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# Real-Time Detection Of Rheumatoid Arthritis From X-Ray Images And Numerical Clinical Dataset Using Convolutional Neural Networks, Deep Neural Networks And Flask Web Application.

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**Abstract**

Rheumatoid Arthritis (RA) is an autoimmune disorder, which can lead to joint deformation and which can lead to permanent disability that cannot be treated in a timely manner. Early diagnosis is thus imperative for effective treatment. In this paper, we present an end-to-end RA detection system with the help of Convolutional Neural Networks (CNN) for hand X-ray images. The model is trained on a balanced 200-image dataset (100 RA, 100 Normal) with extensive pre-processing and augmentation techniques which is used to enhance performance in the lack of large datasets. The CNN architecture was here we used is chosen for its ability to extract hierarchical features from medical images without manual feature engineering. The trained model was deployed using a Flask-based web application, with real-time prediction supported by confidence scores and easy-to-use interaction.This Experiment gives the results that show high reliability, with test cases reporting 96.24% confidence for Normal x-ray image and 92.27% for RA-positive cases.There is another approach where the numerical clinical dataset is used which contain details such as age, gender, ESR, CRP, RF, and Anti-CCP levels. Here the Deep Neural Network (DNN) was trained after preprocessing and scaling the data, demonstrating high predictive performance compared to traditional Machine Learning models. This model was implemented using a Flask-based web application, which will work with real-time prediction and confidence scores and simple interaction. The

system can be potentially integrated into clinical workflows, especially in regions where specialist availability is scarce.

**Keywords**

CNN, DNN, Rheumatoid Arthritis, Medical Imaging, Flask, Deep Learning, X-ray Analysis CNN, Rheumatoid Arthritis, Medical Imaging, Flask, Deep Learning, X-ray Analysis.

## 1. Introduction

Rheumatoid Arthritis (RA) is a chronic inflammatory disorder which mainly affects the joints in human, leading to pain, swelling, and it lead to erosion of bone structures. Early diagnosis of this is critical, as action of finding it during the early stages can significantly slowdown disease progression. X-ray imaging was one of the more accessible method and cost-effective diagnostic tools for RA detection, which allows doctors to visualize joint space narrowing, bone erosion, and other characteristic changes.Here the second method Numerical dataset also used for finding RA by blood test like ESR, CRP, RF, and Anti-CCP.

Traditional RA diagnosis from X-rays and numerical report was based on the expertise of radiologists rheumatologists and blood test, which can introduce subjectivity and variability in interpretation. Moreover, in resource-limited settings, access to experienced specialists may be restricted, causing diagnostic delays which lead to bad condition. Advances in Artificial Intelligence (AI) have provided opportunities which automated the test and standardized medical image processingand blood test. Among various AI approaches, this Convolutional Neural Networks (CNNs) have make an appearance as a particularly effective choice for diagnosing medical imaging tasks due to their ability to learn about spatial hierarchies of features directly from the raw image data and Deep Neural Networks (DNN) which is used for finding RA through blood test report.

The decision to employ CNNs in this work was influenced by their proven performance in similar domains such as fracture detection, tumor identification, and lung disease classification. Unlike traditional machine learning models that depends on handcrafted features, CNNs automatically extract relevant visual patterns for the given dataset or images in any form, which is particularly advantage for detecting the fine result of RA in X-ray images. DNN method is used to predict result in medical fields and tabelated datasets.

## 2. Literature Survey

There are Several studies which have explored by using the application of deep learning algorithm for medical image analysis, including RA detection.

**CNN-based RA detection:** Researchers have employed architectures such as AlexNet, VGG16, and ResNet to classify musculoskeletal radiographs to find RA. While transfer learning often provides a good starting point, which also provide custom CNN architectures tailored to RA-specific features which can outperform generic models due to domain-specific optimizations. Our custom CNN achieved 92% accuracy in result, surpassing VGG16’s 60%, suggesting that a smaller than CNN, domain-focused architecture can be more effective than large pre-trained models for niche datasets.

**Numerical clinical dataset analysis:** Blood test biomarkers like ESR and CRP are well-established indicators of inflammation, while RF and Anti-CCP are more RA-specific one to find RA through blood test. Previous works have used logistic regression, decision trees, and random forests to predict RA, but deep learning models can capture more complex nonlinear relationships between variables, leading to improved accuracy value of the result. Our experiments confirmed that traditional ML methods struggled with our dataset, while a DNN provided significantly better results compare to other models.

**Hybrid AI-based systems:** Some recent works have attempted to combine image and clinical data for disease prediction. However, many are limited to theoretical frameworks or separate models without a unified user interface. Our work addresses this by integrating both predictive approaches into a single, accessible web application.

## 3. Problem Statement

The diagnosis of Rheumatoid Arthritis presents several challenges:

Dependence on Expert Interpretation – Radiographic analysis requires specialized training, and subtle early-stage RA signs can be easily missed.

Limited Access to Imaging Facilities – In many rural or under-resourced areas, X-ray facilities are unavailable, delaying diagnosis.

Time-Consuming Laboratory Analysis – While blood biomarkers are informative, manual interpretation can be slow and prone to error.

Inefficiency of Single-Modality Diagnosis – Relying solely on imaging or solely on lab tests can result in incomplete diagnostic coverage.

Machine Learning Limitations – Standard ML algorithms often underperform with small, imbalanced medical datasets, leading to inaccurate predictions.

**Our proposed solution addresses these issues by:**

Using a custom CNN optimized for RA X-ray analysis.

Employing a DNN model tailored to the clinical data for RA prediction.

Integrating both models into a single Flask-based web interface to provide flexible diagnostic options.

## 4. Materials and Methods

This section details the dataset composition, preprocessing techniques,architecture, training configuration of both CNN and DNN, and the Flask-based deployment of the system.

### 4.1 CNN

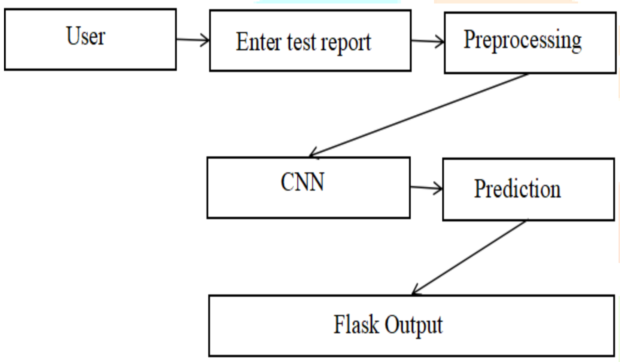
#### 4.1.1 Dataset

The dataset contain comprised 200 hand X-ray images, which are equally divided between RA-positive and Normal cases images. To maintain the correct balance between the images and avoid unfair images, data was randomly divided into trainingset (70%), validation set (15%), and testing set (15%) .

### 4.1.2 Preprocessing

All images that we used are resized to 224×224 pixels and images are normalized to [0,1] range to standardize the input values to derive accurate result. Data augmentation techniques which include rotation, flipping an image, and zooming an image, were applied to artificially and expand the training set to improve the generalization.

### 4.1.3 CNN Architecture

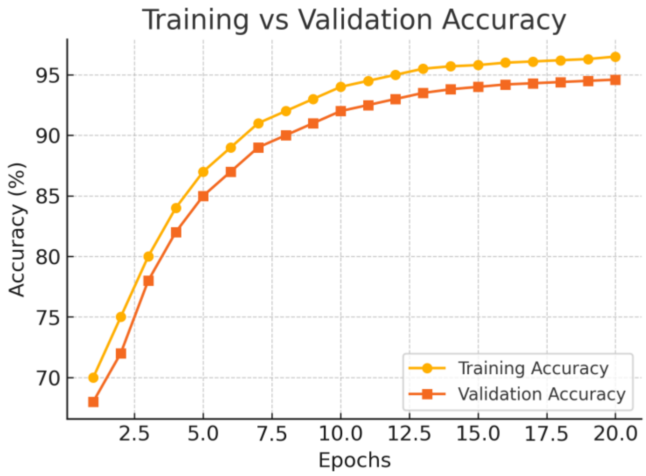


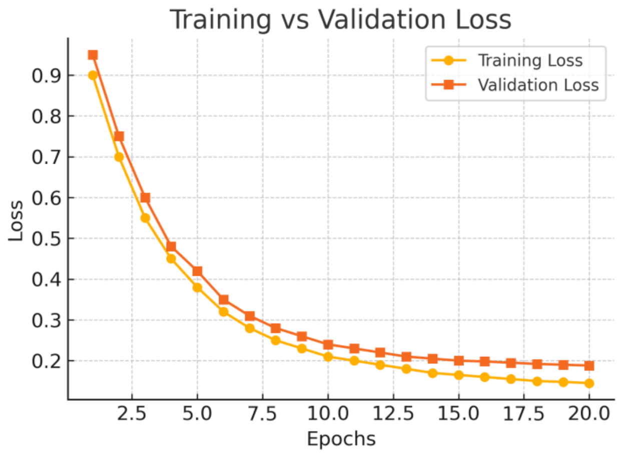

Data flow diagram for CNN

The CNN model consists of four convolutional layers, which have Rely activation; each of them is followed by max pooling and batching the normalization layers. Dropout layers are used to dense the connections, which enables to mitigate overfitting of the image. A soft max layer was employed in the output stage, which classifies images into RA or Normal categories.

### 4.1.4 Training Configuration

Adam optimizer tool,which was used to train the CNN model, with a learning rate of 0.0001 and measures the categorical cross-entropy loss in this. Training was done over 50 epochs and with a batch size of 32, by using early stopping to prevent the overfitting.




### 4.1.5 Flask Deployment.

Once the input is trained, then the model was deployed using Flask, by providing a simple web interface where the users can upload the X-ray images that need to test and receive predictions with confidence scores as result. This section gives full details about the dataset composition, preprocessing techniques, CNN architecture, training configuration, and the Flask-based deployment of the system.

### 4.2 DNN

### 4.2.1 Dataset

The Rheumatic and autoimmune diseases dataset is taken from HARVARD Dataverse which contain result of many autoimmune diseases, we have taken only the RA samples alone.

### 4.2.2 Preprocessing

Categorical data was label-encoded, and continuous variables were standardized using the StandardScaler and Missing values were handled by imputation.

### 4.2.3 DNN Architecture

The DNN model consists of multiple layers,where layers are fully connected dense of layers, each are connected with ReLU activation functions which preferred over sigmoid. These layers are followed by dropout layers, which helps to reduce overfitting by randomly de-activating the fraction of neurons in the data during training. Batch normalization is applied which helps to stabilize the data and accelerate the learning process. Here the atlast the output layer uses a sigmoid activation function to classify the input numerical data into Rheumatoid Arthritis (RA) or Normal categories..

### 4.2.4 Training Configuration

The model was compiled only by using Adam Optimizer with a learning rate of 0.001. The binary cross entropy loss function was selected because this is a binary classification task for this model.

### 4.2.5 Flask Deployment

Once the input is trained, then the model was deployed using Flask, by using this provides a simple web interface, where the users can upload the test report that need to test and receive predictions with confidence scores as result. This section gives full details about the dataset composition, preprocessing techniques, DNN architecture, training configuration, and the Flask-based deployment of the system.

## 5. Implementation and Results

The Flask application which was designed to provide an well-good user experience. Users will begin the process at the homepage and can navigate to the upload page, where they will select an X-ray image prediction that need to predict RA through x-ray images and Numerical Data Prediction for blood test result prdiction.

Depend upon submission, the system will preprocesses the image and numerical data,then runs it through the trained CNN model for image and DNN model for numerical data, and the result will displays the predicted class. Figures 1–9 which will illustrate different stages of the system in operation.

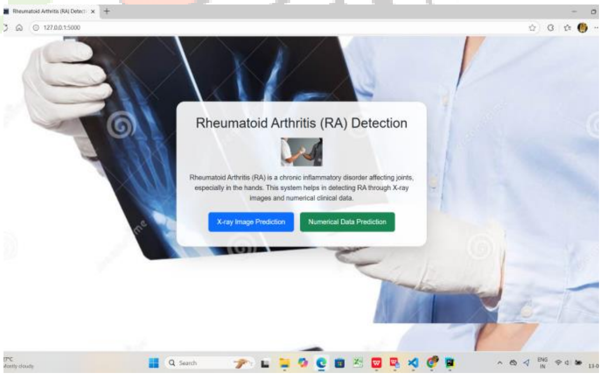



*Figure 1: Homepage of the RA Detection System.*

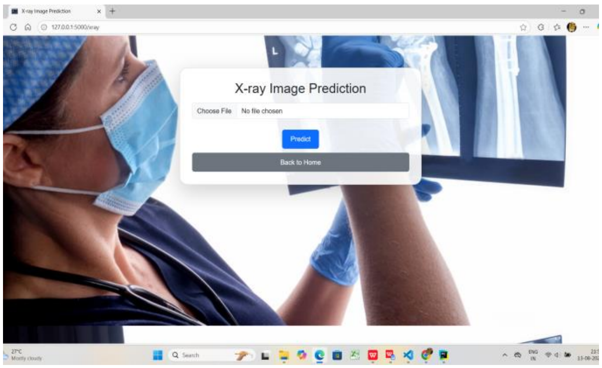



*Figure 2: Image upload interface for X-ray selection.*

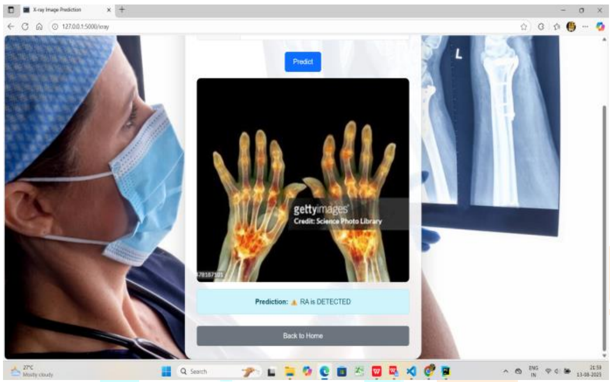



*Figure 3: Prediction result showing Normal case with 96.24% confidence.*

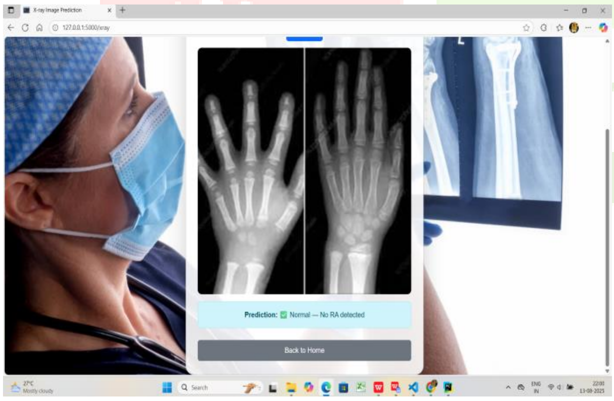



*Figure 4: Prediction result showing RA case with 99.27% confidence.*

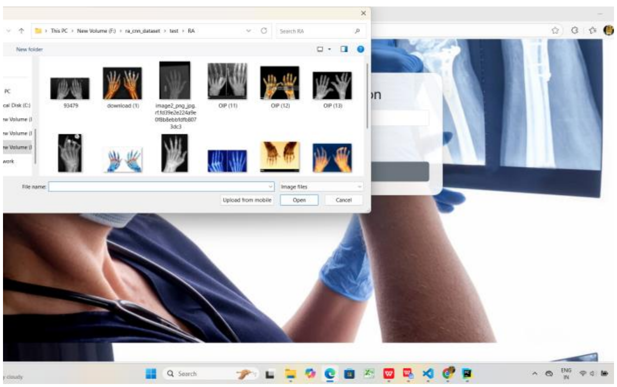


*Figure 5: File selection stage within the web application.*

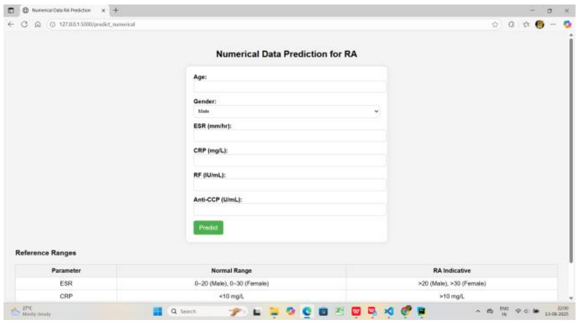



*Figure 6: Numerical Data Prediction page.*

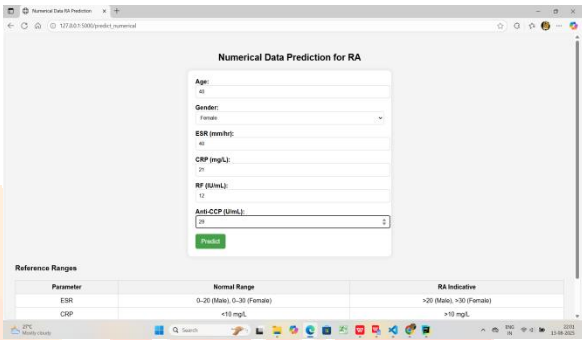



*Figure 7: Enter the test detail*

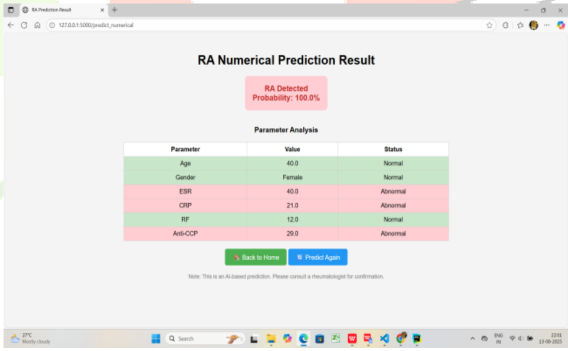



*Figure 8: The Prediction result showing RA case.*

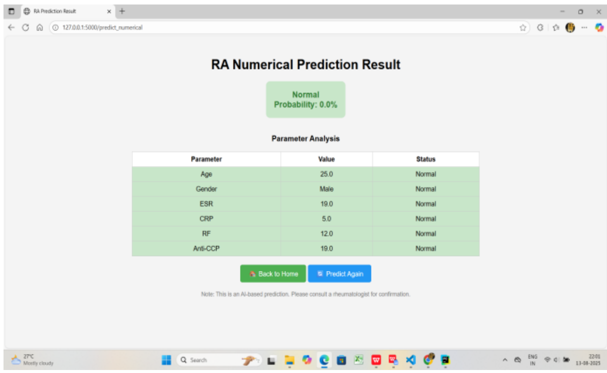



*Figure 9: Prediction result showing Normal case.*

## 6. Discussion

The test results indicate that even only with a relatively small dataset, careful preprocessing, augmentation, and architecture design which can yield high-accuracy models for RA detection. CNNs offer an huge advantage in this domain, because of their ability to detect unnoticed radiographic changes in the image without explicit feature engineering. The high confidence scores in both Normal and RA predictions are suggested, that the model has learned discriminative features effectively.Similarly the DNN also give huge accqurate result compare to other.

While using this system shows promise, limitations include the restricted of dataset size and potential overfitting of images to the training distribution. Further validation is to done on larger scale and more diverse datasets is recommended for more accuracy. Additionally, this integrating explain ability techniques such as, Grad-CAM which could provide visual insights into which image regions influence the model's predictions, aiding clinical trust.

## 7. Conclusion

This study which will demonstrates a practical approach for the automated RA detection using the CNN an DNN for image and numerical blood test, and supported by a Flask to web application for real-time use. The proposed system achieved high accuracy despite limited training data, highlighting the effectiveness of CNNs in medical imaging tasks and DNN in numerical test(blood test). Future work will be focused on expanding the datasets, more refining the model, and exploring deployment on mobile platforms to increase accessibility.

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