and experience of radiologists, making it expensive, time-consuming, and prone to human errors —resulting in missed or incorrect diagnoses [7]–[10].

In recent years, Artificial Intelligence (AI) has established itself as a dominant and potent technology in medical imaging [11], [12]. By automatically and objectively analyzing images, AI can achieve improved levels of accuracy. Hence, incorporating AI into the analysis of Chest X-ray images can aid in reducing subjectivity interpretation by radiologists [13]. However, earlier studies have suggested that the top traditional machine learning AI algorithms, including support vector machines (SVMs) and decision trees, have certain drawbacks. Specifically, they are subjective due to their dependence on expert domain knowledge and manual feature engineering. Additionally, these techniques are not well-suited for handling large unstructured datasets and can be time-consuming [14], [15].

The capability of Deep learning (DL) to mimic human brain behavior in solving intricate problems—by training artificial neural networks in multiple computational layers: has exhibited immense potential in medical imaging analysis [16]–[18]. As a result, DL has emerged as breathtaking AI innovation in Chest X-ray imaging [19]. With the help of the CNN algorithm, it is now viable to effectively analyze and categorize high-dimensional Chest X-ray images [20]. This algorithm extracts relevant patterns and structures from numerous data, regardless of their variation in qualities—without explicitly feature engineering. Hence, it is fast and achieves accurate results at a low cost [21], [22].

This study demonstrates a Deep learning CNN-based algorithm tool that uses Chest X-ray images to diagnose Lung diseases and abnormalities. The paper is structured as follows: Section I provides background information; Section II describes the Materials and proposed Methods; Section III presents the experimental setup and results; and Section IV concludes the paper and discusses future work.

**BIBLIOGRAPHY**

[1] A. Lorensia, R. V. Suryadinata, and I. N. Y. Diputra, “Risk Factors and Early Symptoms Related to Respiratory Disease in Pedicab Drivers in Surabaya,” *KEMAS J. Kesehat. Masy.*, vol. 15, no. 2, Art. no. 2, 2019, Accessed: Apr. 03, 2023. [Online]. Available: http://repository.ubaya.ac.id/37026/

[2] P. Montnémery, P. Bengtsson, A. Elliot, L.-H. Lindholm, P. Nyberg, and C.-G. Löfdahl, “Prevalence of obstructive lung diseases and respiratory symptoms in relation to living environment and socio-economic group,” *Respir. Med.*, vol. 95, no. 9, pp. 744–752, Sep. 2001, doi: 10.1053/rmed.2001.1129.

[3] GBD 2015 LRI Collaborators, “Estimates of the global, regional, and national morbidity, mortality, and aetiologies of lower respiratory tract infections in 195 countries: a systematic analysis for the Global Burden of Disease Study 2015,” *Lancet Infect. Dis.*, vol. 17, no. 11, pp. 1133–1161, Nov. 2017, doi: 10.1016/S1473-3099(17)30396-1.

[4] “Prevalence and attributable health burden of chronic respiratory diseases, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017,” *Lancet Respir. Med.*, vol. 8, no. 6, pp. 585–596, Jun. 2020, doi: 10.1016/S2213-2600(20)30105-3.

[5] H. Kilic *et al.*, “Effect of chronic lung diseases on mortality of prevariant COVID-19 pneumonia patients,” *Front. Med.*, vol. 9, p. 957598, Oct. 2022, doi: 10.3389/fmed.2022.957598.

[6] S. J. Tzotzos, B. Fischer, H. Fischer, and M. Zeitlinger, “Incidence of ARDS and outcomes in hospitalized patients with COVID-19: a global literature survey,” *Crit. Care Lond. Engl.*, vol. 24, no. 1, p. 516, Aug. 2020, doi: 10.1186/s13054-020-03240-7.

[7] D. C. Moncada, Z. V. Rueda, A. Macías, T. Suárez, H. Ortega, and L. A. Vélez, “Reading and interpretation of chest X-ray in adults with community-acquired pneumonia,” *Braz. J. Infect. Dis. Off. Publ. Braz. Soc. Infect. Dis.*, vol. 15, no. 6, pp. 540–546, 2011.

[8] B. Moifo *et al.*, “Inter-Observer Variability in the Detection and Interpretation of Chest X-Ray Anomalies in Adults in an Endemic Tuberculosis Area,” *Open J. Med. Imaging*, vol. 5, no. 3, Art. no. 3, Aug. 2015, doi: 10.4236/ojmi.2015.53018.

[9] R. M. Hopstaken, T. Witbraad, J. M. A. van Engelshoven, and G. J. Dinant, “Inter-observer variation in the interpretation of chest radiographs for pneumonia in community-acquired lower respiratory tract infections,” *Clin. Radiol.*, vol. 59, no. 8, pp. 743–752, Aug. 2004, doi: 10.1016/j.crad.2004.01.011.

[10] S. Sakurada *et al.*, “Inter-rater agreement in the assessment of abnormal chest X-ray findings for tuberculosis between two Asian countries,” *BMC Infect. Dis.*, vol. 12, p. 31, Feb. 2012, doi: 10.1186/1471-2334-12-31.

[11] “Artificial intelligence in healthcare: past, present and future - PubMed.” https://pubmed.ncbi.nlm.nih.gov/29507784/ (accessed Apr. 02, 2023).

[12] K. G. van Leeuwen, M. de Rooij, S. Schalekamp, B. van Ginneken, and M. J. C. M. Rutten, “How does artificial intelligence in radiology improve efficiency and health outcomes?,” *Pediatr. Radiol.*, vol. 52, no. 11, pp. 2087–2093, Oct. 2022, doi: 10.1007/s00247-021-05114-8.

[13] J. T. Wu *et al.*, “Comparison of Chest Radiograph Interpretations by Artificial Intelligence Algorithm vs Radiology Residents,” *JAMA Netw. Open*, vol. 3, no. 10, p. e2022779, Oct. 2020, doi: 10.1001/jamanetworkopen.2020.22779.

[14] A. Yilmaz, A. A. Demircali, S. Kocaman, and H. Uvet, “Comparison of Deep Learning and Traditional Machine Learning Techniques for Classification of Pap Smear Images.” arXiv, Sep. 11, 2020. Accessed: Apr. 03, 2023. [Online]. Available: http://arxiv.org/abs/2009.06366

[15] Y. Lai, “A Comparison of Traditional Machine Learning and Deep Learning in Image Recognition,” *J. Phys. Conf. Ser.*, vol. 1314, no. 1, p. 012148, Oct. 2019, doi: 10.1088/1742-6596/1314/1/012148.

[16] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, Art. no. 7553, May 2015, doi: 10.1038/nature14539.

[17] “Deep Learning Techniques for Biomedical and Health Informatics | SpringerLink.” https://link.springer.com/book/10.1007/978-3-030-33966-1 (accessed Apr. 03, 2023).

[18] A. Anaya-Isaza, L. Mera-Jiménez, and M. Zequera-Diaz, “An overview of deep learning in medical imaging,” *Inform. Med. Unlocked*, vol. 26, p. 100723, Jan. 2021, doi: 10.1016/j.imu.2021.100723.

[19] E. Çallı, E. Sogancioglu, B. van Ginneken, K. G. van Leeuwen, and K. Murphy, “Deep learning for chest X-ray analysis: A survey,” *Med. Image Anal.*, vol. 72, p. 102125, Aug. 2021, doi: 10.1016/j.media.2021.102125.

[20] X. Lessage, S. Mahmoudi, S. A. Mahmoudi, S. Laraba, O. Debauche, and M. A. Belarbi, “Chest X-ray Images Analysis with Deep Convolutional Neural Networks (CNN) for COVID-19 Detection,” in *Healthcare Informatics for Fighting COVID-19 and Future Epidemics*, L. Garg, C. Chakraborty, S. Mahmoudi, and V. S. Sohmen, Eds., in EAI/Springer Innovations in Communication and Computing. Cham: Springer International Publishing, 2022, pp. 403–423. doi: 10.1007/978-3-030-72752-9\_21.

[21] D. R. Sarvamangala and R. V. Kulkarni, “Convolutional neural networks in medical image understanding: a survey,” *Evol. Intell.*, vol. 15, no. 1, pp. 1–22, 2022, doi: 10.1007/s12065-020-00540-3.

[22] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, “Convolutional neural networks: an overview and application in radiology,” *Insights Imaging*, vol. 9, no. 4, pp. 611–629, Aug. 2018, doi: 10.1007/s13244-018-0639-9.