

Automated convolutional neural network-based reject-repeat decision system for chest radiographs

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ABSTRACT

Image quality in radiography is essential for diagnostic accuracy, yet reject-repeat analysis (RRA) is still mostly performed manually and depends on subjective radiographer judgment. Inter-operator variability leads to inconsistent quality data and limits workflow optimization. While many studies evaluate deep learning models for disease classification, research using convolutional neural networks (CNNs) to assess image quality and automate RRA remains limited. This study introduces a novel approach by applying CNNs to classify the causes of image rejection in chest radiography: positioning, exposure, artefacts, and accepted images, integrating these outcomes into a quality-management framework. The aim is to develop and evaluate CNN models (visual geometry group (VGG)-16, residual neural network (ResNet)-101, and dense convolutional network (DenseNet)-201) to support automated RRA using digital imaging and communications in medicine (DICOM)-based radiographs. The dataset comprised DICOM chest images annotated by a panel of radiologists, radiographers, and medical physicists into four technical classes. The CNNs were trained using supervised learning with structured training, validation, and testing splits, and evaluated using accuracy, precision, recall, and F1-score. Results show VGG-16 delivers the most stable and accurate performance across categories. Overall, CNNs effectively automate RRA with greater objectivity and consistency, reducing repeat rates, improving workflow efficiency, and strengthening radiology quality-management systems to enhance patient safety.

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1. INTRODUCTION

Chest radiography is the most commonly performed diagnostic imaging procedure for assessing anatomical structures and detecting clinical abnormalities [1]. It is also an essential component of preoperative evaluation for various types of surgical interventions [2]. Globally, more than two billion chest radiographs are performed annually [3], representing approximately 43% of all radiographic examinations [4]. Given its high frequency of use and its central role in clinical decision-making, ensuring optimal image quality is crucial so that radiological interpretation accurately reflects the patient's pathological condition.

However, technical errors during radiographic acquisition remain common and may compromise image quality, often necessitating repeat exposures. These errors typically involve incorrect patient

positioning, improper exposure settings, or the presence of artefacts that obscure diagnostic information [5]. Such issues not only affect diagnostic accuracy but also carry important clinical and operational consequences. From a radiation-protection perspective, patients are exposed to additional dose when repeat acquisitions are required, despite recommendations from the American Association of Physicists in Medicine (AAPM) that all radiological procedures be justified clinically and performed at the lowest reasonably achievable dose [5]. Furthermore, repeated imaging increases operational costs and reduces service efficiency, consuming staff time and equipment availability, and potentially delaying diagnosis and patient management [6]. These challenges highlight the need for systematic and consistent quality control mechanisms in clinical radiography.

One approach commonly used to address these issues is the reject-repeat analysis (RRA) program. Although quality-control activities can reduce the risk of image degradation, process control alone is insufficient without comprehensive quality assurance management [7]. RRA is recommended as a periodic quality-assurance activity in medical exposure programs [8] and is recognized as an important component in improving radiology service quality [6]. Through systematic evaluation of rejected images—without involving diagnostic interpretation [9], [10]. RRA offers an accessible and cost-effective method for identifying quality-related problems and supporting continuous service improvement. Additionally, RRA provides data on the proportion of rejected images relative to total examinations, which can be used to assess system efficiency and to estimate the economic impact associated with repeat imaging [6].

Radiologists and radiologic technologists play crucial roles in implementing reject-repeat programs. However, subjective judgment frequently leads to inconsistencies in determining whether an image should be rejected or repeated. Current practice still relies heavily on real-time decisions made by personnel, making the evaluation process vulnerable to bias. Efficiency constraints also limit consistent implementation of RRA in clinical workflows. These issues underscore the need for an objective, standardized system that can support accurate reject/repeat decisions. Although modern digital modalities are increasingly equipped with software for reject analysis, such tools are still limited to data processing, while final decisions and categorizations remain dependent on human evaluators. Several studies have documented disagreement among personnel regarding image acceptability [11], [12]. Radiologists tend to accept borderline images that remain diagnostically interpretable, thereby reducing the need for repeat exposures [13]. Meanwhile, significant differences in reject classification between radiologists and technologists have also been reported [14]. These variations motivated our research to develop a system capable of minimizing interpretive discrepancies when determining image acceptance, rejection, and underlying rejection causes. Accordingly, the present study aims to design and evaluate a deep-learning-based system that supports objective, consistent, and workflow-integrated reject-repeat decision-making in clinical radiography.

Previous research on RRA has focused mainly on observational and survey-based assessments of rejected image types and frequencies [15], [16]. In these studies, the determination of rejection categories depended heavily on technologists' subjective judgment [11]. Indicating that most RRA implementations remain conventional and lack objective evaluation tools. Additional studies have reported substantial perceptual differences between technologists and radiologists in determining whether an image should be repeated or accepted [17]. Further emphasizing the need to minimize interpretive bias in RRA decision-making. With the advancement of artificial intelligence (AI), opportunities have emerged to standardize radiographic image-quality assessment. AI-based tools have been shown to improve technologists' accuracy in image presentation and quality auditing tasks [18]. Early machine-learning applications have demonstrated the feasibility of automatically evaluating technical image factors, such as detecting motion artefacts to compare technologist and radiologist assessments [19]. More recently, deep neural networks have been implemented to classify rejected images into major (requiring repeat imaging) and minor (still diagnostically acceptable) error categories [20]. Additional progress has been made through convolutional neural networks (CNN)-based assessment of positioning quality in adult posteroanterior (PA) chest radiographs (e.g., using residual neural network (ResNet)-34), yielding performance comparable to radiologist evaluation [21]. CNNs have recently emerged as the most widely used method for image classification and segmentation across various domains, including diagnostic imaging, surveillance, and industrial automation [22]. Their ability to learn discriminative features directly from images makes CNNs particularly suitable for automating radiograph image quality assessment.

Despite these developments, reject-repeated decisions in clinical practice still rely on manual assessment and are not yet integrated into data-driven decision-support systems. Persistent subjectivity in determining whether an image should be rejected, as well as in classifying the reason for rejection, remains a major challenge. Therefore, establishing standards that ensure consistent, accurate, and accountable decision-making is essential. An AI-based system capable of identifying image-quality issues while simultaneously supporting reject-repeat decisions represents a strategic opportunity for improving radiology service quality.

The novelty of the present study lies in the development of a dedicated dataset and automated reject-repeat decision-support system for radiographic imaging using digital imaging and communications in medicine (DICOM)-based chest radiographs. By incorporating multiple CNN architectures, the system is designed to enhance robustness when encountering variations in image quality, thereby serving as a practical foundation for radiology quality management. Through this approach, the study not only automates quality-classification tasks but also advances RRA toward a more objective, standardized, and workflow-integrated quality-assurance system for clinical radiology.

2. METHOD

In response to the challenges of variability and subjectivity in reject-repeat decision-making within the chest radiography workflow, this study proposes the development of an AI-based decision support system (DSS) designed to standardize image-quality assessment and enhance the efficiency of radiology processes. The system is constructed as a model capable of evaluating the technical quality of radiographic images, determining the need for repeat examinations, and categorizing rejection reasons based on operational considerations consistent with established radiographic technical standards. The overall workflow of the proposed system is illustrated in Figure 1. The workflow begins with the acquisition of digital chest X-ray images using standard radiographic equipment. At this stage, images are obtained following routine clinical protocols, reflecting real-world variability in patient positioning, exposure setting, and technical condition. This non-interventional approach was intentionally adopted to ensure that images or radiographs are evaluated under conditions of actual clinical workflow. Digital chest X-ray images were stored in DICOM format, allowing standardized integration with a picture archiving and communication system (PACS) system that provides substantial flexibility for image acquisition and quality assessment. It also introduces challenges related to exposure latitude and potential for subtle image quality degradation that may not be readily apparent during routine visual inspection. Data collection includes both diagnostically acceptable images and images affected by quality issues, such as position error, exposure inconsistencies, and artefacts. Comprehensive data collection ensures representation of clinically relevant reject-repeat scenarios. Image categories include accepted, rejected due to positioning, rejected due to artefact, and rejected due to exposure. Pre-processing steps included patient de-identification to ensure data privacy, resizing all DICOM images to a standardized input size (256×256 pixels), and pixel intensity normalization before CNN training. Preliminary experiments with conventional image augmentation were conducted during model development. However, because augmentation consistently resulted in lower validation accuracy than training with original clinical DICOM images, the final CNN models were trained without image augmentation to preserve the radiographic technical image quality characteristics required for reject-repeat classification.

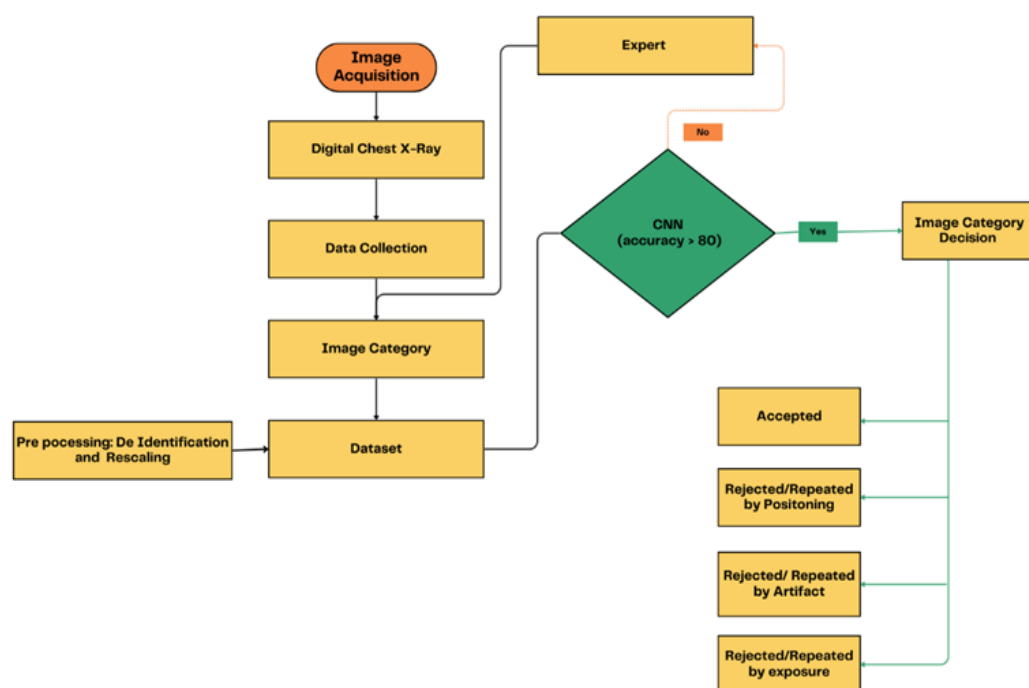


Figure 1. Workflow for image acceptance or repeat/rejection using a CNN-based DSS

Before CNN training, all DICOM images underwent a standardized preprocessing pipeline consisting of DICOM de-identification, resizing to 256×256 pixels, and pixel intensity normalization to the range of 0 – 1. These preprocessing steps ensured consistent image dimensions and intensity scaling across all CNN architectures while preserving the original radiographic quality characteristics. The processed dataset was subsequently partitioned into training (80%) and validation (20%) subsets using random sampling.

2.1. Dataset description

The dataset used in this study consisted of PA chest radiographs acquired from both computed radiography (CR) and digital radiography (DR) systems, as well as images retrieved from the PACS. All images were collected in DICOM format to preserve original metadata and acquisition parameters essential for RRA. A total of 5,589 chest radiographs were obtained from routine clinical examinations over a defined time period and were initially collected (accepted 1,198; artefact: 825; exposure: 1,187; and positioning: 1,266). Due to class imbalance, a subset of 1,203 images was subsequently selected according to predefined criteria, comprising four balance quality categories: accepted (314), positioning error (349), exposure error (295), and artefact-related rejection (245). Data extraction was carried out after institutional ethical approval was granted, and patient confidentiality was ensured through strict DICOM de-identification procedures in accordance with international standards.

2.2. Inclusion and exclusion criteria

The inclusion criteria for image selection were as follows: adult patient chest radiographs, PA projection, acquisition performed using DR technology (CR or DR), and availability of images in DICOM format. Exclusion criteria included: pediatric chest radiographs, lateral or special projections, and non-thoracic radiographic images. These criteria were applied to ensure the selected images met the requirements for the study.

2.3. Image identification and annotation procedure

To ensure high-quality annotations, all images were independently reviewed by a panel consisting of a senior radiographer, a medical physicist, and a radiologist. Each image was assigned to one of the following primary categories: i) acceptable image – images that met technical quality standards and did not require repetition; and ii) rejected image – images that failed to meet technical quality criteria and required repeat acquisition. Rejected images were then subcategorized based on common quality-control criteria in radiography, including: i) positioning errors; ii) exposure errors (underexposure or overexposure resulting from incorrect technical factors); and iii) artefacts that obscure anatomical structures.

A consensus mechanism was applied in cases of disagreement among reviewers to minimize annotation variability. Following expert verification, the dataset was refined from 5,589 to 1,203 images. The final dataset reflects real-world variability in chest radiograph quality, including differences in positioning, exposure settings, and artefacts, thereby enhancing the generalizability of the proposed reject-repeat decision-support system. The dataset was randomly divided into training and testing sets at an 80:20 ratio (962: 241).

2.4. Rationale for selecting VGG-16, ResNet-101, and DenseNet-201

The selection of visual geometry group (VGG)-16, ResNet-101, and dense convolutional network (DenseNet)-201 for DICOM-based medical image analysis was based on the complementary structural advantages of each architecture. VGG-16 provides a stable and straightforward convolutional framework capable of extracting fine-texture features from thoracic structures. ResNet-101 introduces deep residual connections that enable robust feature representation, particularly useful for capturing complex anatomical variability and subtle differences in technical quality. DenseNet-201, on the other hand, maximizes feature reuse and information flow across layers, making it highly effective for primary DICOM datasets that often consist of limited sample sizes but high-resolution images. Together, these architectures form a comprehensive analytical framework that strengthens the performance and robustness of the automated RRA system, thereby supporting more effective quality management for digital radiographic imaging.

The dataset is input into the CNN model for automated image quality classification. The decision node labeled CNN (accuracy > 80%) represents a performance-based confidence threshold. When the model achieves sufficient predictive confidence, it proceeds to automated decision making, otherwise cases are referred back for expert review.

2.5. Convolutional neural networks training configuration

The CNN models were implemented using TensorFlow/Keras with ImageNet pre-trained weights. VGG-16 and DenseNet-201 were fine-tuned by unfreezing the last four convolutional layers, whereas the

last ten layers of ResNet-101 were fine-tuned. Training was performed using stochastic gradient descent (SGD) with an initial learning rate of 0.001, momentum of 0.9, batch size of 16, and 15 epochs. Categorical cross-entropy was adopted as the loss function. A learning-rate scheduler was employed after epoch 10, and ModelCheckpoint automatically stored the model achieving the highest validation accuracy. The training configuration and hyperparameters used for all evaluated CNN architectures are summarized in Table 1.

Table 1. CNN training parameters

Parameter	Value
Input size	256×256
Optimizer	SGD
Learning rate	0.001
Momentum	0.9
Batch size	16
Epoch	15
Loss	Cross entropy
Scheduler	Learning rate scheduler
Checkpoint	Best validation accuracy

As shown in Table 1, all CNN architectures were trained using identical hyperparameter settings, including an input image size of 256×256 pixels, a batch size of 16, 15 training epochs, and the SGD optimizer with an initial learning rate of 0.001 and a momentum of 0.9. Model optimization employed categorical cross-entropy as the loss function, while a learning-rate scheduler gradually reduced the learning rate after epoch 10 to facilitate stable convergence. In addition, a ModelCheckpoint callback was implemented to automatically preserve the model achieving the highest validation accuracy during training, thereby preventing the final model from being selected based solely on the last training epoch.

3. RESULTS AND DISCUSSION

Three CNN architectures—ResNet, DenseNet, and VGG—were trained and evaluated independently on the clinical DICOM dataset. Their performance in classifying radiographs into acceptable and rejected categories is summarized in Table 2. Table 2 presents a quantitative performance evaluation of three CNN models. The comparison uses standard classification metrics: precision, recall, F1-score, and accuracy. Overall, all models achieved satisfactory performance, with VGG-16 demonstrating the highest discriminative capability, followed by ResNet-101 and DenseNet-201. As shown in Table 2, the performance evaluation of the three CNN architectures—ResNet-101, DenseNet-201, and VGG-16—demonstrated notable variation in their ability to classify chest radiograph quality, with all models achieving scores above 80%. Based on precision, recall, F1-score, and accuracy, VGG-16 achieved the best overall performance, attaining a score of 0.92 across all evaluation metrics. These results indicate that VGG-16 is capable of consistently and reliably distinguishing between acceptable and rejected images. ResNet-101 ranked second, with a uniform score of 0.88 across all metrics, while DenseNet-201 showed the lowest performance, with accuracy, precision, recall, and F1-score values of 0.85.

Table 2. Performance of CNN models

Model	Precision	Recall	F1-score	Accuracy
ResNet-101	0.88	0.88	0.88	0.88
DenseNet-201	0.85	0.85	0.84	0.85
VGG-16	0.92	0.92	0.92	0.92

The quantitative performance results of each model are presented in Table 2. For better interpretability, these results are further illustrated in Figure 2. This provides a comparative performance of the evaluated CNN models based on precision, recall, F1-score, and accuracy. The visual representation confirms the numerical trends observed in Table 2. VGG-6 consistently outperforms the other models across all metrics. Although ResNet-101 and DenseNet-201 exhibit relatively stable behavior, a noticeable performance gap remains, particularly for the F1-score of DenseNet-21. These observations suggest that VGG-16 provides a more reliable feature representation for the reject-repeat decision task in chest radiograph analysis.

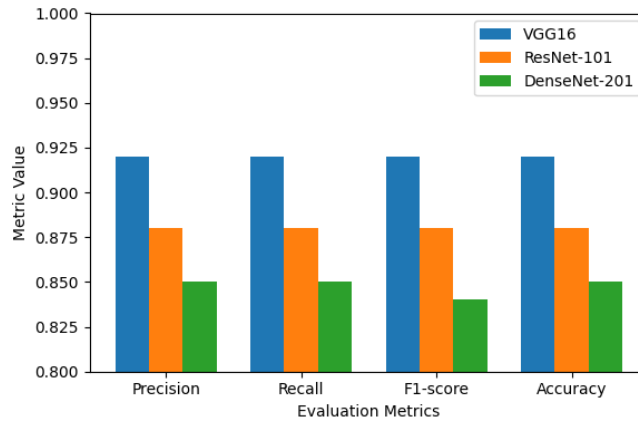


Figure 2. Performance comparison of VGG16, ResNet-101, and denseNet-20

The confusion matrix of VGG-16 presented in Figure 3 demonstrates that the CNN achieved high classification accuracy across all quality-related categories, particularly for exposure and positioning error. Misclassifications were primarily observed between the accept and artefact categories. This reflects the overlap in visual characteristics. When compared with VGG-16 and ResNet-101, the DenseNet-201 model exhibits greater inter-class confusion. Although DenseNet-201 demonstrates excellent performance in detecting exposure error, it shows a higher rate of false negative positioning classification. This limitation is clinically relevant, as a missed positioning error may lead to suboptimal diagnostic quality. VGG-16 demonstrates stronger class separation and more consistent diagonal dominance, supporting suitability for radiographic quality assurance application. Figure 3 presents the confusion matrices obtained from the three evaluated CNN architectures. Figure 3(a) illustrates the classification results produced by VGG-16, Figure 3(b) presents the ResNet-101 model, whereas Figure 3(c) shows the DenseNet-201 model.

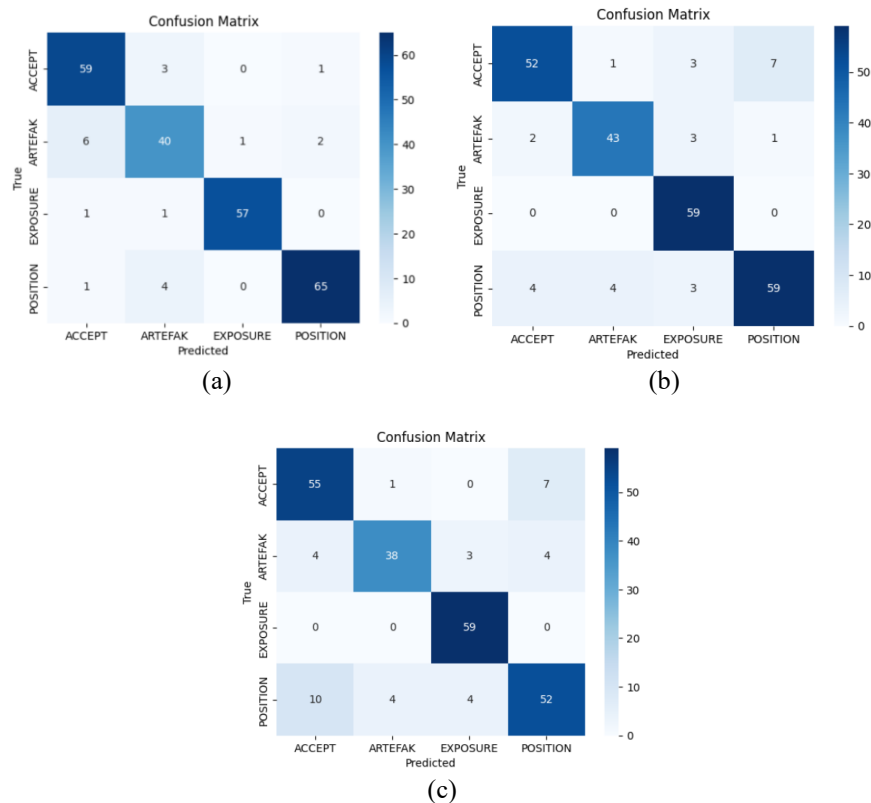


Figure 3. Confusion matrix of (a)VGG-16, (b) ResNet-101, and (c) DenseNet-201

Based on the confusion matrix in Figure 3, Figure 3(a) demonstrates that VGG-16 produced the strongest diagonal dominance, indicating accurate discrimination among accepted images, positioning errors, exposure errors, and artefacts. Misclassification was minimal, supporting its superior performance. Figure 3(b) illustrates the confusion matrix of ResNet-101. Although the model achieved high classification performance, a moderate increase in inter-class confusion was observed compared with VGG-16, particularly between technically similar image-quality categories. Figure 3(c) shows the DenseNet-201 confusion matrix. The model exhibited greater inter-class confusion, especially in positioning-related images, explaining its lower classification performance compared with the other architectures.

Table 3 summarizes the class-error characteristics derived. The table provides a comparative perspective on model behavior within radiographic quality assurance. This summary facilitates interpretation of how each model's misclassification tendencies may influence rejection analysis.

Table 3. Comparison of model error characteristics relevant to radiographic assurances

Aspect	VGG-16	ResNet-101	DenseNet-201
Diagonal domination	Very strong	Moderate	Weakest
False reject (accept → error)	Low	Moderate	Moderate
False accept (position → accept)	Low	Moderate	High
Stability clinical quality assurance (QA)	High	Moderate	Low-moderate

Unlike many medical image classification studies, the final CNN models were trained without image augmentation because preliminary experiments demonstrated consistently lower validation accuracy when augmentation was applied. Although image augmentation is widely employed in deep learning, its effectiveness is highly task-dependent and relies on preserving clinically meaningful image characteristics [23]. The present study focuses on classifying technical image-quality categories rather than pathological abnormalities. Geometric transformations such as rotation or translation may alter positioning characteristics or modify technical quality indicators, thereby introducing inconsistencies between the transformed image and its original quality label. Consequently, preserving the original clinical DICOM images was considered more appropriate for developing an automated reject–repeat classification system. Previous studies have demonstrated that the effectiveness of data augmentation depends on the selected transformation and its ability to preserve the intrinsic characteristics of medical images [24]. The use of original clinical DICOM images without image augmentation preserved the radiographic technical image quality characteristics required for reject-repeat classification. Consequently, the comparative evaluation of VGG-16, ResNet-101, and DenseNet-201 was performed using images that closely represented routine clinical radiographic practice. This approach enabled the models to be evaluated not only based on their classification performance but also on their potential applicability as decision support tools within radiology quality assurance workflows.

From a quality assurance perspective, the clinical consequences of misclassification must be considered alongside performance metrics. False acceptance of positioning error may compromise diagnostic confidence, while excessive false rejection can increase repeat imaging, radiation dose and workflow burden. VGG-16 demonstrated the most favorable balance between precision and recall across clinically critical classes, resulting in stable F1-scores. Its consistent performance, interpretable error pattern, and alignment with established radiographic quality indicators make it particularly well-suited for integration as a decision support tool with radiology QA workflow, where reliability, safety, and operational efficiency are paramount.

The results obtained from the VGG-16 model demonstrate its capability to accurately predict and classify DICOM chest radiographs in accordance with the provided annotations. The figure presents five thoracic images along with their ground-truth labels (true), model predictions (Pred), and class probabilities for each category (accept, artefact, exposure, position). Overall, these findings highlight the ability of VGG-16 to recognize image-quality patterns effectively, while also illustrating the characteristic types of misclassifications that may occur in CNN models trained on radiographic data. Figure 4 presents five representative examples illustrating the prediction behavior of the VGG-16 model in classifying DICOM chest radiographs into four technical categories: accept, artefact, exposure, and position.

- i) Frame 1 (true: position, predicted: artefact), the model assigned a very high probability to the artefact class (99.38%) despite the ground-truth label indicating a positioning error. The prediction suggests that VGG-16 detected high-contrast edges or noise patterns around the shoulder region or the “R” side marker and misinterpreted them as artefacts. This misclassification highlights the model's sensitivity to non-anatomical structures and its tendency to confuse certain irregularities in body alignment with artefactual patterns. Such false-positive artefact predictions reflect the inherent limitation of VGG-16 in distinguishing visually similar technical error features.

- ii) Frame 2 (true: position, predicted: position), the model correctly classified the image with a dominant probability of 93.27%. The radiograph displays noticeable rotation or asymmetric body translation, resulting in abnormal scapular and mediastinal alignment—patterns effectively captured by VGG-16.
- iii) Frame 3 (true: exposure, predicted: exposure), the model again performed accurately, assigning an extremely high probability (99.96%) to the exposure error class. The radiograph appears underexposed, with reduced lung field visibility and diminished mediastinal contrast. VGG-16 successfully recognized the extreme brightness and contrast deviations characteristic of severe exposure errors, demonstrating its strong sensitivity to global intensity distributions.
- iv) Frame 4 shows another correct prediction with an equally high probability (99.96%), representing either marked underexposure or overexposure. The consistency of performance in sequential exposure-error cases indicates that the model effectively leverages histogram-based intensity cues.
- v) Frame 5, the model achieved a correct prediction (98.80%), identifying a positioning error likely caused by rotation or shoulder elevation. Despite the suboptimal overall image quality, VGG-16 accurately captured thoracic asymmetry and alignment deviations, demonstrating robustness in detecting macroscopic positioning anomalies.

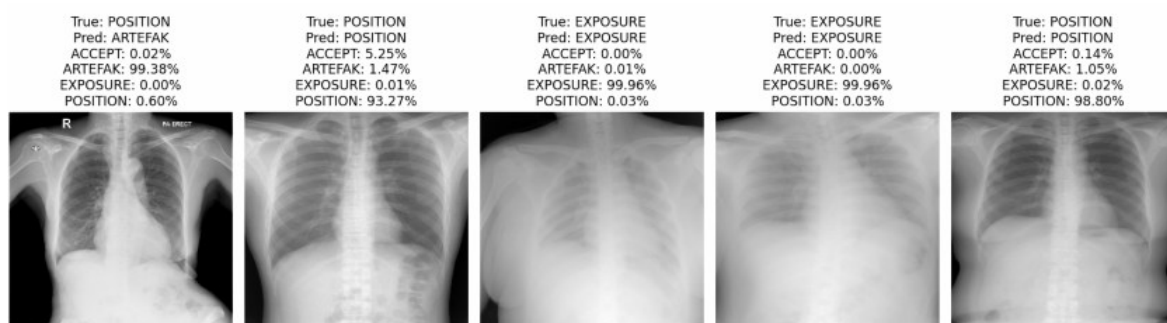


Figure 4. VGG-16 prediction visualization

Collectively, these findings indicate that VGG-16 performs exceptionally well for the exposure and positioning classes—two categories defined by clear, global visual patterns within chest radiography. Conversely, the model struggles with the artefact class, particularly when artefact-like patterns resemble anatomical edges or when non-anatomical objects (e.g., side markers) present strong visual dominance. This limitation is consistent with VGG-16's structural characteristics, which rely on relatively simple hierarchical feature extraction and are less optimal for detecting small, localized, or fine-grained artefacts.

The broader significance of these observations aligns with the growing adoption of CNNs in radiology. CNNs excel at learning hierarchical and adaptive visual patterns, enabling them to extract both global and subtle features from diagnostic images. As highlighted in the referenced literature, AI algorithms, including CNNs, can process data, learn from experience, and solve complex problems that typically require human intelligence [25]. This capability allows CNNs to identify low-quality technical factors—such as positioning errors, improper exposure, or artefacts with precision that is difficult to achieve through manual inspection alone.

Figure 3 demonstrated that the proposed CNN-based system is capable of identifying common image quality issues, such as positioning errors and exposure inconsistencies, which are among the most frequent causes of image rejection in routine radiographic practice. Previous studies by Golnari *et al.* [26] emphasized that positioning technique-related errors constitute a significant proportion of quality control issues reported across various radiographic modalities, including CR, and are often associated with inadequate feedback mechanisms between radiologists and radiographers. This observation is further supported by Fintelmann *et al.* [27] indicating that without systematic monitoring and timely feedback, such technical errors are likely to persist and recur in clinical practice. Accordingly, the implementation of structured, clinically oriented training intervention is necessary to reduce the image rejection rate, enhance diagnostic image quality, and support consistent patient-centered radiographic care.

While CR has substantially improved workflow flexibility and exposure tolerance, these technological advantages do not automatically translate into consistent image quality. In daily clinical practice, image rejection remains a persistent issue, suggesting that human-technology interaction plays a

decisive role. In this context, gaps in technologists' understanding of CR physics and system behavior represent a critical, yet often underestimated, contributor to reject-repeat phenomena. Strengthening education in CR, therefore, emerges not merely as a training requirement but as a necessary condition for sustainable quality improvement. Survey findings by Seeram *et.al.* [28] demonstrate substantial knowledge gaps among technologists in key CR topics, including exposure indicators, exposure creep, quality control tools, reject analysis, and dose image quality optimization.

Within the educational gap, CNN-based automation offers a complementary mechanism to support technologists at the point of image acquisition and decision-making. Beyond image analysis, CNN-based automation strengthens the radiology workflow across the imaging cycle. AI has been shown to improve quality and safety, optimize workflow, increase efficiency, and increase patient satisfaction [25]. Applied at the image-decision stage, CNNs can detect technical errors early, support calculation of repeat rates, reduce unnecessary radiation exposure, and contribute directly to RRA programs. Their role as digital model observers enables objective, reproducible quality assessment—an advantage supported by evidence that machine-learning systems have been used to develop model observers to assess image quality and optimize imaging parameters [25].

Furthermore, the importance of establishing multidisciplinary QA committees and implementing periodic, well-documented reject analysis as integral components of radiology quality management and cost-effectiveness evaluation [29]. Within this framework, the proposed CNN/VGG-16 system can be viewed as a digital evolution of conventional rate as audit, offering the capability for continuous, objective, and prospective monitoring of image quality. Integration of CNNs with DICOM metadata further enhances their value in quality assurance. Previous studies show that CNNs can categorize images using DICOM attributes to ensure accurate hanging protocols and PACS organization: a CNN model categorized X-rays in DICOM format into their appropriate anatomical groups with high precision [22]. This integration is particularly useful for reject analysis, where metadata such as tube voltage (kV), tube current and time (mAs), source image distance (SID), and patient orientation support more nuanced classification of technical errors.

CNN-driven automation also reduces the workload of radiologists and technologists. AI has the potential to improve radiology department management by optimizing workflow efficiency, enhancing quality control, and reducing unnecessary resource utilization [30], [31]. AI can relieve radiologists and technologists of time-consuming tasks so they can focus on complex work [25], helping to alleviate workflow bottlenecks and improve departmental throughput. Ultimately, CNN-based systems offer strategic value to healthcare organizations by enabling the identification of systematic error patterns across shifts, operators, and modalities. Such insights provide actionable evidence for quality-improvement policies, targeted technologist training, and protocol optimization [25]. The application of CNNs further contributes to optimizing workload distribution and operational efficiency within radiology departments. By automating the assessment of image quality, CNNs significantly reduce the time required for manual evaluation by radiographers or radiologists, thereby minimizing workflow bottlenecks during peak operational hours and increasing the overall throughput of radiology suites. This reduction in administrative and repetitive tasks represents a substantial advantage, particularly in clinical environments facing workforce limitations. Ultimately, CNNs offer strategic value for healthcare organizations by enabling the identification of systemic patterns of technical errors. The referenced study emphasizes that AI supports workflow enhancement and process optimization across the imaging cycle [25] underscoring its role in comprehensive quality management. When implemented within an RRA framework, CNNs allow institutions to detect error trends associated with specific shifts, operators, or imaging modalities. These insights provide a strong evidence base for targeted quality-improvement policies, radiographer training initiatives, and the development of more effective and standardized imaging protocols.

From management and sustainability perspective, the integration of AI-based DSS into reject-repeat workflow directly addressed key challenges highlighted in recent literature, including inefficiencies related to repeat examination, cumulative patient radiation dose, and workflow burden [32], [33]. By functioning as a human in the loop system, the proposed approach aligns with recommended governance frameworks for AI implementation in radiology, preserving professional accountability while enhancing decision consistency [34]. The observed performance metrics suggest that AI-assisted reject analysis can serve not only as a technical classification tool but also as a scalable mechanism for continuous quality improvement, cost containment, and patient-centered radiographic practice.

4. CONCLUSION

This study demonstrates that CNNs can effectively and consistently identify radiographic image quality and support automatic reject repeat decision making for digital chest radiographs. Among the evaluated architectures, VGG-16 achieved the most balanced classification performance, while ResNet-101

and DenseNet-201 also showed strong potential for technical image quality assessment. These findings confirm that CNNs can reliably extract radiographic quality features and provide objective, standardized support for quality assurance, thereby reducing inter-operator variability in image evaluation. Furthermore, integrating CNN-based analysis with DICOM metadata offers opportunities to combine visual image characteristics with acquisition parameters, enabling the development of more adaptive and comprehensive quality assurance systems. Although artifacts variability remains a challenge and may require further refinement of feature extraction techniques, the proposed approach demonstrates substantial potential for integration into routine radiology workflows. By supporting reject-repat analysis, improving workflow efficiency, and reducing unnecessary repeat examination in maintaining consistent image quality standards, the proposed CNN-based DSS represents a practical contribution to the digital transformation of radiology quality management and patient safety.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest to declare.

ETHICAL APPROVAL

This study was approved by the Health Research Ethics Committee of Poltekkes Kemenkes Semarang. The approval letter No. 0103/EA/KEPK/2024.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author [DR].

REFERENCES

[1] J. T. Bushberg, J. A. Seibert, E. M. Leidholdt, and J. M. Boone, *The essential physics of medical imaging*. Philadelphia, United States: Wolters Kluwer Health/Lippincott Williams & Wilkins, 2012.

- [2] J. H. Rollins, B. W. Long, and T. Curtis, *Merrill's atlas of radiographic positioning and procedures*, 13th ed., Amsterdam, Netherland: Elsevier Mosby, 2022.
- [3] Y. Akhter, R. Singh, and M. Vatsa, "AI-based radiodiagnosis using chest X-rays: a review," *Frontiers in Big Data*, vol. 6, Mar. 2023, doi: 10.3389/fdata.2023.1120989.
- [4] J. O.-Banahene, E. O. Darko, F. Hasford, E. K. Addison, and J. O. Asirifi, "Film reject analysis and image quality in diagnostic radiology department of a teaching hospital in Ghana," *Nigerian Journal of Radiation Research and Applied Sciences*, vol. 7, no. 4, pp. 589–594, 2014, doi: 10.1016/j.jrras.2014.09.012.
- [5] K. Little *et al.*, "AAPM task group report 305: guidance for standardization of vendor-neutral reject analysis in radiography," *Journal of Applied Clinical Medical Physics*, vol. 24, no. 5, May 2023, doi: 10.1002/acm2.13938.
- [6] K. C. Eze, N. Omodia, B. Okegbunam, T. Adewonyi, and C. C. Nzotta, "An audit of rejected repeated X-ray films as a quality assurance element in a Radiology Department," *Nigerian Journal of Clinical Practice*, vol. 11, no. 4, pp. 355–358, Dec. 2008.
- [7] J. Papp, *Quality management in the imaging series*, 6th ed. St. Louis, United States: Elsevier, 2019.
- [8] International Atomic Energy Agency, *IAEA safety standard: radiation protection and safety in medical uses of ionizing radiation*, IAEA Safety Standards Series No. SSG-46, Vienna, Austria: International Atomic Energy Agency, 2018.
- [9] C. Prieto *et al.*, "Image retake analysis in digital radiography using DICOM header information," *Journal of Digital Imaging*, vol. 22, no. 4, pp. 393–399, Aug. 2009, doi: 10.1007/s10278-008-9135-y.
- [10] G. C. Weatherburn and J. G. Davies, "Comparison of film, hard copy computed radiography (CR) and soft copy picture archiving and communication (PACS) systems using a contrast detail test object," *British Journal of Radiology*, vol. 72, pp. 856–863, Sep. 1999, doi: 10.1259/bjr.72.861.10645191.
- [11] N. Mercieca, J. L. Portelli, and H. J.-Patel, "Mammographic image reject rate analysis and cause – a national Maltese study," *Radiography*, vol. 23, no. 1, pp. 25–31, Feb. 2017, doi: 10.1016/j.radi.2016.07.004.
- [12] J. Mount, "Reject analysis: a comparison of radiographer and radiologist perceptions of image quality," *Radiography*, vol. 22, no. 2, pp. e112–e117, May 2016, doi: 10.1016/j.radi.2015.12.001.
- [13] C. Saade *et al.*, "To repeat or not to repeat: Radiologists demonstrated more decisiveness than their fellow radiographers in reducing the repeat rate during mobile chest radiography," *Radiography*, vol. 27, no. 2, pp. 304–309, May 2021, doi: 10.1016/j.radi.2020.09.003.
- [14] E. Kjelle and C. Chilanga, "The assessment of image quality and diagnostic value in X-ray images: a survey on radiographers' reasons for rejecting images," *Insights into Imaging*, vol. 13, no. 1, Dec. 2022, doi: 10.1186/s13244-022-01169-9.
- [15] B. Hofmann, T. B. Rosanowsky, C. Jensen, and K. H. C. Wah, "Image rejects in general direct digital radiography," *Acta Radiologica Open*, vol. 4, no. 10, 2015, doi: 10.1177/2058460115604339.
- [16] K. J. Little *et al.*, "Unified database for rejected image analysis across multiple vendors in radiography," *Journal of the American College of Radiology*, vol. 14, no. 2, pp. 208–216, Feb. 2017, doi: 10.1016/j.jacr.2016.07.011.
- [17] E. Kjelle, A. K. Schanche, and L. Hafskjold, "To keep or reject, that is the question - a survey on radiologists and radiographers' assessments of plain radiography images," *Radiography*, vol. 27, no. 1, pp. 115–119, Feb. 2021, doi: 10.1016/j.radi.2020.06.020.
- [18] M. Hardy and H. Harvey, "Artificial intelligence in diagnostic imaging: impact on the radiography profession," *British Journal of Radiology*, vol. 93, no. 1108, Apr. 2020, doi: 10.1259/bjr.20190840.
- [19] J. S. Whaley, B. D. Pressman, J. R. Wilson, L. Bravo, W. J. Sehnert, and D. H. Foos, "Investigation of the variability in the assessment of digital chest X-ray image quality," *Journal of Digital Imaging*, vol. 26, no. 2, pp. 217–226, 2013, doi: 10.1007/s10278-012-9515-1.
- [20] S. Kashyap *et al.*, "Artificial intelligence for point of care radiograph quality assessment," in *SPIE 10950, Medical Imaging 2019: Computer-Aided Diagnosis*, Mar. 2019, doi: 10.1117/12.2513092.
- [21] Y. Meng *et al.*, "Automated quality assessment of chest radiographs based on deep learning and linear regression cascade algorithms," *European Radiology*, vol. 32, no. 11, pp. 7680–7690, Apr. 2022, doi: 10.1007/s00330-022-08771-x.
- [22] C. B. Muddaraju, S. Shrinivasa, S. Narasimhamurthy, and V. Sontakke, "Automated diagnosis of brain tumor classification and segmentation of magnetic resonance imaging images," *IAES International Journal of Artificial Intelligence*, vol. 13, no. 4, pp. 4833–4842, Dec. 2024, doi: 10.11591/ijai.v13.i4.pp4833-4842.
- [23] F. Garcea, A. Serra, F. Lamberti, and L. Morra, "Data augmentation for medical imaging: a systematic literature review," *Computers in Biology and Medicine*, vol. 152, Jan. 2023, doi: 10.1016/j.combiomed.2022.106391.
- [24] Z. Hussain, F. Gimenez, D. Yi, and D. Rubin, "Differential data augmentation techniques for medical imaging classification Tasks," in *AMIA Annual Symposium Proceedings Archive*, 2017, vol. 2017, pp. 979–984.
- [25] K. Pierre *et al.*, "Applications of artificial intelligence in the radiology roundtrip: process streamlining, workflow optimization, and beyond," *Seminars in Roentgenology*, vol. 58, no. 2, pp. 158–169, Apr. 2023, doi: 10.1053/j.ro.2023.02.003.
- [26] P. Golnari, D. Forsberg, B. Rosipko, and J. L. Sunshine, "Online error reporting for managing quality control within radiology," *Journal of Digital Imaging*, vol. 29, no. 3, pp. 301–308, Jun. 2016, doi: 10.1007/s10278-015-9820-6.
- [27] F. Fintelmann *et al.*, "Repeat rates in digital chest radiography and strategies for improvement," *Journal of Thoracic Imaging*, vol. 27, no. 3, pp. 148–151, May 2012, doi: 10.1097/RTI.0b013e3182455f36.
- [28] E. Seeram, R. Davidson, S. Bushong, and H. Swan, "Education and training required for the digital radiography environment: a non-interventional quantitative survey study of radiologic technologists," *International Journal of Radiology & Medical Imaging*, vol. 1, no. 1. 2015. doi: 10.15344/2456-446x/2015/103.
- [29] C. Nwankwo, E. Oyekunle, and C. Eneja, "A 2-year comparative assessment of film reject analysis and economic implications at two hospitals in South-Western Nigeria," *Nigerian Journal of Health Sciences*, vol. 20, no. 1, 2020, doi: 10.4103/njhs.njhs_44_20.
- [30] E. Buijs, E. Maggioni, F. Mazziotto, F. Lega, and G. Carrafiello, "Clinical impact of AI in radiology department management: a systematic review," *Radiologia Medica*, vol. 129, no. 11, pp. 1656–1666, Nov. 2024, doi: 10.1007/s11547-024-01880-1.
- [31] M. Zanardo *et al.*, "A critical appraisal of the quality of guidelines for radiation protection in interventional radiology using the AGREE II tool: a EuroAIM initiative," *European Journal of Radiology*, vol. 143, Oct. 2021, doi: 10.1016/j.ejrad.2021.109906.
- [32] A. P. Brady *et al.*, "Developing, purchasing, implementing and monitoring AI tools in radiology: practical considerations. A multi-society statement from the ACR, CAR, ESR, RANZCR & RSNA," *Insights into Imaging*, vol. 15, no. 1, Dec. 2024, doi: 10.1186/s13244-023-01541-3.
- [33] B. Kocak, A. Ponsiglione, V. Romeo, L. Ugga, M. Huisman, and R. Cuocolo, "Radiology AI and sustainability paradox: environmental, economic, and social dimensions," *Insights into Imaging*, vol. 16, no. 1, 2025, doi: 10.1186/s13244-025-01962-2.
- [34] J. Gotte *et al.*, "Implementation of AI in radiology: the perspective of referring physicians," *Insights into Imaging*, vol. 16, no. 1, Dec. 2025, doi: 10.1186/s13244-025-02120-4.

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