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AI for Rheumatoid Arthritis Disease Subtype Classification

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Abstract: Rheumatoid Arthritis (RA) is a chronic autoimmune disease that causes progressive joint inflammation and irreversible structural damage if not diagnosed at an early stage. Accurate classification of RA subtypes, such as seropositive and seronegative RA, along with the identification of erosive joint changes from radiographic images, is essential for effective clinical decision-making. However, conventional diagnostic approaches rely heavily on manual interpretation of laboratory biomarkers and X-ray images, which are time-consuming and subject to inter-observer variability. This work proposes an artificial intelligence–based dual-modal diagnostic framework for automated rheumatoid arthritis disease subtype classification. The system integrates numerical clinical biomarkers and hand X-ray imaging to provide complementary diagnostic insights. The numerical model utilizes six key laboratory parameters—age, gender, rheumatoid factor (RF), anti-cyclic citrullinated peptide (Anti-CCP), C-reactive protein (CRP), and erythrocyte sedimentation rate (ESR)—to classify patients into Healthy, Seropositive RA, and Seronegative RA using an XGBoost classifier. In parallel, an EfficientNet-B3 deep learning model is employed to analyze hand X-ray images for erosive and non-erosive joint damage detection. Experimental evaluation demonstrates that the numerical model achieves an accuracy of 89.28% with a ROC-AUC of 93.21%, while the imaging model attains 85.83% accuracy with a 95.04% recall for erosive cases. The proposed system is deployed as a real-time, web-based clinical decision support tool using Streamlit, providing fast and interpretable predictions. This approach highlights the effectiveness of multimodal AI systems in enhancing early RA diagnosis and subtype classification.

Keywords: Rheumatoid Arthritis, Disease Subtype Classification, Medical Imaging, Machine Learning, Deep Learning, Clinical Decision Support

I. INTRODUCTION

Rheumatoid Arthritis (RA) is a systemic autoimmune disorder characterized by chronic inflammation of synovial joints, leading to progressive cartilage degradation, bone erosion, and long-term disability. Early and accurate diagnosis is crucial, as delayed treatment can result in irreversible joint damage and reduced quality of life. Clinically, RA presents in multiple subtypes, including seropositive RA, seronegative RA, and erosive versus non-erosive disease patterns, each requiring different therapeutic strategies.

Traditional RA diagnosis relies on laboratory biomarkers such as RF, Anti-CCP, CRP, and ESR, combined with radiographic examination of hand joints. While effective, these methods require expert interpretation and are prone to subjectivity, particularly in early-stage disease where radiographic changes are subtle. Furthermore, manual assessment becomes challenging in large-scale clinical settings with increasing patient loads.

Recent advances in artificial intelligence (AI) and machine learning have demonstrated significant potential in automating disease diagnosis by learning complex patterns from heterogeneous medical data. Deep learning models, particularly convolutional neural networks (CNNs), have shown promising performance in medical image analysis, while ensemble learning techniques such as XGBoost excel in structured clinical data classification.

Motivated by these advancements, this research presents a unified AI-based framework that integrates numerical laboratory biomarkers and radiographic imaging to classify rheumatoid arthritis disease subtypes. By combining machine

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learning and deep learning techniques, the proposed system aims to improve diagnostic accuracy, reduce clinician workload, and support early intervention.

II. SYSTEM OVERVIEW AND ARCHITECTURE

The proposed system is a dual-modal artificial intelligence framework designed to classify rheumatoid arthritis disease subtypes by integrating numerical clinical biomarkers and hand X-ray imaging. The architecture follows a modular design that allows independent processing of heterogeneous data sources while enabling unified clinical interpretation.

The system begins with a web-based user interface developed using Streamlit, through which clinicians can input laboratory values or upload hand X-ray images. The numerical input consists of six key clinical parameters—age, gender, RF, Anti-CCP, CRP, and ESR—while the imaging input consists of standard hand radiographs. Separate preprocessing pipelines are implemented for each modality to ensure data consistency and robustness.

Numerical data is validated, normalized, and encoded before being passed to an XGBoost classifier for three-class RA subtype prediction (Healthy, Seropositive RA, and Seronegative RA). In parallel, X-ray images undergo intensity normalization and resizing before being analyzed using a deep learning model based on EfficientNet-B3 for erosive and non-erosive classification.

The outputs from both models are presented together in a unified diagnostic report, including confidence scores and clinical interpretation. This modular architecture ensures scalability, real-time performance, and suitability for deployment as a clinical decision support system.

III. DATASET DESCRIPTION

The proposed system utilizes two distinct datasets corresponding to numerical clinical biomarkers and hand X-ray imaging data. These datasets were selected to reflect real-world diagnostic scenarios in rheumatoid arthritis and to support robust multimodal learning.

1) Numerical Clinical Dataset

The numerical dataset consists of clinical records collected from diagnosed rheumatoid arthritis patients and healthy controls. Each record includes six clinically significant features: age, gender, rheumatoid factor (RF), anti-cyclic citrullinated peptide (Anti-CCP), C-reactive protein (CRP), and erythrocyte sedimentation rate (ESR). Based on serological findings, the dataset is categorized into three classes: Healthy, Seropositive RA, and Seronegative RA.

To ensure unbiased evaluation, the dataset is divided into training, validation, and testing subsets using stratified sampling, preserving the original class distribution across all splits. This strategy prevents model bias toward dominant classes and ensures reliable performance assessment.

2) Imaging Dataset

The imaging dataset comprises hand X-ray images annotated for erosive and non-erosive joint damage. These images capture radiographic features such as joint space narrowing and bone erosion, which are critical indicators of disease progression. The dataset exhibits class imbalance, with erosive cases occurring more frequently than non-erosive cases, reflecting real clinical prevalence.

To address this imbalance during model development, specialized training strategies are adopted at later stages. The imaging dataset is further divided into training, validation, and test sets to enable systematic performance evaluation and generalization analysis.

IV. PREPROCESSING AND FEATURE ENGINEERING

Effective preprocessing is essential to ensure reliable performance of machine learning and deep learning models, particularly when dealing with heterogeneous medical data. In the proposed system, separate preprocessing pipelines are

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implemented for numerical clinical data and imaging data to preserve modality-specific characteristics.

For numerical clinical data, initial validation is performed to verify input ranges and detect inconsistencies. Continuous features such as age, RF, Anti-CCP, CRP, and ESR are normalized using standard scaling to ensure uniform feature contribution during model training. Categorical variables, such as gender, are encoded into numerical form to make them compatible with machine learning algorithms. These steps reduce bias caused by differing feature scales and improve model convergence.

For imaging data, hand X-ray images undergo a sequence of preprocessing operations to enhance image quality and standardize input dimensions. Grayscale images are normalized using percentile-based intensity clipping to suppress extreme intensity values and improve contrast. The images are then resized to a fixed resolution and converted into a three-channel format to meet the input requirements of the deep learning model. Finally, ImageNet-based normalization is applied to align the data distribution with the pre-trained network parameters.

These preprocessing and feature engineering steps ensure consistency, robustness, and improved generalization across both numerical and imaging modalities.

V. MODEL ARCHITECTURE AND TRAINING

The proposed system employs two independently trained models optimized for their respective data modalities: a machine learning model for numerical clinical data and a deep learning model for radiographic image analysis. This separation allows each model to specialize in learning modality-specific patterns while contributing to a unified diagnostic framework.

For numerical clinical data, an **XGBoost classifier** is utilized due to its strong performance on structured datasets and ability to capture non-linear relationships between biomarkers. The model is trained using six input features—age, gender, RF, Anti-CCP, CRP, and ESR—and produces a three-class output corresponding to Healthy, Seropositive RA, and Seronegative RA. Stratified training is employed to preserve class distribution, and early stopping is applied to prevent overfitting and improve generalization.

For imaging-based classification, a deep convolutional neural network based on **EfficientNet-B3** is employed. The model leverages transfer learning by initializing weights pre-trained on the ImageNet dataset and fine-tuning them using hand X-ray images. This approach enables efficient learning despite limited medical imaging data. To address class imbalance between erosive and non-erosive cases, appropriate loss functions and sampling strategies are applied during training.

Both models are trained and validated using separate datasets, and their performance is evaluated on unseen test data to ensure robustness. This dual-model strategy allows the system to effectively integrate laboratory and imaging information for reliable rheumatoid arthritis subtype classification.

VI. PERFORMANCE EVALUATION

The performance of the proposed dual-modal system is evaluated independently for numerical clinical classification and imaging-based erosion detection using standard machine learning evaluation metrics. All evaluations are conducted on unseen test datasets to assess the generalization capability of the models.

For the numerical clinical classification task, the XGBoost model is evaluated using accuracy, precision, recall, F1-score, and ROC–AUC metrics. The model demonstrates strong predictive performance across all three classes—Healthy, Seropositive RA, and Seronegative RA—indicating its ability to effectively learn relationships between clinical biomarkers. High ROC–AUC values further confirm the robustness of the classifier in distinguishing between disease subtypes.

For the imaging-based task, the EfficientNet-B3 model is evaluated using accuracy, class-wise F1-score, and recall, with particular emphasis on erosive case detection due to its clinical importance. The model achieves high recall for erosive cases, indicating strong sensitivity in identifying structural joint damage from hand X-ray images. Although the dataset

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exhibits class imbalance, the applied training strategies improve minority class performance without significantly affecting overall accuracy.

A comparative analysis of multiple deep learning models is conducted for the imaging task to justify model selection. EfficientNet-B3 outperforms alternative architectures in terms of accuracy, F1-score, and computational efficiency, making it suitable for real-time clinical deployment.

A comparative analysis of multiple deep learning models is conducted for the imaging task. As shown in Fig. 1, EfficientNet-B3 achieves the highest test accuracy (85.8%), outperforming ResNet50 (82.5%) and ViT-B/16 (80.0%). Based on this evaluation, EfficientNet-B3 is selected as the final imaging model for erosive and non-erosive RA detection.

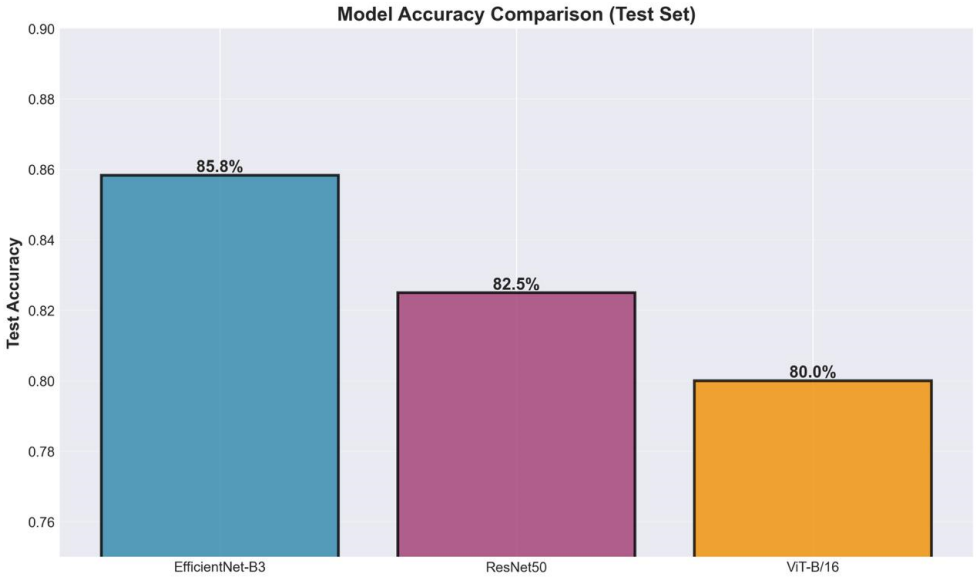

Fig. 1. Test accuracy comparison of deep learning models for hand X-ray–based rheumatoid arthritis classification.

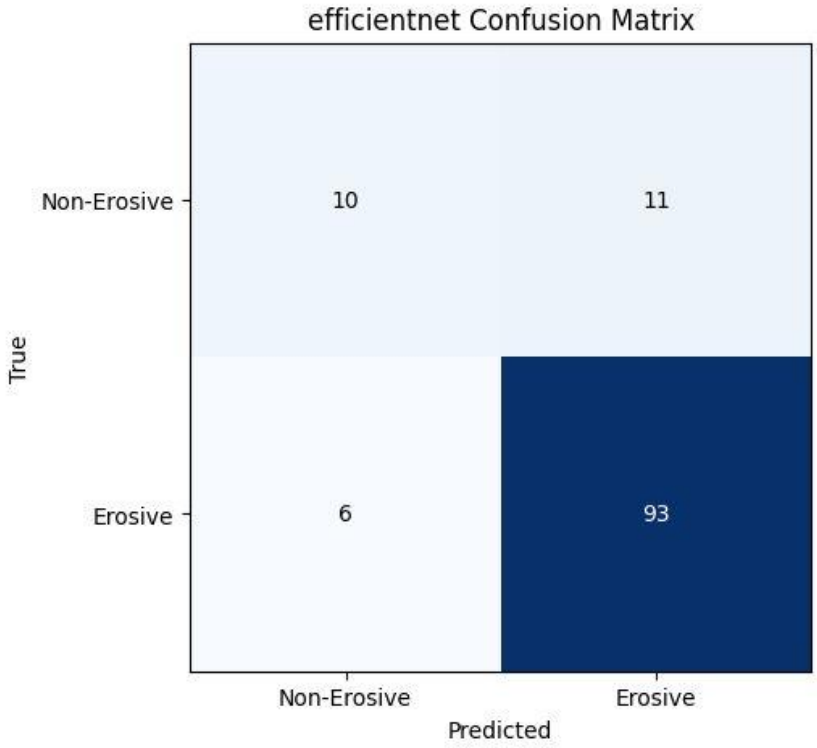

Fig. 2. Confusion matrix of the EfficientNet-B3 model on the test dataset for erosive and non-erosive rheumatoid arthritis classification

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The model correctly identifies the majority of erosive rheumatoid arthritis cases, achieving a high true positive count, which is clinically critical for early disease detection. A smaller number of non-erosive cases are misclassified, reflecting the inherent class imbalance in the dataset. Overall, the confusion matrix confirms the robustness and reliability of the selected imaging model.

VII. DEPLOYMENT AND APPLICATION

The proposed rheumatoid arthritis classification system is deployed as a web-based clinical decision support application to demonstrate its practical usability in real-world healthcare environments. The application is developed using the Streamlit framework, which provides an interactive and lightweight interface for model inference and result visualization.

The deployment framework allows clinicians to input numerical laboratory parameters, including age, gender, RF, Anti-CCP, CRP, and ESR, as well as upload hand X-ray images for automated analysis. Once the inputs are provided, the system performs preprocessing and model inference in real time, delivering diagnostic predictions along with confidence scores within a short response time. This enables efficient clinical workflow integration without the need for specialized hardware or complex installation procedures.

The application is designed to support clinical decision-making rather than replace medical expertise. By presenting clear and interpretable outputs, the system assists clinicians in identifying rheumatoid arthritis subtypes and assessing the presence of erosive joint damage. Such a deployment model is particularly useful in resource-constrained settings, where access to specialized radiology expertise may be limited.

Overall, the deployment demonstrates the feasibility of integrating artificial intelligence–based diagnostic tools into routine clinical practice and highlights the potential of the proposed system to enhance early rheumatoid arthritis detection and patient management.

VIII. CONCLUSION

This work presents a comprehensive artificial intelligence–based framework for rheumatoid arthritis disease subtype classification by integrating numerical clinical biomarkers and hand X-ray imaging. The proposed dual-modal approach effectively combines structured laboratory data with radiographic information to provide a more complete and reliable diagnostic assessment compared to single-modality systems.

The numerical classification model demonstrates strong performance in distinguishing Healthy, Seropositive RA, and Seronegative RA cases using routinely available clinical parameters. In parallel, the imaging-based deep learning model accurately identifies erosive and non-erosive joint damage from hand radiographs, with high sensitivity toward erosive cases, which are clinically significant due to their association with disease progression and irreversible joint damage.

Comparative evaluation of multiple deep learning architectures confirms the suitability of EfficientNet-B3 as the final imaging model, based on its superior accuracy and balanced performance. The confusion matrix analysis further validates the robustness of the selected model by highlighting its strong true positive detection capability for erosive rheumatoid arthritis.

The successful deployment of the system as a web-based application demonstrates its practical feasibility for real-world clinical use. By assisting clinicians with fast, consistent, and interpretable predictions, the proposed system has the potential to support early diagnosis, improve treatment planning, and reduce diagnostic variability.

Future work will focus on expanding the dataset, incorporating additional imaging modalities, and validating the system across multi-center clinical settings to further enhance generalizability and clinical impact.

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