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ARTICLE

Enhancing the Diagnostic Accuracy of Sacroiliitis: A Machine Learning Approach Applied to Computed Tomography Imaging

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Abstract

Aims/Background Sacroiliitis is a challenging condition to diagnose accurately due to the subtle nature of its presentation in imaging studies. This study aims to improve the diagnostic accuracy of sacroiliitis by applying advanced machine learning techniques to computed tomography (CT) images.

Methods We employed five convolutional neural network (CNN) models—Visual Geometry Group 16-layer Network (VGG16), ResNet101, DenseNet, Inception-v4, and ResNeXt-50—to analyze a dataset of 830 CT images, including both sacroiliitis and non-sacroiliitis cases. Each model's performance was evaluated using metrics such as accuracy, precision, recall, F1 score, Receiver Operating Characteristic (ROC), and Area Under the Curve (AUC). The interpretability of the models' decisions was enhanced using Gradient-weighted Class Activation Mapping (Grad-CAM) visualization.

Results The ResNeXt-50 and Inception-v4 models demonstrated superior performance, achieving the highest accuracy and F1 scores among the tested models. Grad-CAM visualizations offered insights into the decision-making processes, highlighting the models' focus on relevant anatomical features critical for accurate diagnosis.

Conclusion The use of CNN models, particularly ResNeXt-50 and Inception-v4, significantly improves the diagnosis of sacroiliitis from CT images. These models not only provide high diagnostic accuracy but also offer transparency in their decision-making processes, aiding clinicians in understanding and trusting Artificial Intelligence (AI)-driven diagnostics.

Key words: sacroiliitis; machine learning; CT image recognition; convolutional neural network (CNN); Grad-CAM visualization

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Introduction

Sacroiliitis is an inflammatory condition affecting the sacroiliac joint, which connects the sacrum to the ilium of the pelvis (Jans et al, 2014). It often arises from excessive mechanical stress due to activities like running or jumping (Al-Mnayyis et al, 2024). Symptoms include lower back pain, decreased lumbar motion, and persistent stiffness (Falowski et al, 2020). Management typically involves rest, physical therapy, pharmacological treatments, and corticosteroid injections or surgery in severe cases (Falowski et al, 2020). Early and effective treatment is crucial to prevent long-term complications. Diagnosis begins with a comprehensive physical examination and may involve imaging modalities such as X-rays, computed

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tomography (CT) scans, and Magnetic Resonance Imaging (MRI) (Cui et al, 2015; Martín-Noguerol et al, 2023). While CT scans assess structural damage, MRI provides a comprehensive view of both bone and soft tissue changes, requiring skilled radiologists for accurate interpretation.

In recent years, there have been significant advancements in the academic field concerning the diagnosis of sacroiliitis. Shenkman et al (2019) developed an algorithm for diagnosing and grading sacroiliitis from CT scans initially performed for lower back pain. Korcakova et al (2022) utilized ultra-low-dose CT with filtration for assessing the sacroiliac joints. Lee et al (2021) explored quantitative analysis techniques using bone single photon emission computed tomography/computed tomography (SPECT/CT) versus planar bone scans for evaluating active sacroiliitis. Kim et al (2023) highlighted the prevalence and underdiagnosis of sacroiliitis in lumbar spine CT scans among low back pain patients. Walsh et al (2017) developed methodologies to extract axial spondyloarthritis (SpA) concepts from electronic medical records.

Machine learning has revolutionized sacroiliitis detection and diagnosis in CT imagery, improving accuracy (Chen et al, 2022; Shenkman et al, 2019). Bressem et al (2021) implemented an artificial neural network for identifying radiographic sacroiliitis indicative of axial spondyloarthritis (axSpA). Lee et al (2021) introduced a method combining Magnetic Resonance (MR) imaging of the sacroiliac joints with a deep-learning network to detect bone marrow oedema, a key indicator of sacroiliitis. Üreten et al (2023) proposed a computer-assisted diagnostic method for evaluating sacroiliac radiographs. Lin et al (2022) developed a deep-learning algorithm using the Short Tau Inversion Recovery (STIR) sequence MRI for detecting active inflammatory sacroiliitis. Aouad et al (2022) proposed a predictive model for identifying active sacroiliitis in patients with chronic inflammatory back pain. Collectively, these studies underscore the diverse methodological advancements in the diagnosis of sacroiliitis, ranging from refined imaging techniques to the integration of machine learning algorithms. The focus on enhancing diagnostic accuracy through various modalities, including CT, MRI, and SPECT/CT, reflects a significant shift towards precision in detecting this condition. The adoption of Artificial Intelligence (AI) and machine learning further demonstrates the field's evolution towards more sophisticated, data-driven approaches. These developments pave the way for more accurate, efficient, and early diagnosis, which is crucial for the effective management and treatment of sacroiliitis.

This study aims to enhance the diagnostic accuracy of sacroiliitis using CT images through advanced machine learning techniques. By employing multiple convolutional neural network (CNN) models, including Visual Geometry Group 16-layer Network (VGG16), ResNet101, DenseNet, Inception-v4, and ResNeXt-50, we seek to mitigate methodological bias and provide robust insights. Using a real-world dataset collected from hospital settings, our research ensures high relevance and applicability to clinical practices. We also integrate Gradient-weighted Class Activation Mapping (Grad-CAM) technology (Selvaraju et al, 2017) to visualize the decision-making processes of CNN models, facilitating transparency and trust in machine learning as a diagnostic tool. Ultimately, developing a precise and reliable machine learning model for classifying CT images of sacroiliitis represents a significant advancement in medical imaging, potentially improving patient outcomes through quicker and more accurate clinical decision-making.

Methods

The Proposed System

The system implemented in this study is specifically engineered for the classification of CT images of sacroiliitis through the application of advanced deep-learning/machine learning techniques, as illustrated in Fig. 1. The operational framework of the system is delineated in a multi-step flowchart encompassing data collection and preprocessing, deployment of multiple deep-learning algorithms, performance evaluation, and Grad-CAM visualization.

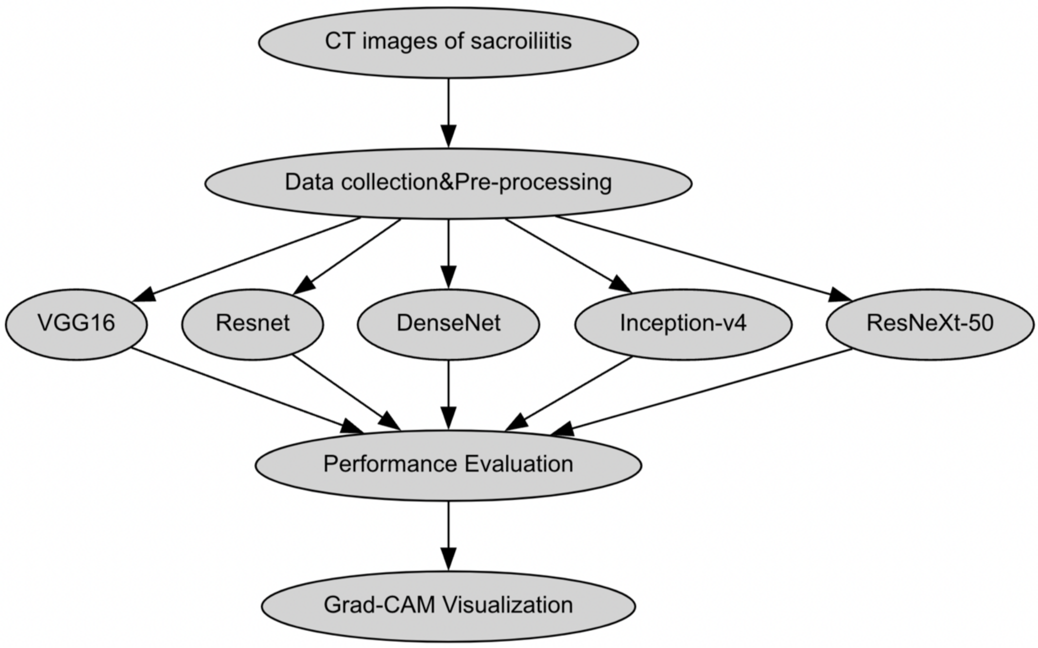

Fig. 1. Schematic utilizing deep-learning and machine learning for the categorization of sacroiliitis on computed tomography (CT) scans. VGG16, Visual Geometry Group 16-layer Network; Grad-CAM, Gradient-weighted Class Activation Mapping.

Initially, a collection of CT images depicting sacroiliitis was sourced from multiple hospital databases. These images underwent a rigorous preprocessing phase to enhance their quality, ensuring they were optimized for subsequent analysis by machine learning algorithms. This preprocessing involved standardizing image dimensions, enhancing contrast, and removing artefacts that could potentially skew the analysis.

Following preprocessing, the images were input into five distinct deep-learning algorithms: VGG16, ResNet101, DenseNet, Inception-v4, and ResNeXt-50. These models were selected based on their established efficacy and widespread adoption in image classification tasks within the scientific community. Each model was tasked with classifying images into one of two categories: sacroiliitis or non-sacroiliitis.

To assess the effectiveness of these algorithms, standard performance metrics such as accuracy, sensitivity, specificity, precision, and F1 score were employed. These metrics provided a quantitative basis for comparing the models, facilitating the identification of the algorithm that most accurately classifies sacroiliitis in CT images.

Lastly, to augment the interpretability of the models' decision-making processes, Gradient-weighted Class Activation Mapping (Grad-CAM) visualization was utilized. This advanced visualization technique highlights the specific regions within the images that significantly influenced the models' classification decisions. By providing visual explanations, Grad-CAM helps medical professionals gain a deeper understanding of the predictive behaviours of the models. Additionally, it assists in pinpointing areas of uncertainty within the models' analyses, offering potential avenues for further refinement to enhance both the accuracy and reliability of the diagnostic system.

Data Collection and Pre-Processing

In this study, a dataset of 830 CT images was collected from three local hospitals located in Ningbo, Zhejiang, China. The dataset consisted of 254 CT images of sacroiliitis (positive) and 576 CT images of non-sacroiliitis (negative), all of which had a resolution of 512 × 512. The collection and use of these images were approved by the Institutional Review Board (IRB) of each participating hospital.

The classification of CT images into sacroiliitis and non-sacroiliitis groups was rigorously based on established clinical and radiographic criteria. Sacroiliitis cases were identified through a combination of clinical evaluation and radiological features consistent with inflammatory changes in the sacroiliac joints. These features include joint space changes, sclerosis, erosions, and bone marrow oedema, which are indicative of sacroiliitis. Each diagnosis was confirmed by at least two experienced radiologists to ensure the accuracy and reliability of classification. Non-sacroiliitis cases refer to those that showed no evidence of such inflammatory changes and were not confirmed by similar expert review.

Inclusion Criteria:

• CT images of patients aged 18 and above.

• Images showing clear views of the sacroiliac joint.

Exclusion Criteria:

• Images with significant artefacts.

• Images of patients with a history of sacroiliac joint surgery.

The first stage of this study involves preprocessing, which is a crucial step in the machine learning process. Preprocessing ensures that data are cleaned and prepared appropriately for analysis and modelling. In this study, CT images are observed using OpenCV (Open Source Computer Vision Library is an open-source computer vision and machine learning software library. It was originally developed by Intel and is now supported by the OpenCV.org foundation. The foundation responsible for its ongoing development and maintenance is located in Palo

Alto, CA, USA), and their size, angle, and grayscale masks are adjusted to ensure consistency and suitability for analysis by machine learning models. Additionally, randomly cut Principal Component Analysis (PCA) and whitening techniques are employed during preprocessing. Randomly cut PCA reduces the dimensionality of high-dimensional data while preserving important features, while whitening normalizes data by removing correlations between features and reduces the influence of irrelevant features on machine learning models.

Fig. 2 provides a comparison between preprocessed and original images. To address the uneven distribution of positive and negative data in the original dataset, data augmentation techniques are employed. These techniques involve generating additional training samples by applying transformations such as rotation, scaling, and flipping. This increases the size of the training dataset and enhances the model's ability to generalize. Fig. 3 shows the data augmentation operation applied to CT images in this study.

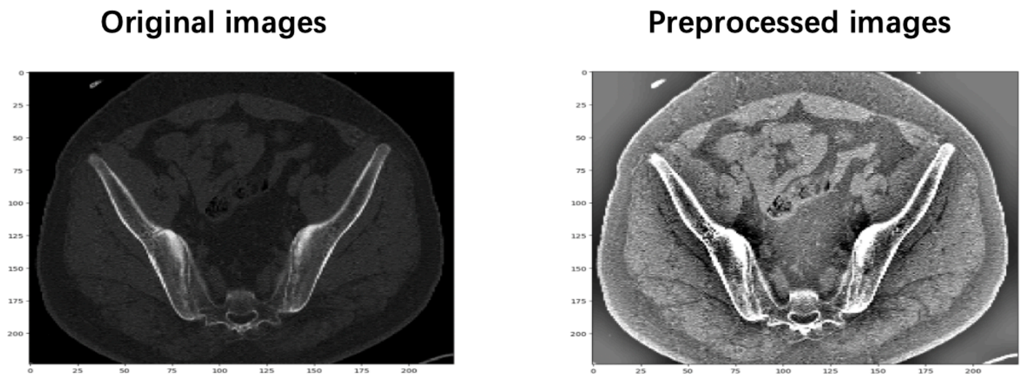

Fig. 2. Comparison between preprocessed and original images.

After undergoing preprocessing, the images are partitioned into distinct subsets including the training, validation, and test sets. The training set is utilized for instructing the machine learning algorithm, while the validation set serves as a means of refining hyperparameters and avoiding overfitting. The test set is ultimately employed to assess the model's efficacy when processing previously unseen data.

Training

The training phase involved the utilization of five distinct CNN models: VG G16, ResNet101, DenseNet, Inception-v4, and ResNeXt-50. These models were chosen based on their proven effectiveness in various image classification tasks and their unique architectural features well-suited for medical imaging analysis. VGG16 offers deep layers for feature extraction, ResNet101 facilitates the training of deep networks with its residual connections, DenseNet enhances feature reuse, Inception-v4 efficiently manages multi-scale representations, ResNeXt-50 strikes a balance between model complexity and computational efficiency. This diverse

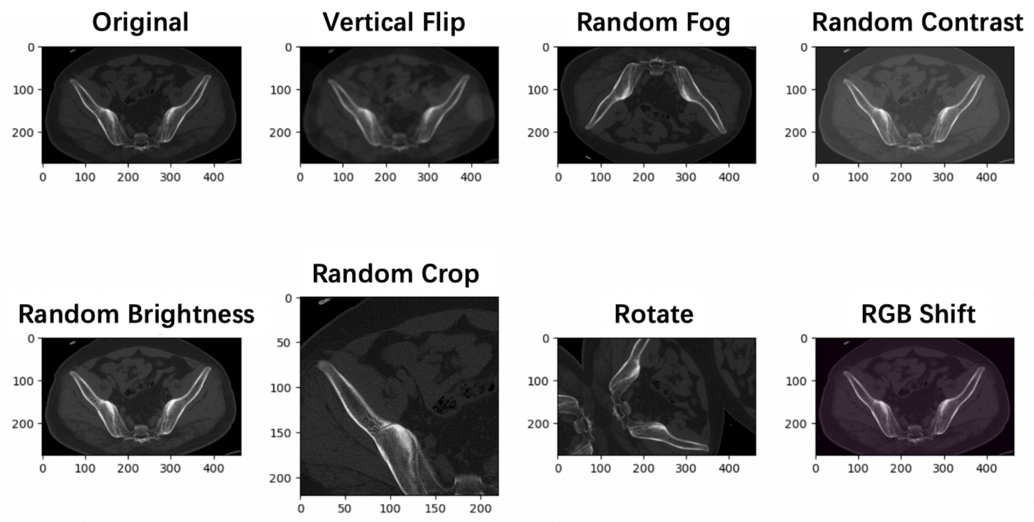

Fig. 3. Data augmentation operation applied to CT images includes various operations to enrich the dataset. These operations involve: Vertical flip, Random fog, Random contrast, Random brightness, Random crop, Random rotate, and Random Red, Green, Blue (RGB) shift.

set ensures a comprehensive evaluation of model performance across different architectural approaches.

Each model was trained using preprocessed CT images of sacroiliitis, with the dataset divided into training, validation, and testing sets in a 70:15:15 distribution ratio. To ensure compatibility with the dataset, the models underwent fine-tuning procedures, adjusting hyperparameters such as learning rate, batch size, and number of epochs for optimal performance.

VGG16, introduced in 2014 by Simonyan and Zisserman (Simonyan and Zisserman, 2014), features a deep architecture with 16 layers and 3×3 convolutional filters followed by 2×2 max-pooling layers. ResNet, developed by He et al (2016), addresses the vanishing gradient problem with its innovative use of shortcut connections. DenseNet, proposed by Huang et al (2017), stands out with its dense connectivity between layers, enhancing feature propagation and reuse. Inception-v4, an evolution of Inception-v3 by Szegedy et al (2016), offers increased depth and width with factorized convolutions to streamline computational demands. ResNeXt-50, a variant introduced by Xie et al (2017), utilizes grouped convolutions to efficiently manage computational resources while maintaining robust performance in image classification tasks.

For performance evaluation, we utilized technical indicators such as Accuracy, Precision, Recall, F1 score, Receiver Operating Characteristic (ROC), and Area Under the Curve (AUC). These metrics assess the models' ability to correctly classify CT images of sacroiliitis, reflecting their diagnostic accuracy and reliability. A stratified 10-fold cross-validation technique was employed to ensure a thorough evaluation, with results averaging across the folds to determine the models' overall effectiveness.

Grad-CAM

After training the CNN models, we utilized Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize and interpret the decision-making processes. This technique highlights the critical areas of an input image that significantly influence the classification outcomes (Selvaraju et al, 2017). Using the trained models, we created Grad-CAM maps by deriving gradients from the final convolutional layer's feature maps. These gradients helped identify the most influential regions within the images, such as the sacroiliac joint area, enhancing our understanding of the model's focus areas and aiding in refining its accuracy. Ultimately, Grad-CAM serves as a valuable tool for elucidating model behavior, providing insights that are crucial for optimizing performance.

Results

Fig. 4 illustrates the convergence of the training process for five different convolutional neural network (CNN) models—VGG16, ResNet101, DenseNet, Incepti on-v4, and ResNeXt-50—used for classifying CT images of sacroiliitis. It's evident that all five models exhibited an increase in accuracy with each epoch of training.

The VGG16 model started with an accuracy of 0.72 and reached 0.92 after 20 epochs. ResNet101 began with an initial accuracy of 0.79 and achieved 0.95 within the same timeframe. DenseNet started at 0.75 and increased to 0.95. Inception-v4 began with 0.85 and reached 0.97. The ResNeXt-50 model, starting with an accuracy of 0.86, demonstrated the highest accuracy of 0.99 after 20 epochs. These results indicate that all five CNN models were capable of learning and enhancing their classification performance with each epoch of training. However, the rate of improvement varied among the models, with VGG16 exhibiting the slowest rate of improvement and ResNeXt-50 showing the fastest.

Additionally, Table 1 presents the evaluation results of the trained CNN models for classifying CT images of sacroiliitis. The table includes key performance metrics: Accuracy, Area Under the Curve (AUC), Recall, and F1 score. From the results in Table 1, it is clear that all models achieved high accuracy, with ResNeXt-50 outperforming the others with an accuracy of 99%. The AUC values also suggest that ResNeXt-50 had the best performance, achieving an AUC of 98%, followed closely by Inception-v4 with an AUC of 95%. In terms of recall, ResNeXt-50 again led with a recall rate of 97%, indicating its superior ability to identify true positive cases of sacroiliitis. The F1 score, which considers both precision and recall, was highest for ResNeXt-50 at 98%, demonstrating its overall effectiveness in classifying CT images of sacroiliitis.

These results indicate high accuracy across all models, with ResNeXt-50 achieving the highest accuracy of 99%, followed closely by Inception-v4 at 97%. Similarly, ResNeXt-50 and Inception-v4 exhibited the highest AUC values and recall values, indicating their superior performance in correctly identifying positive cases. Additionally, ResNeXt-50 and Inception-v4 outperformed other models in terms of F1 score, demonstrating a balanced measure of precision and recall. Therefore,

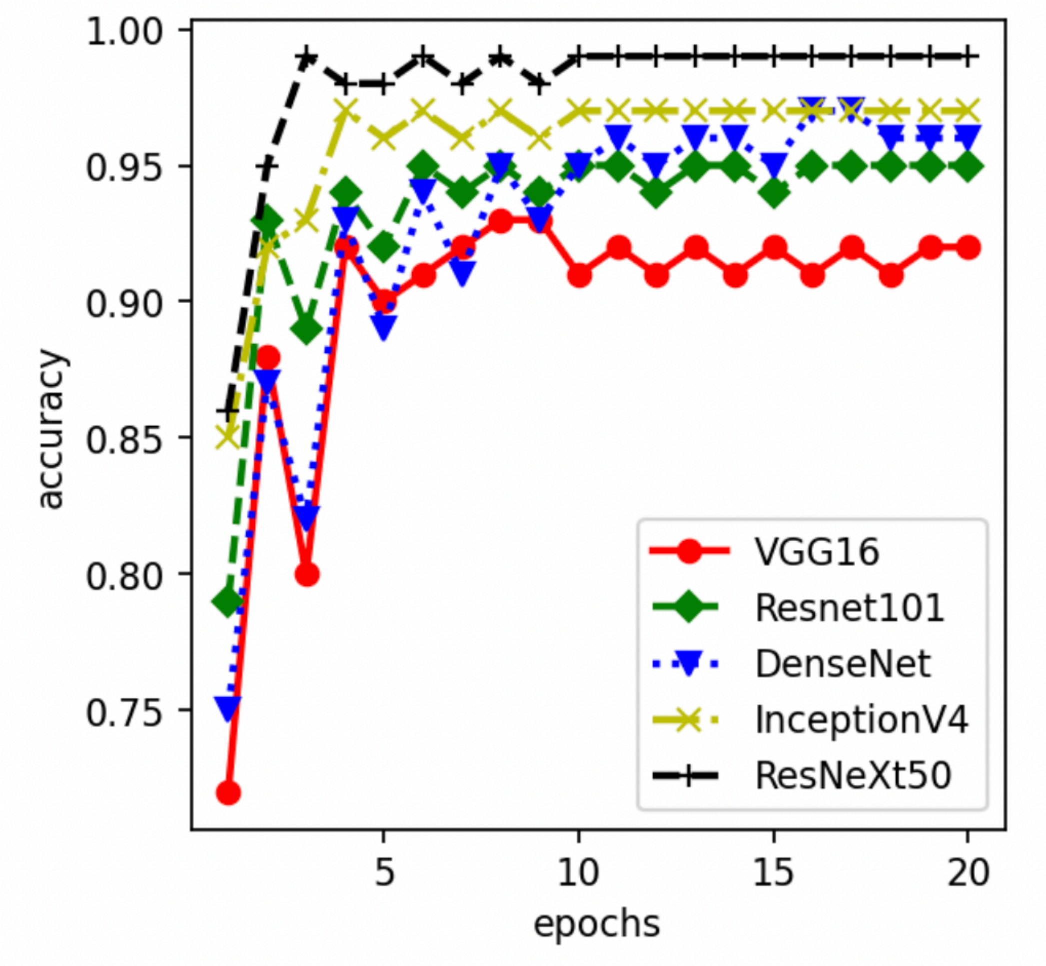

Fig. 4. Comparing the training performance of 5 convolutional neural network (CNN) models for sacroiliitis classification in CT expression images.

ResNeXt-50 and Inception-v4 are identified as the most suitable models for the classification of CT expression images of sacroiliitis.

The Grad-CAM visualization results were obtained to analyze the performance of the trained models and identify the regions of the image most important for the classification of sacroiliitis expression. Grad-CAM technology generated a heatmap of the mixture model, indicating the regions of the image that contributed most to the final classification decision.

Fig. 5 presents a comparison between a positive case of sacroiliitis manually marked by a doctor and the Grad-CAM heatmap. It can be observed that the areas with high sacroiliitis characteristics detected by Grad-CAM technology align closely with the manual observation results.

Discussion

The evaluation results of the trained CNN models for the classification of CT expression images of sacroiliitis indicate that ResNeXt-50 and Inception-v4 are the most accurate and reliable models for this task. The results of the training process for the five CNN models are promising, with all models achieving high accuracy on

Table 1. Evaluation results of trained convolutional neural network (CNN) models for classifying computed tomography (CT) expression images of sacroiliitis.

Model	Accuracy	AUC	Recall	F1 score
VGG16	92%	85%	82%	87%
ResNet101	95%	90%	89%	92%
DenseNet	96%	92%	91%	94%
Inception-v4	97%	95%	94%	96%
ResNeXt-50	99%	98%	97%	98%

AUC, Area Under the Curve.

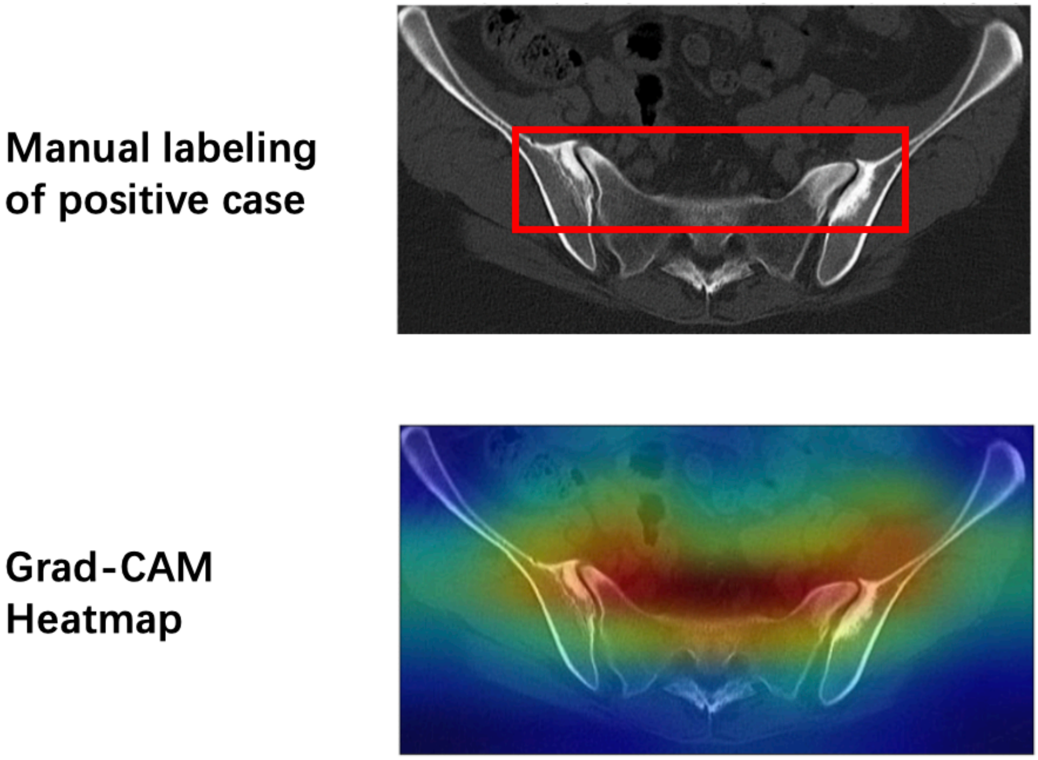

Fig. 5. Comparison between a positive case of sacroiliitis manually marked by doctor (red box) and the Grad-CAM heat map.

the CT expression images of sacroiliitis. ResNeXt-50 achieved the highest accuracy of 0.99, suggesting that its unique architecture and efficient use of computational resources allow it to learn complex patterns in the CT expression images indicative of sacroiliitis.

In the context of this study on the classification of sacroiliitis CT images, Re sNeXt-50 outperformed other CNN models due to its ability to learn and identify complex features in the CT images. CT images contain a large amount of detailed information, and ResNeXt-50 is able to effectively extract and utilize this information for classification.

The other models in the study, such as DenseNet and Inception-v4, also perform very well with high accuracy, AUC, recall, and F1 score, demonstrating the potential of machine learning techniques in the diagnosis and classification of medical images. The trained models can potentially be used to aid in the diagnosis and treatment of sacroiliitis, which is a significant step towards improving patient outcomes. In addition to their application in diagnosing sacroiliitis, the CNN models employed in this study—VGG16, ResNet101, DenseNet, Inception-v4, and ResNeXt-50—have also been utilized in the diagnosis of other diseases across various medical fields. For instance, VGG16 and ResNet101 have been instrumental in the detection of pulmonary diseases from chest X-ray images (Vieira et al, 2021), while DenseNet has shown promise in identifying features of diabetic retinopathy in retinal images (Farag et al, 2022). Inception-v4 has been applied in skin cancer classification through dermatoscopic images (Emara et al, 2019), and ResNeXt-50 has been used in the evaluation of pathological brain images in neurology (Quon et al, 2020). These diverse applications highlight the versatility and robustness of these models in handling complex imaging datasets across different domains of medical diagnostics.

The accuracy achieved by the models in this study indicates their ability to discern features distinguishing between sacroiliitis and normal CT expression images. This promising result suggests that accurate classification can facilitate early diagnosis and treatment of sacroiliitis. However, it's imperative to validate model performance on a larger dataset to mitigate overfitting to the training data. Fine-tuning hyperparameters such as learning rate, batch size, number of epochs, optimizer, and activation functions can achieve a better balance between underfitting and overfitting, leading to improved model performance. Further assessments are necessary to confirm the effectiveness of these models on diverse datasets and optimize hyperparameters.

The results of Grad-CAM visualization suggest that the trained models accurately identified the most crucial regions of sacroiliitis expression. The heatmap generated by Grad-CAM technology provided valuable insights into the models' inner workings, enabling further refinement of the training process and enhanced accuracy. These results aligned with doctors' observations, indicating the models' ability to accurately identify regions crucial for classification. Such findings may inform future research in medical image analysis and contribute to the development of more precise and efficient diagnostic tools for sacroiliitis.

Conclusion

In conclusion, this study underscores the potential of machine learning, particularly convolutional neural networks, in accurately classifying CT expression images of sacroiliitis. By employing multiple algorithms and utilizing a real-world dataset collected from hospitals, the results obtained in this study are more applicable to the actual clinical environment, thus rendering them more useful for medical professionals. Additionally, the study incorporates model interpretation using Grad-CAM technology, which provides visual explanations of the model's decision-making process.

The evaluation results of the trained CNN models indicate that ResNeXt-50 and Inception-v4 are the most suitable models for the classification of CT expression images of sacroiliitis, achieving high accuracy, AUC, recall, and F1 scores. However, it's worth noting that the effectiveness of machine learning models may vary depending on the dataset, preprocessing methodologies, and hyperparameters utilized. Therefore, further examination is required to confirm their reliability on diverse datasets and to optimize their hyperparameters.

This study provides significant insights into the capability of machine learning in precisely diagnosing sacroiliitis. It also underscores the importance of employing real-world datasets and interpretation techniques for models to enhance their applicability and interpretability in clinical settings.

Key Points

- The study leverages a diverse set of advanced convolutional neural network models, including VGG16, ResNet101, DenseNet, Inception-v4, and ResNeXt-50, to analyze CT images for sacroiliitis, ensuring comprehensive coverage and comparison of different architectural approaches.
- Employing Grad-CAM technology enhances transparency and interpret ability by providing visual insights into the decision-making processes within CNNs. This allows for a deeper understanding of how the models arrive at their classification decisions, improving trust and facilitating further refinement.
- The study demonstrates notable accuracy in sacroiliitis diagnosis, particularly with the ResNeXt-50 and Inception-v4 models. Their high accuracy suggests their potential utility in clinical settings, where precise and reliable diagnosis is crucial for effective patient management.
- Analysis is conducted on a substantial dataset comprising 830 CT images, providing a robust basis for training and testing the machine learning models. The large dataset enhances the generalizability of the findings and increases confidence in the models' performance.
- The study acknowledges the importance of additional validation across more diverse datasets to ensure the robustness of the models and optimize their performance. This recognition underscores the commitment to continuous improvement and refinement of the models for practical clinical application.

Availability of Data and Materials

The datasets used during the current study are available from the corresponding author on reasonable request.

Author Contributions

QSF and XHY designed the research study. XRY, XYH, WBW, and JKZ performed the research, including data collection and model training. XHY provided expert guidance on the experimental design and data analysis. QSF and XHY analyzed the data, ensuring the robustness and validity of the findings. QSF drafted the manuscript, with significant input and revisions from all authors. All authors contributed to important editorial changes of the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The present study followed the Declaration of Helsinki and was approved by the Human Research Ethics Committee of Ningbo No. 2 Hospital (No.SL-KYSB-NBEY-2021-043-01). The written informed consent was obtained from all subjects participating in the trial, and their information was stored and used for research anonymously.

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Conflict of Interest

The authors declare no conflict of interest.

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