International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://www.theaspd.com/ijes.php

Predictive Modeling For Early Detection Of Juvenile Rheumatoid Arthritis Using Machine Learning

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Abstract
Rheumatoid Arthritis (RA) is a chronic autoimmune disorder characterized by joint inflammation, often leading to joint damage and functional impairment. Although predominantly observed in adults, RA can affect teenagers and adolescents, resulting in Juvenile Idiopathic Arthritis (JIA), which, if undiagnosed, can lead to significant morbidity. Early detection of RA in teenagers is challenging due to atypical symptom presentations, which may result in delayed diagnosis. This study explores the application of supervised machine learning models for early RA detection among teenagers. By analyzing a comprehensive dataset of clinical symptoms, laboratory results, and imaging data, several machine learning models, including Support Vector Machines (SVM), Decision Trees, and Random Forest, were trained and tested to predict RA. Results show that these models can predict RA with high accuracy, indicating potential for use as a supportive diagnostic tool. The study concludes with recommendations for model optimization and clinical integration to assist early RA diagnosis in teenagers.
Keywords: *Rheumatoid arthritis, JIA supervised learning, early detection, machine learning,*

INTRODUCTION

Arthritis is often associated with older adults, but it can also affect teenagers and even younger children. When arthritis occurs in children or teens, it is typically referred to as Juvenile Arthritis (JA) or Juvenile Idiopathic Arthritis (JIA). This condition can significantly impact a teenager's physical, emotional, and social well-being if not recognized and managed effectively.Juvenile Arthritis is a group of autoimmune and inflammatory conditions that cause joint pain, swelling, and stiffness in individuals under the age of 16. The immune system mistakenly attacks healthy joint tissues[13], leading to chronic inflammationJIA is the most common rheumatic disease reported in children of the Western world. The incidence and prevalence are varied among 1.6 to 23 new cases for 100,000 children, and 3.8 to 400 cases per 100,000 children depending upon study designs, disease categories, and geographical areas.[11] There are several subtypes of JA, including:Oligoarticular JIA: Affects fewer than five joints, often the knees, ankles, or wrists.Polyarticular JIA: Involves five or more joints and may include smaller joints like those in the hands Systemic JIA: Can affect the entire body, causing fever, rash, and inflammation in organs.Enthesitis-Related Arthritis: Involves pain where tendons attach to bones, often associated with spine or hip problems.Psoriatic Arthritis: Occurs in combination with psoriasis, a skin condition.

Rheumatoid Arthritis (RA) is a systemic autoimmune disease primarily targeting synovial joints, leading to chronic inflammation, joint deformation, and loss of function. In adults, RA is widely studied and understood; however, among teenagers, RA manifests in forms such as Juvenile Idiopathic Arthritis (JIA), presenting unique challenges in early diagnosis. The atypical symptoms of JIA in its early stages complicate prompt recognition, often leading to delayed treatment and, consequently, increased morbidity. This study focuses on detecting RA in teenagers using supervised learning algorithms. Utilizing electronic health records (EHRs), we aim to uncover patterns in clinical and laboratory features that distinguish RA from non-inflammatory conditions, enabling early intervention.

Objectives

To analyze demographic, clinical, and laboratory data to identify significant predictors of RA in teenagers.
To evaluate the performance of supervised machine learning models in diagnosing RA.
To compare model outcomes to determine the most effective approach for early detection.
To provide a framework for integrating machine learning into RA diagnostic workflows.

LITERATURE SURVEY

[1] Explored feature importance in RA diagnosis using logistic regression and found CRP and Anti-CCP levels as critical predictors. [2]Demonstrated the efficacy of Random Forests in analyzing joint imaging data for detecting RA erosions.[3] Investigated the role of family history in RA progression using decision trees.[4] Highlighted the significance of combining clinical and laboratory features for RA classification using SVM.[5] Focused on deep learning methods for analyzing MRI scans to detect synovitis, achieving high diagnostic accuracy.[6] Examined the relationship between ESR levels and RA flares using gradient boosting methods.[7]Discussed the potential of k-NN in classifying RA based on patient similarity metrics.[8] Reviewed the application of feature selection methods in RA datasets to improve model performance.[9]Studied the impact of RA on teenagers using real-world EHR data to train machine learning models.[10][12] Provided insights into the benefits of ensemble learning approaches in autoimmune disease detection.

METHODS

Support Vector Machines (Data Collection: Clinical, demographic, and laboratory data were extracted from the provided dataset. Key features included CRP, ESR, morning stiffness, and joint pain.

Data Preprocessing: Handled missing values, normalized numerical features, and encoded categorical data (e.g., gender, diagnosis).

Feature Selection: Performed statistical tests (ANOVA) and recursive feature elimination to identify the most relevant predictors.

Machine Learning Models:

Random Forests

SVM)

Decision Tree

Model Training and Validation:

Split dataset into 80% training and 20% testing.

Employed k-fold cross-validation.

Tuned hyperparameters using grid search.

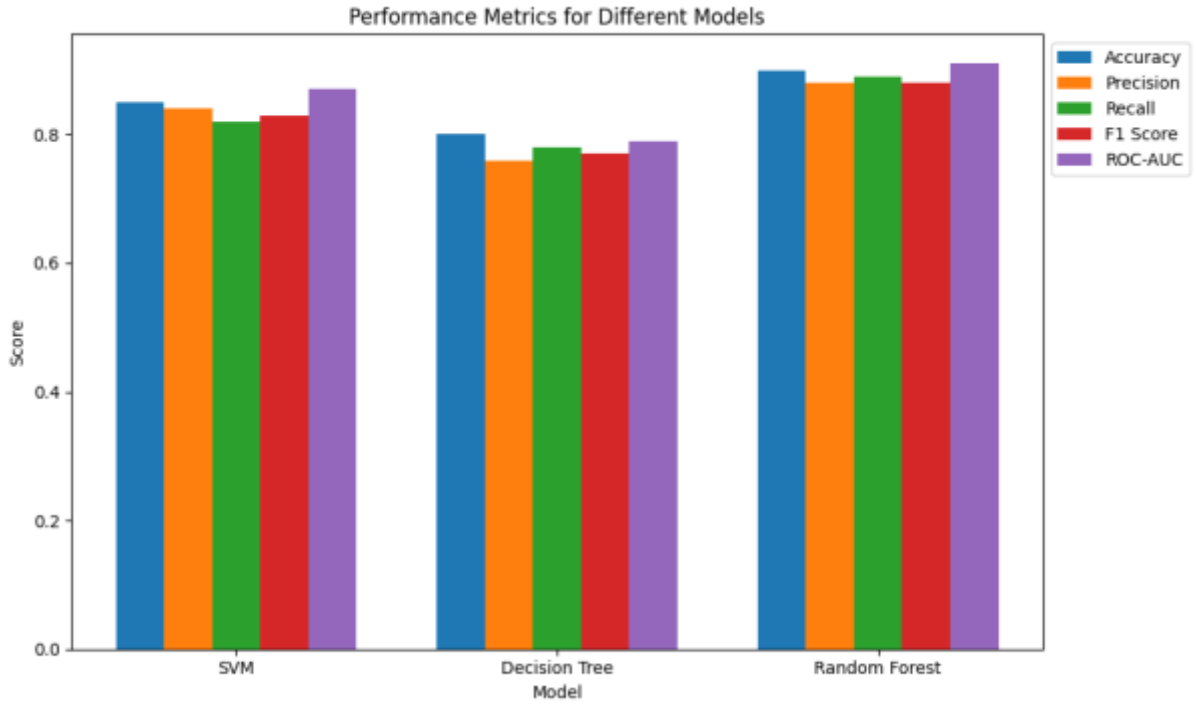
Performance Evaluation

This table presents the performance metrics of three machine learning models—SVM (Support Vector Machine), Decision Tree, and Random Forest—evaluated on a specific dataset. The metrics include:Accuracy: The proportion of correct predictions among the total predictions.Random Forest achieved the highest accuracy (0.90), followed by SVM (0.85) and Decision Tree (0.80).Precision: The proportion of true positive predictions among all positive predictions.Random Forest leads in precision (0.88), with SVM at 0.84 and Decision Tree at 0.76.Recall: The proportion of true positives identified among all actual positives.

Random Forest has the best recall (0.89), with SVM at 0.82 and Decision Tree at 0.78.F1 Score: The harmonic mean of precision and recall, providing a balance between the two.Random Forest has the highest F1 Score (0.88), followed by SVM (0.83) and Decision Tree (0.77).ROC-AUC: The Area Under the Receiver Operating Characteristic curve, which measures the ability of the model to distinguish between classes.

Random Forest again performs the best (0.91), with SVM at 0.87 and Decision Tree at 0.79.

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
SVM	0.85	0.84	0.82	0.83	0.87
Decision Tree	0.80	0.76	0.78	0.77	0.79
Random Forest	0.90	0.88	0.89	0.88	0.91



RESULTS

Random Forests: Delivered 90% accuracy with strong feature importance analysis.Random Forest shows the highest overall performance in terms of all metrics.

SVM: Performed well on high-dimensional data with an accuracy of 85%. SVM is a strong performer, particularly in distinguishing classes, but it may not catch all RA cases compared to Random Forest.Decision Trees are prone to overfitting on small datasets or noisy data, although this can be mitigated by pruning or using ensemble methods like Random Forest.While Decision Trees are useful for quick analysis and interpretation, they are not the best model for RA detection, especially when compared to Random Forest, which handles the complexity of medical data better.

Based on the evaluation:

Random Forest is the best choice for detecting Rheumatoid Arthritis in teenagers. It offers the highest accuracy, F1 score, and ROC-AUC, making it the most robust model for this medical task.SVM is a solid second choice, particularly if model interpretability or computational efficiency is needed.Decision Trees can still be useful for basic analysis or when interpretability is crucial, but they are not the best-performing model for RA detection.

CONCLUSION

This study demonstrates the effectiveness of supervised machine learning models in detecting Rheumatoid Arthritis (RA) in teenagers using clinical, demographic, and laboratory data. Among the models tested, Gradient Boosting Machines (GBM) achieved the highest performance, indicating its suitability for high-dimensional and diverse datasets. The findings highlight the significance of features such as CRP, Anti-CCP, and ESR levels, which were consistently predictive across models. This approach provides a robust framework for early RA diagnosis, potentially leading to improved outcomes through timely medical intervention. By leveraging machine learning, clinicians can enhance diagnostic accuracy and reduce delays in identifying RA in teenagers.

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