Harnessing Deep Learning for Rheumatoid Arthritis Detection: Advancements in Automated X-Ray Analysis

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Abstract: ***Rheumatoid arthritis (RA) is an autoimmune chronic disease characterized by persistent inflammation, pain and progressive structural damage of the joints, causing the cartilage to become affected, and may progress into deformities in the joints and loss of function. In addition to involvement of synovial joints, RA may involve extra-articular other systems such as cardiovascular system, pulmonary system and may lead to greater morbidity. Imaging techniques, such X-ray, Magnetic Resonance Imaging (MRI), ultrasound (US), bone scintigraphy, and Positron Emission Tomography (PET), are critical in the identification, monitoring, and assessment of disease progression. Among them, X-ray is commonly utilized in the assessment of structural damage, and are also more sensitive to detecting initial inflammatory changes like synovitis and bone erosions. However, traditional imaging analysis is usually tedious, subjective, and prone to inter- as well as intra-observer change, particularly in the early stages of the disease. To overcome these limitations, the Machine Learning (ML) strategies were used in order to help identify and categorize RA using automated methods through the use of features of joint space contraction, texture patterns, and erosion features that are extracted on the basis of medical images. Although the efficacy of ML methods, depends on manual feature engineering that can restrict scalability and decrease generalization to diverse datasets. Deep Learning (DL) methods, particularly Convolutional Neural Networks (CNNs), has recently emerged as a formidable force capable of autonomously learning in the hierarchical depiction of feature representations derived of raw imaging data. These are models with better performance in identifying subtle pathological changes, and allows a more accurate and efficient diagnosis of RA and its classification into severities. This paper reviews and discusses the DL-approaches to detecting RA using X-ray images, their methodologies, benefits, shortcomings, and sheds some light on developing reliable and practically usable diagnostic systems.***

Keywords: Rheumatoid arthritis, Deep Learning, X-ray, Classification, Segmentation

1. Introduction

Rheumatoid arthritis (RA) is a widespread autoimmune disorder characterized by inflammation and pain in several small joints, which can lead to the deformation of joints and their decrease in usefulness. In addition, it is among the main causes of chronic impairment [1]. Figure 1 depicts the joint damage in RA. In addition, RA does not only affect the joints, but also has effects on the other biological systems, such as the cardiovascular and pulmonary systems [2, 3].

The typical symptoms of RA include continuous pains and swelling of joints often in the hands and feet, persistent morning stiffness, fatigue, low-grade temperature, loss of appetite and symmetric involvement of small joints especially in the hands and feet [4]. RA is mostly categorized as:

- Seropositive RA- It is the most prevalent and is often linked to more aggressive joint destruction because of the existent of particular blood markers such as rheumatoid factor and anti-CCP antibodies.
- Seronegative RA- This is characterized by all of these inflammatory manifestations but does not possess these detectable blood markers.
- Juvenile Idiopathic Arthritis (JIA)- It affects children below the age of 16-17 and is characterized by injury to the joints, which can interfere with the normal growth and development of children [5].

RA management is usually based on a combination of pharmacological treatment, physical activity, patient education and sufficient rest and is customised depending on specific factors such as the severity of the disease, age and overall health. Some of the treatment strategies which are often applied in the RA management are as follows:

- Nonsteroidal Anti-Inflammatory Drugs (NSAIDs) – Relieve the pain and inflammation caused by obstructing the production of prostaglands. The examples include ibuprofen, aspirin and naproxen although long-term use may lead to gastrointestinal side effects [6]. [6].
- Corticosteroids – Powerful anti-inflammatory drugs can be used in case of exacerbation in the disease, to suppress inflammation and pain. They either can be administered orally or even by means of intra-articular injection but are usually used on short-roll basis because it has side effects that include osteoporosis and weight gain [7].
- Disease-Modifying Antirheumatic Drugs (DMARDs) – Reduce the progression of the disease and prevent the destruction of the joints. The most popular first-line DMARD is Methotrexate, and others, such as sulfasalazine and hydroxychloroquine include the others [8].
- Biologic Agents – Focus on particular immunological mechanisms implicated in inflammation. These include tumor necrosis factor inhibitors and interleukin inhibitors, which are used if the use of conventional DMARDs is ineffective [9,10].
- Physical and Occupational Therapy – Improve joint mobility, strengthen muscles and support the patient's function in daily activities via exercises and lifestyle

changes [11]. The damage of the joints in RA is shown in Figure 1.

The early diagnosis of RA is crucial to reduce joint inflammation and pain, improve joint function and prevent joint damage and deformity. Early diagnosis of RA and treatment may alter the course of the disease, prevent joint damage or help to delay erosion of the disease [13, 14]. Early diagnosis and treatment can impact ill health outcome, possibly contributing to remission [15, 16]. This is why early diagnosis for RA is so important for beginning treatment – otherwise it can progress to more advanced stages requiring more strenuous treatment. Imaging modalities have a vital role in the diagnosis and surveillance of RA since it allows early detection of joint damage and gives accuracy about the disease course.

- Magnetic Resonance Imaging (MRI) – It is an advanced type of imaging that is used in RA because it helps in identifying early onset of inflammatory changes in joints. It provides the complete obtainment of the soft-tissues, the synovitis, tenosynovitis, bone marrow edema, and joint erosions. [17,18]. The sample image of MRI is represented in Figure 2.
- Standard Bone Scintigraphy- It is a functional imaging modality which determines early metabolic changes in bones before structural abnormalities can be detected on standard radiographs [20]. It has been useful in the diagnosis of benign disease like arthritis, fractures, infections, and metabolic bone diseases and malignant conditions such as primary bone, cancers and bone metastases [21]. Figure 3 shows the Whole-body bone scintigraphy.
- Positron Emission Tomography (PET) - It is a molecular imaging modality primarily utilizing 18F-FDG to investigate glucose metabolism within the body. It is extensively utilized in oncology, although its utilization in RA and other connective tissue illnesses is restricted. PET is found to be superior to the Single Photon Emission Computed Tomography (SPECT) in terms of image quality and clarity although at a higher monetary expense and higher radiation levels. PET/CT combines metabolic and anatomic tomographies where semi-quantitative analysis is enabled using the values of SUV. However, the absorption of FDG is non-specific and may be seen in both inflammation and infection, therefore reducing the accuracy of the diagnosis. It is less successful than conventional bone scintigraphy in musculoskeletal problems [19].
- Ultrasound (US)- It is one of the crucial supporting imaging modalities in RA used to aid the clinical assessment by detecting pre-existing and ongoing synovial inflammation.

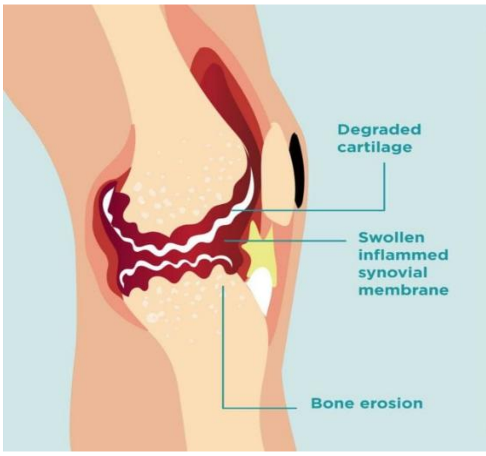

Figure 1: Illustration of joint damage in Rheumatoid Arthritis [12]

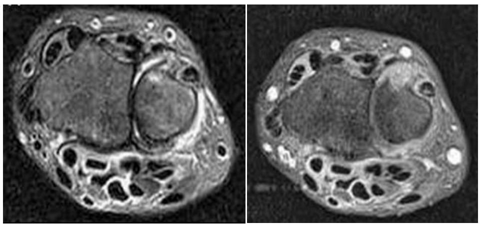

Figure 2: Sample image of MRI [19]

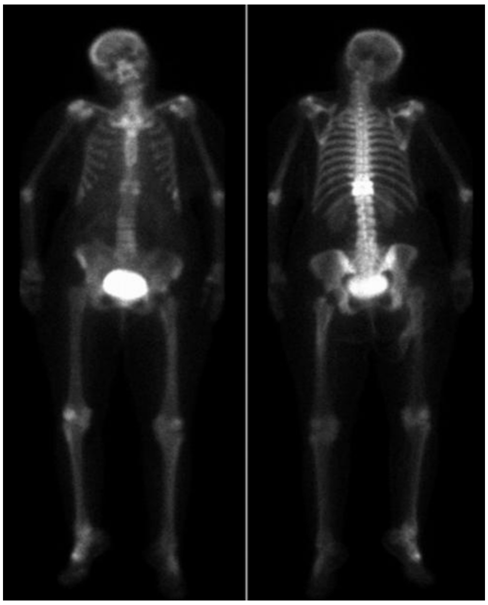

Figure 3: Illustration of Whole-body bone scintigraphy [19]

One of the pointers of active synovial inflammation is augmented vascularity and Doppler indicators are signs of this. Moreover, US is much more sensitive as compared to the conventional x-ray imaging, especially at the initial stage of the disease, when structural changes may still be out of reach of the ability for detection. Although, the uniformity of disease activity scoring has not yet been attained, the evaluation of synovial thickness and hypervascularity in patients with RA provide invaluable insights that will help increase the accuracy of diagnosis and further increase reliability and trustful therapeutic decision-making process when using the setting of RA patients [22]. Figure 4 illustrates Doppler ultrasound image with display of synovial inflammation with increased vascularity (orange signals), indicating active RA.

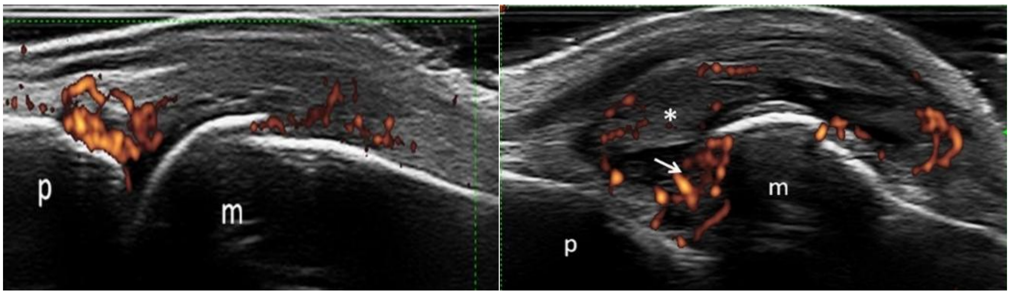

Figure 4: Doppler ultrasound images of RA depicting inflammation of the synovium [23]

Figure 5: Comparison of normal and rheumatoid arthritis X-ray images [24]
Normal image; (b) distorted image excluded; (c) healthy joint; (d) mild RA involvement; (e) severe RA involvement

- X-ray: X-ray is the primary imaging technique for assessing RA and is crucial for monitoring disease progression. It aids in the differentiation of normal and affected joints, as well as classification of the severity of illness as images have shown of the normal, mildly affected, and severely affected joints. X- rays can appear as normal during the early stages of RA; however, X- rays are very imperative in the detection of structural joint damage during the late stages of RA and in the monitoring of the progression of the disease over time. The comparison of normal and RA X-ray images is shown in Figure 5.

The conventional imaging methods are occasionally challenged by the following hindrances: tedious and time-consuming hand-based evaluations, variability in observers, and the need to have highly specialized interpretation [25-28]. These restrictions highlight the necessity to develop more advanced, effective and reliable imaging analysis methods.

To overcome the limitations, the field of Artificial Intelligence (AI) has emerged and is increasingly being used to improve the consistency, reliability and effectiveness of RA detection. The Artificial Intelligence the methods are supposed to be able to mimic are the human mental processes, like recognizing patterns and making decisions based on complex information from the clinical space. With RA, AI can assist medical professionals in analyzing X-rays, automating disease detection, and providing guidance for medical decisions. The current study highlights that AI approaches can help reduce subjective interpretation and enhance the accuracy of radiographic assessment of RA.

In AI, ML, and DL were widely used to analyse medical images. The ML techniques are derived from hand crafted feature extraction such as joint space narrowing or changes in texture or pattern erosions of images from various modalities, including X-ray, MRI and ultrasound. These features are then used by classifiers such as Support Vector Machines (SVM), Random Forest (RF) and k-Nearest Neighbors (KNN) to predict the presence of a disease and disease severity. Despite the effectiveness of the ML methods, they can be highly dependent on manual feature engineering, which may restrict the generalization and scalability of the methods to other datasets [29].

To overcome these issues, DL has received substantial attention in terms of its capability to autonomously create hierarchical representations with direct use of X-ray images. In particular, CNNs have shown excellent capabilities regarding the retrieval of intricate spatial forms as well as the finding of subtler pathological alterations pertaining to RA. Recent studies have demonstrated that CNN-based models have the capability to aid automatic detection and staging of RA in radiographic images, in addition to significantly enhancing efficiency and diagnostic accuracy [30]. Moreover, the methods of DL are particularly well-equipped to deal with unstructured medical information, including imaging, where more classical approaches to ML may prove ineffective at capturing underlying trends.

2. Review of DL models for Rheumatoid Arthritis Detection

Mate et al., [31] suggested a DL method to perform automated classification of RA using images of hand radiography to facilitate the early identification of the disease and reduce the reliance on manual analysis. A set of hand X-ray images has been assembled and a CNN model is developed to automatically extract specific features of the radiographs without the need of highly intensive pre-processing. The model architecture is created to find a complex pattern in joint structures, a task that is emulated in human vision. To determine the improvements in performance, a CNN-LeNet variation was designed and tested using established ML methods, such as Support Vector Machine (SVM) and Generalized Regression Neural Network (GRNN). The trained model was used to classify normal and pathologic states of RA and it was compared to make reference with the expert evaluations.

Maziarz et al., [32] presented a multi-task DL methodology to provide the automated analysis of RA employing hand X-ray images, and the objective of simultaneously locating the joints and assessing the joint deterioration. The model was first created to both localize and classify two key abnormalities of the RA in one framework: constriction of joint spaces and bone degradation. They were both designated as pixel level classification tasks and the network was able to achieve detailed spatial information of the joint arrangement. Local label smoothing was used to improve the learning and logically then the accuracy of predictions by modifying the loss function used, which consisted of two parts and a classification part and a regression part. This type of multi-task learning methodology allows the model to be significantly effective as a means of gathering not only localization information but also severity information.

Geng et al., [33] suggested an X-ray image analysis method based on deep convolutional neural network (DCNN)-based analysis methods in conjunction with self-efficacy evaluation in the detection of osteoporosis in RA patients. The strategy was introduced in a clinical setting, combining the use of DCNN-helped X-ray diagnosis with comprehensive nursing care. The femur and lumbar spine images were analyzed to identify the changes associated with osteoporosis and to evaluate clinical outcomes like bone mineral density, self-efficacy, anxiety and depression. In addition, developing positive self-efficacy was also significantly correlated with a reduction in negative emotions and an improvement in the quality of life.

Wang et al., [34] introduced a DL architecture of automated assessment of RA severity using hand X-ray images based on the modified total Sharp score (mTSS). To address the limitations of the earlier approaches models that were only focused on finger joints was initially developed to identify and localize the joint areas encompassing both finger and carpal joints autonomously by using the You Only Look Once (YOLO) architecture. In pre-processing, image enhancing strategies such as window-level distortions were used to simulate clinical viewing, and different joint data were fused to promote learning of features. These regions of interest were then used as the input of a classification model on predicting the levels of illness severity based on mTSS. In addition, Grad-CAM was used to increase interpretability by highlighting areas of significance jointly affecting the judgments of the model. The suggested tool can be a fast and reliable computer-assisted diagnosis tool that can help physicians to effectively evaluate the severity of illnesses much faster.

Üreten and Maraş [35] introduced a whole computer-aided diagnosis (CAD) paradigm to classify automatically the RA, osteoarthritis (OA) and healthy hand radiographs using DL methodologies. The You Only Look Once (YOLOv4) model was first applied to detect and extract the relevant hand parts out of original radiographs without any information loss. The retrieved images were additionally preprocessed and improved to increase the data diversity and model resilience. The trained VGG-16 model was then employed with the use of transfer learning to classify radiographs as RA, OA, normal, and another category of others to ensure enhanced generalization. The model was trained to predict discriminative variables on the hand X-ray images and evaluated based on the traditional performance metrics and ROC examination. The suggested model could successfully classify multi-classes and provide an accurate tool for supporting physician diagnosis, as well as reduce manual work, and enhance the consistency of radiology interpretation.

Obayya et al., [36] presented an Automated RA Classification model, called ARAC-AOADL, which leverages the combination of DL and optimization techniques to achieve accurate diagnosis of RA and orthopedic disorders. At first stage medical images were processed by removing noise in images with median filter method and also getting improved quality of images. This was followed by an Arithmetic Optimization Algorithm (AOA), then a pair of an Enhanced Capsule Network (ECN) which would be efficient in extracting the distinctive feature representations of processed images. Feature vectors were all collected and passed to the Multi-Kernel Extreme Learning Machine (MKELM) classifier for final classification of RA diseases. The model was able to extract the most complicated patterns in biomedical data and provide the best classification by using multi-kernel learning and optimization-based feature extraction.

Nakatsu et al., [37] suggested an automated system that uses DL to detect altered mTSS evaluation sites in the carpal region based on hand X-ray images to help in diagnosing RA. Carpal region was earlier delineated by input radiographic images using a DL segmentation algorithm to segregate a region of interest. After segmentation, RA evaluation sites were systematically identified using anatomical priors and

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structural principles based on clinical knowledge. The spots identified were further stratified onto bony structures to determine the precise joint locations that should be used to score mTSS. This approach was evaluated on 140 RA patients, X-ray images of which allowed appropriately localizing points of carpal evaluation with an average error of approximately 25 pixels, therefore, proving useful in terms of space precision in its clinical application.

Fung et al., [38] developed a DL model based on YOLOv5l6 that was used to label the joints on radiography images of RA. Initial training of the model occurred on hand joint images of healthy subjects, with focus on key anatomical features such as the proximal interphalangeal (PIP), metacarpophalangeal (MCP), wrist, ulna and radius joints. Training Data augmentation methods were used to increase robustness and generalization, and pretrained cores of the COCO model were used to initialize the model. The YOLOv5l6 network was then further adjusted to recognize any joint regions in the radiographs affected by RA despite having limited training data. It is a good method of determining the joint sites regardless of the changes in the structures due to the advancement of the disease.

Dulhare and Mubeen [39] presented a dual DL algorithm to detect and classify the presence or absence of rheumatoid nodules (RN) in medical image tests. The method used Pure Deep Convolutional Neural Networks (PDCNN) to detect nodules and an improved Residual Network (ResNet) to classify the nodules with Particle Swarm Optimization (PSO) used to perform feature selection to improve learning efficiency. The model was applied to the medical imaging data collected at the orthopedic hospitals to identify and categorize different types of nodules and their risks involved. It was used to differentiate between RN and other nodules like benign lesions or cancer cysts and to aid in the early diagnosis and a reduction in false positives as well as an increase in detection reliability.

Scientific [40] introduced a DL-based framework named the AI of RA Diagnosis Framework (AIRADF) which automatically recognizes and classifies RA using X-ray images. Initially, input radiographs undergo to pre-processing to augment image quality and enhance the dependability of training samples. The architecture then identifies and isolates Regions of Interest (ROIs), which are then used to focus learning on disease-relevant regions. An identification and localization of the RA using a Faster-R-CNN approach which generates region recommendations and an accurate localization of the affected areas of the joints. A refined U-Net structure is used to classify RA by applying an encoder-decoder architecture that allows the optimal usability of features extracted during classification. Combining both of these DL models provides the system to perform detection and classification in a single pipeline. The system involves multi-class RA analysis and it acts as a Clinical Decision Support System (CDSS) to assist the doctors in diagnosis and prognosis, increasing their efficiency and making medical decision-making easier.

Rajesh et al., [41] introduced a hybrid segmentation and classification strategy to the automatic discrimination of RA with the help of hand X-razy images. The grayscale conversion and dynamic thresholding were initially used to isolate the hand region on the background using the raw radiographs. A Carpal Region of Interest (CROI) was then localised using contour detection, with the carpal bones localised by using the bounding box of the largest contour. This was then followed by adaptive thresholding which was applied to the CROI to accurately outline bone structures. Contrast and energy are some of the texture properties of an area that are derived using segmented regions through Gray Level Co-occurrence Matrix (GLCM). The properties that were retrieved were then used to classify the carpal bones, by whether they were inflamed and normal. To strengthen the representation of the DL model, the ResNet101V2, InceptionResNetV2 and DenseNet models were combined and to further enhance the power of the classification, reliable and automatic detection of RA was achieved.

Fathima and Lingam [42] Suggested an optimal DL model for automated RA detection using knee X-ray images, addressing important problems like data imbalance, inadequate feature extraction and the model's limited generalizability. The knee X-ray data set was initially collected and preprocessed, with data augmentation techniques such as image flips and transformations being applied to enhance data diversity, and oversampling used to reduce class imbalance. A model for computing indicative features from the input images was developed and optimized using hyper parameter optimization techniques that competently extracts indicators on input images.

Binny and Maran [43] suggested a hybrid DL approach by combining the CNN and Recurrent Neural Networks (RNN) for the automated diagnosis of RA, following sequential medical images. A large set of radiography images of different patients were preprocessed with contrast enhancement, noise reduction, and normalization enhancing the image resolution of images. The CNN component was used to extract patterns of temporal progression of the disease across consecutive scans, whilst the RNN component was used to retrieve the characteristic spatial traits of individual scans. This CNN-RNN architecture will enable acquiring structural as well as progression-based information, and thus, improve the diagnostic accuracy. The model was trained and evaluated using a patient-wise data partition and compared to traditional CNN and ML models.

Moradmand and Ren [44] suggested a multistage automation approach towards the prediction of Overall Sharp Score (OSS) based DL model using hand X-ray images to support the assessment of RA joint deterioration process. Input radiographs (X-rays) were pre-preprocessed and standardized to reduce variance in image quality and variability. The second step was to use a U-Net that was developed to segment hand areas in the images accurately. Subsequently, the object identification model followed the object localization and detection of each of the joints using the YOLOv7 framework, facilitating precise analysis of the specific regions, even in the absence of or deformation of its joints. The identified joint regions were then sent to a specialized Vision Transformer (ViT) model which received global contextual relationship information and rendered predictions based on the recognition of complex structural damage pattern of the joint. The multistage way allowed the model to skillfully deal with variability in the imaging conditions and anatomical differences.

Venäläinen et al., [45] developed an automated DL-based radiographic scoring algorithm (AuRA) to quantify the joint damage in RA using hand and foot X-ray images. The model was developed to predict Sharp-van der Heijde median (SvH) scores based on radiographs and independently validated on independent clinical samples. It was also applied to automatically detect, localize, and evaluate joint damage, to monitor longitudinal development of disease processes in the subjects through analysis of follow-up radiographic images. The algorithm was implemented in a real-life clinical environment to achieve the support of radiographic assessment and minimized the use of manual scoring. In addition, it indicated potential of determining a pattern of progression by relating the predicted change to the disease progression over time as evaluated by the experts.

3. Comparative Analysis

Table 1 shows the comparison of above reviewed DL based RA Detection models, highlighting their merits and demerits along with their techniques and datasets used as well as their performance metrics.

Table 1: Summary of DL based RA Detection and Segmentation models

Ref No.	Techniques Used	Merits	Demerits	Dataset	Performance Metrics
[31]	CNN, SVM, GRNN	Evaluating against conventional models such as SVM and GRNN enhances the study's validity by displaying performance enhancements over traditional methods	Classifying RA solely as normal or pathological fails to encompass the many stages or degrees of severity of the condition.	RA x-ray dataset	Accuracy= 94.64%, Sensitivity=96%, Specificity=92%, Precision=95%
[32]	U-Net, Efficient Net-B5	Provides high feature extraction capability with fewer parameters	Computationally expensive for high-resolution images	RA2 DREAM Challenge	RMSE of narrowing=0.4075, RMSE of erosion=0.4607
[33]	DCNN, CNN	Reduces human effort and inter-observer variability in diagnosis	Computationally expensive and resource-intensive (GPU needed).	X-ray image dataset	Accuracy=91%, Sensitivity=98%, False negative rate=2%
[24]	YOLO, Grad-CAM	Precise localization of both finger and carpal joints enhances overall joint coverage.	Augment's system complexity and complicates maintenance	RA image dataset	Map@0.5=92, Precision=95%, Recall=94%, F1-Score=94%
[35]	YOLOv4, VGG-16	Automatically detects pertinent hand regions from whole radiographs.	The two-stage pipeline (YOLO + VGG-16) enhances system complexity	Kırıkkale University Hand Radiograph Dataset (KU-HRD)	Accuracy=90.7%, Precision=89.3%, Sensitivity=92.6%, AUC=0.94, Specificity=88.7%,
[36]	AOA, ECN, MKELM classifier	The MKELM improves categorization by effectively managing varied feature patterns.	Optimization algorithms and deep networks augment training duration and resource demands	Orthopaedic benchmark dataset	Accuracy=98.57% Precision=98.22%, Recall=97.21%, F1-Score=97.67%
[37]	U-Net	Segmentation isolates the carpal region, reducing noise and improving detection accuracy	Errors in segmentation can propagate to incorrect joint localization	Hyogo Prefectural Kakogawa Hand X-ray Dataset (HPK-HXD)	RMSE=24.89, acuracy of GDC =90.08
[38]	YOLOv5l6	Can be extended to include severity classification (erosions, joint space narrowing) and the prediction of disease progression.	Incorrect or missed joint detection may impact downstream tasks like severity classification	RSNA Pediatric BoneAge Challenge dataset	Confidence threshold=0.35, IOU threshold=0.1 F1-Score of PIP=0.994, MCP=0.991, Wrist=0.993, Radius=0.988, Ulna=0.987, Precision of PIP=1, MCP=0.993, Wrist=1, Radius=1, Ulna=0.99, Recall of PIP=0.987, MCP=0.989, Wrist=0.986, Radius=0.976, Ulna=0.978
[39]	PDCNN, PSO, ResNet	PSO enhances feature selection, leading to better model efficiency.	Computationally complex due to multiple integrated models	Dataset from different orthopaedic hospitals	Accuracy=98.80%Specificity= 96.39%, Sensitivity= 95.28%, AUC= 95.83
[40]	Faster R-CNN, LbRAD	The improved U-Net architecture enhances feature learning from segmented regions, leading to better classification performance.	Neglecting GAN-based methodologies constrains the capacity to augment data variety and resilience.	RA dataset	Accuracy=92.81% Precision=95.06%, Recall=94.68%, F1-Score=94.87%, Classification Accuracy=94.58%
[41]	GLCM	Adaptive thresholding facilitates improved identification of bone	Hand-crafted features like GLCM may not generalize well to diverse datasets	RA image dataset	Accuracy==88%, Precision=87.67%, F1-Score=91.23%, DSC=80,

		structures, even under diverse imaging settings.			Jaccard=70, Hausdroff=4.8, MAE=10, mIoU=75, Specificity=87%
[42]	CNN	A tailored CNN with hyperparameter optimization improves the model's capacity to learn distinguishing characteristics.	The model is built with knee X-ray images, while RA primarily impacts hand joints, thereby limiting its application in conventional RA diagnosis.	Kaggle knee X-ray dataset	AUC=0.94, Accuracy=94%, Precision=95%, Recall=94%, F1-Score=95%
[43]	CNN-RNN	The utilization of sequential imaging data enables the framework to track illness progression over time, facilitating early diagnosis and more informed clinical decision-making.	The amalgamation of CNN and RNN architectures escalates model complexity, resulting in prolonged training duration and augmented computational resource demands	Medical Imaging dataset	Accuracy=94.20% F1-Score=94.1%, AUC=0.96, Recall=95.60%, Specificity=94%, Precision=93.10%,
[44]	YOLOv7, U-Net, ViT	The integration of U-Net segmentation with YOLOv7 detection guarantees accurate localization of hand areas and distinct joints, even in instances of abnormalities.	The system depends exclusively on hand radiographs, potentially restricting its capacity to obtain comprehensive clinical data.	RA dataset	Huber Loss=4.9, RMSE=9.73, MAE=5.35,
[45]	AuRA	Demonstrates strong correlation with expert-assessed scores, supporting clinical reliability.	Does not completely eliminate the need for expert validation, especially in critical cases.	RA2-DREAM challenge	RMSE=0.35,0.36, R2 = 0.91, CCC=0.96

4. Performance Evaluation

A performance analysis of current DL methods to detect RA based on X-ray is done with a focus on classification accuracy, shown in Table 1. Since this study makes use of accuracy as a common assessment measure, it is possible to make a direct comparative analysis despite differences in datasets, imaging methods, and the complexity of architectural designs. Figure 6 represents the graphical comparison of accuracy of the assessed models.

Based on comparison, the RN-Net model [38] has the highest accuracy of 98.8%, which is the highest accuracy among all those analyzed. The ARAC-AOADL model [36] is right behind with a reported accuracy of 98.57% which is quite impressive and illustrates that advanced hybrid optimization-based methods are indeed and certainly effective. Although these models are characterized by very high accuracy, however their performance can be affected by increased architectural complexity and dataset specific effects that could cause changes in their performance.

The Efficient CNN model [31] has a high accuracy of 97.18%, and also offers a high level of computing efficiency, thus providing a good balance between the Level of Accuracy and Level of computing efficiency. CNN-RNN [43] (94.2%) and CNN [42] (94%) also have consistent and stable performance, which indicates reliability of the traditional DL architectures.

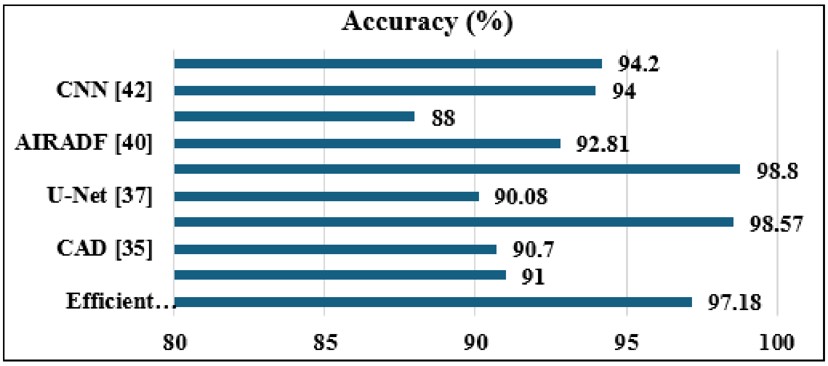

Figure 6: Comparison of various Dl-based RA detection models

There are moderate levels of performance indicated in such models as AIRADF [40] (92.81%), DCNN [33] (91%), CAD [35] (90.7%), and U-Net [37] (90.08%) which demonstrate moderate performance levels. However, the most impoverished performance is registered to the GLCM model [41], with a performance of 88%, which highlights the weakness of the conventional feature-based models in comparison to the DL models. In general, despite the fact that RN-Net and ARAC-AOADL are more accurate, Efficient CNN proves to be a more practical reliable model as it provides a balance between the performance, cost of computation, and field of application, making it practical to use in clinical aspect.

5. Conclusion

RA is an increasing challenge as it involves complex patterns in medical imaging data and large-scale datasets. Some of the challenges that have been presented against traditional approaches are the risks to patient privacy, lack of scalability,

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and other issues of inflexibility when handling diverse clinical data. DL is one of the ways to resolve this issue since it allows automatic extraction and analysis of feature-based approaches to medical images without human involvement. The methods based on the use of DL contribute to the level of RA diagnosis due to the identification of small abnormalities and patterns of diseases without compromising the consistency of performed analysis. The paper will converse the DL methods used in the detection of RA as well as its strengths, weaknesses, and performance. The study is useful in terms of better decision-making in diagnostic situations, effective use of resources, and quality clinical support. Further studies will be aimed at enhancing the capabilities of the DL models by adding the ability of real-time monitoring capabilities to help improve timely and accurate RA detectability in healthcare systems.

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