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AIRADF: ARTIFICIAL INTELLIGENCE ENABLED CLINICAL DECISION SUPPORT SYSTEM FOR DIAGNOSING RHEUMATOID ARTHRITIS USING X-RAY IMAGES

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ABSTRACT

Medical image analysis plays a crucial role in healthcare, particularly in computer vision applications. Artificial Intelligence (AI) has greatly contributed to solving various issues in the healthcare industry, including disease diagnosis and classification. Rheumatoid Arthritis (RA) is an autoimmune disease that causes serious health problems. The current learning-based approaches for RA diagnosis require improvements in pipelining and optimizations. In this paper, we propose a deep learning-based framework called Artificial Intelligence (AI) for RA Diagnosis Framework (AIRADF). This framework includes functionality for preprocessing and training Region of Interests (ROIs) for automatic RA detection and classification. The RA detection process utilizes a deep learning model known as Faster RCNN, while RA classification is carried out by an enhanced UNet model. We introduce an algorithm called Learning Based Rheumatoid Arthritis Detection (LbRAD). Our empirical study using X-ray images demonstrates that the proposed algorithm outperforms many existing deep learning models in RA detection and classification, achieving the highest accuracy of 92.81% and 94.58%, respectively. Additionally, our framework enables multi-class classification beyond RA detection, resulting in a Clinical Decision Support System (CDSS) that can aid healthcare professionals in RA prognosis.

Keywords – *Rheumatoid Arthritis, Deep Learning, Artificial Intelligence, Image Processing, Rheumatoid Arthritis Prognosis*

1. INTRODUCTION

Rheumatoid arthritis is a disease that can affect feet, wrists, or joints in hands with chronic pain full of stone. Diagnosis of this disease is a specific issue: the lack of particular markers associated with re. It is essential to diagnose early to help healthcare professionals plan treatment procedures [1]. As the disease does not provide direct symptoms, rheumatologists must depend on various clues to diagnose OR A complete stop. With the emergence of artificial intelligence and deblurting models based on improved neural networks that mimic human brain process, it is now possible to solve problems in healthcare domain [2]. Deep learning models are found to be effective in medical image analysis. Models like convolutional neural network CNN are found to be efficient in the extraction of features from images that help in the automatic detection of specific diseases. In other words, deep learning models are widely used for disease diagnosis by analyzing medical images of various modalities [3], [5]. Concerning R A there are many regions of interest such as wrist fingers on the feet fully stove. With the help of supervisor learning, it is possible to train a deep learning classifier towards diagnosis of re and classification of its categories.

There are many existing approaches found in the recent literature. Medical imaging has relied on interpretation driven by the viewer. Switching to quantitative biomarkers can improve diagnostic and therapy choices [6]. For safe decision-making in healthcare, it is imperative to comprehend and measure uncertainty in AI models. In particular, in medical imaging, Bayesian approaches are widely used [7]. Deep learning models play a crucial role in the osteoporosis preventive and treatment recommendations provided by a clinical decision support system that was built and tested [12]. Through the analysis of clinical data, artificial intelligence facilitates clinical decision-making. Effective cell decision prediction is achieved using ML approaches such as RBF and MLP [15]. While AI disrupts sectors, the pharmaceutical industry lags. Industry 4.0 and customized medicine are promoted by automated medication manufacturing using artificial intelligence in 3D printing [18]. In various medical domains, machine learning efficiently supports early detection and individualized therapy for autoimmune illnesses [21]. Millions of people worldwide die from heart disease (HD), which is a severe global health problem. The prediction that is made early is essential [32]. Reviewing studies on sustainable healthcare technology, the paper discusses issues and patterns [33]. A technique is presented for pathology's deep learning models, improving diagnostic accuracy with little annotation work [35]. The literature shows that deep learning models are widely used in medical image processing. There is a need for improving the pipeline with optimizations towards the detection of RA. The motivation behind the research carried out in this paper is to have an enhanced deep learning model towards leveraging performance when compared with the state of the art regarding accurate detection of rheumatoid arthritis. Our contributions to this paper are as follows.

1. We proposed a deep learning-based Artificial Intelligence (AI) framework, which enabled the RA Diagnosis Framework (AIRADF).
2. We proposed an algorithm known as Learning Based Rheumatoid Arthritis Detection (LbRAD).
3. Our empirical study with a prototype using X-ray images revealed that the proposed algorithm outperforms many existing deep learning models in RA detection and classification with the highest accuracy.

The remainder of the paper is structured as follows—section 2 reviews prior works about using learning based approaches for RA detection. Section 3 presents the proposed methodology, the underlying framework, and algorithm for automatic RA detection and classification. Section 4 presents our experimental study with X-ray images besides providing the critical findings. Section 5 concludes this paper's proposed research and gives scope for future endeavors.

2. RELATED WORK

This section presents review of the literature on prior works about RA detection. Akinnuwesi *et al.* [1] observed that, all around the world, rheumatoid arthritis (RA) is a leading cause of disability and mortality, particularly in Africa. Diagnoses are more accurate when a decision support system is used. Garcia *et al.* [2] investigated a number of articles spanning various illnesses and data kinds to demonstrate AI's growing incorporation in rheumatology research. Imtiaz *et al.* [3] compared classical and deep learning approaches to diagnose arthritis. In medicine, deep learning helps in the prediction and diagnosis of disease. Maini *et al.* [4] identified that CVD/stroke in RA presents difficulties. The accuracy of risk assessment is increased when DL is combined with biomarkers for GBBM and RBBM. Graf *et al.* [5] outperformed physicians in diagnosing patients, highlighting the need for digital technologies and thorough patient data in rheumatology.

Desouza *et al.* [6] found that, previously, medical imaging has relied on interpretation driven by the viewer. Making the switch to quantitative biomarkers can improve diagnostic and therapy choices. Seoni *et al.* [7] investigated and found that, for safe decision-making in healthcare, it is imperative to comprehend and measure uncertainty in AI models. In particular, in medical imaging, Bayesian approaches are widely used. Xiaoli *et al.* [8] suggested an innovative method that combines machine learning and temporal correlation characteristics for long-term clinical effectiveness evaluation. Khalifa and Albadawy [9] improved chronic illness management, readmission risk detection, customized treatment, prognosis, risk assessment, and mortality prediction, all of which will enhance clinical prediction. Elsabagh *et al.* [10] used AI in medicine improves risk assessment, diagnosis, and individualized care, particularly in sickle cell disease (SCD).

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Jamrat *et al*. [11] enhanced clinical decision-making and medication interaction screens by combining genetic and non-genetic elements for precision medicine. Bonaccorsi *et al*. [12] observed the osteoporosis preventive and treatment recommendations provided by a clinical decision support system built and tested. Chithra and Nedunchezhian [13] used gene expression profiles, a novel classifier called DNCM-ICSA can accurately discriminate between RA patients and controls. Pan *et al*. [14] found that, with tremendous accuracy, the Enhanced Deep Learning Convolutional Neural Network (EDCNN) assists in accurately identifying cardiac disease. Salau and Jain [15] found that, through the analysis of clinical data, artificial intelligence facilitates clinical decision-making. Effective cell decision prediction is achieved using ML approaches such as RBF and MLP.

Martinho *et al*. [16] discussed about health AI techniques that are vital. Concerns about trust, regulation, and explainability in AI are highlighted in four viewpoints surveyed medical professionals provide. Mehta [17] offered comprehensive medical malpractice coverage and supports surgery and diagnostics. Healthcare AI progresses from simple rules to brain-like systems. Elbadawi *et al*. [18] observed that while AI disrupts sectors, the pharmaceutical industry lags. Industry 4.0 and customized medicine are promoted by automated medication manufacturing using artificial intelligence in 3D printing. Boquete *et al*. [19] analyzed by AI systems to find biomarkers for fibromyalgia. Notable variations in the retinal layers point to a possible diagnostic tool. Magna *et al*. [20] presented a potential recommendation system for breast cancer detection that uses machine learning and natural language processing.

Danieli *et al*. [21] explored and said that various medical domains, machine learning efficiently supports early detection and individualized therapy for autoimmune illnesses. Conrad *et al*. [22] found that, apart from modern technology like AI, precision medicine projects require human participation and trust, hence reshaping the treatment of autoimmune diseases. Yildiz *et al*. [23] used various techniques, machine learning models enhanced the diagnosis of anaemia, reaching high accuracy and providing decision assistance. Bonakdari *et al*. [24] emphasized precision medicine and customized therapy to improve the care of patients with arthritis using interactive prediction models. Yang *et al*. [25] focused on early ADR and toxicity detection that are being revolutionized by AI and ML, which are also improving pharmacovigilance, patient safety, and drug discovery.

Prasad and Kumar [26] innovated in COVID-19 research, such as medication repurposing and structural biology, are driven by AI and ML; nonetheless, obstacles still exist. Wang *et al*. [27] focused on EHR data, and latent illness clusters and patient subgroups are found using unsupervised machine learning, namely LDA and PDM. Kora *et al*. [28] researched on health applications, such as fuzzy-model-based PC-based coronary disease diagnosis, which is driven by an emphasis on physical fitness. Ahmad *et al*. [29] extended bioinformatics; translational bioinformatics combines biological data to minimize risks and costs for effective medication discovery. Hannan *et al*. [30] provided an IoT-based wearable cardiac monitoring device which has the potential to save lives and enhance patient care.

Mottaqi *et al*. [31] developed AI-powered machine learning approaches to counteract the COVID-19 pandemic's problems. Reshan *et al*. [32] observed that millions of people worldwide die from heart disease (HD), which is a severe global health problem. Prediction that is made early is essential. Nti *et al*. [33] advanced quickly, making it difficult for academics to understand its scope fully. Reviewing studies on sustainable healthcare technology, this paper discusses issues and patterns. Cague *et al*. [34] used quantitative information extracted from medical pictures; radiomics helps clinicians make better judgments and better understand diseases. Validation trials and multidisciplinary cooperation are critical to its future. Uegami *et al*. [35] presented a technique for pathology's deep learning models, improving diagnostic accuracy with little annotation work.

Tripathi *et al*. [36] demonstrated how AI may leverage deep learning for innovative therapeutics in medication creation. We discuss potential uses and directions for generative models. Baik *et al*. [37] used primarily lab test data AI models, significantly boosting ones, perform robustly in the efficient classification of non-COVID pneumonia from COVID-19. Safaei *et al*. [38] connected to several chronic conditions, obesity is a serious worldwide health problem. Prediction and early detection are aided by machine learning. Assi *et al*. [39] indicated that photoacoustic imaging (PAI) has potential. The International

Photoacoustic Standardization Consortium (IPASC) works to overcome obstacles to adoption. Scherer *et al.* [40] observed that hereditary and environmental variables can contribute to the development of ACPA-positive and --negative rheumatoid arthritis. The immune system reacts differently. The literature shows that deep learning models are widely used in medical image processing. There is a need for improving the pipeline with optimizations towards the detection of RA. Other important approaches found in the literature include hash based [42], annotation based [43], index based [44] and re-ranking based [45]. From the literature it was observed that there is need for leveraging rheumatoid arthritis detection performance with novel deep learning approaches.

3. METHODOLOGY

We proposed a methodology that includes a deep learning framework with underlying deep learning models, the proposed algorithm, and an evaluation methodology for the automatic detection and classification of RA.

3.1 Problem Definition

Provided an X-ray image consisting of wrist and fingers, developing a deep learning-based framework that exploits AI to automatically detect and classify RA is a challenging problem to consider.

3.2 Proposed Framework

We proposed a deep learning based framework known as Artificial Intelligence (AI) enabled RA Diagnosis Framework (AIRADF) for automatic detection and classification of RA. The framework is based on a supervised learning approach that provides image data processing, training ROIs, faster RCNN for RA detection, and the enhanced UNet for classification. The framework has provision for image preprocessing for both training and test datasets. Training ROIs is a phenomenon in which the faster RCNN model can learn about RA detection and localization of different joints associated with fingers and wrist in the given test sample. The enhanced UNet model is used to classify given test sample into normal, mild and severe.

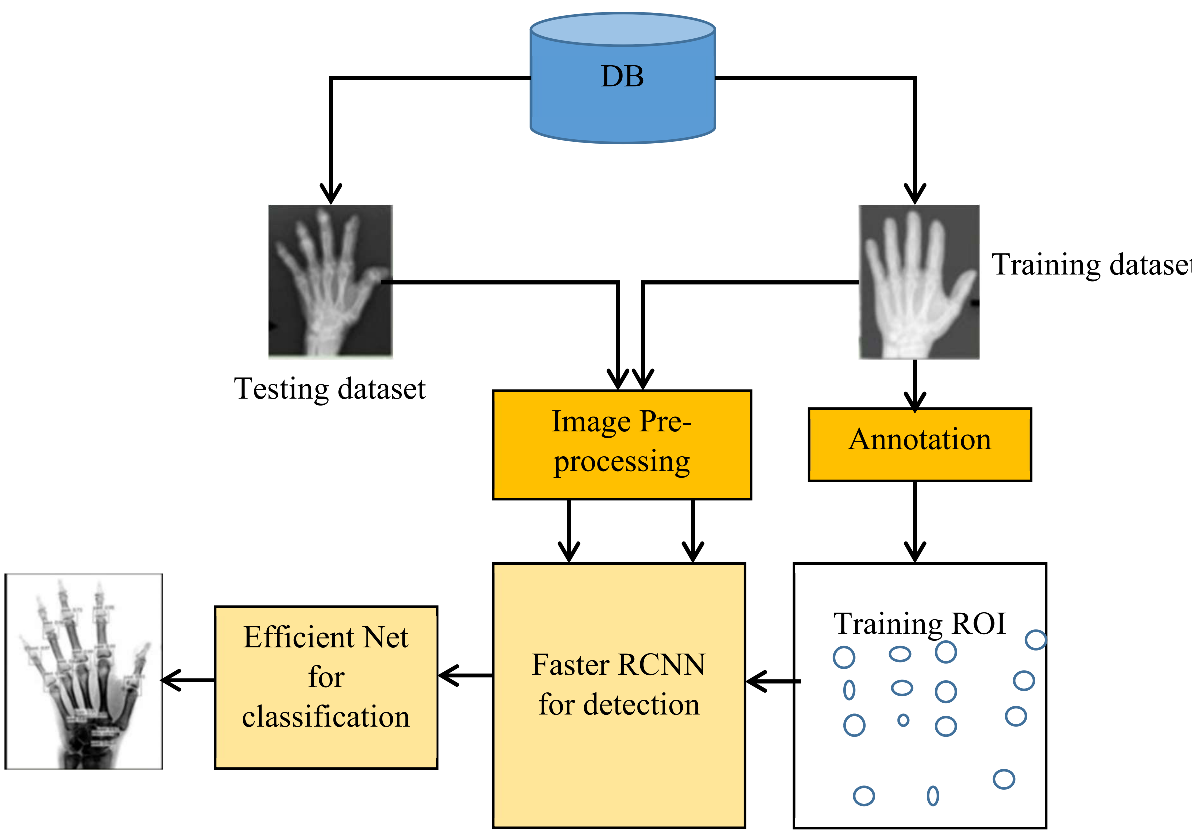

Figure 1: The proposed deep learning framework known as AIRADF

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The preprocessing module of the framework performs various mechanisms like image conversion and data augmentation to improve diversity of training and test samples besides feature enhancement. Different image pre-processing techniques employed by the framework are illustrated in Figure 2. The given X-ray image is subjected to window-level adjustment towards leveraging ROI features. The image preprocessing techniques include window level, ROI feature enhancement approach, data augmentation, which enhances the diversity of training and test samples followed by mosaic. In the preprocessing method, the mosaic approach includes reading images and combining images—the mosaic approach results in samples that improve detection performance of deep learning models.

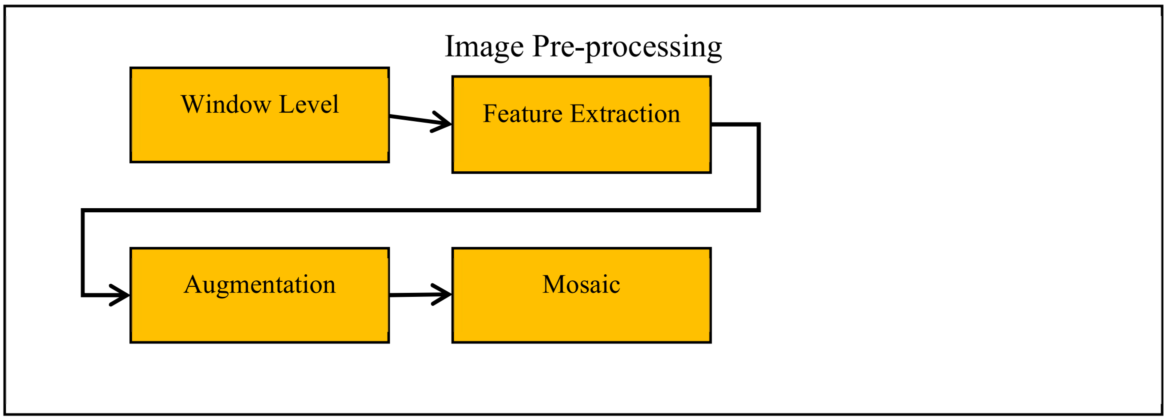

Figure 2: Different approaches involved in image reprocessing

The data augmentation process in the proposed framework includes different techniques like displacement, stretching, brightness adjustment, and general shifting. It also consists of the mosaic method, which leverages training and test samples in terms of diversity. With data augmentation, the data is made ready with improved samples that can be used by neural networks to automatically detect and localize RA besides classification of RA. The proposed framework exploits the faster RCNN model widely used in object detection and classification research. This paper uses a faster RCNN model to detect RA and localization of different joints associated with ROIs like fingers and wrist. The softmax involved in faster RCNN performs the detection process while the bonding box regressor performs the localization of joints. The architecture of the faster RCNN model is shown in Figure 3.

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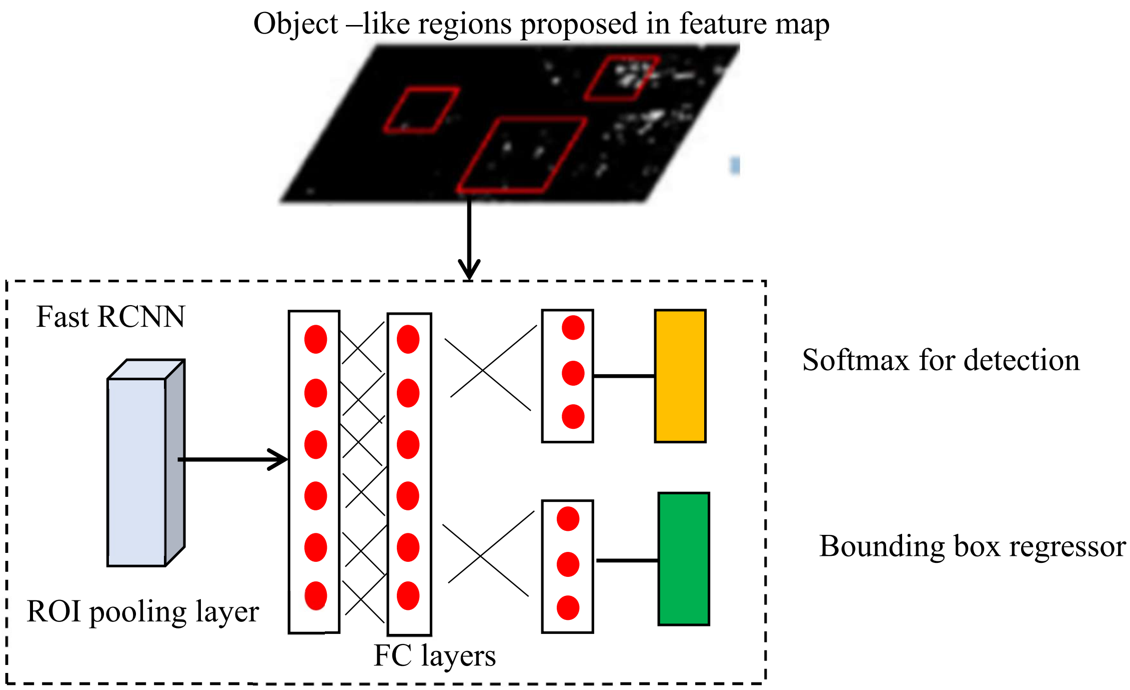

Figure 3: Illustrates the architecture of faster RCNN model

The faster RCNN model exploits the Region Proposal Network (RPN), which generates region proposals from the given test sample to perform detection and localization. The RPN involved in the faster RCNN model plays an important role in extracting region proposals that are very significant for the speedier model convergence towards detection and localization of RA. The model uses a loss function, which efficiently determines the difference between prediction and ground truth. A positive label is assigned based on IoU. The loss function of the model is as expressed in Eq. 1.

$$L(\{p_i\},\{t_i\})=\frac{1}{N_{cls}}\sum_i L_{cls}(p_i,p_i^*) + \gamma\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*) \quad (1)$$

where the anchor probability is denoted as p_i while p_i^* denotes ground truth, negative anchor is denoted as 0 while the positive anchor is denoted as 1.

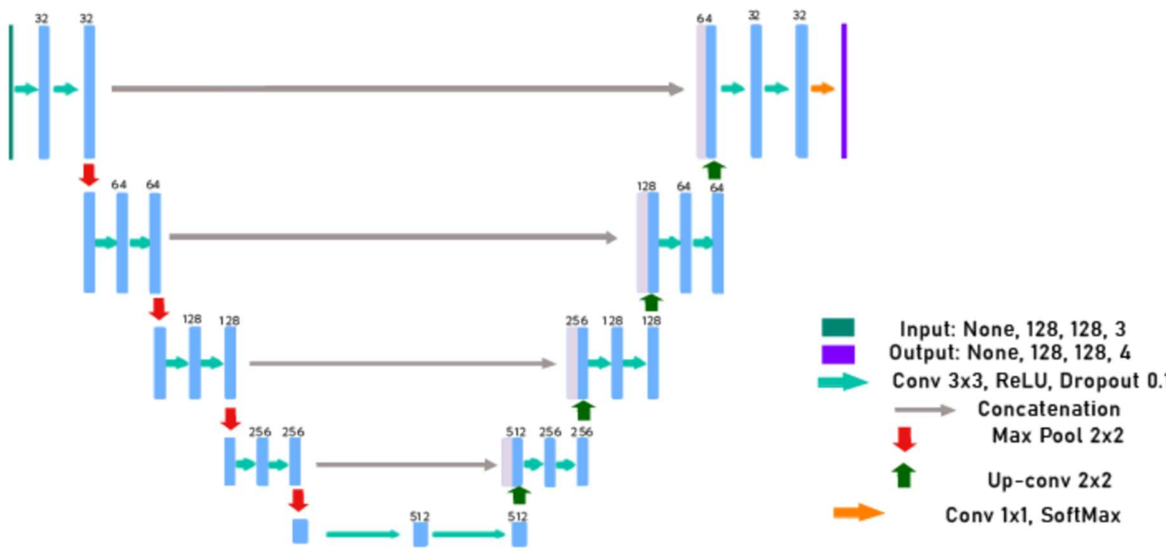

Figure 4: Architecture of enhanced UNet model used for multiclass classification

As presented in Figure 4, the enhanced UNet model is provided with its U-shaped architecture. It has a contracting path and also expanding path forming U-shaped architecture. Contracting path resembles a typical CNN architecture. It contains two convolutions of 3x3 size followed by an activation function ReLU. To downsample, the model uses 2x2 max pooling meant for feature optimization. With the down-sampling step, the number of features is increased in the UNet model. On the other hand, the expansive path comprises transposed convolutional layers of 2x2 size. The expansive path is meant to up-sample the feature map associated with the contracting path. In the network's last layer, convolution of 1x1 is used for feature mapping towards multiclass classification. With this, the proposed system helps detect RA and its multiclass classification into three categories: normal mild and severe.

3.3 Proposed Algorithm

We proposed an algorithm known as Learning Based Rheumatoid Arthritis Detection (LbRAD). It exploits two deep learning models, which foster RCNN and enhanced UNet, towards automatic detection and classification of RA samples.

Algorithm: Learning Based Rheumatoid Arthritis Detection (LbRAD)
Input: RA dataset D
Output: RA detection and classification results R, performance statistics P

1. Begin
2. D'←ImagePreprocessing(D)
3. D"←Augmentation(D')
4. (T1, T2)←DataSplit(D")
5. Configure faster RCNN model m1
6. Configure enhanced UNet model m2
7. Compile m1
8. Compile m2
9. Train m1 using T1
10. Train m2 using T1
11. Save m1 and m2 for future reuse
12. Load m1
13. R←Test(m1, T2) //detection
14. P←Evaluate(R, ground truth)
15. Display R
16. Display P
17. R←Test(m2, T2) //classification
18. P←Evaluate(R, ground truth)
19. Display R
20. Display P
21. End

Algorithm 1: Learning Based Rheumatoid Arthritis Detection (LbRAD)

As presented in Algorithm 1, it takes the RA dataset as input. It performs RA detection and classification with the help of two deep learning models like, faster RCNN and enhanced UNet model. The algorithm has provision for image processing techniques to improve the training and test samples. Besides, the algorithm has data augmentation approach in which different methods are used to enhance diversity of test and training samples in the dataset. The dataset is divided into 80% training and 20% testing. Since

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two models are involved in the proposed system, each model is trained with the training data and then evaluated for their performance in terms of RA detection and multiclass classification respectively.

3.4 Dataset Details

The RA dataset [41] has X-ray data of 400 patients comprising three different classes such as healthy, mild, and severe.

3.5 Performance Evaluation Method

Since we used a learning based approach, metrics derived from confusion matrix are used for evaluation our methodology. Based on the confusion matrix, the predicted labels of our method are compared with ground truth to arrive at performance statistics. Eq. 2 to Eq. 5 express different metrics used in the performance evaluation.

$$\text{Precision (p)} = \frac{TP}{TP+F} \quad (2)$$

$$\text{Recall (r)} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score} = 2 * \frac{(p * r)}{(p+r)} \quad (4)$$

$$\text{Accuracy} = \frac{TP+}{TP+TN+FP+F} \quad (5)$$

The measures used for performance evaluation result in a value that lies between 0 and 1. These metrics are widely used in machine learning research.

4. EXPERIMENTAL RESULTS

This section presents experimental results obtained through a prototype application implemented to realize the framework provided in Figure 1. Observations are made regarding RA detection localization of joints about ROI and multi-class classification of test samples into normal/healthy, mild, and severe. The proposed framework has two deep learning models, faster RCNN and enhanced UNet. The former is meant for RA detection, while the latter is intended for multi-class classification. The experimental results are also provided regarding RA detection and classification achieved by the aforementioned models. The experimental results of the enhanced UNet model are compared against existing deep learning models like EfficientNet, ResNet-50, VGG-16, and InceptionV3.

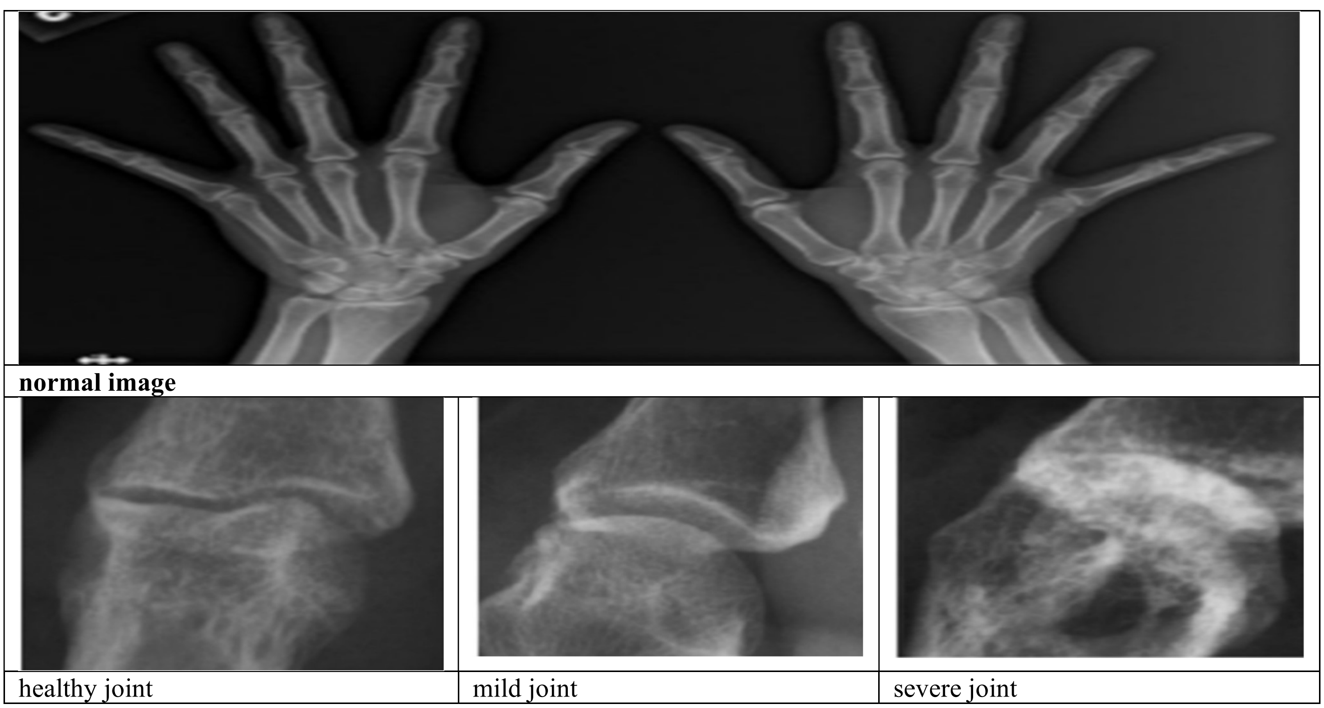

Figure 5: Shows X-ray images of ordinary and RA affected samples

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As presented in Figure 5, the average image sample reflects no RA disease. The healthy joint also reflects no RA, while mild and severe joint are the affected samples.

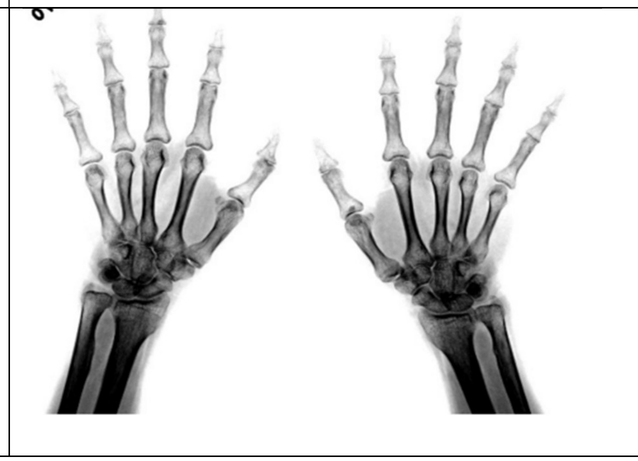
Input Image	Window level adjustment
	

Figure 6: Shows input image and its corresponding window level adjustment

As presented in Figure 6, the input X-ray image is provided along with window-level adjustment dynamics visualized as part of image pre-processing.

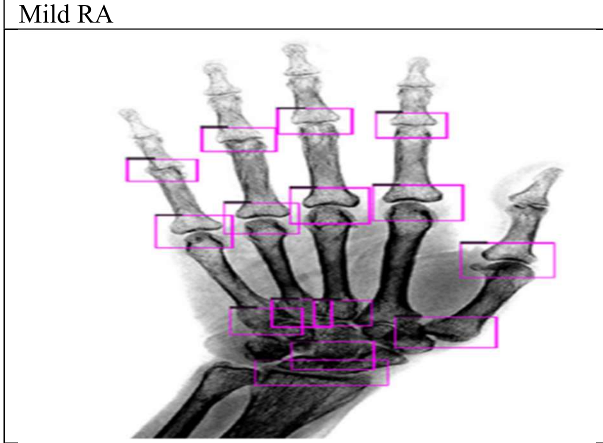
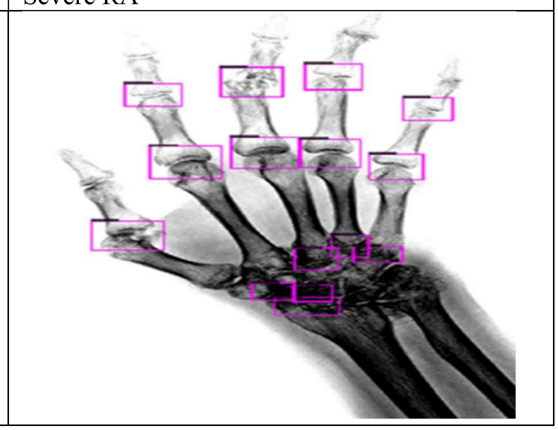
Mild RA	Severe RA
	

Figure 7: Shows the localization of joints reflecting mild RA sample and severe RA sample

Figure 7 shows a mild RA sample on the left side and a severe RA sample on the right side. Both samples are visualized with localization of joints. The localization process, along with the detection of RA, is done by a faster RCNN model.

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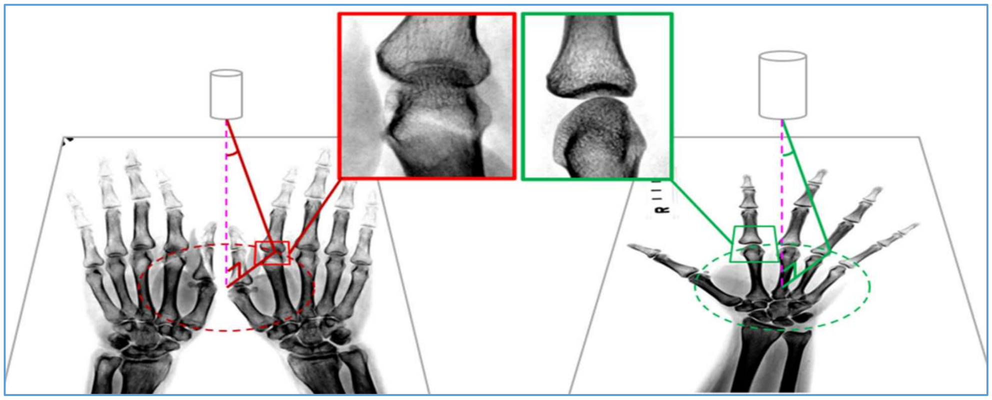


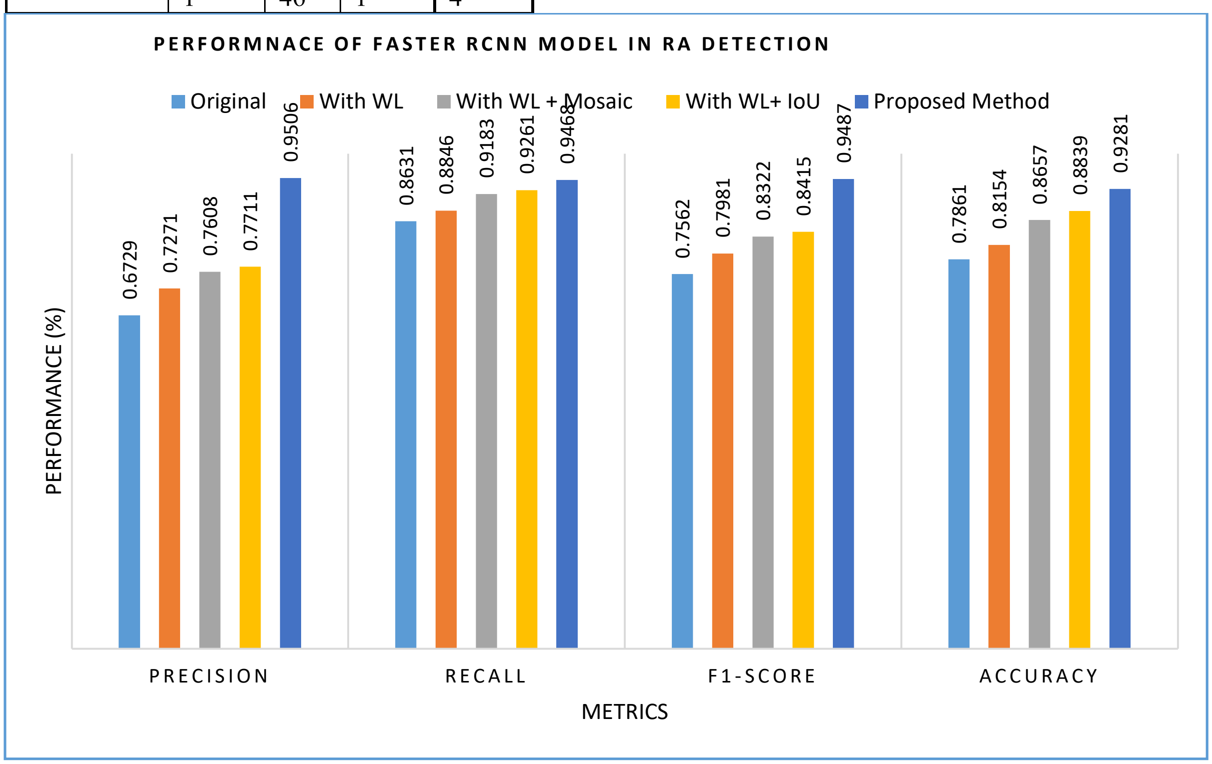
Figure 8: Shows test samples and projection of joints

As presented in Figure 8, the test samples are provided along with their joints projected to ascertain the details.

Table 1: Performance of Faster RCNN model in RA detection

Faster RCNN	Precision	Recall	F1-Score	Accuracy
Original	0.6729	0.8631	0.7562	0.7861
With WL	0.7271	0.8846	0.7981	0.8154
With WL + Mosaic	0.7608	0.9183	0.8322	0.8657
With WL+ IoU	0.7711	0.9261	0.8415	0.8839
Proposed Method	0.9506	0.9468	0.9487	0.9281

Table 1 presents the performance of a faster RCNN model with different image preprocessing techniques and data augmentation.



Figured 9: Performance of faster RCNN model with different image processing and augmentation techniques

As presented in Figure 9, the results of the faster RCNN model are provided with different augmentation and image processing techniques. Without any image processing technique, faster

RCNN achieved 67.29% precision, 86.31% recall, 75.62% F1-score and 78.61% accuracy. With the window level approach, the model achieved 72.71% precision, 88.46% recall, 79.81% F1 score and 81.54% accuracy. With window level and mosaic approach, the deep learning model achieved 76.08% precision, 91.83% recall, 83.22% F1-score and 86.57% accuracy. With the combination of window level and IOU approaches the faster RCNN model could achieve 77.11% precision, 92.61% recall, 84.15% F1-score and 88.39% accuracy. The proposed data augmentation and preprocessing techniques along with faster RCNN model could achieve 95.06% precision, 94.68% recall, 94.87% F1-score and 92.81% accuracy. From the results, it is observed that the proposed methodology for augmentation and image processing along with a faster RCNN model could achieve highest accuracy 92.81%.

Table 2: Shows results of multiclass classification by the enhanced UNet model

Measures	Performance (%) for all RA Classes		
	Healthy	**Mild**	**Severe**
Precision	0.9479	0.8954	0.9381
Recall	0.9862	0.8319	0.8924
F1-Score	0.9667	0.8625	0.9147
Accuracy	0.9874	0.9029	0.9471

As presented in Table 2, the multi-class classification performance of enhanced UNet model are provided for three different RA classes like healthy, mild and severe.

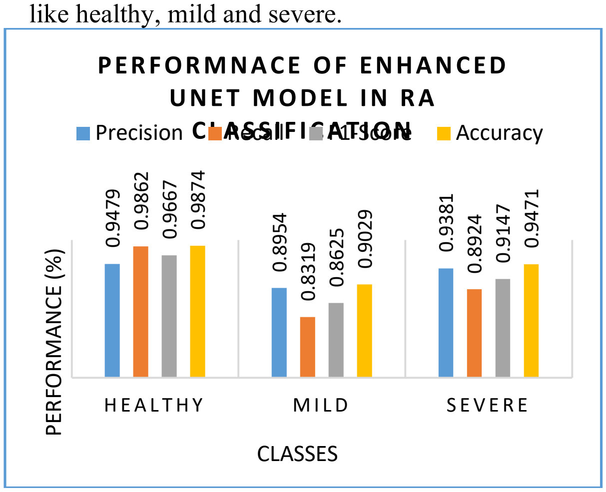


Figure 10: Classification results of enhanced unit model

As presented in Figure 10, it is observed that the enhanced UNet model could perform multi-class classification by identifying and classifying given test samples as healthy or mild or severe with respect to RA. For healthy class the enhanced UNet model achieved 94.79% precision, 98.62% recall, 96.67% F1- score and 98.74% accuracy. The mild class identified by enhanced UNet model could achieve 89.54% precision, 83.19% recall, 86.25% F1-score and 90.29% accuracy. The severe class determined by enhanced UNet model could achieve 93.81% precision, 89.24% recall, 91 .47% F1-score, and 94.71% accuracy.

Table 3: Performance comparison among various deep learning models for RA classification

Model	Accuracy
Enhanced UNet (Proposed)	0.9458
EfficientNet	0.8954
ResNet-50	0.9163
VGG-16	0.9237
InceptionV3	0.9059

As presented in Table 3, the performance of various deep learning models for RA classification is provided in terms of accuracy.

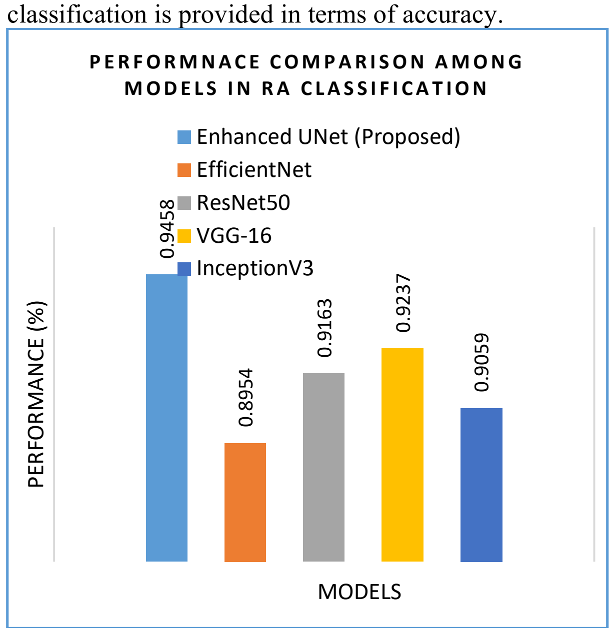


Figure 11: Performance comparison among deep learning models in RA classification

As presented in Figure 11, different deep learning models are compared for their performance in RA classification in terms of accuracy. Higher in accuracy of any model indicates better performance. The InceptionV3 model could achieve 90.59% accuracy, the VGG16 model 92.37% accuracy, the ResNet50 model 91.63%, the EfficientNet model 89.54%, and the proposed enhanced UNet model could achieve the highest accuracy at 94.58%.

5. DISCUSSION

In this paper, we proposed a deep learning framework for automatic detection and classification of RA. The framework is developed in such a way that it can act as a Clinical Decision Support System (CDSS) that helps healthcare professionals in RA prognosis. In the process of developing the framework there is strong preprocessing which helps in improving the training samples. The framework enables detection of RA and also classification. Besides, the proposed system has provision for training ROIs in order to detect and localize different portions of the sample where there is probability of RA. The proposed deep learning framework exploits region proposals by faster RCNN model towards more efficient detection and localization of RA in the given test sample. Moreover, the framework enables classification of RA with the help of enhanced UNet model which is based on encoder decoder phenomenon. With the usage of two deep learning models the framework achieves RA detection and localization. The empirical study is made with X-ray images as this kind of image modality is widely used in the diagnosis of RA. The proposed system is not without its limitations as discussed in section 5.1.

5.1 Limitations

The proposed framework for automatic detection of RA has certain limitations. The dataset used in the empirical study has a limited number of samples and does not help in generalizing the findings in the research. The deep learning models like faster RCNN and enhanced UNet used in the proposed framework can be improved further with the hyperparameter optimization. The overall framework can also be improved by exploiting Generative Adversarial Network (GAN) architecture to leverage RA detection performance.

6. CONCLUSION AND FUTURE WORK

We proposed a deep learning-based framework known as Artificial Intelligence (AI) enabled RA Diagnosis Framework (AIRADF). The framework is designed based on a supervised learning process for automatic diagnosis of RA. The framework has functionality for preprocessing and training of Region of Interests (ROIs) for automatic RA detection and classification. There are number of ROI objects associated with RA in human hands and joints. Therefore, training ROIs is given importance in the proposed framework. The RA detection process is done using deep learning model known as Faster RCNN while RA classification is carried out by an enhanced UNet model. We proposed an algorithm known as Learning Based Rheumatoid Arthritis Detection (LbRAD). Our empirical study with X-ray images reveals that the proposed algorithm outperforms many existing deep learning models in RA detection and classification with the highest accuracy, 92.81% and 94.58%, respectively. Our framework achieves multi-class classification besides RA detection, resulting in a Clinical Decision Support System (CDSS) that can help healthcare professionals in RA prognosis.

6.1 Limitations and Future Directions

The proposal system has some limitations. The data used in the research may not be sufficient to generalize the findings, so it's important to evaluate the proposed system with a more diverse set of data samples. Another important consideration is the need to utilize generative adversarial network-based deep learning to diversify the research. In the future, we intend to enhance our framework by improving the methodology to overcome these limitations.

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