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A SURVEY ON ANKYLOSING SPONDYLITIS (AS) DETECTION AND PREDICTION USING MACHINE LEARNING AND DEEP LEARNING - REVIEW

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Abstract : **Ankylosing spondylitis (AS) is a chronic inflammatory illness caused by sacroiliitis that primarily affects men. X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and digital imaging and communications in medicine (DICOM) images all play significant functions in AS detection. The goal of this research is to investigate the knowledge of AS and present a comprehensive assessment of artificial intelligence (AI) techniques. In this paper, potential of AI, machine learning (ML), and deep learning (DL) to aid in the early identification of AS and the forecasting of more successful patient-specific treatment. For AS diagnosis, ML (K Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes (NB), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), and Artificial Neural Network (ANN)) and DL (Recurrent Neural Network (RNN), Deep Neural Network (DNN), Convolutional Neural Network (CNN), pretrained CNNs, and transformer models) trained models have created. The extensive healthcare systems require the timely and efficient support of ML and DL techniques. Benefits are mainly higher in lacking person specialists and investigative resources. The review describes the many types of methodologies, dataset descriptions, and limits of earlier efforts to identify gaps. It offers comprehensive details of the most recent improvements at various stages of AS identification and therapy. Overall, this work supports future research in this area and offers a thorough analysis of AS diagnosis.**

IndexTerms **- Axial Spondyloarthritis, Ankylosing Spondylitis, X-rays, MRI, CT, DICOM, artificial intelligence, Machine Learning, deep learning, bone marrow edema, and sacroiliac joints.**

1. INTRODUCTION

Ankylosing Spondylitis (AS) is described by inflammatory lower back discomfort and it is prevalent provocative rheumatic condition that changes the axial skeleton, [1]. The condition causes inflammatory discomfort, which originates in the sacroiliac joints and progresses throughout the spine. Sample images of both a healthy and an arthritic spine are displayed in Figure 1. The course of the disease is influenced by both extrinsic and hereditary factors [2]. Back pain is the most prevalent clinical symptom. However, the diagnosis is typically omitted, and it takes an average of 8–11 years after the illness first arises [3]. Misdiagnosis might result in patients receiving unneeded therapies or in their recovery being delayed [4]. When combined with clinical symptoms and imaging results, it has been diagnosis using the enhanced New York criteria [5,6]. In order to validate the diagnosis, structural alterations in the sacroiliac joint are identified using conventional radiography. AS is detected by X-rays, DICOM images, CT [7,8], and MRI [9,10,11].

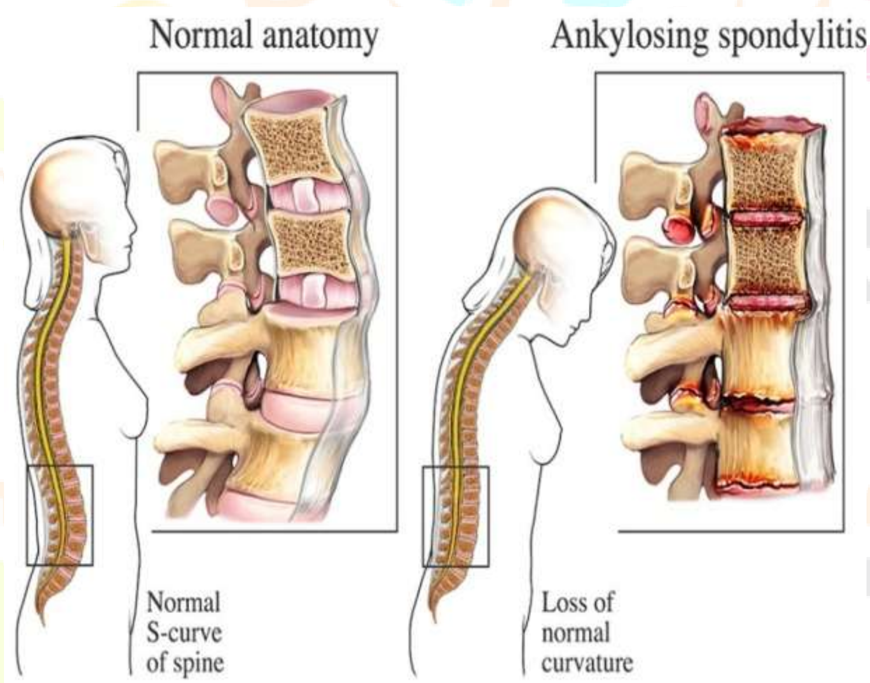

FIGURE 1.SAMPLE IMAGES FOR NORMAL SPINE, AND ANKYLOSING SPONDYLITIS

Traditional X-rays are the main diagnostic technique. However, irreversible structural alterations have not yet occurred, and X-rays are unable to identify inflammation in the early stages of the disease [12]. Direct radiographs are a rapid and simple way to diagnose AS at facilities with specialists. However, the diagnosis of AS may be delayed in basic healthcare institutions due to a lack of specialists who can identify it early [13]. Patients can lose the ability to carry out their regular activities. Because of the potential financial, psychological, and socioeconomic implications for both the individual and society, the functional limitation is crucial.

The most common imaging method for diagnosing AS is X-rays, although in patients who might have early-stage AS, their sensitivity is low. Furthermore, the early phases of the disease, when irritation is present and permanent structural alterations have not yet occurred, are not detectable by X-rays. Compared to X-rays, CT is more sensitive and consistently identifies pathological alterations in the bones. However, the routine use of conventional CT for the diagnostic diagnosis of AS has been limited due to its high radiation dose.

MRI can be used to identify the disease in its early stages [14, 15, 16]. Early symptoms of sacroiliitis, such as subchondral bone marrow edema (BME) have been found in MRI. MRI is an essential diagnostic technique in the management of spondyloarthritis (SpA) and can identify both active and chronic alterations before they become structural changes [17]. When assessing individuals with stirring back pain in SpA, imaging is essential because it aids in early detection and suitable therapy to avoid permanent alterations [18]. Sacroiliac and spinal edema must be treated in order to prevent impairment and stop the progression of BME. Successful therapy of AS requires early diagnosis and individualized treatment [19,20].

Particularly when combined with MRI, artificial intelligence (AI) has great promise for the detection of AS [21]. Large datasets can be used to learn AI algorithms patterns unique to AS, which they can then use to analyze new MRI scans [22]. AI systems are able to recognize these anomalies, evaluate the probability of AS, and examine the distribution and intensity of different aspects in these images. AI may potentially increase the accuracy of AS diagnosis when paired with clinical assessments, patient symptoms, and other medical information. AI algorithms are able to provide crucial evaluations for the diagnosis of AS through the examination of symptoms and risk variables.

In this manner, machine learning (ML) and deep learning (DL) approaches can be used to detect AS effectively. The AI subfields of ML and DL concentrate on employing algorithms that are fed large quantities of data with highest accuracy for decision-making. ML techniques may be able to find data and patterns, including diagnoses, treatments, and prescriptions. However, classical causal modeling and data-driven prediction methods have slightly different underlying assumptions.

The analysis of peripheral blood mononuclear cells (PBMC) [23], messenger ribonucleic acid (mRNA) expression profile [24], radiography [25], clinical data [26], and other [27, 28], machine learning (ML) techniques like K Nearest Neighbor (KNN), Support Vector Machines (SVM), Naïve Bayes (NB), Random Forest (RF), Decision Tree (DT), and Artificial Neural Network (ANN) have been introduced for AS diagnosis. DL methods including CNN, DNN, and RNN have been developed for AS analysis. Nevertheless, the outcomes of these techniques must satisfy diagnostic criteria when the data from many sources are too similar or perhaps too complicated for the human eye to recognize. A lot of work has been done recently to diagnose AS using ML and DL techniques. A lot of work has been done recently to diagnose AS using ML and DL techniques. However, the classification impact fulfill the diagnostic requirements, more sophisticated DL models are needed when compared to ML methods.

In this review determine the present state of ML and DL use in various contexts at several stages of AS diagnosis and therapy. In order to give researchers and clinicians effective in this field with a new, helpful resource, we conducted this study to the increased researchers in the make use of ML and DL for AS diagnosis, as well as a lack of significant review papers offering insightful information. In order to draw a conclusion for future research development, it also examines the advantages and disadvantages.

2. REVIEW ON MACHINE LEARNING METHODS

Castro-Zunti et al., [13] suggested statistical ML and DL techniques to analyze CT images to identify erosion, which is an early AS sign. The dataset included of 681 grayscale CT scans with a single sacroiliac joint. The input features for KNN and RF algorithms were generated using the Local Binary Pattern (LBP) and Gray-Level Co-occurrence Matrix (GLCM). The redesigned InceptionV3 architecture was built and tested. RF classifiers outperform KNN classifiers by precision, recall, F1-score, accuracy, and area under the receiver operating characteristic curve (AUC-ROC) after eightfold cross-validation. They found that the deep learning classifier trained without minimizing validation loss was best and achieves an eightfold cross-validation accuracy, recall, and ROC AUC of 99.0%, 97.5%, and 0.97.

Canayaz et al., [29] suggested developing and validating machine learning algorithms for identifying AS using Short Tau Inversion Recovery (STIR) sequencing MRI data. It starts with the construction of a GLCM from MRI images, Haralick features are extracted, and trains KNN and SVM models. Dataset, AS was detected using 696 MRI scans. To prevent overfitting, models were trained and tested on 70% of the dataset using a 10-fold cross-validation technique, with the remaining 30% being used for validation. The ML-based model performed better in terms of precision, sensitivity/recall, specificity, false positive rate (FPR), false negative rate (FNR), F1-Score, and accuracy. The system also offers an effective strategy for early and correct diagnosis of AS, which is important for timely intervention and treatment planning.

Hu et al., [30] established that profiling hip participation in AS via a radiomics-based approach is doable. In order to standardize the voxel spacing, all images were resampled to the same voxel size. Additionally, noise was removed from images using a predetermined bin size of 25 for image discretization. Radiomic features were obtained from the pelvic MRI. Invariant radiomic features were removed, and redundancy was investigated. Z-score standardization was used to normalize the dataset. Then, agglomerative hierarchical clustering utilising the Ward linkage criterion and Euclidean distance calculation was employed to identify radiomics-based patient categories. Totally 167 patients assisted in validating and interpret developed phenotypes based on clinical histories and MRI. Between January 2019 and September 2022, AS patients with hip joint discomfort were retrospectively assessed and had pelvic MRI exams performed at the First Medical Center of the Chinese People's Liberation Army (PLA). The findings show that unsupervised machine learning algorithms can transform complex radiomics data into clinically meaningful and interpretable classifications of hip involvement in AS. The suggested model outperforms the others, as evidenced by the Delta area plot and Cumulative Distribution Function (or CDF) curve. All analyses used two-sided P values to determine significance.

Jiaet al., [31] presented a SCJAYA algorithm that combines cooperative predation and salp swarm foraging behavior into the JAYA algorithm. The cooperative predation method is used to reduce the risk of convergence on local optima, while the inclusion of salp swarm behavior is intended to speed up convergence and improve the results of the conventional JAYA algorithm. Additionally, the binary SCJAYA-Fuzzy K Nearest Neighbor (bSCJAYA-FKNN) classifier was proposed to increase the accuracy of AS diagnosis. Metrics like specificity, accuracy, F-measure, Matthews Correlation Coefficient (MCC), and computing time were all better with the proposed model.

Joo et al., [32] suggested a consensus classification method that makes use of a generalized linear model, NB, DT, KNN, and SVM. Over a two-year period, radiographic progress was assessed using the modified Stoke Ankylosing Spondylitis Spine Score (mSASSS). For a validation research conducted between 2008 and 2017, data from a separate cohort of 173 axSpA patients was imported from the Catholic University of Korea Yeouido St. Mary Hospital in Seoul, Republic of Korea. These patients clinical profiles were entirely self-made, and they satisfied the requirements for axSpA categorization set out by the Assessment of SpondyloArthritis International Society (ASAS) [33]. When it came to accuracy, f-measure, precision, and recall, the proposed model fared better than the others.

Prabha and Hassan [34] offered ML approaches to improve patient-specific treatment planning and enable early AS detection. Describe the various techniques and their usefulness at different phases of AS diagnosis and therapy, with an eye on identifying knowledge gaps for further research. Through the development of distinct characteristic profiles for AS patients and the identification of novel biomarkers associated with AS, these technologies can facilitate early detection. Certain patient therapies can be supported by their ability to predict the course of AS and rehabilitation responses. Sadly, inadequately big datasets from several centers did not capture a variety of clinical variables.

Ahammad et al., [35] introduced an ANN to estimate radiographic progression in patients affected with AS. Adding additional data, such as spinal column radiography or even lifetime data, could improve the performance of model. The accuracy of Model A and Diagnose B has been compared by creating a clinical model that attains a 2.5% reach while accounting for the AS features listed in the classification criteria. Model A/B has shown better clinical progress in the model used to predict the prognosis of individuals with AS. There are 681 images of a single sacroiliac joint in the collection. These Regions of Interest (RoI) for the sacroiliac joints were identified using Digital Imaging and Communications in Medicine (DICOM) frames from 53 patients' abdomen and pelvic CT scans. To guarantee that every ROI image was orientated consistently, each right joint was then horizontally fipped. The technology process employed data collected from multiple hospitals. The accuracy, precision, recall, and f-measure of the suggested model are better to current models.

Deodhar et al.,[36] established a mathematical predictive model to assist detect AS early, based on the medical and pharmacy claims histories of patients with and without AS. Data on administrative claims from more than 182 million patients (January 2006-February 2018) was obtained from the Truven Health MarketScan® Commercial and Medicare Supplemental databases. It was determined which features set AS patients apart from matched controls using a linear regression model. The patients who were most likely to develop AS were then selected by using these characteristics as inputs to build Model A/B. Model A(SVM)/B(KNN), which had been developed and created in Segment 1, was evaluated for prediction power by following up with patients who were predicted to have AS in Segment 1. Several metrics are employed to evaluate the suggested model, including AUC, FPR, and Positive Predictive Value (PPV).

Liu et al., [37] introduced semi-supervised segmentation and radiomics analysis based diagnostic model with MRI images for BME and sacroiliitis. The objective of this study was to enhance the diagnosis of BME and sacroiliitis in AS patients. In dataset totally includes of 257 patients (155 with sacroiliitis and 175 with BME). Totally, 514 MRI images of the sacroiliac joint (SIJ) are examined to get a diagnosis. To detect sacroiliitis and BME, models such as SVM, Logistic Regression (LR), and light gradient boosting machine (LightGBM) are trained using radiomics characteristics from T1-weighted image (T1WI), and Surgical Tattoos in Infrared (STIR). On SIJ segmentation, the semi-supervised segmentation performance is evaluated using the Dice coefficient. AUC, sensitivity, specificity, and accuracy are used to evaluate performance. This technique offers a viable tool for enhancing diagnosis in clinical settings and may assist physicians in making better decision. Table 1 shows the comparative analysis of ML methods for AS detection.

Sun et al., [53] developed on the LR classification with unique subtype for AS. The pathogenesis of AS was then uncovered by examining the variations in the immunological microenvironment. RF and Least Absolute Shrinkage and Selection Operator (LASSO) regression were utilized to screen and find predictive factors for the new AS. Immune cell infiltration datasets, and the findings were confirmed using routine blood test data from 5720 non-AS patients and 3671 AS patients. Compared to other models, the suggested model yields superior outcomes.

Kennedy et al., [54] proposed DT model for AS diagnosis. Secure Anonymised Information Linkage was utilized as databank. Using their regular data, AS patients were matched with controls that had no history of AS or axSpA diagnoses. Men and women data were evaluated independently. Principal Component Analysis (PCA) and feature/variable selection were used to create DTs had the greatest average F value.

Zhu et al., [55] consist of 348 individuals with AS were screened using the modified New York criteria at the First Affiliated Hospital of Guangxi Medical University using a comprehensive blood routine examination, liver function, and kidney function. The patients were split into training and validation groups at random using random sampling. Screened feature variables using three ML techniques (SVM- Recursive Feature Elimination (RFE), RF, and LASSO). Patients with AS can be satisfactorily predicted by the suggested ML model.

TABLE 1.COMPARATIVE ANALYSIS OF MACHINE LEARNING METHODS FOR AS DETECTION

AUTHORS	METHODS	TYPE OF STUDY	DATASET	METRICS
Castro-Zunti et al., [13]	KNN&RF	Image based Detection	681 grayscale Joint Photographic Experts Group (JPEG) CT	Accuracy, precision, recall, F1-Score, and AUC-ROC
Canayaz et al., [29]	KNN and SVM	Image based Detection	696 MRI images	Precision, sensitivity/recall, specificity, False Positive Rate, False Negative Rate, F1-Score, and accuracy
Hu et al., [30]	unsupervised agglomerative hierarchical clustering	Image based Detection	First Medical Center of the Chinese People Liberation Army General Hospital	Delta area plot and Cumulative Distribution Function curve
Joo et al., [32]	NB, DT, KNN, and SVM	Image based Detection	Yeouido St. Mary Hospital at the Catholic University of Korea	Accuracy, f-measure, precision, and recall
Ahammad et al., [35]	ANN	Image based Detection	Data was gathered from several hospitals	Precision, recall, f-measure and accuracy
Deodhar et al., [36]	SVM and KNN	Image based Detection	Truven Health MarketScan® Commercial and Medicare Supplemental databases	PPV, FPR and AUC
Liu et al., [37]	SVM, LR, and LightGBM	Image based Detection	514 MRI images of the sacroiliac joint	Dice coefficient. AUC, sensitivity, specificity, and accuracy
Sun et al., [53]	RF and LASSO regression	Blood Test Data	3671 AS patients and 5720 non-AS patients	Correlation, AUC
Kennedy et al., [54]	Decision Tree	Blood Test Data	Secure Anonymised Information Linkage (SAIL) databank – includes GP data (Read Codes), hospital data (ICD-10), rheumatology data (SNOMED-CT), mortality data	Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, F1 score, ROC-AUC

Zhu et al., [55]	Machine Learning: LASSO, Random Forest, SVM-RFE	Blood Test Data	708 patients (AS and non-AS)	AUC, Sensitivity, Specificity, PPV, NPV, Concordance Index (C-index), Calibration Curve, Decision Curve Analysis

3. REVIEW OF DEEP LEARNING METHODS

Koo et al., [38] created a CNN model to detect the corners of the cervical and lumbar vertebral bodies in individuals with AS. The Digital Diagnost (Philips) and Discovery XR656 (GE Healthcare) were used to perform a digital radiography assessment of the spine. Using a key-point identification technique, the disk points between the bodies were identified from the DICOM image of the cervical and lumbar spine radiographs. A CNN model has been created to assess the vertebral bodies' corners. 5245 lumbar lateral and 5083 cervical radiographs from 1280 AS patients make up the dataset. Sensitivity, specificity, PPV, F1-score, and accuracy for mSASSS are used to quantify the outcomes.

Canayaz et al., [39] introduced GLCM with DL-based AS classification system. The proposed model has been trained on 21 Haralick features from GLCM. This method provides insights into surface texture characteristics, potentially streamlining the classification process. Model demonstrates comparatively highest accuracy and biased power, offering a promising alternative to computationally intensive training methods. Moreover, on the validation dataset, the model achieves highest accuracy, sensitivity, F1-score, and an AUC.

Shenkman et al., [40] developed a novel computerized algorithm for diagnosing and evaluating sacroiliitis CT images. Firstly, the RoI is extracted using heuristics and a U-Net classifier that includes the pelvic joint region. Secondly, the RoI is refined to identify both sacroiliac joints using a four-tree RF. Thirdly, each CT slice individual sacroiliitis is graded using a traditional slice CNN classifier. Fourthly, sacroiliitis is diagnosed and graded by combining the individual slice grades using an RF. Slice grading allows for high case grading accuracy with little datasets and yields findings that are noticeably superior when compared to model-based technique. According to tests conducted on 484 sacroiliac joints, the suggested model had the increased classification accuracy, sensitivity, and AUC.

Zhang et al., [41] devised a fully automatic technique to SIJ and further grading diagnosis sacroiliitis associated with AS on CT. At two hospitals, a total of 435 CT samples are collected from AS and control patients. The SIJ was segmented using No-new-UNet (nnU-Net), and sacroiliitis was graded using a three-class technique utilizing a 3D CNN. The ground truth for the grading was the scores of three seasoned musculoskeletal radiologists. The relative volume difference (RVD), Jaccard, and dice coefficients are used to measure the U-Net segmentation of SIJ data. Precision, recall/sensitivity, specificity, f1-score, accuracy, ROC, and AUC are used to assess classification results.

Bressem et al., [42] developed a Deep Neural Network (DNN) to identify structural alterations and active inflammation that are suggestive of axSpA during sacroiliac joint MRI. It included 593 patients who had axSpA and sacroiliac joint MRIs that were centrally analyzed. For MRI denoising, artifact reduction, and intensity distribution homogenization across MRI scans, the 3D U-Net architecture was created. To categorize structural alterations suggestive of axSpA or active inflammatory changes, the 3D dual-encoder Residual Network 101 (ResNet-101) is introduced. The decision model was visually explained using gradient-weighted class activation mappings using AUC, sensitivity, and specificity. In community and university hospitals, MRI evaluations were performed on five groups of individuals with axSpA clinical suspicion between January 2006 and September 2020.

Lin et al., [43] developed an attention U-net for axSpA diagnosis. The MRI scans were to be examined for bone marrow oedema by an impartial radiologist and rheumatologist who were not aware of the ground truth masks. To create the ground truth masks from which "fake-colour" images were generated, RoI was generated from bone marrow oedema, a trustworthy indicator of active inflammation. For testing, validation, and image purposes, the original and fake-color photographs were randomly assigned. The experiments included 63 participants with non-specific back pain (NSBP) and 326 participants with axial SpA. The algorithm outperformed a rheumatologist in terms of sensitivity and specificity, but it was on level with a radiologist.

Li et al., [44] developed an ensemble CNN model for the diagnosis of AS. It uses 539 pelvic radiographs (PXRs) from three other centers for testing and 5,389 PXRs from 5,014 patients at Guangxi Medical University First Affiliated Hospital for training. The recommended model improves the performance of the final ensemble machine learning model, which is created by combining the four best-performing models using the stacking technique. The F1-score, AUC-ROC, recall, accuracy, and precision were among the performance indicators. Clinical prediction models are created to identify and triage high-risk patients. MRI images are collected using a smartphone to assess the specialist diagnostic effectiveness.

Castro-Zunti et al., [45] established a novel CNN model to classify AS on MRI. In the dataset, 56 patients have a total of 534 AS and 606 controls SIJ extracted using three standards MRI. For classification, compared modified/optimized variants of ResNet50, InceptionV3, and Visual Geometry Group 16 (VGG16). CNN is optimized by learning rate and refined through the use of six-fold cross-validation. You Only Look Once v5 (YOLOv5) based SIJ detectors have been introduced for AS. CNN models perform noticeably better than models trained on all MRI sequences when they are trained on images including the Red Green Blue (RGB) combination of the sequences. Highest cross-validation accuracy, sensitivity, specificity, and AUC-ROC were attained by the proposed model.

Han et al., [46] developed a novel automatic algorithm for measuring and grading AS-hip arthritis using MRI. A novel 3D-UNet segmentation network and a 2D classification network based on ResNet50 are employed. The suggested model assessed the performance of segmentation and classification models that were trained on the training images. After obtaining the inflammatory segmentation results from MRI images, the hip joint was evaluated based on the segmentation findings. Totally 141 cases were subjected to a retrospective analysis, 40 patients were part of the validation cohort and 101 patients were part of the derived cohort. Proposed model is compared with various approaches for the metrics like Dice coefficient, and accuracy.

Lee et al., [47] developed a novel method for CNN-based BME detection and sacroiliac joint MRI. 79 patients who came to Chung-Ang University Hospital had a total of 815 slices of SIJ region MRI images. The portions of the original MRI that do not contain the sacral and iliac bones are removed in order to create RoI. Each subject unique MRI classification data is used to determine whether or not they have sacroiliac arthritis. The classification findings were validated using the gradient-weighted class activation mapping approach. When ResNet18 is applied for individual MRI, RoI shows better performance for BME in terms of precision/PPV, recall/sensitivity, specificity, F1-Score, Negative Predictive Value (NPV), accuracy, and AUC-ROC curve. A median filter was also used to represent the context information and enhance overall performance.

Shuai et al., [48] used Fourier Transform Infrared (FTIR) spectroscopy on dried serum samples to diagnose AS and rheumatoid arthritis early using deep learning models. In all, 243 dried serum samples were gathered for the investigation, comprising 81 samples from each of the following groups: AS, RA, and healthy controls. Based on the Multi-Scale Convolutional Neural Network (MSCNN), three MSC modules with varying specifications were created to efficiently fuse the local information and improve the capacity of model for generalization. The MSCNN model was then integrated with FTIR to provide a quick, accurate, and non-invasive diagnosis of AS, RA, and healthy controls. By incorporating FTIR, this study can be utilized to diagnose AS and RA quickly and accurately. Classification evaluation metrics like precision, recall/sensitivity, specificity, accuracy, and AUC has been evaluated after ten-fold cross validation.

Tas et al., [49] used MRI and a pre-trained hybrid model to diagnose AS. MRI dataset that includes contrast-enhanced MRI as well as two different anatomical planes: axial and coronal. The three well-known pretrained CNNs (DenseNet201, ResNet50, and ShuffleNet) were used in the ASNet. The transfer learning method was used to create deep features through these pretrained CNNs. Two MRI-generated feature vectors were used in each pretrained network. The KNN classifier was utilized in the AS diagnosis process. The 18 ASNet results should then be combined using the Iterative Majority Voting (IMV) process. For the final model, performance metrics like accuracy, precision, recall, and F1-score were evaluated using the three datasets.

Castro-Zunti et al., [50] established a three-stage pipeline for computer vision diagnostics using SIJ localization/extraction and YOLOv5. The proposed approach was trained and evaluated using a dataset of CT scans from 35 AS patients and 65 control patients acquired at Jeonbuk National University Hospital (JBNUH). Vision Transformer (ViT)+InceptionV3 hybrid architecture is used to classify SIJs as AS or control. More training data and the capacity to capture global representations are typically needed for ViT. A machine learning model is utilized to forecast AS based on aggregated/normalized SIJ categorization findings. General radiologists and others who are less trained in musculoskeletal disorders may find the procedure particularly helpful because it can be challenging to recognize and characterize AS. Performance criteria such as precision/PPV, recall, accuracy, and

AUC were used to assess the finished model. Table 2 shows the comparative analysis of deep learning methods for AS detection.

TABLE 2.COMPARATIVE ANALYSIS OF DEEP LEARNING METHODS FOR AS DETECTION

AUTHORS	METHODS	TYPE OF STUDY	DATASET	METRICS
Koo et al., [38]	CNN	Image based Detection	Dataset includes of 5083 cervical and 5245 lumbar lateral radiographs from 1280 AS patients who had radiographs	Sensitivity, specificity, PPV, F1-score and accuracy
Shenkman et al., [40]	CNN	Image based Detection	484 sacroiliac joints CT	Accuracy, sensitivity, and AUC
Zhang et al., [41]	3D CNN	Image based Detection	At two hospitals, a total of 435 CT samples are taken	Precision, recall, specificity, f1-score, accuracy, ROC, and AUC
Bressem et al., [42]	3D dual-encoder Residual Network 101	Image based Detection	Five groups of patients with axSpA clinical suspicion were MRI at community and university hospitals between January 2006 and September 2020	Sensitivity, specificity, and AUC
Lin et al., [43]	Attention U-net	Image based Detection	326 persons with axial SpA and 63 participants with non-specific back pain (NSBP)	Sensitivity and specificity
Li et al., [44]	Ensemble CNN	Image based Detection	539 pelvic radiographs (PXRs) from three other centers for testing and 5,389 PXRs from 5,014 patients at Guangxi Medical University First Affiliated Hospital	Accuracy, precision, recall, F1-score, and AUC-ROC
Castro-Zunti et al., [45]	CNN	Image based Detection	MRI dataset	Accuracy, sensitivity, specificity, and

				AUC-ROC
Han et al., [46]	2D ResNet50	Image based Detection	Totally 141 cases were subjected to a retrospective analysis, 40 patients were part of the validation cohort and 101 patients were part of the derived cohort	Dice coefficient, and accuracy
Lee et al., [47]	CNN	Image based Detection	815 slices, were taken from 79 patients who came to Chung-Ang University Hospital	Precision, recall , specificity, F1-Score, Negative Predictive Value , accuracy, and AUC-ROC curve
Shuai et al., [48]	MSCNN	Image based Detection	243 dried serum samples	Precision, recall, specificity, accuracy, and AUC
Tas et al., [49]	DenseNet201, ResNet50, and ShuffleNet	Image based Detection	MRI dataset that includes contrast-enhanced MRI as well as two different anatomical planes: axial and coronal	Precision, recall, F1-score, and accuracy
Castro-Zunti et al., [50]	Vision Transformer +InceptionV3 hybrid architecture	Image based Detection	Dataset of CT scans from 35 AS patients and 65 control patients obtained at Jeonbuk National University Hospital	Precision/PPV, recall, accuracy, and AUC

4. INFERENCES FROM EXISTING WORKS

In addition, this work fills a significant gap in research investigating interpretable ML models for AS detection [50, 51]. However, the ML-based model appears to be very promising for use in practice, especially in the early diagnosis of AS and, consequently, intervention, which would benefit patients. DL is data-driven, meaning that better performing and less biased models with greater generalizability may be achievable with more and varied patient training data. Limitations of recent works are relatively small AS sample size, which arises because AS is not a highly prevalent disease. For rare diseases, the limited number of cases often makes it difficult to obtain sufficient data. When training future iterations of the model, larger dataset is considered and increasingly representative dataset while also integrating synthetic data. After increasing the size of the dataset, will continue on DL based detection models with high interpretability, and comparisons will be made with the ML-based models.

5. CONCLUSION AND FUTURE WORK

This work comprehensive analysis of AS diagnosis methods are presented, systematically classified based on model, and input modalities, encompassing traditional techniques, ML methods, DL methods, and other methods. This regular review highlights the efficiency of ML & DL methods in AS imaging diagnostics across MRI, CT, and X-ray modalities, and metrics used to assess them. Numerous investigations and studies are carried out which have noticeably enhanced considerate of the AS, and it have assist the development of new strategies for AS detection. It has been studied that among the various techniques, each technique has its own strength and weaknesses. Clear comparative analysis of the designs and results of advanced methods within each category is also carried out. Review conclude that the AS detection of DL methods gives improved results than the ML methods across various modalities. To improve the generalizability of these AI models, larger datasets and more external and prospective validation are necessary, as demonstrated by the limited sample sizes observed in several studies. Future work, will focuses on developing DL model for AS detection with multimodal modality, different MRI modalities, and real time dataset to enhance AS detection. Although a balanced distribution of the AS diagnoses has been achieved, and medical images has been collected based on the gender.

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