

Implementation of Contrast Limited Adaptive Histogram Equalisation in CNN-Based Pneumonia Detection Using Chest X-ray Images: A Systematic Literature Review

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ABSTRACT

Pneumonia remains a major global health burden, and chest X-ray (CXR) interpretation is constrained by image quality and observer variability. Contrast Limited Adaptive Histogram Equalisation (CLAHE) is widely used to enhance local contrast before convolutional neural network (CNN) classification, yet its contribution has not been synthesised systematically. This study aims to review how CLAHE is implemented in CNN-based pneumonia detection, which architectures accompany it, how it relates to diagnostic performance, and which methodological gaps remain. A systematic literature review following the PRISMA 2020 guidelines was conducted on the Scopus database for 2021–2026; of 82 records identified, 21 journal articles were included and analysed through thematic synthesis. Four themes emerged: CLAHE implementation strategies, CNN architectures and learning strategies, performance of CLAHE-based pipelines, and methodological robustness. CLAHE was rarely applied alone; it was combined with normalisation, denoising, and augmentation and was increasingly optimised or modified. Transfer learning models dominated, and the highest reported accuracies ranged from 92% to 99.78%. However, heterogeneous datasets, CLAHE parameters, validation protocols, and metrics, together with scarce ablation and external validation, prevent attributing these gains to CLAHE alone. Standardised preprocessing, ablation-based reporting, multicentre validation, and explainable AI are needed to make CLAHE-based CNN systems clinically reliable.



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INTRODUCTION

Pneumonia remains one of the leading causes of respiratory morbidity and mortality worldwide, particularly among children, older adults, and immunocompromised individuals. Delayed diagnosis increases the risk of severe complications and mortality, making early and accurate detection essential for effective clinical management. Chest X-ray (CXR) imaging remains the primary diagnostic modality because it is widely available, cost-effective, and capable of identifying pulmonary abnormalities associated with pneumonia. However, manual interpretation is often affected by image quality, observer variability, and radiologists' experience, potentially leading to inconsistent diagnoses. Consequently, artificial intelligence (AI),

particularly deep learning, has become an important approach for supporting computer-aided diagnosis (CAD) systems (Bhatt & Shah, 2023; Singh et al., 2023).

Among deep learning approaches, Convolutional Neural Networks (CNNs) have become the dominant architecture for automated pneumonia detection because they learn hierarchical image features directly from medical images without handcrafted feature engineering. Recent advances in transfer learning, attention mechanisms, and hybrid deep learning frameworks have further improved classification performance, particularly when labelled medical datasets are limited (Bhatt & Shah, 2023; Kusk & Lysdahlgaard, 2023; Singh et al., 2023). Nevertheless, growing evidence indicates that CNN performance depends not only on network architecture but also on input image quality. Kusk & Lysdahlgaard (2023), for example, showed that degrading radiographs with Gaussian noise affects the pneumonia detection performance of CNNs, highlighting the importance of image quality and preprocessing in deep learning-based pneumonia detection.

Image preprocessing has become an essential component of modern deep learning pipelines because variations in image contrast, illumination, acquisition conditions, and background noise may obscure clinically relevant pulmonary structures and reduce the feature extraction capability of CNNs. Among available enhancement techniques, Contrast Limited Adaptive Histogram Equalisation (CLAHE) has attracted considerable attention because it improves local image contrast while limiting excessive noise amplification, thereby preserving diagnostically important anatomical structures (Siddiqi & Javaid, 2024). Unlike global histogram equalisation, CLAHE divides an image into small contextual regions (tiles), equalises the histogram of each tile, clips histogram bins above a predefined limit, and redistributes the clipped pixels before interpolating tile boundaries. These two parameters, the clip limit and the tile grid size, determine the balance between contrast enhancement and noise amplification.

Recent studies increasingly integrate CLAHE with image normalisation, denoising, data augmentation, transfer learning, and advanced CNN architectures to improve pneumonia classification performance (Buriboev et al., 2025; George et al., 2022; Rifai et al., 2024). However, because CLAHE is commonly implemented within comprehensive preprocessing pipelines, its individual contribution to CNN performance remains difficult to distinguish, creating the need for a systematic synthesis of the existing evidence.

Despite substantial advances in CNN-based pneumonia detection, several important research gaps remain. Existing studies have primarily focused on developing CNN architectures, whereas the implementation and contribution of CLAHE have received comparatively less attention. Furthermore, the combined use of CLAHE with multiple preprocessing techniques and learning strategies makes its specific impact difficult to determine. Methodological heterogeneity in datasets, preprocessing workflows, CNN architectures, validation procedures, and evaluation metrics further limits direct comparison across studies. Previous surveys have discussed deep learning for pneumonia detection broadly (Siddiqi & Javaid, 2024), but no systematic review has specifically synthesised the implementation of CLAHE while simultaneously examining preprocessing strategies, CNN architectures, diagnostic performance, and methodological robustness.

Accordingly, this systematic literature review aims to synthesise the current evidence regarding the application of CLAHE in CNN-based pneumonia detection using chest X-ray images. Four research questions guide this review: (1) **RQ1:** How has

CLAHE been implemented in CNN-based pneumonia detection using chest X-ray images? (2) **RQ2:** What CNN architectures and learning strategies have been employed in conjunction with CLAHE for pneumonia detection? (3) **RQ3:** How does CLAHE-based preprocessing influence the diagnostic performance of CNN models for pneumonia detection? (4) **RQ4:** What methodological strengths, limitations, and future research directions can be identified from the existing literature on CLAHE-based CNN pneumonia detection? By answering these questions, the review provides an integrated map of current practice and an evidence-based agenda for future research.

METHOD

This study employed a Systematic Literature Review (SLR) to synthesise and critically evaluate the existing literature on the implementation of CLAHE in CNN-based pneumonia detection using chest X-ray images. The review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological transparency, reproducibility, and systematic reporting throughout the review process (Page et al., 2021). Because considerable methodological heterogeneity was identified among the retrieved studies, a qualitative thematic synthesis was adopted instead of a quantitative meta-analysis. The overall review process consisted of five sequential stages: search strategy, eligibility criteria, study selection, data extraction, and thematic synthesis.

Literature Search Strategy

The literature search was performed using the Scopus database because it provides broad coverage of high-quality peer-reviewed journals across artificial intelligence, computer vision, medical imaging, and computer science. In addition, Scopus offers comprehensive indexing, standardised bibliographic metadata, and advanced search functionalities that facilitate systematic and reproducible literature retrieval. Restricting the search to a single, well-established database also ensured consistency throughout the screening and selection process.

The search was conducted on 25 July 2026 and was limited to studies published between 2021 and 2026. This publication period was selected to capture the most recent developments in deep learning techniques, transfer learning strategies, and image preprocessing approaches for pneumonia detection while excluding earlier studies that may not adequately reflect current advances in CNN-based medical image analysis. Only English-language, peer-reviewed, final published journal articles were included to ensure the scientific quality and maturity of the retrieved evidence. The initial search retrieved 82 records. The detailed search parameters are presented in Table 1.

Table 1. Literature search strategy

Item	Description
Database	Scopus
Search date	25 July 2026
Search period	2021–2026
Search fields	Title, abstract, and keywords
Language	English
Document type	Journal article
Publication status	Final published articles
Access	Open access
Search query	CLAHE AND (CNN OR "deep learning") AND pneumonia AND "chest X-ray"
Initial records identified	82

Eligibility Criteria and Study Selection

The study selection process was conducted according to the PRISMA 2020 framework, which consists of the identification, screening, eligibility, and inclusion stages (Page et al., 2021). Records were first checked for duplicates and then screened sequentially by publication year, document type, language, subject area, and open-access availability. The remaining full-text reports were assessed against predefined inclusion and exclusion criteria, as summarised in Table 2.

Table 2. Inclusion and exclusion criteria

Criteria	Inclusion criteria	Exclusion criteria
Publication year	Published between 2021 and 2026	Published before 2021
Language	English	Languages other than English
Document type	Peer-reviewed journal articles	Conference papers, reviews, book chapters, editorials, letters, notes, theses, and dissertations
Publication status	Final published articles	Articles in press or unpublished manuscripts
Research scope	CLAHE implementation for CNN-based pneumonia detection using chest X-ray images	Studies unrelated to CLAHE, CNN/deep learning, pneumonia detection, or chest X-ray imaging
Methodology	CLAHE applied as an image preprocessing technique in deep learning models	Studies that did not implement CLAHE or did not use CNN/deep learning
Outcomes	Quantitative performance metrics (e.g., accuracy, precision, recall, F1-score, AUC, sensitivity, specificity)	Studies without quantitative evaluation results
Accessibility	Open-access full text available	Abstract-only or inaccessible full text

As illustrated in Figure 1, no duplicates were found among the 82 records identified. Screening by publication year excluded 3 records ($n = 79$), screening by document type excluded 41 records ($n = 38$), no records were excluded by language ($n = 38$), screening by subject area excluded 7 records ($n = 31$), and screening by open-access availability excluded 5 records ($n = 26$). During full-text assessment, 5 reports were excluded because they did not use CLAHE ($n = 2$), did not use CNN or deep learning ($n = 1$), did not focus on pneumonia detection from chest X-rays ($n = 1$), or did not report relevant performance metrics ($n = 1$). Consequently, 21 studies satisfied all eligibility criteria and were included in the qualitative synthesis.

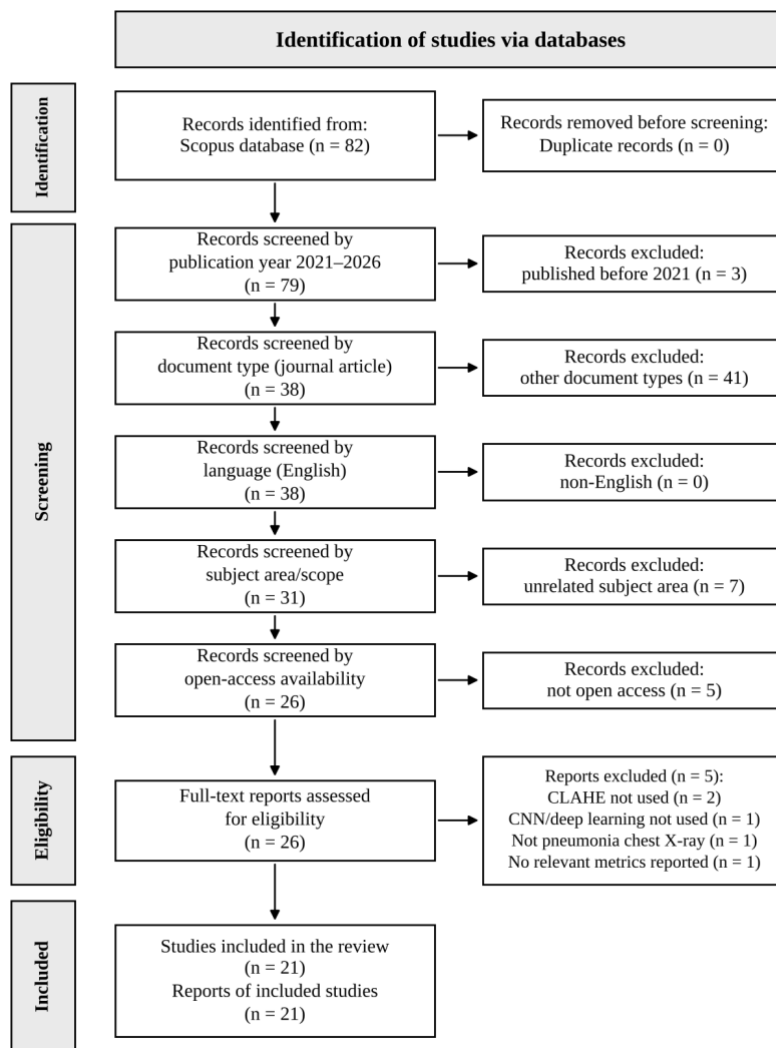


Figure 1. PRISMA 2020 flow diagram of the study selection process

Data Extraction

Relevant data were systematically extracted from each of the 21 included studies using a structured data extraction form developed based on the objectives of this review. The extraction process was performed to ensure consistency in data collection and to facilitate comparison across the selected studies. The extracted information included publication details, dataset characteristics, image preprocessing techniques, CLAHE implementation, CNN architecture, learning strategy, validation method, evaluation metrics, and the principal findings related to pneumonia detection. The variables extracted from each study are presented in Table 3.

Table 3. Data extraction framework

Data item	Description
Bibliographic information	Author(s), publication year, and country
Dataset characteristics	Dataset name, number of images, classes, and data source
Image preprocessing	Preprocessing techniques applied before model training
CLAHE implementation	Position, parameters, and variant of CLAHE within the pipeline
CNN architecture	CNN model or deep learning architecture employed
Learning strategy	Custom CNN, transfer learning, ensemble, or hybrid approach
Validation method	Training–testing split, cross-validation, or independent testing
Evaluation metrics	Accuracy, precision, recall, F1-score, sensitivity, specificity, and AUC
Main findings	Principal findings related to CLAHE implementation and detection performance

Data Synthesis

The extracted data were analysed to identify recurring patterns, methodological similarities and differences, and emerging research trends concerning the implementation of CLAHE in CNN-based pneumonia detection. A qualitative thematic analysis was performed because substantial heterogeneity was observed across the included studies regarding datasets, preprocessing pipelines, CNN architectures, learning strategies, validation procedures, and evaluation metrics. The synthesis involved reviewing, comparing, and interpreting the extracted evidence before grouping studies with similar methodological characteristics into themes aligned with the four research questions. Performance values were recorded exactly as reported by the original authors; because test sets, class definitions, and validation protocols differ, these values were compared descriptively rather than pooled statistically.

RESULTS AND DISCUSSION

Overview of the Included Studies

The 21 included studies were published within the 2021–2026 search window and addressed binary pneumonia detection, multi-class discrimination between pneumonia, COVID-19 pneumonia, and normal radiographs, or broader multi-class lung disease classification in which pneumonia was one of the target classes. Most studies relied on publicly available CXR repositories, such as the Chest X-Ray Images (Pneumonia) dataset from the Guangzhou Women and Children's Medical Center, the COVID-19 Radiography Database, and ChestX-ray14. Table 4 summarises the characteristics of representative included studies for which the dataset, the role of CLAHE, the model, and the reported performance could be extracted consistently.

Table 4. Characteristics of representative included studies

Study	Dataset / classes	Role of CLAHE	Model and learning strategy	Best reported performance
Nneji et al. (2022)	Pneumonia CXR images	One of three enhanced input channels (with LBP and CECED)	Inception-V3 on the CLAHE channel, shallow CNN, MobileNet-V3; feature concatenation	Acc 98.3%; Sens 98.9%; Spec 99.2%
Çiğ et al. (2023)	COVID-19 Radiography Database; three classes	Clip limit and tile parameters optimised by multi-objective cuckoo search	CNN trained on optimised CLAHE images	Acc 99.16%; Prec 99.20%; Sens 98.99%
Shamrat et al. (2023)	ChestX-ray14; 14 classes incl. pneumonia	CLAHE with Gaussian filtering and augmentation	MobileLungNetV2 (fine-tuned MobileNetV2); Grad-CAM	Acc 96.97%; Prec 96.71%; Rec 96.83%; Spec 99.78%
Vinodhini et al. (2023)	6,432 CXR images; COVID pneumonia, pneumonia, normal	HE and CLAHE applied as enhancement before training	CNN and improved VGG16	Acc 96%
Kassylkassova et al. (2023)	Pneumonia CXR images	CLAHE within preprocessing and augmentation	2D deep CNN with 24 hidden layers (custom)	Acc 97.2%
Rifai et al. (2024)	Pneumonia CXR images	White balance followed by CLAHE	MobileNetV2 (transfer learning)	—
Mahamud et al. (2024)	Multi-class lung disease CXR incl. pneumonia	CLAHE, denoising autoencoder, gamma correction, augmentation	DenseNet201 transfer learning; SHAP, LIME, Grad-CAM, Grad-CAM++	Acc 99.20%; Prec 99%; Rec 99%
Chandranegara et al. (2024)	Pneumonia CXR images	CLAHE combined with augmentation (three scenarios)	ResNet-RS-based CNN	Acc 92%
Shilpa et al. (2024)	Pneumonia CXR images	CLAHE with k-fold cross-validation	ResNet50, MobileNetV2, AlexNet, EfficientNetB0, Xception	EfficientNetB0: Acc 99.78%; Spec 99.54%
Buriboev et al. (2025)	Chest X-Ray Images (Pneumonia), 5,856 images; binary	Modified CLAHE: adaptive tiles, variance-guided clipping, entropy-weighted redistribution	CNN; five-fold cross-validation	Acc 98.7%; Prec 99.3%; Rec 98.6%; F1 97.9%
Mustapha et al. (2025)	Guangzhou Women and Children's Medical Center CXR	Resizing to 224×224, CLAHE, augmentation	Hybrid CNN with modified Swin Transformer; Optuna TPE tuning	Acc 98.72%; F1 0.9872

Note: Acc = accuracy; Prec = precision; Rec = recall; Sens = sensitivity; Spec = specificity; LBP = local binary pattern; CECED = contrast-enhanced Canny edge detection; HE = histogram equalisation; — = value not extracted.

Several observations emerge from Table 4. First, the target task varies from binary normal-versus-pneumonia classification (Buriboev et al., 2025; Mustapha et al., 2025) to three-class settings that include COVID-19 (Çiğ et al., 2023; Vinodhini et al., 2023) and 14-class thoracic disease classification (Shamrat et al., 2023). Second, CLAHE is typically applied after resizing and before augmentation or model training, but its configuration differs considerably between studies. Third, transfer learning with pretrained ImageNet backbones is more common than training custom CNNs from scratch. Other included studies extend this picture to COVID-19 detection with homomorphic transformation and a VGG-inspired CNN (George et al., 2022), hybrid multi-wavelet and deep convolutional features with a support vector classifier

(Aljoboury et al., 2025), and CNN ensembles for pneumonia detection (Bhatt & Shah, 2023).

RQ1: CLAHE Implementation Strategies

The synthesis identified four strategies for implementing CLAHE, summarised in Table 5. The most frequent strategy treats CLAHE as a fixed-parameter component of a broader preprocessing pipeline. Shamrat et al. (2023) combined CLAHE with Gaussian filtering and data augmentation before training a customised MobileNetV2, while Mustapha et al. (2025) resized images to 224×224 pixels, applied CLAHE, and augmented the data before training a hybrid CNN–Swin Transformer. Chandranegara et al. (2024) compared three preprocessing scenarios involving CLAHE and augmentation and reported 92% accuracy for the best scenario, showing that the benefit of CLAHE depends on the rest of the pipeline.

Table 5. Strategies for implementing CLAHE in CNN-based pneumonia detection

Strategy	Description	Representative studies
Pipeline component	Fixed-parameter CLAHE combined with resizing, normalisation, filtering, and augmentation before training	Shamrat et al. (2023); Kassylkassova et al. (2023); Chandranegara et al. (2024); Mustapha et al. (2025)
Combined enhancement	CLAHE paired or compared with other enhancement operators such as HE, white balance, gamma correction, or denoising	Vinodhini et al. (2023); Rifai et al. (2024); Mahamud et al. (2024)
Optimised or modified CLAHE	Clip limit and tile size tuned by metaheuristics or redesigned to adapt to local image statistics	Çiğ et al. (2023); Buriboev et al. (2025)
Multi-channel input	CLAHE image used as one of several complementary representations fed to parallel networks	Nneji et al. (2022)

The second strategy pairs CLAHE with other enhancement operators. Vinodhini et al. (2023) applied histogram equalisation and CLAHE to 6,432 CXR images before training a CNN and an improved VGG16, Rifai et al. (2024) combined white balance with CLAHE before MobileNetV2 classification, and Mahamud et al. (2024) built a pipeline consisting of CLAHE, a denoising autoencoder, gamma correction, and augmentation. These studies treat contrast enhancement and noise suppression as complementary rather than competing steps, which is consistent with the sensitivity of CNNs to image noise reported by Kusk & Lysdahlgaard (2023).

The third and most recent strategy optimises or redesigns CLAHE itself. Instead of manually fixing the clip limit and tile grid, one study tuned these parameters with multi-objective cuckoo search and reported improved three-class detection performance (Çiğ et al., 2023). Buriboev et al. (2025) went further by modifying the algorithm with adaptive tile sizing, variance-guided clipping, and entropy-weighted histogram redistribution, so that enhancement adapts to the local statistics of each radiograph. The fourth strategy, represented by Nneji et al. (2022), uses the CLAHE-enhanced image as one of three input channels, together with local binary pattern and contrast-enhanced Canny edge representations, each processed by a different network before feature concatenation.

Across these strategies, the reporting of CLAHE parameters was inconsistent. Many studies described CLAHE only qualitatively, without specifying the clip limit, tile

grid size, colour space, or the order of operations relative to normalisation. This gap matters because the same nominal technique can produce visibly different images under different parameters, and it limits the reproducibility of otherwise well-performing pipelines. The general structure of the pipelines reported in the included studies is summarised in Figure 2.

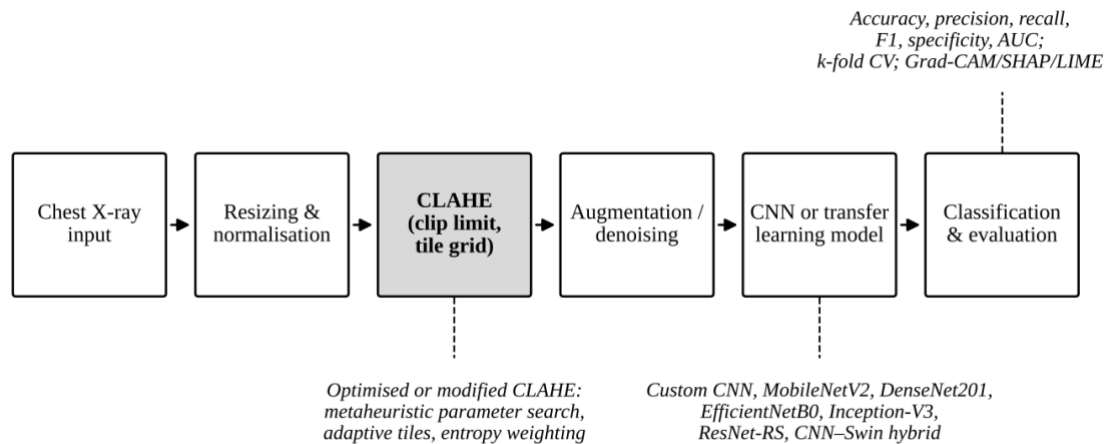


Figure 2. Generalised CLAHE–CNN pipeline for pneumonia detection synthesised from the included studies

RQ2: CNN Architectures and Learning Strategies

The second theme concerns the CNN architectures and learning strategies combined with CLAHE. Transfer learning with ImageNet-pretrained backbones was the dominant strategy. MobileNetV2 was used by Rifai et al. (2024) and, in a customised form, by Shamrat et al. (2023); DenseNet201 was fine-tuned by Mahamud et al. (2024); and Shilpa et al. (2024) benchmarked ResNet50, MobileNetV2, AlexNet, EfficientNetB0, and Xception, with EfficientNetB0 performing best. Lightweight architectures such as MobileNetV2 and EfficientNetB0 are attractive because they reduce computational cost while preserving accuracy, which supports deployment in resource-constrained settings, as illustrated by the Android-based system of Mahamud et al. (2024).

Custom CNNs remain relevant when researchers aim to control model capacity or analyse the effect of preprocessing directly. Kassylkassova et al. (2023) designed a 2D deep CNN with 24 hidden layers, Buriboev et al. (2025) trained a CNN on images enhanced by their modified CLAHE, and Vinodhini et al. (2023) compared a CNN with an improved VGG16. A third group adopted multi-network or hybrid designs: Nneji et al. (2022) combined Inception-V3, MobileNet-V3, and a shallow CNN; Chandranegara et al. (2024) used a ResNet-RS-based model; and Mustapha et al. (2025) fused convolutional features with a modified Swin Transformer whose hyperparameters were tuned with the Optuna tree-structured Parzen estimator. Ensemble approaches (Bhatt & Shah, 2023) and hybrid deep feature–classical classifier pipelines (Aljoboury et al., 2025) further show that CLAHE is architecture-agnostic and can be placed in front of very different learning systems.

These findings indicate that methodological innovation is no longer centred solely on developing new CNN architectures. Instead, recent research increasingly integrates preprocessing optimisation, transfer learning, attention mechanisms, and hyperparameter optimisation. CNN performance should therefore be interpreted as the outcome of methodological integration rather than architectural complexity alone.

RQ3: Diagnostic Performance of CLAHE-Based Pipelines

The highest accuracies reported by the studies in Table 4 are compared in Figure 3. Reported accuracy ranged from 92% (Chandranegara et al., 2024) to 99.78% (Shilpa et al., 2024), and six of the ten studies with an extractable accuracy value reported at least 98%. Very high values were achieved by pipelines that combined CLAHE with additional enhancement and transfer learning, such as DenseNet201 with a denoising autoencoder and gamma correction (Mahamud et al., 2024), and by pipelines in which CLAHE itself was optimised or modified (Buriboev et al., 2025; Çiğ et al., 2023).

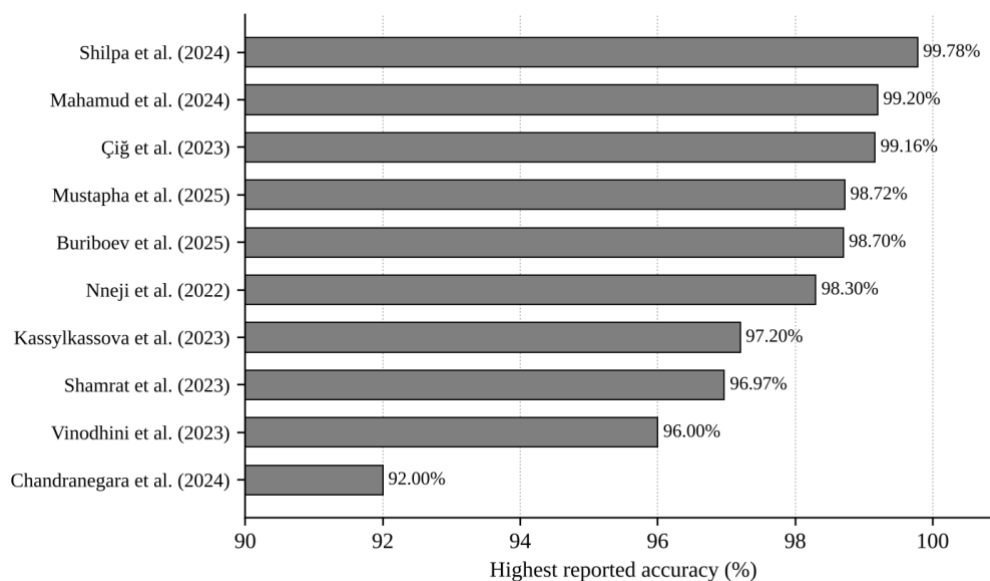


Figure 3. Highest accuracy reported by representative included studies

Beyond accuracy, several studies reported complementary metrics. Buriboev et al. (2025) reported a precision of 99.3%, a recall of 98.6%, and an F1-score of 97.9% under five-fold cross-validation; Nneji et al. (2022) reported a sensitivity of 98.9% and a specificity of 99.2%; and Shamrat et al. (2023) reported a specificity of 99.78% across 14 classes. The increasing use of precision, recall, sensitivity, specificity, F1-score, and AUC reflects growing recognition that accuracy alone is insufficient, particularly for imbalanced datasets in which the pneumonia class dominates.

However, these figures cannot be interpreted as the effect of CLAHE alone. Most studies simultaneously changed several components, including the backbone network, augmentation policy, hyperparameter optimisation, and data split, and few reported ablation experiments that trained the same model with and without CLAHE. The values in Figure 3 were also obtained on different datasets, class definitions, and test protocols, so a higher accuracy in one study does not imply a better method than a lower accuracy in another. The evidence therefore supports a conditional conclusion: CLAHE is consistently associated with high-performing pipelines and can improve results when it

is tuned and combined with suitable preprocessing, but its isolated contribution remains insufficiently quantified.

RQ4: Methodological Robustness and Future Research Directions

The fourth theme identifies methodological heterogeneity as the principal limitation of the current literature. Considerable variation was observed in datasets, CLAHE parameter settings, preprocessing pipelines, CNN architectures, optimisation algorithms, validation strategies, and evaluation metrics. Such diversity substantially limits the reproducibility and comparability of reported findings and makes it difficult to isolate the specific contribution of CLAHE to diagnostic performance (Aljoboury et al., 2025; Çiğ et al., 2023; Rifai et al., 2024).

Several methodological strengths were also observed. Cross-validation was used by Buriboev et al. (2025) and Shilpa et al. (2024), which reduces the dependence of results on a single data split. Explainable AI was integrated by Shamrat et al. (2023) through Grad-CAM and by Mahamud et al. (2024) through SHAP, LIME, Grad-CAM, and Grad-CAM++, allowing clinicians to verify whether the model attends to pulmonary regions rather than to artefacts. Such explanations are particularly relevant to CLAHE because contrast enhancement can amplify text markers, borders, and devices that a model may exploit as shortcuts.

At the same time, most investigations relied on internal validation with public datasets that may not represent real-world clinical variability in acquisition devices, patient populations, and image quality. External or multicentre validation was rare, patient-level splitting was seldom described, and computational cost was rarely reported. Future research should therefore prioritise (1) standardised reporting of CLAHE parameters and their position in the pipeline; (2) ablation studies comparing identical models with and without CLAHE and with alternative enhancement methods; (3) external and multicentre validation; (4) consistent reporting of sensitivity, specificity, F1-score, and AUC with confidence intervals; and (5) explainable AI and efficiency analysis to support clinical deployment. The mapping between the research questions, themes, and key findings is summarised in Table 6.

Table 6. Summary of the thematic synthesis by research question

RQ	Theme	Key synthesis
RQ1	CLAHE implementation strategies	CLAHE is embedded in multi-step pipelines; optimised and modified variants are emerging; parameter reporting is inconsistent
RQ2	CNN architectures and learning strategies	Transfer learning (MobileNetV2, DenseNet201, EfficientNetB0, Inception-V3, ResNet) dominates; custom and hybrid CNN–transformer models also appear
RQ3	Performance of CLAHE-based pipelines	Highest reported accuracies of 92%–99.78%; gains are pipeline-level and rarely isolated through ablation
RQ4	Methodological robustness and future directions	Heterogeneous datasets and metrics, limited external validation, and emerging but uneven use of XAI

Implications and Contributions of This Review

The findings provide a broader understanding of how CLAHE contributes to CNN-based pneumonia detection. Rather than demonstrating that CLAHE independently improves diagnostic performance, the reviewed evidence indicates that its effectiveness depends on the interaction between image preprocessing, CNN

architecture, learning strategy, and methodological design. From a computer vision perspective, this reflects an important shift in feature learning: convolutional filters extract hierarchical representations directly from input images, so improving local contrast enables more informative feature extraction while preserving clinically relevant anatomical structures (Siddiqi & Javaid, 2024). Nevertheless, image enhancement alone cannot guarantee superior classification performance (George et al., 2022).

From a theoretical perspective, the review reinforces the role of preprocessing as an integral part of feature learning rather than a preliminary cosmetic step. From a practical perspective, it offers guidance for researchers developing AI-assisted diagnostic systems: CLAHE should be configured and reported explicitly, evaluated through ablation, and combined with robust validation and explainability. Rather than asking whether CLAHE improves CNN performance, future investigations should ask under which conditions of dataset, architecture, and parameter setting it provides the greatest benefit. This review is limited by its use of a single database, the open-access filter, and the English-language restriction, which may have excluded relevant studies, and by the heterogeneity of the included studies, which precluded meta-analysis.

CONCLUSION

This systematic literature review examined the implementation of CLAHE in CNN-based pneumonia detection using chest X-ray images by synthesising evidence from 21 studies selected according to PRISMA 2020. The review shows that CLAHE has become a widely adopted preprocessing technique that is usually embedded in multi-step pipelines with normalisation, denoising, and augmentation, and that recent work increasingly optimises or modifies CLAHE itself. Transfer learning with architectures such as MobileNetV2, DenseNet201, EfficientNetB0, Inception-V3, and ResNet-based models dominates, and the highest reported accuracies of representative studies ranged from 92% to 99.78%.

However, the contribution of CLAHE cannot yet be isolated, because studies differ in datasets, CLAHE parameters, validation protocols, and metrics and rarely include ablation or external validation. Future research should standardise CLAHE reporting, conduct controlled ablation and multicentre validation, report a complete set of diagnostic metrics, and incorporate explainable AI to improve the reliability, transparency, and clinical applicability of computer-aided pneumonia diagnosis systems.

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CONFLICT OF INTEREST

The author declares that this research was conducted in the absence of any commercial, financial, or other relationships that could be construed as potential conflicts of interest.

AUTHOR CONTRIBUTIONS

Tias Nur Anggara was solely responsible for the conceptualization of the study, development of the research methodology, literature search and selection, data extraction, thematic synthesis, interpretation of the findings, and preparation, review, and editing of the manuscript. The author approved the final version of the manuscript for publication.

GENERATIVE AI STATEMENT

The author declared that generative artificial intelligence (AI) tools were used to assist with language refinement and improve the clarity and readability of the manuscript. All AI-assisted content was reviewed and verified by the author, who remains fully responsible for the accuracy, originality, integrity, and final content of the published article.

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