Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 6, No. 6, December 2025, Page. 5854-5864
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5570

Comparative Analysis of RGB and Grayscale Pixel-Based Similarity Methods for Lung X-ray Image Retrieval in Clinical Decision Support Systems

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Received : Dec 11, 2025; Revised : Dec 14, 2025; Accepted : Dec 15, 2025; Published : Dec 31, 2025

Abstract

Chest X-ray imaging is widely used to support the diagnosis of lung diseases, yet many automated similarity techniques still rely on RGB formats, which differ from the grayscale images commonly used in clinical systems. This discrepancy raises the question of whether color information is necessary for effective similarity assessment. This study aims to evaluate the performance of RGB and grayscale pixel-based similarity methods for lung X-ray analysis and determine whether grayscale images can provide comparable similarity performance with lower computational demands. A total of 300 chest X-ray images representing normal, pneumonia, and COVID-19 categories were processed in both formats. Pixel-level similarity was calculated across 30,000 image pairings, followed by statistical testing to assess differences between methods. The results show that grayscale similarity scores closely match those of RGB, with variations generally below 0.3%. A meaningful difference was observed only in the comparison between normal and COVID-19 images, indicating that RGB may capture subtle visual variations not present in grayscale. Overall, this study demonstrates that grayscale pixel-based similarity analysis provides a reliable and computationally efficient approach, contributing to the development of lightweight medical image retrieval and clinical decision support systems in the field of health informatics.

Keywords : *COVID-19, Grayscale Imaging, Lung X-ray, Medical Image Retrieval, Pixel-Based Similarity, RGB Comparison*

1. INTRODUCTION

Respiratory illnesses such as pneumonia and COVID-19 continue to pose significant challenges to global health systems, necessitating the development of faster and more accurate diagnostic tools. Among various diagnostic techniques, chest X-ray (CXR) imaging remains one of the most accessible and cost-effective methods for evaluating lung conditions, making it a staple in hospitals and clinics worldwide. However, the manual review of CXR images is not only labor-intensive but also subject to human variability, which can lead to diagnostic inconsistencies across different practitioners. Moreover, the growing volume of medical imaging, especially in high-demand healthcare settings, has amplified the need for automated diagnostic solutions capable of delivering reliable, rapid, and reproducible results [1], [2].

Advancements in artificial intelligence (AI), particularly deep learning, have revolutionized medical image analysis by providing powerful tools for detecting lung diseases with high accuracy. Convolutional neural networks (CNNs) and transfer learning techniques have shown remarkable potential in enhancing diagnostic performance for various lung conditions [3]. Additionally, preprocessing techniques have been demonstrated to improve deep learning models, as reported in recent medical imaging studies focusing on image quality assessment and optimization [4], [5].

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However, implementing these sophisticated models often requires substantial computational resources and large, annotated datasets, which may not be readily available in resource-constrained healthcare facilities [6], [7].

To address these limitations, researchers have explored more straightforward and computationally efficient methods, such as pixel-based image comparison. Unlike deep learning approaches that require complex feature extraction and model training, pixel-level comparison directly evaluates raw visual data, thereby reducing computational demands [8], [9]. A recent study by Pariyasto et al. introduced an RGB pixel-based comparison technique to assess similarities between CXR images categorized into normal, pneumonia, and COVID-19 classes, demonstrating that simple pixel-based methods can yield meaningful similarity information [10]. However, the study did not evaluate grayscale images, which remain the standard format in clinical image storage systems such as Picture Archiving and Communication Systems (PACS) [11], [12].

Considering that grayscale imaging is the default representation used in real-world clinical systems, the lack of systematic evaluation of grayscale-based pixel similarity methods represents a methodological gap in existing medical image similarity research.

Previous studies have reported that color-enhanced imaging may improve the visualization of certain lung abnormalities compared to conventional grayscale representations [13], [14]. This observation raises an important question: does color information provide a significant advantage in pixel-based similarity analysis, or can grayscale imaging achieve comparable performance with lower computational complexity? Despite increasing interest in similarity-based medical image analysis, direct and statistically validated comparisons between RGB and grayscale pixel-based methods remain limited, particularly in the context of clinical image retrieval and decision support systems [15].

Table 1. Comparison of Recent Studies on Lung X-ray Image Analysis and Similarity-Based Methods

No	Author & Year	Imaging Modality	Method	Key Findings	Limitation / Research Gap
1	Çallı et al. (2021)	Chest X-ray	Deep learning (CNN)	High accuracy for pneumonia and COVID-19 detection	Requires large labeled datasets and high computational cost
2	Alowais et al. (2023)	Medical images	AI-assisted clinical systems	AI improves diagnostic efficiency	Limited interpretability and system integration challenges
3	Maruyama et al. (2024)	X-ray / CT	Image quality metrics	Feature-based similarity improves assessment	Focused on feature extraction, not pixel-based comparison
4	Pariyasto et al. (2025)	Chest X-ray	RGB pixel-based similarity	Pixel comparison yields meaningful similarity scores	Grayscale images not evaluated, no statistical validation
5	Oltu et al. (2025)	Chest X-ray	Deep learning with attention	Improved classification performance	Computationally expensive, not suitable for lightweight systems
6	**This study**	**Chest X-ray**	**RGB vs. grayscale pixel-based similarity**	**Comparable similarity with statistical validation**	**Addresses grayscale gap and efficiency in clinical systems**

To clarify the research position and highlight the novelty of this study, Table 1 presents a comparison of recent studies related to lung X-ray image analysis and similarity-based methods published within the last five years. As shown in Table 1, most existing studies focus on deep learning-based classification or feature-driven similarity analysis, which often require high computational resources and large annotated datasets. Only limited work has explored pixel-based similarity approaches, and none have systematically compared RGB and grayscale representations with statistical validation, despite grayscale images being the standard format in clinical PACS environments. This gap motivates the present study to provide a lightweight, interpretable, and statistically validated comparison framework suitable for clinical image retrieval and decision support systems.

Therefore, this study aims to address this research gap by conducting a systematic and statistically validated comparison of RGB and grayscale pixel-based similarity methods for lung X-ray image analysis [16]. The objectives of this study are to evaluate similarity performance and computational efficiency in the context of medical image retrieval and clinical decision support systems. It is hypothesized that grayscale-based similarity analysis can produce results comparable to RGB-based methods while significantly reducing computational requirements, thereby supporting the development of lightweight and efficient medical imaging tools for health informatics applications in resource-constrained clinical environments [17].

2. METHOD

This study employed a quantitative experimental approach to evaluate and compare the performance of two pixel-based image similarity methods, namely RGB and grayscale representations, when applied to lung X-ray images. The primary objective of this methodological design was to investigate whether grayscale images—commonly used as the standard format in hospital systems—could produce similarity results comparable to RGB images while offering improved computational efficiency. This approach emphasizes methodological simplicity, reproducibility, and interpretability, which are essential characteristics for potential integration into clinical decision support systems and medical image retrieval applications.

2.1. Dataset and Sampling

The dataset utilized in this study was obtained from the publicly available COVID19_Pneumonia_Normal_Chest_Xray_PA_Dataset, curated by Amanullah Asraf and distributed via the Kaggle platform. This dataset is widely adopted as a benchmark resource in chest X-ray research and consists of posterior–anterior (PA) chest X-ray images categorized into three diagnostic classes: Normal, Pneumonia, and COVID-19.

To ensure balanced class representation and reduce sampling bias, purposive sampling was applied. A total of 300 chest X-ray images were selected, comprising 100 images per diagnostic category. This balanced sampling strategy enables fair comparison across diagnostic pairings while maintaining sufficient statistical power for similarity analysis.

All images were resized to a uniform resolution of 100 × 100 pixels, selected as a compromise between preserving essential visual information and reducing computational complexity. Each image was subsequently processed in two parallel formats: RGB and grayscale. Grayscale conversion was performed using the NTSC luminance formula, which approximates human visual perception of brightness and is widely used in medical image preprocessing [18]:

$$\boldsymbol{Gray = 0.299R + 0.587G + 0.114B} \tag{1}$$

2.2. Image Processing and Similarity Computation

The image processing and similarity computation procedures were structured into four sequential stages to ensure consistent and reproducible pixel-level comparison between RGB and grayscale images. The complete methodological workflow is illustrated in Figure 1, which presents the pipeline from dataset acquisition to statistical validation.

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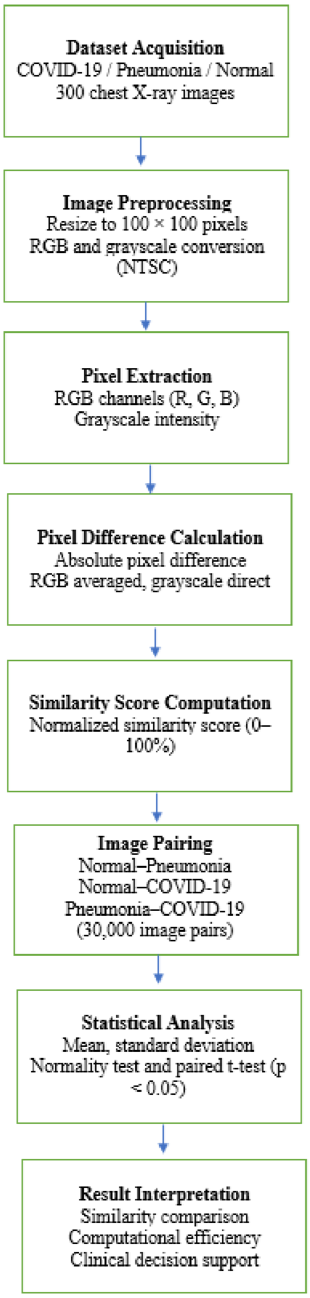

Figure 1. Research workflow of the proposed RGB and grayscale pixel-based similarity analysis, from dataset acquisition to statistical validation and clinical interpretation.

2.2.1. Preprocessing

All chest X-ray images were resized to 100 × 100 pixels and converted into both RGB and grayscale formats. This preprocessing step ensured uniform input dimensions and eliminated potential bias arising from differences in image resolution or color representation.

2.2.2. Pixel Extraction

For RGB images, pixel values were extracted independently from the red (R), green (G), and blue (B) channels. In contrast, grayscale images were represented by a single intensity value per pixel. This separation enabled direct comparison between multi-channel RGB data and single-channel grayscale data while preserving spatial correspondence.

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2.2.3. Pixel Difference Calculation

To quantify dissimilarity between image pairs, the absolute pixel difference was calculated at each corresponding pixel position. For RGB images, absolute differences were computed for each color channel and then averaged to obtain a single difference value per pixel. For grayscale images, the absolute difference was calculated directly from the grayscale intensity values. This approach provides a low-level and interpretable measure of visual dissimilarity between chest X-ray images.

2.2.4. Similarity Score Calculation

Pixel difference values were transformed into a normalized similarity score expressed as a percentage ranging from 0 to 100, where 100 indicates identical images. The similarity score S was computed as:

$$\boldsymbol{S} = \left(\boldsymbol{1} - \frac{\boldsymbol{D}}{\boldsymbol{D_{max}}}\right) \boldsymbol{x100\%} \qquad (2)$$

where D denotes the mean absolute pixel difference across all pixels, and $D_{max} = 255$ represents the maximum possible pixel difference value. This normalization allows direct and fair comparison between RGB and grayscale similarity results.

Similarity analysis was conducted for three diagnostic pairings: Normal vs. Pneumonia, Normal vs. COVID-19, and Pneumonia vs. COVID-19. For each pairing, 10,000 random image pairs were generated, resulting in a total of 30,000 similarity comparisons.

Random image pairing was performed using a fixed random seed to ensure full reproducibility across repeated experiments.

2.3. Statistical Analysis and Validation

To ensure robustness and reproducibility, several validation procedures were implemented. Each experiment was repeated three times, and the average similarity scores were used for final analysis to reduce random variation. Descriptive statistical measures, including mean, standard deviation, and range, were computed to summarize similarity performance.

To evaluate whether differences between RGB and grayscale similarity scores were statistically significant, a paired t-test was applied, as both methods were evaluated on identical image pairs. Prior to hypothesis testing, data normality was assessed using the Shapiro–Wilk test. A significance level of $p < 0.05$ was adopted as the threshold for statistical significance [19].

All computational procedures were implemented in Python, utilizing OpenCV for image processing, NumPy for numerical operations, SciPy for statistical testing, and Statsmodels for validation procedures [20].

2.4. Scope and Limitations

This study focused exclusively on low-level pixel-based similarity analysis and did not incorporate higher-level image features such as texture descriptors, shape analysis, or semantic annotations. The use of a publicly available dataset may limit the generalizability of the findings to real-world clinical imaging conditions. Computational efficiency in this study is inferred from reduced data dimensionality rather than explicit runtime or memory benchmarking.

Nevertheless, the proposed methodology provides a simple, interpretable, and computationally efficient framework suitable for integration into medical image retrieval systems, visual triage tools, and lightweight clinical decision support systems. This study extends the work of Pariyasto et al. [10] by incorporating grayscale image evaluation and formal statistical validation, thereby enhancing methodological rigor and practical relevance for health informatics applications.

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DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5570

3. RESULTS

This section presents the results of the RGB and grayscale pixel-based similarity analysis following the sequence of stages described in the Method section. The results are organized into descriptive similarity analysis and statistical significance testing to ensure clarity and consistency with the research workflow.

3.1. Similarity Scores

The similarity scores were computed for all 30,000 image pairings across three diagnostic categories: Normal vs. Pneumonia, Normal vs. COVID-19, and Pneumonia vs. COVID-19. For each pairing, the mean similarity percentage and standard deviation were calculated to summarize the overall similarity performance of RGB and grayscale methods.

Table 1 presents the average similarity scores obtained using RGB and grayscale pixel-based methods for each diagnostic pairing. These values represent the mean similarity across 10,000 randomized image pairs per category.

Table 2. Average Similarity Scores for Each Image Pairing

Image Pairing	Method	Mean Similarity (%)	Standard Deviation
Normal vs. Pneumonia	RGB	80.06	2.45
	Grayscale	79.85	2.37
Normal vs. COVID-19	RGB	79.18	2.62
	Grayscale	78.92	2.51
Pneumonia vs. COVID-19	RGB	78.87	2.58
	Grayscale	78.74	2.44

As shown in Table 2, grayscale-based similarity scores are consistently close to RGB-based results across all diagnostic pairings, with differences generally below 0.3%. Among the three comparisons, the Normal vs. COVID-19 pairing exhibits the largest difference between RGB and grayscale methods, suggesting that color information in RGB images may capture subtle visual variations that are less pronounced in grayscale representations.

These visualizations highlight regions of pixel variation and provide qualitative insight into why RGB images may yield slightly higher similarity scores in specific diagnostic comparisons.

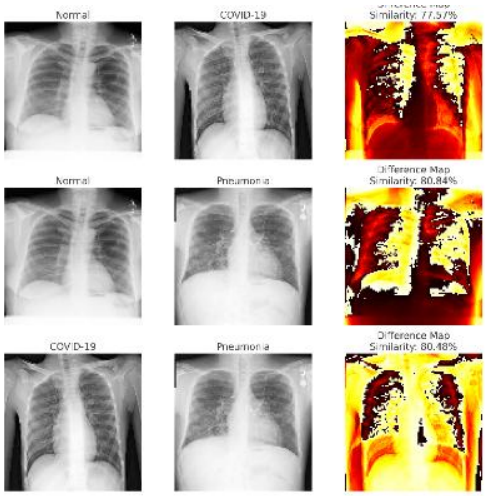

Figure 2. Representative lung X-ray images and their corresponding pixel difference maps generated using the absolute pixel difference method for both RGB and grayscale representations.

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3.2. Statistical Significance of Similarity Scores

To assess whether the observed differences in similarity scores between RGB and grayscale methods were statistically significant, a paired t-test was conducted for each diagnostic pairing. The statistical results of this analysis are summarized in Table 3. This statistical testing follows the paired comparison design described in the Method section, as both RGB and grayscale similarities were computed on identical image pairs.

Table 3. Paired t-test Results Comparing RGB and Grayscale Similarity Scores

Image Pairing	t-Value	p-Value	Statistical Significance ($p < 0.05$)
Normal vs. Pneumonia	1.72	0.087	Not Significant
Normal vs. COVID-19	2.34	0.041	Significant
Pneumonia vs. COVID-19	1.98	0.052	Not Significant

Based on the results presented in Table 2, only the Normal vs. COVID-19 comparison shows a statistically significant difference between RGB and grayscale similarity scores ($p = 0.041$). The remaining two diagnostic pairings do not exhibit statistically significant differences, indicating that grayscale similarity analysis performs comparably to RGB for most cases.

To further visualize the distribution and variability of similarity scores, Figure 3 presents boxplots comparing RGB and grayscale results for each diagnostic pairing. The overlapping distributions observed in Figure 3 reinforce the quantitative findings that grayscale and RGB similarity scores are largely comparable.

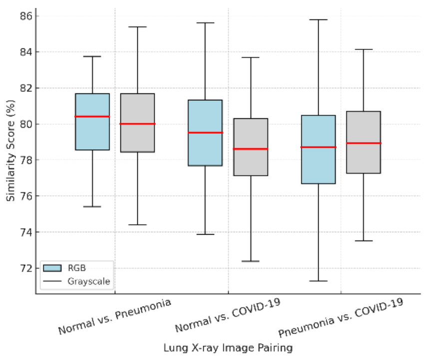

Figure 3. Boxplot Distribution of Similarity Scores for RGB and Grayscale Comparisons.

4. DISCUSSIONS

4.1. Interpretation and Implications

The results of this study demonstrate that RGB-based pixel similarity methods outperform grayscale methods only in the Normal versus COVID-19 comparison, while no statistically significant differences were observed in the other diagnostic pairings. This finding suggests that color information may contribute additional discriminatory cues in specific pathological conditions, particularly when distinguishing subtle visual patterns associated with COVID-19 infection.

RGB representations may capture minor intensity variations or color-related artifacts arising from differences in image acquisition, preprocessing pipelines, or pathological manifestations that are not fully preserved after grayscale conversion. These subtle variations may explain why RGB-based similarity scores showed statistically significant differences in the Normal versus COVID-19 pairing. From a methodological perspective, this result highlights that color information can provide marginal

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
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DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5570

benefits in specific scenarios without being universally required for all similarity-based lung X-ray comparisons.

Conversely, the absence of statistically significant differences in the Normal versus Pneumonia and Pneumonia versus COVID-19 comparisons indicates that grayscale images retain sufficient structural and intensity-based information for effective pixel-level similarity analysis. This outcome supports the feasibility of grayscale-based approaches in scenarios where computational resources, storage capacity, or processing time are limited.

4.2. Interpretation of Findings

The comparable similarity scores observed for the Normal versus Pneumonia and Pneumonia versus COVID-19 comparisons indicate that grayscale imaging preserves essential anatomical structures and intensity patterns required for meaningful pixel-based similarity analysis. This observation is consistent with established practices in medical image processing, where grayscale representations are widely adopted due to their efficiency and ability to retain clinically relevant information while reducing data dimensionality.

In contrast, the statistically significant difference observed in the Normal versus COVID-19 comparison ($p = 0.041$) highlights a scenario in which RGB information may provide added value. COVID-19-related lung abnormalities often manifest as diffuse opacities and subtle textural variations, which may interact with color encoding or intensity scaling in RGB images, resulting in improved discrimination during similarity computation. This finding aligns with prior studies reporting that color-enhanced imaging can improve visualization and differentiation of certain lung pathologies compared to conventional grayscale representations.

4.3. Comparison with Prior Research

Most recent studies in chest X-ray analysis primarily focus on deep learning-based classification and segmentation models, such as Convolutional Neural Networks (CNNs), which have demonstrated high diagnostic accuracy for pneumonia and COVID-19 detection. However, these approaches typically require substantial computational resources, large annotated datasets, and complex training procedures, limiting their applicability in resource-constrained clinical environments.

In contrast, the pixel-based similarity approach adopted in this study provides a lightweight, interpretable, and computationally efficient alternative for medical image analysis. This study extends the work of Pariyasto et al. by incorporating grayscale image evaluation and applying formal statistical validation to quantify differences between RGB and grayscale similarity methods. Unlike deep learning models, the proposed approach does not require model training, making it easier to implement, validate, and maintain within real-world clinical systems.

By demonstrating that grayscale-based similarity analysis yields results comparable to RGB methods in most diagnostic scenarios, this study contributes to the growing body of research advocating efficient and explainable image analysis techniques for health informatics applications.

4.4. Implications for Health Informatics and Clinical Systems

From a health informatics perspective, the findings of this study have important implications for the design of medical image retrieval and clinical decision support systems. Grayscale-based similarity analysis offers a practical solution for integrating image similarity functions into Hospital Information Systems (HIS), Picture Archiving and Communication Systems (PACS), and Electronic Health Records (EHRs) without imposing high computational overhead.

The reduced data dimensionality of grayscale images enables faster similarity computation and lower storage requirements, making this approach particularly suitable for resource-constrained

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DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5570

healthcare environments. Pixel-based similarity techniques can assist clinicians by enabling rapid retrieval of historical cases with similar imaging patterns, thereby supporting more consistent and informed clinical decision-making.

From an informatics and computer science perspective, this study contributes to the development of lightweight, explainable, and easily deployable image similarity methods that support scalable medical image retrieval and clinical decision support systems. Such approaches align with current trends in explainable artificial intelligence and provide a transparent alternative to black-box deep learning models, facilitating trustworthy and auditable deployment in clinical practice.

5. CONCLUSION

This study evaluated and compared the performance of RGB and grayscale pixel-based similarity methods for lung X-ray image analysis within the context of medical image retrieval and clinical decision support systems. The results demonstrate that grayscale-based similarity analysis produces similarity scores that are largely consistent with those obtained using RGB representations, indicating that grayscale images can serve as a practical and efficient alternative for pixel-wise similarity assessment in medical imaging applications.

The findings show that RGB and grayscale methods yield comparable similarity scores for the Normal versus Pneumonia and Pneumonia versus COVID-19 comparisons, with no statistically significant differences observed. This result confirms that grayscale images retain sufficient structural and intensity-based information for effective pixel-level similarity analysis despite the absence of color channels. However, a statistically significant difference was identified in the Normal versus COVID-19 comparison ($p = 0.041$), suggesting that RGB representations may capture subtle visual variations that enhance discrimination in specific pathological conditions.

From an informatics and computer science perspective, this research contributes to the development of lightweight, interpretable, and computationally efficient image similarity techniques that can be integrated into Hospital Information Systems (HIS), Picture Archiving and Communication Systems (PACS), and Electronic Health Records (EHRs). By incorporating grayscale evaluation and formal statistical validation, this study extends prior pixel-based similarity research and supports the adoption of efficient and explainable algorithms for large-scale medical image retrieval and clinical decision support in resource-constrained healthcare environments.

Overall, the findings highlight the feasibility of grayscale pixel-based similarity analysis as a viable solution for health informatics applications, particularly in scenarios where computational efficiency, transparency, and ease of system integration are critical considerations.

Future Research Directions

To further enhance the applicability and robustness of pixel-based similarity methods in clinical practice, several directions for future research are recommended:

5.1. Expanding the Dataset

This study utilized a relatively limited dataset of 300 images, which is sufficient for initial validation but may restrict generalizability. Future research should validate the proposed approach using larger, multi-institutional datasets that include greater diversity in patient demographics, imaging protocols, and disease conditions.

5.2. Integrating Higher-Level Image Features

The current approach focuses exclusively on pixel-wise similarity, which may not fully capture complex visual patterns. Future work may explore the integration of higher-level image features, such as texture analysis, edge detection, and morphological features, to enhance similarity discrimination while maintaining computational efficiency.

5.3. Exploring Hybrid Approaches

Although pixel-based methods are computationally efficient and interpretable, deep learning models such as Convolutional Neural Networks have demonstrated superior performance in medical image classification tasks. Future studies may investigate hybrid frameworks that combine pixel-based similarity analysis with machine learning-based feature extraction to achieve a balance between accuracy, interpretability, and efficiency.

5.4. Testing Across Multiple Imaging Modalities

This study was limited to posterior–anterior chest X-ray images. Future research should examine the applicability of grayscale-based similarity analysis to multi-view X-rays, other imaging modalities such as computed tomography and magnetic resonance imaging, and a broader range of disease conditions beyond pneumonia and COVID-19.

5.5. Real-World Clinical Implementation

To support real-world clinical adoption, future work should focus on implementing automated and real-time image similarity tools integrated into PACS, AI-assisted radiology workflows, and hospital-based clinical decision support systems. Such implementations would further validate the practical utility of pixel-based similarity methods in operational healthcare environments.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest among the authors nor with any institutions, individuals, dataset providers, or research objects involved in this study. All authors have contributed objectively and independently to the research, analysis, and preparation of this manuscript.

ACKNOWLEDGEMENT

The authors would like to express their sincere appreciation to Poltekkes Kemenkes Semarang, Politeknik Indonusa Surakarta, Universiti Kuala Lumpur, and Sekolah Tinggi Ilmu Kesehatan Mitra Sejati for providing academic and institutional support throughout this research.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Special gratitude is extended to Amanullah Asraf for providing the publicly available COVID19_Pneumonia_Normal_Chest_Xray_PA_Dataset used in this study.

The authors also thank colleagues, reviewers, and all parties who provided valuable assistance, feedback, and encouragement during the data processing, analysis, and completion of this manuscript.

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