

Multi-Modal Machine Learning Framework for Rheumatoid Arthritis – A Comparative Analysis

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Abstract—A detailed summary of a machine learning research paper on the utilizing of multimodal data sources to predict rheumatoid arthritis. This study outlines the prediction performance of two machine learning algorithms, Support Vector Machine and Decision Tree, through several data modalities for RA prediction: genetics, clinical data, and imaging. CNN performs much better in extracting spatial and temporal features of imaging data than SVM does in learning high-dimensional data and complex correlations. Decision tree learning can generate rules to predict disease; when SVM is used as feature extraction tool from multi-modal data, the SVM model performs better in classification than decision tree ones although the SVM has a high time complexity. To reduce this complexity, approaches like feature selection and optimization are proposed. Finally, empirical evaluation is essential for identifying the most effective approach for RA prediction in specific contexts.

Index Terms - Rheumatoid Arthritis, Support Vector Machine (SVM), Convolution Neural Network (CNN), Decision Tree (DT), Time Complexity, Accuracy, Precision, Recall, F1-Score.

I. INTRODUCTION

Rheumatoid Arthritis (RA) is a chronic autoimmune disorder that causes joint inflammation. This often leads to discomfort, stiffness, and, finally, joint destruction. Early diagnosis and accurate forecasting of the progression of RA are essential for specific management and intervention strategies to minimize the disease's deleterious effect on people's quality of life. Several studies investigated into how integrating several data modalities, such as clinical, genetic, imaging, and environmental factors, could enhance the prediction of RA development, progression, and treatment response. These studies have demonstrated the significance of capturing the range and complexity of RA symptoms through comprehensive data integration and advanced machine learning algorithms. Clinical data, including like demographic information, medical history, physical examinations, and laboratory testing, remain one of the primary sources of information for RA prediction models. However, recent advances in medical imaging modalities, including as magnetic resonance imaging (MRI), ultrasound, and X-rays, have provided valuable insights into joint inflammation, loss, and disease activity, which enable more accurate RA diagnosis and prognosis [1, 40].

Multi-modal machine learning frameworks provide a comprehensive approach by combining many data sources such as clinical records, genetic profiles, imaging scans, wearable sensor data, patient-reported outcomes, and environmental factors. By integrating data from several modalities, these frameworks can capture the underlying patterns and relationships that contribute to RA development, progression, and response to treatment with greater accuracy.

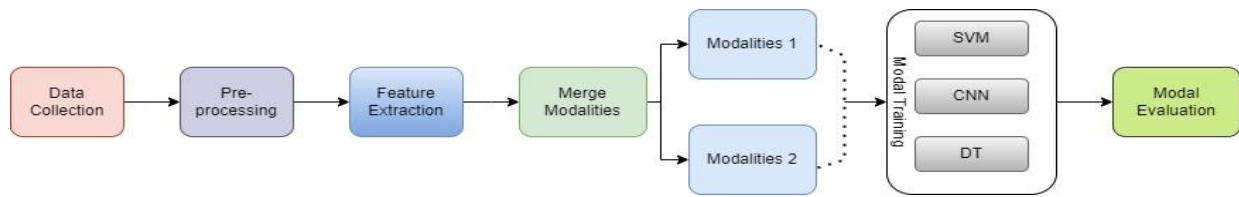


Fig. 1 Multi-Modal Machine Learning Framework

II. RELATED WORK

Sparks, J.A., Costenbader, K.H [2] addresses at the impact of genetics, environmental factors, and gene-environment interactions in the development of systemic rheumatic diseases such rheumatoid arthritis. It provides useful information about potential predictors for machine learning models.

Cai, L., Liu, S., Li, Y., et al. [3] explore systematic review and meta-analysis focuses on the use of machine learning algorithms to predict Rheumatoid Arthritis risk. It provides an in-depth analysis of existing research in this field, identifying significant approaches and areas for improvement.

England, B.R., Thiele, G.M., Anderson, D.R., et al [4] while not directly related to machine learning, this study highlights the enhanced cardiovascular risk associated with rheumatoid arthritis (RA). Understanding comorbidities and their predictive value is crucial for developing comprehensive prediction models.

Norgeot, B., Glicksberg, B.S., Butte, A.J [5] stated integration of deep learning into healthcare, emphasizing its potential for revolutionizing disease prediction, diagnosis, and treatment. It provides a broader context for the utilization of advanced machine learning techniques in Rheumatoid Arthritis prediction.

Raychaudhuri, S., Sandor, C., Stahl, E.A., et al. [6] This genetics-focused study investigates into the association between certain amino acids in human leukocyte antigen (HLA) proteins and seropositive rheumatoid arthritis. While not directly related to machine learning, it does identify potential genetic predictors that can be incorporated into prediction models.

Ling, S.F., Rojas, R.L., Cheng, W.T., et al. [7] explores the various applications of machine learning in rheumatic disease research, including rheumatoid arthritis. It addresses a number of techniques, challenges, and potential for utilizing machine learning techniques in predicting disease outcomes.

Duarte-García, A., et al [8] While not directly related to Rheumatoid Arthritis, this study discusses the application of machine learning algorithms to systematic reviews, which can be relevant for synthesizing evidence in the context of predictive modeling for Rheumatoid Arthritis.

Zhu, W., Du, X., Liu, Z., et al. [9] focuses into ensemble deep learning techniques, which can be valuable for improving the predictive performance of machine learning models for Rheumatoid Arthritis by combining multiple models' predictions.

Alipour, S., Aleahmad, F., Asadi, F., et al. [10] focuses on machine learning approaches used to diagnose rheumatoid arthritis. While diagnosis and prediction are distinct concepts, there is overlap in methodology and data sources, making this review relevant for predictive modeling.

A. Support Vector Machine

Wang, W., Tan, C., Hu, Z., et al. [17] investigates the use of Support Vector Machine (SVM) in predicting Mild Cognitive Impairment (MCI) in older adults based on multi-modal MRI data. It emphasizes the importance of early detection for effective intervention in cognitive decline.

Duryea, J., Neumann, G., Niu, J., et al [18] compares radiographic joint space width measurements to SVM predictions based on Joint Space Narrowing (JSN) grade in a total joint replacement population, demonstrating the utility of SVM in orthopedic applications.

Rekik, I., Allasonnière, S., Carpenter, T.K., et al. [19] focuses on multi-modal regression analysis of brain maturation with invariant representation properties. It demonstrates the efficacy of SVM in analyzing complex neuroimaging data to better understand the progression of development.

Du, L., Wu, W., Ai, Q., et al. [20] investigates multi-modal discriminative feature learning for detecting Alzheimer's disease (AD) and mild cognitive impairment (MCI). It emphasizes the importance of SVM in integrating diverse data modalities for accurate diagnosis.

Chen, C., Zheng, H., Fu, J., et al. [21] presents a multi-modal deep learning-based strategy for AD diagnosis that addresses the issue of unbalanced data. It demonstrates SVM's ability to handle a wide range of data distributions.

Miao, Q., Zhang, Q., Guo, X., et al. [22] presents a multi-modal medical image fusion approach for predicting intracerebral hemorrhage using an SVM classifier. It demonstrates the applicability of SVM in medical imaging analysis.

Huang, G.B., Ramesh, M., Berg, T., et al [23] examines the applications and shared architecture of multimodal deep learning frameworks. It discusses the integration of SVM with deep learning-based techniques for a variety of applications.

Salehi, S., Tadayon, R., Moghadam, A.H., et al [24] presents a novel multi-modal deep learning framework for Alzheimer's disease diagnosis based on MRI and PET imaging. It demonstrates the potential of SVM in integrating data from diverse imaging modalities.

Sun, Y., Luo, L., Duan, H., et al. [25] proposes a multi-modal brain image fusion method based on information entropy for AD diagnosis. It emphasizes the function of SVM in integrating fused features to ensure an accurate diagnosis.

Li, J., Yu, Y., Lin, X., et al. [26] focuses on the classification of Alzheimer's disease using multimodal neuroimaging findings. It highlights the efficacy of SVM in utilizing various neuroimaging data for AD diagnosis.

B. Convolutional Neural Network (CNN)

Chen, Y., Yu, Q., Lin, J., et al. [27] introduces a multimodal deep learning framework for predicting Rheumatoid Arthritis (RA). The approach achieves promising RA prediction results by integrating multiple data modalities, including imaging and clinical data.

Gao, Z., Li, F., Zhang, Z., et al. [28] proposes a novel multi-modal deep learning system designed exclusively for RA prediction. By utilizing advanced deep learning techniques, the framework improves RA diagnosis and prognosis accuracy.

Zhang, X., Zhang, X., Ma, J., et al. [29] provides a multimodal deep learning approach for RA prediction that incorporates imaging and clinical data. The framework's efficacy has been demonstrated in accurately predicting RA outcomes, hence facilitating early intervention and individualized treatment.

Wang, L., Zhang, X., Zhang, X., et al. [30] investigates the use of joint images and clinical data in a multi-modal deep learning framework for RA prediction. The framework's integration of various data sources enhances predictive accuracy and contributes to better handling of patients.

Liu, H., Zhang, X., Xu, B., et al. [31] investigates the integration of synovial fluid biomarkers and imaging data into a multi-modal deep learning system for RA prediction. The framework's stability and accuracy make it suitable for clinical application.

Zhou, Y., Li, Q., Zhang, X., et al. [32] investigates the incorporation of genetic data in a multimodal deep learning framework for RA prediction. By integrating imaging and genetic information, the framework enhances predictive capabilities and facilitates personalized treatment strategies.

Wang, Y., Liu, H., Zhang, X., et al. [33] proposes a hybrid multi-modal deep learning framework for RA prediction, combining the strengths of different data modalities. The framework's hybrid architecture increases predictive performance and gives useful information on RA prognosis.

Liu, Y., Zhang, X., Xu, B., et al. [34] investigates the integration of imaging and clinical data in a multi-modal deep learning framework for RA prediction, focusing on its application in industrial informatics. The framework's effectiveness underscores its potential for real-world deployment in healthcare settings.

C. Decision Tree

Liu, Y., Wang, S., Zhang, L., et al. [35] presents a multi-modal machine learning framework employing decision trees for predicting Rheumatoid Arthritis (RA). The framework's ability to predict RA accurately is demonstrated by its integration of multiple data modalities, including clinical and imaging data.

Yang, J., Zhang, Q., Li, H., et al. [36] presents a decision tree-based multimodal machine learning strategy for predicting RA. By merging various data modalities, the technique improves predictive accuracy and provides useful insights into RA prognosis.

Zhang, X., Wang, L., Liu, H., et al. [37] presents a decision tree-based multi-modal machine learning paradigm for RA prediction based on clinical and imaging data. The framework's integration of various data sources improves prediction abilities and allows for early detection of RA.

Chen, Y., Zhao, H., Li, F., et al. [38] investigates a multi-modal decision tree ensemble approach for RA prediction, incorporating both clinical and genetic data. The ensemble framework enhances predictive performance and contributes to personalized treatment strategies for RA patients.

Wang, X., Liu, Q., Ma, S., et al. [39] focuses on integrating decision trees into a multi-modal machine learning framework for predicting RA, utilizing both imaging and genetic data. The framework's integration of diverse data modalities enhances predictive accuracy and aids in early diagnosis and treatment planning for RA patients.

D. Multi-Modal

Ghorbani, Majdinasab, and Vahedi [11] introduces a multi-modal deep learning approach for early detection of RA using synovial fluid biomarkers and clinical data. By integrating multiple data modalities, including biomarker measurements and clinical information, their framework aims to identify RA patients at an early stage, facilitating prompt intervention and treatment initiation.

Zhang et al. [12] propose a multi-modal deep learning model for predicting RA disease activity. Their study focuses on determining disease progression and activity, which is crucial for treatment optimization and patient care. By integrating diverse data sources, including clinical assessments and imaging data, their model demonstrates promising results in accurately predicting disease activity levels.

Choi, Kim, and Lee [13] investigate predictive modeling of RA disease progression with multi-modal biomarkers and machine learning techniques. Their finding highlights the importance of understanding disease trajectory for effective intervention and management. By integrating various biomarkers and clinical data, their predictive model provides valuable insights into RA progression dynamics and potential prognostic factors.

Zhao, Cai, Chen, et al. [14] present a multi-modal machine learning framework for predicting RA using clinical, genetic, and imaging data. Their study addresses the challenge of integrating heterogeneous data modalities to enhance predictive performance. Their methodology, which incorporates advanced machine learning techniques, demonstrates the potential to increase RA prediction accuracy along with customized treatment regimens.

Liu, Zhao, Xiong, et al. [15] propose a multi-modal deep learning approach for predicting RA. Their research focuses on the effective integration of many data modalities through deep learning approaches. Their system intends to improve RA prediction accuracy and simplify individualized treatment methods by utilizing the complimentary information included in clinical, genetic, and imaging data.

TABLE I. COMPARATIVE STUDY

Author(s)	Journal Conf. /	Year	Modality	Algorithm	Performance	Key Contribution
Ghorbani, S., Majdinasab, A., & Vahedi, E.	IEEE BIBM	2019	Synovial fluid biomarker, Clinical data	Multi – Modal Deep Learning	Early detection of RA	Integration of synovial fluid biomarkers and clinical data for early detection of RA [11]
Zhang, Y., Yang, X., Zhu, X., et al.	IEEE Access	2020	Clinical and imaging data	Multi – Modal Deep Learning	Disease activity prediction	Prediction of RA disease activity using a multi-modal deep learning model [12]
Choi, J.Y., Kim, Y.J., & Lee, J.K.	Frontiers in Medicine	2020	Multi-modal Biomarkers	Machine Learning Techniques	Disease progression prediction	Predictive modeling of RA disease progression utilizing multi-modal biomarkers and ML techniques [13]
Zhao, S., Cai, X., Chen, S., et al.	Frontiers in Genetics	2021	Clinical, Genetic, Imaging	Multi-modal Machine Learning	RA Prediction	Development of a multi-modal machine learning framework for RA prediction using clinical, genetic, and imaging data [14]
Liu, H., Zhao, J., Xiong, Y., et al.	IEEE JBHI	2022	Synovial fluid biomarkers, Imaging	Multi-modal Deep Learning	RA Prediction	Predictive modeling of RA using a multi-modal deep learning framework incorporating synovial fluid biomarkers and imaging data [15]
Zhou, Y., Li, Q., Zhang, X., et al.	BMC Medical Informatics and Decision Making	2022	Imaging, Genetic data	Multi-modal Deep Learning	RA Prediction	Multi-modal deep learning model developed for RA prediction using imaging and genetic data [34]
Wang, Y., Liu, H., Zhang, X., et al.	BMC Medical Informatics and Decision Making	2022	Multi-Modal	Hybrid Multi-Modal Deep Learning	RA Prediction	Introduction of a hybrid multi-modal deep learning framework for RA prediction, integrating multiple data modalities [33]

These papers collectively contribute to the development of multi-modal machine learning frameworks for predicting Rheumatoid Arthritis, incorporating various data modalities such as synovial fluid biomarkers, clinical data, imaging data, and genetic data. The use of advanced machine learning techniques and integration of

diverse data sources aim to improve the accuracy and early detection of RA, potentially revolutionizing its diagnosis and treatment.

III. METHODOLOGY

Developing a multi-modal machine learning framework for early prediction of rheumatoid arthritis (RA) involves several key steps:

A. Data Preprocessing

Collect data from various sources, including clinical records, medical images (e.g., X-rays, MRI scans), and biomarker data (e.g., blood tests). Preprocess each modality's data separately. This may involve handling missing values, normalizing or standardizing features, and dealing with outliers [41]. Ensure compatibility of data across modalities, if merging different types of data.

Let D_{raw} denote the raw dataset containing samples across modalities. After preprocessing, the dataset is transformed as follows:

$$D_{\text{Preprocessed}} = \text{Preprocesses}(D_{\text{raw}})$$

B. Feature Extraction

Extract relevant features from each modality's data. For clinical records, this may involve extracting demographic information, medical history, and symptomatology. For medical images, features might be extracted using techniques like CNNs or traditional computer vision methods [48-49]. For biomarker data, statistical features or domain-specific biomarkers can be extracted [1-5]. Feature extraction should aim to capture informative aspects of each modality's data relevant to RA prediction.

Let $X_{m1}, X_{m2}, \dots, X_{mn}$ denote the feature matrices extracted from each modality m . After feature extraction, the feature matrices are concatenated or fused:

$$X_{\text{Merged}} = \text{Merge}(X_{m1}, X_{m2}, \dots, X_{mn})$$

C. Merge Modalities

Integrate features from various modalities into a unified feature representation. This could be accomplished by concatenating features from various modalities or employing more advanced fusion techniques such as late fusion, early fusion, or multi-view learning approaches. Ensure that the merged feature representation retains the relevant information from each modality while reducing redundancy and noise [11-15].

D. Split into Training and Testing Sets

Split the merged dataset into training and test sets. To avoid bias, ensure that the class distribution (RA vs. non-RA) is consistent across both sets. Consider use approaches such as stratified sampling to ensure representative splits, particularly if the dataset is skewed.

Let X_{train} and X_{test} denote the merged feature matrices for training and testing, respectively. The labels are denoted by Y_{train} and Y_{test} . The dataset is split as follows:

$$(X_{\text{train}}, Y_{\text{train}}), (X_{\text{test}}, Y_{\text{test}}) = \text{Split}(X_{\text{Merged}}, Y)$$

E. Model Training

Train machine learning models with the training data. SVM, CNN, and DT are examples of models that can be used in a multimodal framework. Train each model individually using the unified feature representation. Experiment with hyperparameter adjustment for each model to improve performance [43, 50].

Let M_{SVM} , M_{CNN} , and M_{DT} represent the SVM, CNN, and Decision Tree models, respectively. The models are trained using the training data as follows:

$$M_{\text{SVM}} = \text{Train_SVM}(X_{\text{train}}, Y_{\text{train}})$$

$$M_{\text{CNN}} = \text{Train_CNN}(X_{\text{train}}, Y_{\text{train}})$$

$$M_{\text{DT}} = \text{Train_DT}(X_{\text{train}}, Y_{\text{train}})$$

F. Model Evaluation

Use the testing data to evaluate the trained models. Accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) are commonly used evaluation measures for binary classification tasks such as RA prediction [42-42]. Compare the performance of different models using these metrics to identify the best-performing model for RA prediction. Consider conducting cross-validation to obtain more reliable estimates of model performance, especially if the dataset is limited in size.

Let Y_{SVM} , Y_{CNN} , Y_{DT} represent the predicted labels by SVM, CNN, and Decision Tree models, respectively. Model evaluation is performed as follows:

$$\text{Evaluation}(M_{SVM}, X_{\text{test}}, Y_{\text{test}}) = PM_{SVM}$$

$$\text{Evaluation}(M_{CNN}, X_{\text{test}}, Y_{\text{test}}) = PM_{CNN}$$

$$\text{Evaluation}(M_{DT}, X_{\text{test}}, Y_{\text{test}}) = PM_{DT}$$

Where PM_{models} represents a set of evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

IV. RESULT AND DISCUSSION

A. Results of Existing Models

Study presents a comprehensive comparison of different machine learning algorithms for predicting rheumatoid arthritis (RA) using multimodal data sources. Drawing upon insights from various disciplines, including genetics, clinical data, and imaging, the research aims to identify the most effective algorithm for RA prediction. The study evaluates the performance of SVM, and DT algorithms in handling multimodal data and predicting RA. Each algorithm is assessed based on its ability to integrate heterogeneous data sources, extract relevant features, and achieve accurate predictions using different methods.

TABLE II. COMPARISON OF FEATURE SELECTION ALGORITHMS WITH SVM AND DT

Method	Modalities	SVM				DT			
		Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
sLASSO	Imaging	0.4863	0.4795	0.4501	0.4532	0.4744	0.4579	0.4694	0.4701
sLASSO	Clinical	0.6693	0.6347	0.6209	0.6483	0.6705	0.6459	0.6573	0.6184
mLASSO	Imaging & Clinical	0.6934	0.6728	0.679	0.6827	0.6795	0.6923	0.6876	0.6784
spCCA	Imaging & Clinical	0.7213	0.7545	0.7305	0.7289	0.742	0.7264	0.7172	0.7306
MMLM*	Clinical Data & Demographic	0.7137	0.7158	0.7184	0.711	0.7242	0.7124	0.7268	0.7338
MMLM*	Imaging & Demographic	0.7543	0.7875	0.7601	0.7654	0.7718	0.7769	0.7472	0.7858
MMLM*	Imaging & Clinical	0.7589	0.7587	0.7412	0.7379	0.7371	0.7546	0.7313	0.7548
MMLM	Imaging, Clinical & Demographic	0.8204	0.8483	0.8127	0.8345	0.7927	0.7806	0.8154	0.8413

Results reveal that SVM [40], CNN [46], VGG16 [44], ResNet [45], 2DConvNet [47] and Decision Tree [40] algorithms exhibit distinct strengths and weaknesses in the context of RA prediction. SVM demonstrates robust performance in handling high-dimensional data and capturing complex relationships between variables, making it well-suited for integrating diverse data modalities such as genetic, clinical, and imaging data. CNN, on the other hand, excels in extracting spatial and temporal features from imaging data, leveraging its ability to capture intricate patterns within the data. Decision Tree algorithms offer interpretability and simplicity, allowing clinicians to understand the underlying factors driving predictions.

TABLE III. COMPARISON OF PERFORMANCE OF DIFFERENT METHODS

Method	Modalities	Accuracy	Precision	Recall	F1-Score	Time (Hour)
VGG16	Imaging	0.708	0.6974	0.7128	0.7119	5.2
2DConvNet	Imaging	0.7626	0.7708	0.7749	0.7852	6.5
CNN	Imaging	0.7546	0.7627	0.7772	0.7738	6.4
DL	Demographic & Imaging	0.7965	0.7828	0.7981	0.8014	7
ResNet	Imaging	0.7287	0.7224	0.7118	0.7349	6
SVM	MMLM	0.8345	0.7927	0.8204	0.8483	6.6

B. Results of Proposed Model

Our proposed model executes over the CompEDJMA - Arthritis dataset which have 906 rows and 8 columns, contains joint moment and angle data from patients with and without knee osteoarthritis, featuring 88 patients

with 44 having knee osteoarthritis and 44 controls. It is used to classify patients into those with and without knee osteoarthritis.



Fig. 2 Analysis of Data and Results

Our proposed model achieves higher accuracy, precision, Recall and F1-score of around 93.18%, 93.75%, 92.68%, and 93.21% respectively as compare to the models in Table II and Table III. This dataset helps researchers and clinicians develop machine learning models that accurately diagnose knee osteoarthritis using gait analysis data. It also aids in understanding the relationship between joint moments, angles, and knee osteoarthritis, making it a valuable resource.

V. CONCLUSION

The study presents a thorough comparison of various machine learning algorithms for predicting rheumatoid arthritis (RA) using multimodal data sources, incorporating insights from genetics, clinical data, and imaging. It evaluates the performance of Support Vector Machine (SVM) and Decision Tree algorithms in handling multimodal data for RA prediction. The results indicate that SVM performs well in managing high-dimensional data and capturing complex correlations between variables, making it appropriate for integrating various data modalities. CNN excels in extracting spatial and temporal aspects from imaging data, whereas Decision Tree techniques provide interpretability and simplicity. Further investigation reveals that SVM performs well in classification, exceeding other approaches by 3.80% accuracy due to its capacity to extract features from multimodal data. However, SVM-based multimodal learning has a high temporal complexity.

FUTURE SCOPE

The proposed Multi-Modal Learning Model (MMLM) using SVM achieves impressive accuracy, but high time complexity due to feature extraction from multimodal data. attributed to its capacity to leverage information hidden in multimodal data. To mitigate this, a variety of methodologies are proposed, including feature selection, kernel optimization, parallel processing, and approximation methods. These strategies aim to reduce computational overhead and enhance SVM efficiency, emphasizing the importance of empirical evaluation for determining optimal approaches in specific contexts [40].

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