

MRI-Based Framework for Ankylosing Spondylitis Diagnosis

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Abstract. Ankylosing spondylitis (AS) is a progressive inflammatory disease of the sacroiliac joints and spine, and its early inflammation can be detected only with magnetic resonance imaging (MRI). Manual detection of early inflammation on MRI is time-consuming, inconsistent, and subjective, which delays diagnosis and treatment. This paper presents an automated approach to detecting AS from MRI scans. The approach segments and classifies MRI images automatically and makes the classification more interpretable. The framework combines several deep learning models. An Attention U-Net segments the sacroiliac joints in the MRI scans. A hybrid convolutional neural network (CNN) and Transformer architecture then classifies each image as AS-positive or AS-negative and attempts to assign the disease stage (normal, early, moderate, or advanced). This architecture uses EfficientNet to extract detailed local features and Vision Transformer blocks to capture global context. Finally, gradient-weighted class activation mapping (Grad-CAM) gives a visual explanation of each decision. On 962 test images, the framework detected AS with 88.67% accuracy; stage grading remained limited, with 60.40% stage accuracy, and most early and moderate cases were predicted as advanced.

Keywords. Ankylosing spondylitis; MRI; deep learning; Attention U-Net; hybrid CNN-Transformer; medical image segmentation; stage-wise classification; explainable AI; Grad-CAM

I. INTRODUCTION

Ankylosing spondylitis (AS) is an inflammatory disorder that causes pain and stiffness in the spine and sacroiliac joints [1], [2]. Early diagnosis is essential to prevent complications and slow disease progression [3]. Research has shown that magnetic resonance imaging (MRI) is one of the most effective tools for detecting the inflammation associated with AS, which can go unnoticed with other imaging methods [4]-[6]. However, radiological reading of the images is tedious and requires considerable expertise.

Recent developments in machine learning and deep learning for medical image analysis have produced various computer-aided diagnosis methods [7], [8]. Convolutional neural network (CNN) approaches have proven effective at recognizing spatial features in MRI images, and segmentation networks such as U-Net have helped to identify important anatomical locations [9]-[11]. Despite these advances, automated AS diagnostic systems still face difficulties with interpretability and with the scarcity of labeled MRI data [12]-[17]. To address these problems, this paper proposes an MRI-based framework that combines an Attention U-Net, a hybrid CNN-Transformer, and gradient-weighted class activation mapping (Grad-CAM) for automatic AS diagnosis [18]-[20].

II. RELATED WORK

Deep learning and medical imaging techniques for diagnosing AS from MRI have advanced steadily [8], [18]. Several studies have confirmed that CNN models can recognize in-

flammatory patterns and abnormalities in the sacroiliac joints [3], [21]. Transfer learning with pretrained feature extraction layers has also improved diagnostic accuracy for AS [1]. In addition, approaches built on segmentation models such as U-Net have improved classification accuracy by localizing clinically significant regions [9], [11].

Current approaches nevertheless have drawbacks. First, many models work as black boxes and give no explanation that would increase clinical trust in their results [8], [10]. Second, many models require fully labeled datasets, which are costly and time-consuming to obtain in medical imaging [9], [13]. Third, several systems are designed only for binary disease detection and offer neither stage-wise classification nor explanation [4], [22].

To address these problems, the proposed approach uses an Attention U-Net for segmentation, a hybrid CNN and Transformer architecture for classification, and Grad-CAM for explanation.

III. PROPOSED WORK

A. Overview of the Proposed System

The framework detects AS and attempts to classify its stage automatically from MRI images of the sacroiliac joint [7], [21]. It uses CNNs to extract features from the medical images and draws on the context-learning ability of Transformers [11].

The system follows an end-to-end deep learning approach. First, each image is preprocessed to improve its quality and reduce noise [8]. An Attention U-Net then de-

tests the sacroiliac joint regions and focuses on the clinically important structures [21]. The extracted region is passed to the hybrid CNN-Transformer, which detects AS and classifies its stage [1], [22]. Finally, Grad-CAM visual explanations make the system's predictions easier to interpret [10].

B. Dataset Description

The framework uses MRI scans of the sacroiliac joint obtained from public medical imaging datasets and repositories [3], [18], [22]. An initial set of 900 labeled MRI images was extended with slices from the LSD, SPIDER, OSF, and T-SEG datasets to form a database of 2,137 grayscale MRI images covering the AS stages [9], [13], [16], [23]. All images were rescaled to 256×256 grayscale PNG images, and the metadata and labels were stored in CSV files [11].

Augmentation with changes in brightness, contrast, and orientation increased the diversity and generalizability of the images, giving a dataset of 6,411 images [1], [8], [21]. This dataset was divided into training, validation, and test sets in the proportions 70:15:15, with 4,487, 962, and 962 images, respectively.

C. Preprocessing and Data Augmentation

Before training, the MRI images passed through several preprocessing stages that enhance image quality and improve model results [8]. First, the images were converted to unsigned 8-bit format and normalized for consistency across the dataset [11]. Contrast-limited adaptive histogram equalization (CLAHE) was then applied to improve the visibility of sacroiliac joint structures and inflammation [18]. To increase clarity, Gaussian smoothing was applied, and the images were resized to 256×256 pixels [1].

For the deep learning models, the grayscale MRI images were converted to three-channel format where needed [21]. Rotation, flipping, brightness, and noise changes were applied to images from the training set only [8], [23].

D. Proposed Hybrid CNN-Transformer Architecture

The hybrid CNN-Transformer design automates the detection of AS and the classification of its stages from MRI images [1], [21]. The preprocessed MRI images are first fed into EfficientNetB0, which extracts local features that capture the intensity, texture, and structure of the sacroiliac joint [11]. Training proceeds in two stages: the first trains the Transformer and classification layers, and the second fine-tunes the CNN backbone [22].

The resulting feature maps are flattened into tokens and processed by multi-head self-attention in the Transformer blocks, which identify global spatial relations between features in the MRI image [11]. Attention also keeps the model focused on important anatomical regions such as the sacroiliac joints [21]. The final layer performs binary AS detection and classifies the AS stage (normal, early, moderate, or advanced) with a weighted focal loss function and dropout [13], [23].

E. Training Procedure

The training strategy was chosen to overcome the small data size, class imbalance, and multi-task learning problems common in medical imaging [8], [23]. All models were built in PyTorch and trained on an NVIDIA L4 GPU [11].

The hybrid CNN-Transformer used a two-step training procedure: the Transformer and classifier blocks were first trained with the CNN backbone frozen, and the deeper CNN layers were then fine-tuned to improve feature learning [22]. Multi-task learning was used to predict the binary AS label and the stage at the same time, with greater weight on the binary prediction [7], [13]. Model checkpointing, dropout regularization, and early stopping were used to prevent overfitting [1], [21].

The experiments used 256×256 MRI scans with a batch size of 32. The Attention U-Net was trained for 60 epochs and the classification model for 80 epochs. The learning rate was 0.001 with a cosine schedule and a minimum of 0.000001, and label smoothing of 0.1 was applied. Focal loss was used for classification to handle class imbalance, and the segmentation loss combined Dice loss and binary cross-entropy (BCE) loss as

$$L_{\text{seg}} = 0.5 L_{\text{Dice}} + 0.5 L_{\text{BCE}}. \quad (1)$$

Class imbalance was handled with focal loss combined with label smoothing, and training used the Adam optimizer with a linear warm-up and a cosine annealing schedule [7], [11], [13], [23].

F. Explainability Framework

The framework includes explainable artificial intelligence (XAI) to make the AS diagnosis process more transparent and reliable [8], [10]. Grad-CAM produces heatmaps that show which regions of the sacroiliac joints drive each prediction, which supports both interpretation and error analysis [1], [18], [21].

IV. RESULTS AND DISCUSSION

The MRI-based framework performed sacroiliac joint segmentation, AS classification, and staging with the Attention U-Net and the hybrid CNN-Transformer [1], [21]. Grad-CAM showed the image areas that contributed to the model's decisions [8], [10]. Fig. 1 shows the confusion matrix for binary classification on the 962 test images.

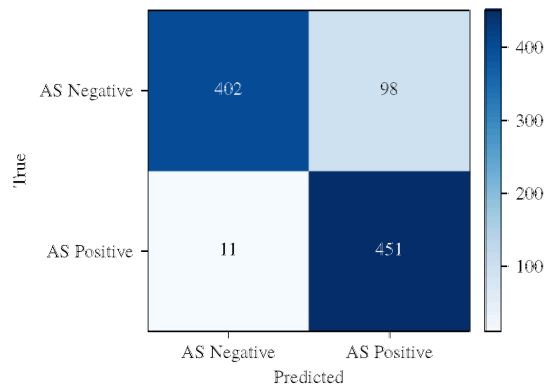


Fig. 1. Confusion matrix of the proposed hybrid CNN-Transformer model for binary classification of AS (AS-positive vs. AS-negative).

The quantitative results in Table 1 show strong AS classification in terms of accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) [1], [21]. Stage-wise classification was harder because adjacent stages look similar [10], while segmentation reached high Dice and intersection over union

(IoU) scores, indicating successful localization of the sacroiliac joint [9], [21].

TABLE 1. PERFORMANCE METRICS OF THE PROPOSED HYBRID CNN-TRANSFORMER MODEL

Metric	Hybrid CNN-Transformer
Binary accuracy	88.67%
Binary precision	90.04%
Binary recall	88.67%
Binary F1-score	88.62%
AUC-ROC	0.9459
Stage accuracy	60.40%
Stage F1-score	60.32%
Segmentation Dice	0.831
Segmentation IoU	0.711

The stage confusion matrix in Fig. 2 shows the difficulty of predicting more than two classes at once [13], [23]. The classifier predicted most normal (402 of 500) and advanced (132 of 162) cases correctly but confused the early, moderate, and advanced stages: 100 of 153 early cases and 109 of 147 moderate cases were predicted as advanced, and only 23 early and 24 moderate cases were graded correctly. Stage grading therefore remains limited, with an overall stage accuracy of 60.40% [3], [22].

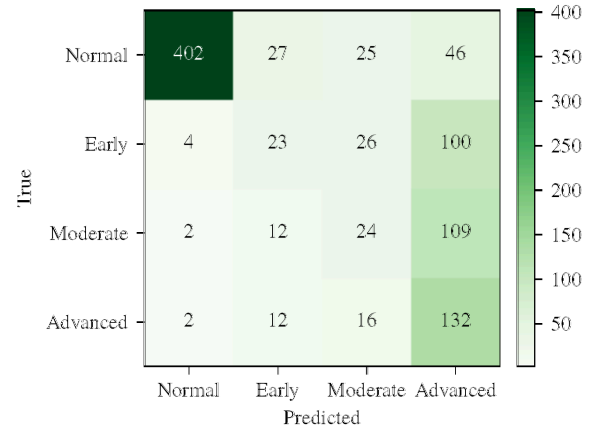


Fig. 2. Confusion matrix of the proposed hybrid CNN-Transformer model for stage-wise classification of AS.

The explainability layer makes clear which MRI regions contributed to each decision [8], [10]. As Fig. 3 shows, advanced-stage cases produced strong activations near the sacroiliac joint area, whereas normal cases produced weak activations because inflammation was absent [3], [18], [23]. Activations for the early and moderate stages were wider because their features are similar, but the sacroiliac joint remained the target area [10], [13], [21].

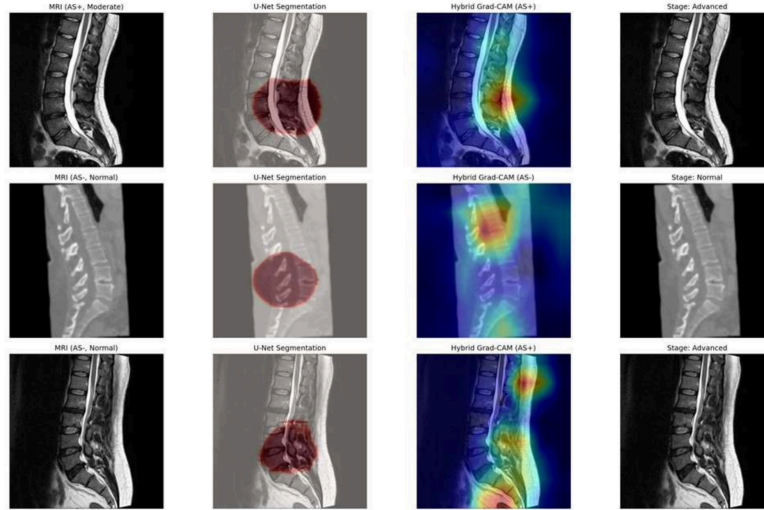


Fig. 3. Disease prediction and stage classification with the segmentation mask and Grad-CAM visualization.

V. CONCLUSION

The proposed MRI-based approach offers an automated way to detect AS. The Attention U-Net segmented the sacroiliac joint area with a Dice score of 0.831, and the hybrid CNN-Transformer model, which uses both local and global MRI information, detected AS with 88.67% accuracy on the test set. Stage grading remains limited: the stage accuracy was 60.40%, and most early and moderate cases were predicted as advanced, so the framework does not yet reliably distinguish the early, moderate, and advanced stages of AS. Grad-CAM also improves the explainability of the model's predictions by showing the MRI regions responsible for each decision.

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AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

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DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

This study used publicly available sacroiliac joint MRI images from public medical imaging repositories, including slices from the LSD, SPIDER, OSF, and T-SEG datasets.

ETHICS STATEMENT

This study used publicly available, de-identified data and did not involve direct interaction with human participants or animals; ethical approval was therefore not required.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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