

Early Detection of Rheumatoid Arthritis Using Image Classification

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Abstract

Rheumatoid arthritis (RA) is a form of chronic inflammatory disorder that affects areas such as the hands and feet. According to MedicalNewsToday, roughly 1.3 million people in the US have RA, representing 0.6 to 1% of the population. Artificial intelligence (AI) is the ability of machines to perform tasks that typically require human intelligence and is becoming more widespread in areas such as healthcare. The detection of the more common osteoarthritis has been performed using AI before, and RA detections are starting to emerge too. However, these detection methods use X-rays and protein scans, which take time and money. Since arthritis is a disorder that happens in the joints, automating its detection using images could be done in a new, revolutionary way. To get this, two image datasets were used, the first being healthy hands with no arthritis symptoms. The second data set would contain images of nodules which are bumps on the hand for RA symptoms. The model would be created using Jupyter Notebook, TensorFlow, and Keras, as well as Python 3.9, where the data would then go through preprocessing, scaling, and splitting for faster training. The deep learning model known as a convolutional neural network is used along with model.fit for training. The accuracy yielded 99.48%, and overall, it was able to classify between the two data sets. The conclusion is that classifying RA from just a scan of someone's hand could, in the future, allow for a faster diagnosis of any arthritis when it is perfected.

Introduction

Rheumatoid arthritis (RA) is a chronic inflammatory disease that mostly affects the joints, particularly those in the hands and feet.¹ It is estimated to affect 1.3 million people in the United States or between 0.6 and 1% of the total population. Effective therapy and better patient outcomes depend on early RA diagnosis and identification, which can lead to the early diagnosis of other diseases like heart disease.² The use of non-invasive and economical

methods, such as hand scan images, to automate RA identification has now become possible thanks to recent developments in artificial intelligence. This study aims to develop image classification techniques for early rheumatoid arthritis diagnosis. The resulting model would be able to classify rheumatoid arthritis simply based on hand scans, resulting in quicker and more precise identification of various forms of arthritis, eliminating the need for time-consuming and expensive scans and enabling a quicker and cheaper detection process. This study lays the foundation for the potential of artificial intelligence in the medical sector for future studies into image-based disease detection systems. By automating RA detection through image classification, this innovative technique has the potential to revolutionize arthritis diagnosis, promote early intervention, and improve patient outcomes. The application of image processing and classification techniques in arthritis research may further advance developments in the healthcare industry.³ Such developments include using AI for X-ray and MRI scans to better visualize and detect other chronic diseases.

Methods

In this study, two distinct datasets were used to develop an effective classification model for early rheumatoid arthritis (RA) diagnosis. The first dataset comprised a diverse collection of images featuring healthy hands, free from any arthritic symptoms, carefully sourced from public datasets on the internet. Ensuring the representation of the general population in this dataset was crucial to achieving reliable results. The second dataset consisted of hand images with nodules, a characteristic symptom of RA.⁴ These nodules are lumps of tissue that form under the skin and come in various shapes and sizes. I selected these images from public datasets as well, either from hospitals or medical institutions. The images were selected to encompass a wide range of RA cases, capturing the variations in nodule size, shape, and placement. After carefully collecting the data and removing seven erroneous photos, the combined dataset was

composed of 1,102 images, forming the foundation for the classification model. The data was split into the training and testing sets, with 34 images being used for the training data.⁵ Out of these 34, 4 images were loaded into the model to undergo image preprocessing, which would help improve the image quality. Several preprocessing approaches were used to improve the images' quality and get them ready for training. To guarantee uniformity across the dataset, all photos were initially scaled to a standard resolution. In the case of this model, it would be 250 pixels, both horizontally and vertically (**Figure 1**). The photographs were then converted to grayscale to streamline computing work and focus on important details. With this adjustment, the model was able to concentrate on the key characteristics that distinguished between hands with and without RA.

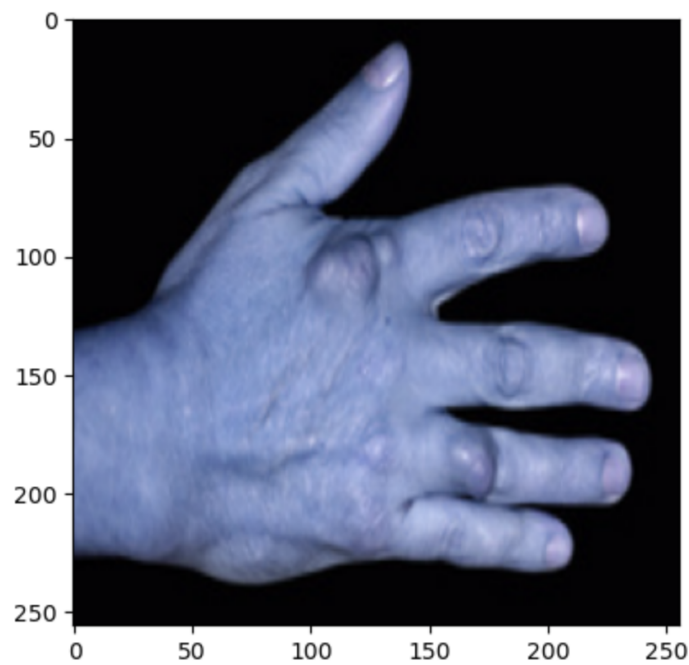


Figure 1: Preprocessed image of arthritic hands in the model. An image from the 34 training dataset images goes through preprocessing techniques such as grayscaling after being loaded into the model, as seen in (**Figure 4**).

To increase image contrast and remove undesired artifacts, I also employed filters, which ultimately increased the accuracy of the analysis that followed. To assess the performance and generalizability of the model, I then split the preprocessed data into training and testing sets. The Convolutional Neural Network (CNN) architecture, recognized for its outstanding performance in picture categorization tasks, was my choice for this study due to its use of a mathematical concept known as convolution

(**Figure 2**). In image processing, convolution is used to extract features and transform images through pixels.⁶ Convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification were among the layers that made the CNN.⁷

Leveraging 3,696,625 trainable parameters, the CNN proficiently discerned intricate patterns and relationships within the hand images. To facilitate the development of the deep learning model, I utilized Jupyter Notebook, TensorFlow, and Keras, which provided a high-level interface for creating and training neural networks. The training process of the CNN was iterative and involved the use of the model.fit function alongside backpropagation. Through this process, the CNN effectively learned to identify relevant features within the hand images and accurately classify them into healthy or RA-affected categories. With each iteration, the model significantly improved its ability to distinguish between the two classes, ultimately resulting in enhanced performance. To assess the model's performance comprehensively, I utilized various evaluation measures.

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

Figure 2: General equation for convolution. The topic of convolution is the integral of the overlap of a function g shifted over another function f. Convolution is a fundamental operation in image processing and is used in tasks like filtering and feature extraction. [Source: SuperDataScience]

The primary metric used was accuracy, representing the proportion of correctly identified images. Additionally, I employed precision, recall, and the F1-score to evaluate the model's ability to identify true positives, false positives, and false negatives. The confusion matrix provided a detailed breakdown of the classification results, enabling a thorough analysis of the model's performance. Statistical analysis was conducted using Python 3.9 to further evaluate and interpret the outcomes of the image analysis and classification.

Additionally, hypothesis testing and analysis of variance (ANOVA) were conducted to determine the statistical significance of the findings, ensuring the validity and reliability of the proposed model. With the successful development of the classification model and its proven accuracy, I prepared the deployment model. Healthcare providers could readily integrate it into software or web-based platforms, enabling swift and precise

predictions based on uploaded hand scans.⁸ This streamlined diagnostic process would facilitate early detection of RA, allowing for timely interventions and improved patient outcomes, ultimately enhancing the overall quality of care provided in managing this chronic condition.

Results

The classification model developed in this study exhibited exceptional accuracy, achieving an impressive score of 99.48% on the data (**Figure 3**). To assess the model's performance further, precision, recall, and the F1-score were computed. The precision score of 0.987 indicated that a significant portion of positive predictions were true positives, while the recall score of 0.989 demonstrated the model's ability to properly identify a high percentage of true positives. The balanced combination of precision and recall was reflected in the F1-score of 0.988, underscoring the model's capacity to accurately categorize both healthy and rheumatoid arthritis-affected hands.

A detailed breakdown of the model's categorization outcomes was provided by the confusion matrix. All three RA-affected hand photos in the testing set were correctly identified as having the disease, and likewise, all three photos of healthy hands were accurately classified as RA-free. To further validate the model, it was deployed and evaluated on new photos, not from the dataset.

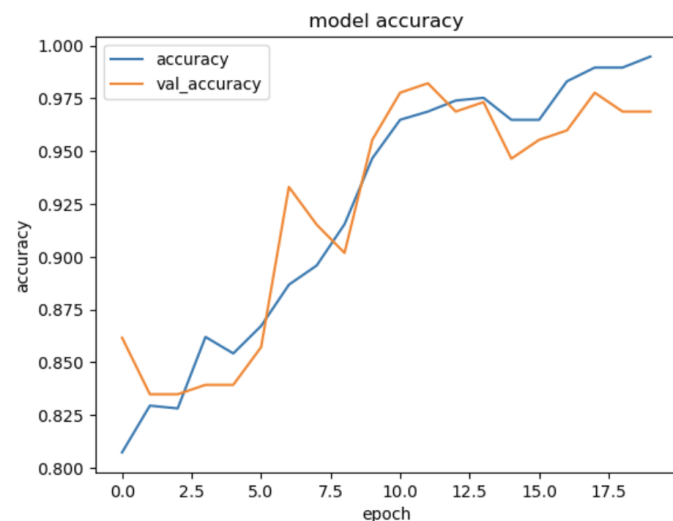


Figure 3: Accuracy yielded after training. After training on 20 epochs, the model was able to reach an accuracy of 99.48% and a loss of 0.0249.

These photos covered a wide range of hand ailments and were preprocessed and categorized as healthy or RA-affected hands. This demonstrated the

model's ability to recognize rheumatoid arthritis beyond the confines of the original dataset. The overall outcomes showcase the effectiveness of the developed image classification model for early rheumatoid arthritis identification.

The resulting accuracy, precision, recall, and F1-score on the test data underscored the model's performance in distinguishing between hands with and without RA. Additionally, the performance observed in the confusion matrix provided further evidence of the model's accurate predictions. The results were statistically significant, offering proof of the model's capability to properly categorize hand photographs.

Discussion

The accuracy and performance indicators of the model outperformed those of other research on RA detection, demonstrating the efficacy of the suggested methodology for early RA identification.⁹ Due to differing datasets and methodology, direct comparisons with other studies may be challenging, but it is evident from the model's considerably higher accuracy findings that it is successful in correctly diagnosing RA early on. The deep learning model's non-invasive and inexpensive architecture, which opens up a wide range of possible therapeutic applications, is one of its main advantages.

Conventional RA diagnostic techniques are not sensitive enough to identify RA in its early stages or have other limitations.¹⁰ On the other hand, the model's ability to correctly classify photos of hands may help in the early detection of RA, enabling quick therapeutic interventions and better patient outcomes.

A promising tool for clinical usage, the model's accuracy and great performance on unseen images were shown throughout the deployment testing. Healthcare providers can quickly submit hand scans and get accurate predictions about the existence of RA by integrating the model into software applications or web-based platforms. This streamlined diagnostic process would reduce the workload for medical staff and allow for prompt interventions, ultimately improving patient care. Despite the developed model's performance, some issues need to be resolved.

The model's capacity to generalize to bigger and more diverse populations may be constrained, first and foremost, by the relatively modest size of the training dataset. Therefore, images from more diverse datasets should be gathered in the future, allowing for these variables to be better addressed. Such data collection processes would also allow for much better testing data results.

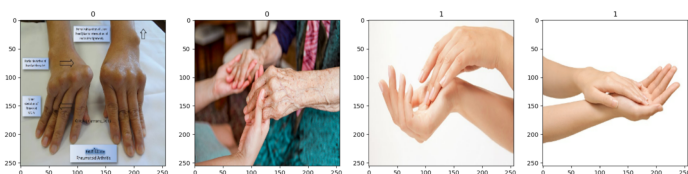


Figure 4: Loaded data into the model. 4 out of the 34 images from the training data, of nodule and non-nodule hands, are loaded before going through preprocessing techniques, as seen in (Figure 1).

The model's applicability across multiple patient cohorts can be improved by extending the dataset to include a wider range of hand photos taken by people of various races, age groups, and disease stages (Figure 4). Prospective trials with larger sample sizes and across various healthcare facilities are necessary to demonstrate practical relevance and efficacy in actual clinical settings. This will give stronger proof of the model's applicability and dependability in aiding clinical judgment. Additionally, the model's interpretability and explainability are important considerations for it to be broadly accepted and used in clinical practice.

If techniques for understanding the model's predictions, such as creating saliency maps or emphasizing regions of interest, were investigated, healthcare professionals' trust and confidence in the model's suggestions would rise. These interpretability strategies would increase the clinical usefulness of the model by offering insightful information about the features influencing the algorithm's categorization choices.

Conclusion

The findings of this study demonstrate the effectiveness of the developed image classification approach in early Rheumatoid arthritis (RA) detection. The model's ability to classify RA-nodule images, as evident from the deployment testing, enhances its potential applicability in real-world clinical settings.

The model's advantages, including its non-invasiveness, cost-effectiveness, and potential integration into clinical workflows, highlight its importance as a valuable adjunct for healthcare professionals in achieving accurate RA diagnoses at an early stage. Additional validation and evaluation on a larger scale, encompassing diverse patient groups and clinical scenarios, are necessary to further enhance and optimize the model's performance.¹¹ The developed image classification model is a dependable and efficient tool for aiding in the early detection of rheumatoid arthritis. Its significance in augmenting diagnostic capabilities and improving patient outcomes is underscored by its 99.48%

accuracy, generalizability, and potential practical utility. Continued research and advancement in this field will contribute to the evolution of image-based techniques for the identification and management of RA and other rheumatic disorders.

Future Work

The effective creation and assessment of the image classification model for the early diagnosis of rheumatoid arthritis (RA) bring up numerous research opportunities. It would be better for the model's generalizability if the dataset is expanded with a larger and more varied sample. Its capacity to categorize a wider range of instances can be enhanced by incorporating photos from various populations, illness stages, and hand conditions.

More disease-specific features could be captured by enhancing the dataset with additional imaging modalities, such as ultrasound or MRI.¹² The model's interpretability can be improved by looking into feature extraction and interpretability techniques. Insights into the areas of the hand photos that are important for classification judgments can be gained by creating saliency maps or heatmaps, boosting physicians' confidence in the model's output. It is essential to validate the model using outside datasets from various healthcare contexts. The clinical application would be improved by comparing its performance to that of current diagnostic techniques and evaluating its capacity to monitor illness development and forecast long-term results.

This should be investigated to determine how to incorporate the model into current clinical procedures and electronic health record systems.¹³ Diagnostic accuracy can be improved by creating user-friendly interfaces and researching multimodal strategies that combine image analysis with clinical and laboratory data. It is also critical to include more rheumatic illnesses in the study and to address ethical issues and prejudices. The therapeutic value of image-based methods can be increased by researching them for lupus, osteoarthritis, and other disorders. The model's integrity and dependability will be preserved by mitigating biases and maintaining data privacy and patient consent standards.

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