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Advanced Diagnostic Framework for Rheumatoid Arthritis Through Deep Learning Analysis

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In Rheumatoid Arthritis (RA), the hallmarks are pain, swelling, and deformities of the joints. Early and accurate diagnosis is critical to ensuring effective care and preventing irreversible joint damage. Examples of deep learning (DL) approaches include convolutional neural network strategies and a specialized deep-learning decision-support system (DLDSS). This model uses well established convolutional neural network (CNN) models to learn from MRI and X-rays of medical imaging to automatically detect critical features that sign the existence of the disease rheumatoid arthritis (RA). Through intensive training on a large set of photographs with labels, the CNN model learns to recognize complex patterns associated with RA progression. The finely-tuned model is highly sensitive and specific to determine and categorise abnormalities in RA-affected joints. Main Aim of the DLDSS (Decision Support System for Deep Learning): DLDSS help in increasing the interpretability of the deep learning model and suggest insights to treat. The result from the CNN-based model is combined with clinical data, prior patient medical history and other associated biomarkers to create a comprehensive aiding scheme for decision-making (OC-1). Moreover, this universal approach verifies precise diagnosis, which allows for an informed evaluation of the extent of RA and types of treatment needed for affected individuals. The proposed Decision System is a thorough examination was conducted using many datasets to evaluate the Effectiveness in diagnosis of RA and there by demonstrating the The usability of our proposed Decision System. The CNN and DLDSS collaboratively use the context information in a way to improve decision making accuracy. It does this by utilizing the power of deep learning frameworks to process images. In conclusion, the RA Predictive Diagnosis also demonstrates a meaningful headway in the medical intensive-analysis arena. The system, which has been integrated with state-of-the-art CNN algorithms using a new DLDSS has the ability to improve the accuracy and effectiveness of RA diagnosis, leading to better patient outcomes and treatment customization.

Keywords: Convolutional Neural Network (CNN), Deep Learning Decision support system (DLDSS), Deep learning; neural networks.

1. Introduction

The total quantity of rheumatologists is constantly falling, yet the demand for referrals to rheumatology services is rising (1). This scarcity of rheumatologists causes patients to endure long wait times between the start of their symptoms and the visit, diagnosis, and start of treatment. Rheumatologists must triage patients in order to lessen the irreversible damage that uncontrolled inflammatory illness causes. The vast majority of patients sent to rheumatologists do not ultimately develop inflammatory rheumatic disease (the IRD), despite a variety of triage and screening techniques (2). There are no objective rheumatology triage guidelines, in contrast with emergency medicine, and this insufficiently standardized triage judgments degrades the quality of therapy.

Recent guidelines from league of Associations for Rheumatology (EULAR) highlight the extra usefulness of telehealth patient pre-assessment as a means to improve rheumatology referrals and help prioritize patients with suspected IRD. Currently in operation in Germany, Report is a computerized rheumatology referral system that automatically prioritizes incoming recommendations for rheumatology patients based on the likelihood of each appointment (3). The individual IRD likelihood is computed using an objective, weighted total score. Physician referral sources or patients themselves may use the tool. According to recent studies, Report was well-liked and thought to be user-friendly by patients; yet, its diagnostic accuracy was only somewhat accurate. Artificial intelligence (AI) has shown remarkable efficacy in enhancing diagnosis accuracy across several domains. In the field of rheumatology, advanced deep learning technologies have recently demonstrated expert-level accuracy in diagnosing radiographic images. Additionally, sophisticated machine learning algorithms have successfully predicted the likelihood of flare-ups in patients with rheumatoid arthritis (4). Thus far as we know, no study has looked into how machine learning can help sort patients into groups when they are sent to rheumatic facilities. The objective of the research was to examine if the use of machine learning might improve the precision of the digital rheumatology self-referral system Report in diagnosing inflammatory rheumatic disorders with more efficiency.

2. Literature Review

[1] For most people with RA, which is a long-term inflammatory disease that causes pain, damage, and paralysis in the joints, tailored biologic treatment can help right away. Still, people who don't get better with care often have refractoriness, which makes their quality of life worse. It costs a lot for biotech treatments as well. Plasma samples from 144 RA patients who were ready to start anti-tumor nuclear factor (anti-TNF) medicine were given to us. These samples were sent to Olink Proteomics in Uppsala, Sweden, where studies used four screens with a total of 92 proteins for proximity extension. It was passed by a total of 89 patient samples that were part of the anti-TNF treatment responder data. Our machine learning-based model, ATRPred (anti-TNF response to treatment prediction), can tell a RA patient how well anti-TNF treatment will work by being 81% accurate, 75% sensitive, and 86% specific. ATRPred may help save money and keep patients who don't respond from having bad results by letting doctors give anti-TNF treatment to those who are most likely to benefit from it. R is what ATRPred is made of.

[2] Patients suffering rheumatoid arthritis (RA) those who received their diagnosis within the last ten years have a far better prognosis than those who received their diagnosis twenty years

ago. The accessibility of new, efficient medications, early therapy beginning, and treatment modifications based on disease activity have all contributed to a rise in the long-term prognosis of the condition. However, rather than being tailored to each patient, current therapy approaches continue to be population-based. Appropriate prognostication about several variables is necessary for decision-making processes related to the delivery of customized treatment. The techniques for assessing the effectiveness of prediction models are covered in this article. Furthermore, I draw attention to the progress made in risk assessment with respect to three treatment choices that are pertinent to managing the symptoms of RA and are made on a daily basis in the clinic: the best time to start DMARDs for patients who are just beginning arthritis treatment; the appropriate level of initiation of treatment; and the likelihood of the patient responding to a specific therapy. The bulk of prognostic tools developed from arthritis and RA are inaccurate or lack validation, with the exception of a model that predicts the development of RA. As a result, bedside decisions regarding individualized treatment for RA and arthritis remain distant.

[3] RA is an auto-immune disease that hurts the joint system and causes flare-ups that last for a long time and affect the whole body. Arthritis (RA) often gets worse over time, which makes it harder to do physical activities and raises the risk of getting tired and hurting your joints. In general, RA hurts the cartilage in bones and joints, which weakens and destroys joints and muscle joints. Ensemble methods are used to sort medical conditions into groups based on RA in this study. The phrase "real-RA data" comes from a Sakthi Rheumatol center, which has 1000 patient records (750 with RA and 250 without). This dataset has a classification problem with a lot of number information. Three group algorithms were used in this research: SVM, Ada-boosting, and random subspace. Random Forest and k-NN are used by these ensemble classifiers to find the classifier's baseline measures. Tenfold cross-validation is used to sort data into groups, and precision, accuracy, and ROC are some of the performance measures that are used to judge the results. It was interesting to compare these measures' values to those of baseline methods and various ensemble classifications. This optimality describes how well starting classifiers work when using ensemble classifiers, which is a big gain.

[4] Need for deep learning-based techniques to be explainable is becoming more and more pressing, particularly in domains where critical decisions must be made quickly, like medical image analysis. The role of explainable AI (XAI) in deep learning-powered medical image analysis is provided in this survey. To categorize medical image analysis techniques based on deep learning, a set of XAI criteria is presented. Next, a survey and anatomical location classification are applied to papers on XAI approaches in medical picture analysis. An overview of potential applications of XAI at medical image analysis is provided in the paper's conclusion.

[5] There are 700,000 people in Japan who have rheumatoid arthritis (RA), and that number rises by 30,000 every year. The prognosis of the patient can be improved by early and suitable treatment based on the progression of RA. The previously modified Total Sharp (MTS), which is a commonly utilized tool in the assessment of rheumatoid arthritis progression. Acquiring the MTS rating is a time-consuming process that involves numerous sessions of X-ray imaging on both the foot and hand. This rating has to be obtained several times during the year. It is necessary to use the computerized mTS score calculating mechanism. The finger joint identification method and the support vector machine-based mTS score estimate method are

proposed in this paper. Based on 45 RA patients' X-ray pictures, the suggested method was found to identify finger joints with an accuracy of 81.4 %and to estimate the JSN score and erosion with an accuracy of 64.3% and 50.9%, respectively.

[6] Deep neural networks can be leveraged as a candidate mechanism to replicate a large-scale learning from historical context to predict future disease activity as part of a clinical decision support system. Adaptive Net is a state-of-the-art neural network specifically trained on the variability and incompleteness of clinical data. This has called repetitive connections. This technique uses a unique neural network trained to predict disease outcomes for individual rheumatoid arthritis (RA) patients based on a patient registry. These include demographic data, history and physical records, test results, pharmaceutical data, clinical assessment results, patient reported outcomes, and patient data. We extracted these factors from the Swiss Clinical Quality Management in Rheumatic Diseases (SCQM) database; the latter database has been created throughout well structured training and validation (Hoffman et al. 2014), and has a population of approximately 9500 patients and 65,000reported visits The network uses its forecasting abilities to predict the frequency of disease activity going forward, and also to detect the presence of current RA disease activity. This is conducted using regression analysis and classification methods, based on the DAS28-BSR as the primary endpoint

[7] As such, the most common worldwide autoimmune disease, rheumatoid arthritis, an inflammatory joint disease. Among the most heavily used second-line agents are tumor necrosis factor inhibitors (TNFi). Although TNFi may work for some people, it can suppress the immune system, leading to infections and other adverse events. As a result, it is important to have the ability to predict patient responses to TNFi, which is required in making proper decision for the most therapeutic course of treatment. This study learned a generative neural network structure called Variational Autoencoder (VAE) to predict whether the patients were on TNFi therapy a year after the initiation. We trained two versions of a tabulated dataset with Swedish register data to construct a supervised learning algorithm called Supervisor VAE (SVAE), which combines a VAE with a classifier neural network. 7341 patient records make up the datasets, and our SVAE produced an AUROC rating of 0.615 on the validation results. However, in contrast to prior machine learning models employed for the identical prediction task, SVAE outperformed choice trees and elastic net, while receiving lower marks from random woods and gradient-boosted tree of choice. The results obtained by the SVAEs tested for this thesis were below the acceptable discrimination threshold, even with the regularization impact that VAEs offer during classification training.

[8] This work focuses on a sophisticated diagnosis tool, employing deep learning analysis for Rheumatoid Arthritis (RA). The system employs advanced Deep Machine Learning Decision Support Systems (DLDSS) as well as Convolutional Neural Networks which are in order to enhance the accuracy and efficiency of diagnosis of RA. Machine learning utilizing CNN technology has been utilized to identify specific joint abnormalities associated with RA by leveraging sophisticated image-processing algorithms to extract detailed patterns from medical images. Finally, the DLDSS incorporates multiple types of patient information programs (such as genetics, clinical records) as “inputs” to provide a more complete and accurate “composite health function” evaluation of an individual. Comprehensively, our solution combines the information derived from different technologies to support personalized consideration for the treatment decision and simplifies the diagnosis for the personalization of

RA treatment. The proposed system is a significant step towards a comprehensive, data-driven approach to rheumatology management of rheumatoid arthritis and may ultimately lead to decrease in its risks

[9] Doctors in cancer screening created the term "overdiagnosis" to describe indolent malignancies found through screening that would never have manifested as health issues. Overdiagnosis increases worry, expenses, and the need for needless medical care (overtreatment). Overdiagnosis & overtreatment are rarely discussed in rheumatology, although they are probably happening. This viewpoint examines the possible connection between overdiagnosis and overtreatment and our existing views about the treatment of inflammatory rheumatic illnesses. The next debate will focus on six key paradigms in modern rheumatology: evidence-based rheumatology, precision medicine, remission, rigorous therapy, early diagnosis, and prognosis and risk assessment. It is determined that all paradigms include the inherent risk of overdiagnosis and overtreatment, notwithstanding the significant advancements they have brought about. Thus, a little prudence is necessary.

[10] In the last 30 years, there has been a notable change in the medical results for individuals with rheumatoid arthritis (RA) because to advancements in treating inflammation with both classic synthetic and biologic disease-modifying antirheumatic drugs (DMARDs). Some patients on current treatment may experience persistent remission, which raises concerns regarding the best management practices for this patient subgroup. In order to obtain a more customized and dynamic therapy approach for RA, tapering down or stopping DMARDs altogether seems like a promising idea these days, especially for patients who have completely controlled their condition with DMARD treatment. The most recent advancements in DMARD tapering are covered in this review article. The article discusses novel approaches to achieve drug-free remission and gives a summary of previous research on the subject. Concepts for identifying individuals who qualify for DMARD reduction are also discussed, as are prospective approaches for utilizing biomarkers in the future to forecast the likelihood of a disease relapse following the start of DMARD tapering. Ultimately, these results are weighed against the goal of curing RA patients and helping them fully control their inflammation.

Table 1 Detailed literature synthesis

Reference	Technology	Focus	Pros	Cons	Potential Applications
[1] Smolen et al.	Clinical Guidelines	Standardize RA treatment	-Consistent approach across patients - Improves communication between doctors	- May not consider individual variations in disease severity or response to medication	-Informing treatment decisions for rheumatologists
[2] Cuppen et al.	Systematic Review	Review existing research	Personalized treatment for RA	- Analyzes potential benefits of tailoring treatment to individual patients	-Limited exploration of practical implementation in clinical settings

[3] Schett et al.	Clinical Evidence Review	Analyze existing studies	Optimizing medication use in RA	- Evaluates strategies for safely reducing medication dosage	- Lacks discussion on future research directions for tapering strategies
[4] Landewé	Expert Opinion	N/A	Potential for overtreatment in RA	- Raises awareness of potential harms from excessive medication use	- Lacks data-driven analysis to quantify overtreatment rates
[5] Krittanawong et al.	Machine Learning	Analyze existing research	Predicting cardiovascular disease	-Demonstrates potential of machine learning for disease prediction in general	-Not specific to Rheumatoid Arthritis
[6] Uddin et al.	Machine Learning	Compare algorithms	General disease prediction	- Analyzes strengths and weaknesses of different machine learning algorithms	- Doesn't focus on a specific disease like RA
[7]Vodenicarevic et al.	Machine Learning	Predict disease flare-ups	Identifying RA patients at risk for flare-ups	- Explores using machine learning to predict worsening of RA symptoms	- Limited details provided on methodology and data used
[8] Norgeot et al.	Deep Learning	Forecast clinical outcomes	Predicting long-term disease course	- Investigates using deep learning to predict future health outcomes in RA patients	- Relies on specific electronic health record data format, limiting generalizability
[9] Hügle et al.	Deep Neural Networks	Analyze complex clinical data	Analyze various data types for RA management	- Demonstrates potential of deep-neural structure to handle diverse clinical data	- Requires large collection of data and significant computational power
[10] Hochreiter & Schmidhuber	Long Short-Term Memory (LSTM) Networks	N/A	Process sequential data	- Introduced LSTM networks with potential for analyzing sequential data like disease progression	- Not directly related to RA research, but the technology has potential applications
[11] Ipsen NB, Mattei P, Frellsen J.	ICML2020	Machine Learning	Address missing data in deep learning	Techniques for handling missing data in	- Improves the robustness and generalizability of deep

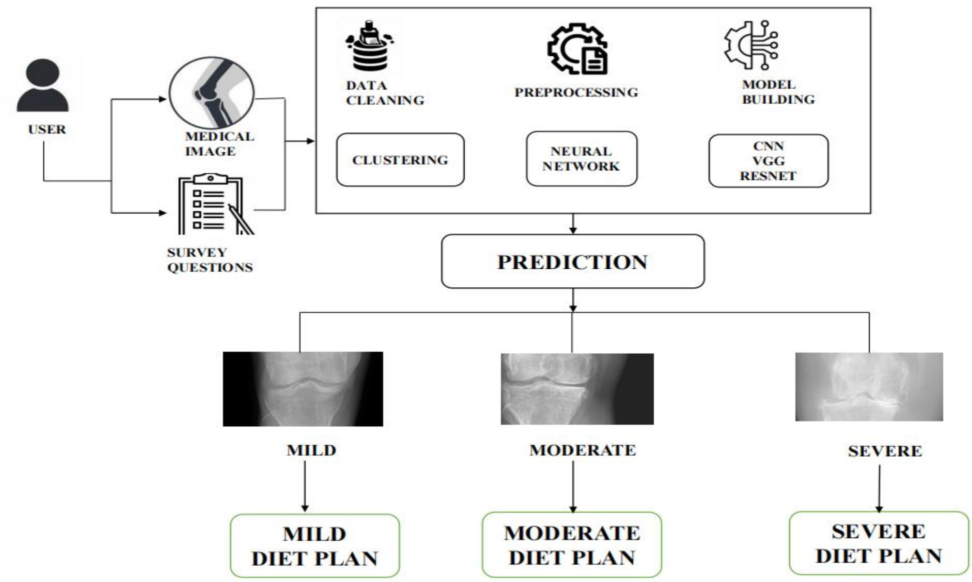
				deep learning models	learning models in healthcare applications
[12] M W. Nowacki AS, Kattan.	EGEMS (Wash DC).	N/A	Address missing data in EHR-derived data	Solutions to dealing with incomplete data.	- Improves the robustness and generalizability of deep learning models in healthcare applications

3. Research Methodology

3.1 Dataset Preprocessing

The following stages are applied to any image that is currently being processed: enhancement of images, segmentation, feature extraction, preprocessing, picture capture, and classification, among other techniques. A flow chart illustrating the conventional methodology used by the investigators is shown. Fig 1.

Figure 1 Advanced Diagnostic Framework



Data Preprocessing is a sort of image enhancement in image processing that improves some aspects of the image or removes unwanted distortions in order to set up the image for further processing. A unique method known as sparse aware noise reduction employing convolutional neural network networks (CNNs), which is detailed below, was used by More and Singla [32] to reduce the noise (SANR CNN). Model training images were then created for each knee by Chang et al. [33] using the Euclid transform to align a slice about a previously selected, cropped, and scaled template.

After that, pictures were chosen for training models for each knee from the middle slice, 11 neighboring slices on the left side of the center slice, and 11 nearby slices on the medial aspect of the center slice. Histogram Equalization and Gaussian Filtering were employed by Verghese et al. [35]. An asymmetric diffusion filter and a median filter were used by Snekhalatha et al. and others [20] to preprocess the image and eliminate background noise.

Algorithm for diagnostic framework was given below which clearly explain the process of DLDSS

Algorithm 1

RADiagnosticFramework

Input: RGB Image.

Output: Labelled mask image with bounding box.

```
Begin
  Step 1: Initialize Parameters
  initializeParameters()
  Step 2: Data Preprocessing
  images, clinical_data = loadData()
  preprocessed_images = preprocessImages(images)
  processed_clinical_data = preprocessClinicalData(clinical_data)
  Step 3: Build model
  cnn_model = buildCNN()
  Step 4: Train the model
  train_set,validation_set= splitDataset(preprocessed_images,processed_clinical_data)
  trained_cnn = trainCNN(cnn_model, train_set, validation_set)
  Step 5: Evaluate CNN Performance
  test_set = loadTestDataset()
  performance_metrics = evaluateCNN(trained_cnn, test_set)
  saveModel(trained_cnn)
  Step 6: Build Deep Learning Decision Support System (DLDSS)
  dldss = buildDLDSS(trained_cnn, processed_clinical_data)
  Step 7: Train the DLDSS
  trained_dldss = trainDLDSS(dldss, train_set)
  Step 8: Evaluate DLDSS Performance
  dldss_performance_metrics = evaluateDLDSS(trained_dldss, test_set)
```

Step 9: Deploy the System

deploySystem(trained_dldss)

Step 10: Output Results

diagnosis = generateDiagnosisReport(trained_dldss)

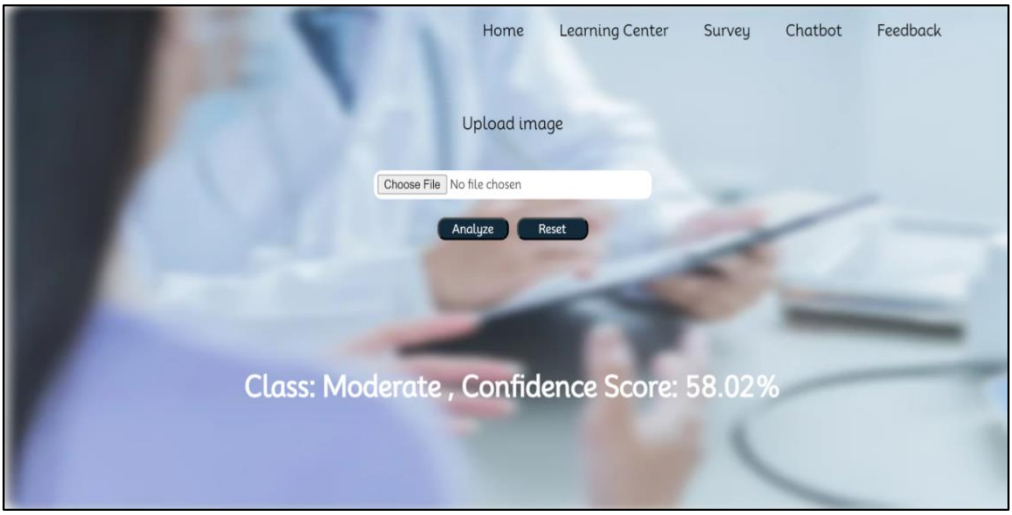
presentResults(diagnosis)

End

3.2 Segmentation

Image segmentation refers to the technique of partitioning a digital image into many distinct regions. Both sides of the subjects' bodies' knees were captured in thermal pictures using a FLIR camera that was linked to a computer [20]. During the data preparation process, Maziarz the authors [36] converted the joint centers annotations with a segmentation mask.

Figure 2 User access gateway-login



Certain pixels are linked to the corresponding joint's joint center, whereas other pixels are linked to a different backdrop class. The fuzzy c-means approach was utilized by Yan et al. [38] to segment the photos in this investigation. Using this segmentation method, the region of interest was divided into subregions according to the clusters identified in the item. Segmenting images is done using the MATLAB platform. Dang and Allison (2019) employed the clever operator that functions based on segmentation. They used canning operators, who helped them find edges. The most popular method for identifying edges and segmenting an image is this one. Given its exceptional noise immunity and ability to identify edges, the amazing edge detector is regarded as one of the most effective edge detectors available today.

3.3 Diet and Exercise Methodologies

Personalized Nutritional Advice: Implement a system that looks at patient data, including dietary restrictions, preferences, and medical background. Utilize this information to provide customized dietary guidelines for the treatment of inflammation related to rheumatoid arthritis.

Recognizing Foods That Inflame:Convolutional neural networks, or CNNs, were taught to identify foods that induce inflammation through the use of textual descriptions or picture analysis. Provide them with quick feedback on what foods they choose, along with alternatives.

Personalized Exercise Plans: Utilize deep learning methods to create personalized exercise plans that consider the patient's physical condition, pain thresholds, and range of motion. The system may progressively alter and develop the training regimens because it continuously monitors the patient's progress.

Real-time Move Analysis: Evaluate the patient's movements during exercise by integrating computer vision techniques with the CNN. Give quick feedback on proper technique to prevent overstretching joints, and adjust the training schedule accordingly. Fig 3 shows the questionnaire used to analyse the disease and also to suggest the diet and physical activities to the affected person. Fig 4 shows the sample Diet and physical activities suggested.

Figure 3 sample questionnaire

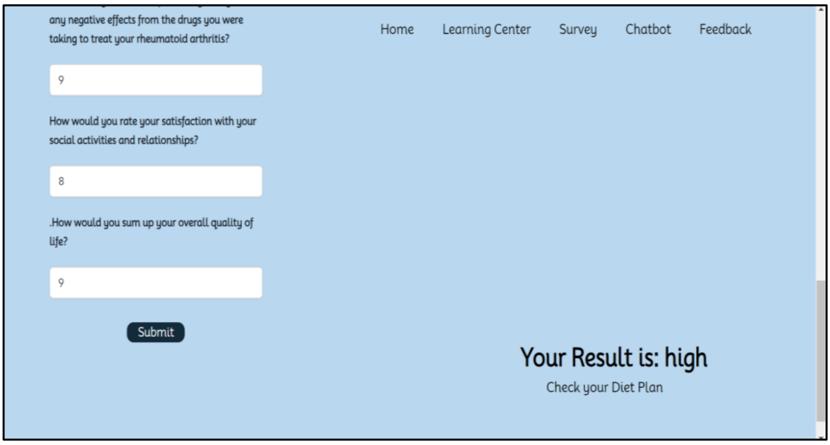
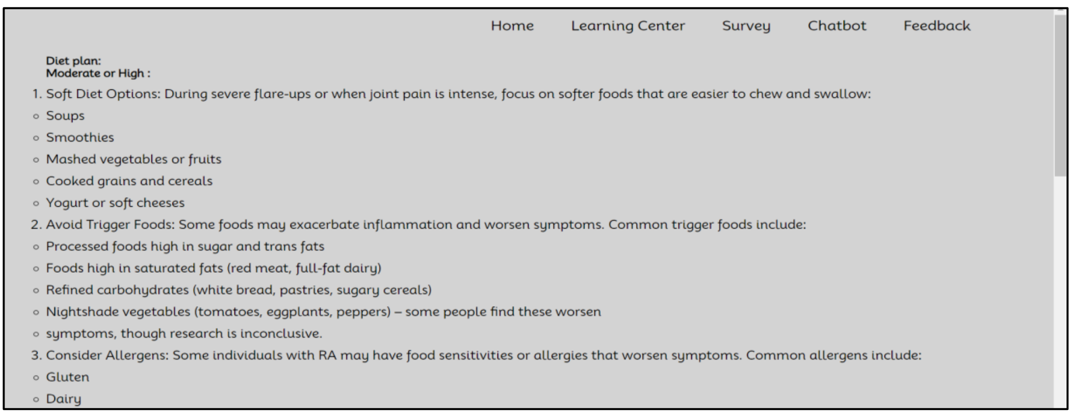


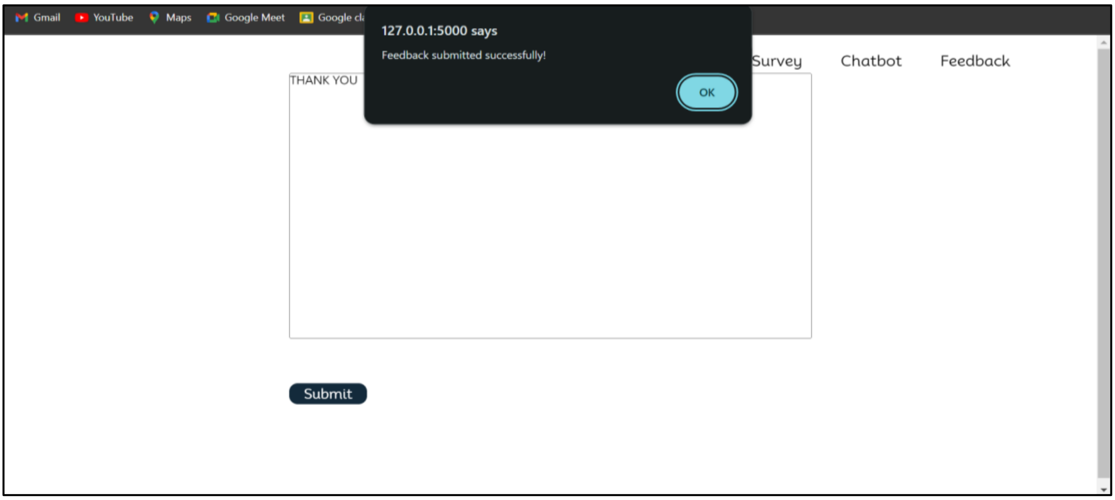
Figure 4 Suggested Diet Plan



3.4 Chatbot Methodologies

The Tracking and Reporting of Problems: Create a chatbot interface where users may report symptoms on a daily basis, medication adherence, and general health. The chatbot may interpret user input using natural language processing and update the DLDSS with relevant information. Educational Support: Develop a chatbot that serves as an informational tool, providing information on rheumatoid arthritis, its therapies, and lifestyle modifications. It can offer proactive guidance and reminders for taking prescription drugs, making appointments for examinations, and upholding wholesome routines. Figure 5 shows the discussion forum used for communication and building connect between various patients and physicians.

Figure 5 Discussion Forum



3.5 Classification

At this point, the classifiers get the features that were extracted from the input photographs and are trained using them. The classifiers compare the parameters using the record set to generate the output. The researchers used a combination of machine learning and image processing classifiers to classify the outputs. The study's conclusions indicate that certain basic classification techniques were used.

4. Result And Discussion

The studied literature on algorithms using deep learning for identifying RA has some promising answers to fill in the research gaps, but it also has significant drawbacks and need for development. First off, because high-quality data is hard to get by, expanding the number of samples of datasets might not always be feasible even though doing so could increase the models' accuracy. Thus, in order to increase the amount of training data and strengthen the models' resilience, researchers can think about employing data augmentation approaches. Second, while utilizing different cross-validation methods could shorten the models' training time, it might also cause overfitting and subpar generalization capabilities. As a result, while selecting a cross validation technique, researchers must be sure to strike a balance between computational economy and generalization performance.The table 2, 3, 4, 5 and 6 shows the discrimation of various model with developed DLDSS, the table shows comparison of various result parameters. Similarly, the figure 6, 7, 8, 9 and 10 depicts the comparison plot of various models. The models like ResNet-50, VGG-16, Inception V3, MobileNetV2. The table 4.6 shows the values of training loss, validation loss, training accuracy and validation accuracy. Fig. 4.6 depicts the plot for the same.

Table 2: Model vs Execution time

Model	Execution time(sec)
ResNet-50	0.4
VGG-16	0.5
InceptionV3	0.3
MobileNetV2	0.6
DLDSS	0.2

Figure 6 Execution time plot of various algorithm

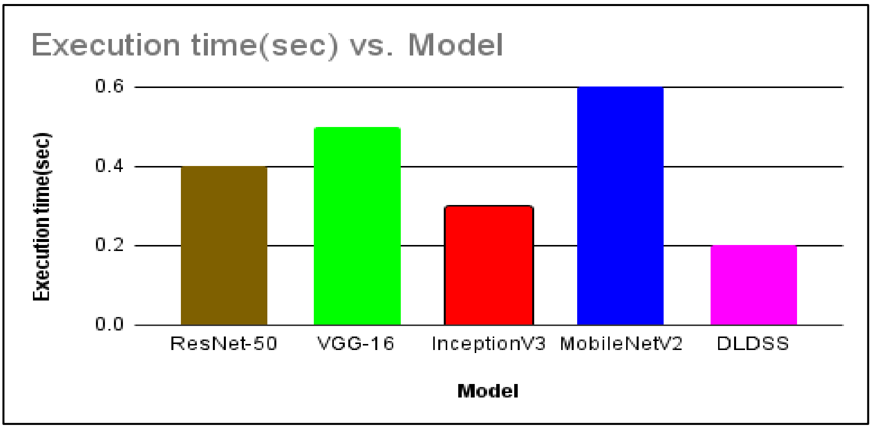


Table 3 Model vs Precision value

Model	Precision value
ResNet-50	85
VGG-16	83
InceptionV3	87
MobileNetV2	81
DLDSS	88

Figure 7 Precision value plot of various algorithm

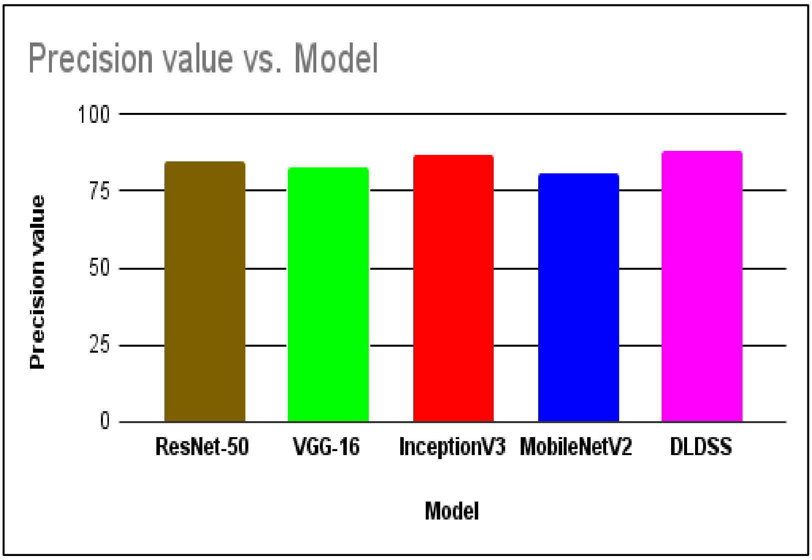


Table 4 Model vs Recall value

Model	Recall value
ResNet-50	90
VGG-16	88
InceptionV3	92
MobileNetV2	86
DLDSS	94

Figure 8 Recall value plot of various algorithm

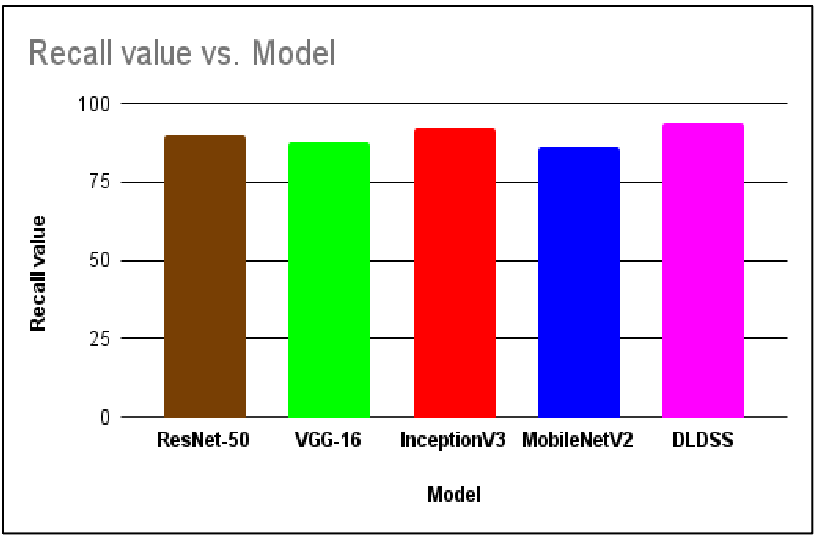


Table 5 Model vs F1 Score

Model	F1 score
ResNet-50	87
VGG-16	85
InceptionV3	89
MobileNetV2	83
DLDSS	90

Figure 9 F1 Score plot of various algorithm

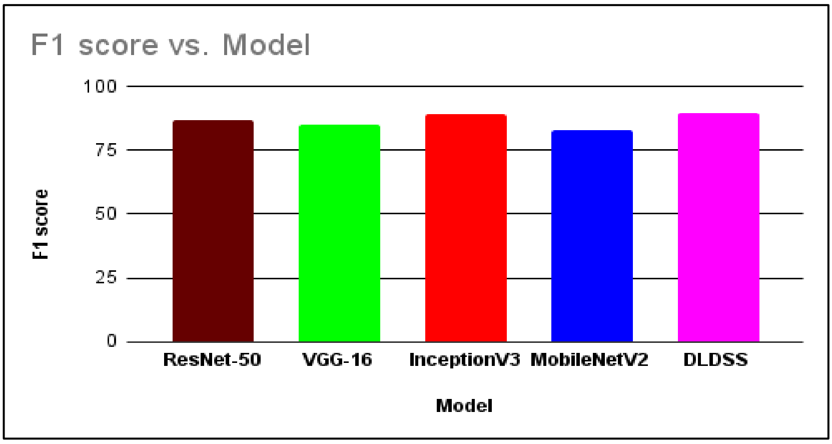


Table 6: Model vs Accuracy value

Model	Accuracy
ResNet-50	92
VGG-16	90
InceptionV3	92
MobileNetV2	89
DLDSS	94

Figure 9 F1 Accuracy value plot of various algorithm

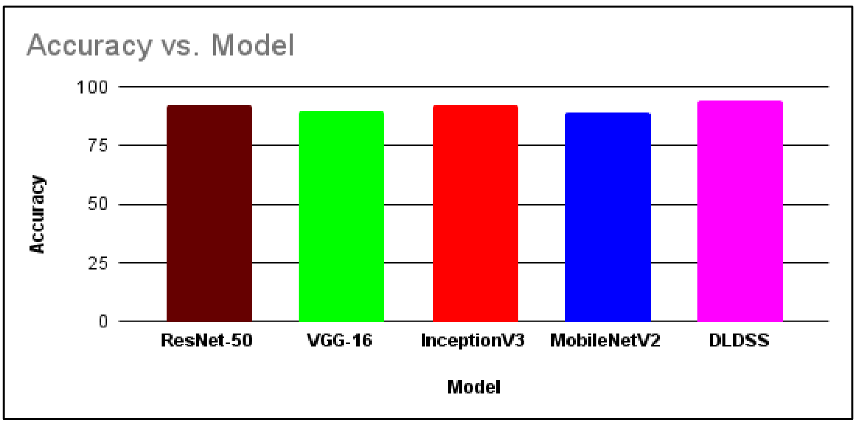
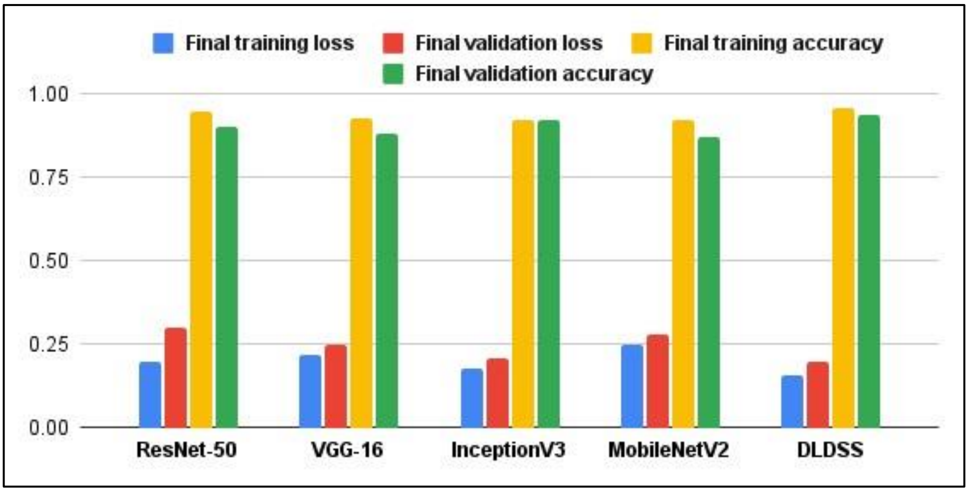


Table 7 Discrimation of various model.

Parameter	ResNet-50	VGG-16	InceptionV3	MobileNetV2	DLDSS
Final training loss	0.2	0.22	0.18	0.25	0.16
Final validation loss	0.3	0.25	0.21	0.28	0.2
Final training accuracy	0.95	0.93	0.92	0.92	0.96
Final validation accuracy	0.9	0.88	0.92	0.87	0.94

Figure 10 Discrimation plot of various model.



5. Conclusion

Three different ensemble classifiers with different baseline techniques are used in this work to process a variety of RA-based medical datasets. This inquiry utilizes a real-time dataset obtained from the Rheumatology center. The prediction rate and comparison of the expected approach are achieved by using baseline classifiers such as Random Forest (RF) and k-Nearest Neighbors (k-NN), as well as the three most well-known ensemble classifiers: Support Vector Machines (SVM), AdaBoosting, and Random Subspace (RSS). The experimental findings also indicate that the performance of an ensemble classifier is influenced by the specific combination of data and classifier type used. However, this task is chosen, and these classifiers must be implemented on these datasets. In order to determine classification algorithms that prioritize efficiency, some performance variables were excluded.

These indicators include overall accuracy of predictions, precision, and ROC. This study use the 10fold cross-validation evaluation approach to determine the model's greater yield. When comparing the findings to the real-time dataset, SVM with KNN demonstrates superior performance in accurately predicting outcomes compared to other ensemble classifiers. Various techniques and their applications in the ensemble model have been explored to improve the accuracy of diagnosis and maybe enhance health indicators in the future.

Future work

The studied literature on algorithms using deep learning for identifying RA has some promising answers to fill in the research gaps, but it also has significant drawbacks and need for development. First off, because high-quality data is hard to get by, expanding the number of samples of datasets might not always be feasible even though doing so could increase the models' accuracy. Thus, in order to increase the amount of training data and strengthen the models' resilience, researchers can think about employing data augmentation approaches. Second, while utilizing different cross-validation methods could shorten the models' training time, it might also cause overfitting and subpar generalization capabilities. The current image processing & machine learning methods need to be upgraded in order to gather more useful information from the photos. The focus of the research should be on creating a device that comes in one kit with both software and hardware components. Therefore, a thorough analysis of several image processing and machine learning methods for the purpose of identifying and categorizing RA and OA has been carried out in an ethical manner.

References

1. Smolen JS, Landewé R, Bijlsma J, et al.. "EULAR recommendations for the management of rheumatoid arthritis with synthetic and biological disease-modifying antirheumatic drugs", 2017.
2. Cuppen BV, Welsing PM, Sprengers JJ, et al.. "Personalized biological treatment for rheumatoid arthritis: a systematic review with a focus on clinical applicability. Rheumatology (Oxford)", 55(5):826–39, May 2016.
3. Schett G, Emery P, Tanaka Y, et al.. "Tapering biologic and conventional DMARD therapy in rheumatoid arthritis: current evidence and future directions", 75(8):1428–37. doi: 10.1136/annrheumdis-2016-209201,August 2016.
4. Landewé RBM. "Overdiagnosis and overtreatment in rheumatology: a little caution is in order", 77(10):1394–1396. doi: 10.1136/annrheumdis-2018-213700,October 2018.
5. Krittanawong C, Virk HUH, Bangalore S, et al., "Machine learning prediction in cardiovascular diseases: a meta-analysis", Sci Rep. September 2020;10(1):16057. doi: 10.1038/s41598-020-72685-1.
6. Uddin S, Khan A, Hossain ME, Moni MA. "Comparing different supervised machine learning algorithms for disease prediction", BMC Med Inform Decis Mak. 19(1):281. doi: 10.1186/s12911-019-1004, December 2019.
7. Vodenicarevic A, Van der Goes M, Medina O, de Groot M. "Predicting Flare Probability in Rheumatoid Arthritis using Machine Learning Methods", 7th International Conference on Data Science, Technology and Applications; 2018.
8. Norgeot B, Glicksberg BS, Trupin L, et al.. "Assessment of a Deep Learning Model Based on Electronic Health Record Data to Forecast Clinical Outcomes in Patients With Rheumatoid Arthritis", JAMA Netw Open, 2(3):e190606. doi: 10.1001/jamanetworkopen.2019.0606, March 2019.
9. Hügle M, Kalweit G, Hügle T, Boedecker J. "A Dynamic Deep Neural Network For Multimodal Clinical Data Analysis", Stud Comput Intell Springer Verl. 2020.
10. Hochreiter S, Schmidhuber J. "Long short-term memory", Neural Computing;9(8):1735–80. 10.1162/neco.1997.9.8.1735, Nov 1997
11. Ipsen NB, Mattei P, Frellsen J. "How to deal with missing data in supervised deep learning", ICML 2020.

12. Wells BJ, Chagin KM, Nowacki AS, Kattan MW. "Strategies for handling missing data in electronic health record derived data", EGEMS (Wash DC);1(3):1035. doi: 10.13063/2327-9214.1035, 2013.
13. LeCun Y, Bengio Y, Hinton G. "Deep learning. Nature", 521(7553):436–44. doi: 10.1038/nature14539, May 2015.
14. Pierre Isnard A, Issa N, Barnetche T, Richez C, Schaeverbeke T. "Meta-analysis of clinical and radiological efficacy of biologics in rheumatoid arthritis patients naive or inadequately responsive to methotrexate", 80(4):386–92. doi: 10.1016/j.jbspin.2012, Jul 2013.
15. Joo YB, Kim Y, Park Y, et al.. "Biological function integrated prediction of severe radiographic progression in rheumatoid arthritis: a nested case control study", Arthritis Res Ther, 19(1):244. doi: 10.1186/s13075-017-1414-x, Oct 2017.
16. Roodenrijs NMT, van der Goes MC, Welsing PMJ, et al.. " Is prediction of clinical response to methotrexate in individual rheumatoid arthritis patients possible? A systematic literature review", 87(1):13–23. doi: 10.1016/j.jbspin.2019.04.002, Jan 2020.
17. Hügle M, Omoumi P, van Laar JM, Boedecker J, Hügle T. "Applied machine learning and artificial intelligence in rheumatology", Rheumatol Adv Pract., 4(1):rkaa005. doi: 10.1093/rap/rkaa005, 2020.
18. Luo C, Zhang N, Wang X. "Time series prediction based on intuitionistic fuzzy cognitive map" Soft Comput, p. 6835–6850,2020
19. Breiman L. Machine Learning, Volume 45, Number 1—SpringerLink. vol 45, 5–32,2001
20. Roodenrijs NMT, van der Goes MC, Welsing PMJ, et al.. "Is prediction of clinical response to methotrexate in individual rheumatoid arthritis patients possible? A systematic literature review", 87(1):13–23. doi: 10.1016/j.jbspin.2019.04.002, Jan 2020.
21. J. Abedin, J. Antony, K. McGuinness, K. Moran, N.E. O'Connor, D. Rebholz-Schuhmann, J. Newell, "Predicting knee osteoarthritis severity: comparative modeling based on patient's data and plain x-ray images", 2019.
22. J. Antony, K. McGuinness, K. Moran, N.E. O'Connor, "Automatic detection of knee joints and quantification of knee osteoarthritis severity using convolutional neural networks", International Conference on Machine Learning and Data Mining in Pattern Recognition, Springer, 2017.
23. A. Chattopadhyay, M. Maitra, "Mri-based brain tumor image detection using cnn based deep learning method", Neurosci. Inform. 2022.
24. P. Chen, L. Gao, X. Shi, K. Allen, L. Yang, "Fully automatic knee osteoarthritis severity grading using deep neural networks with a novel ordinal loss", Comput. Med. Imaging Graph., pp. 84-92, 2019.
25. A. Deodhar, M. Rozycki, C. Garges, O. Shukla, T. Arndt, T. Grabowsky, Y. P, "mark Use of machine learning techniques in the development and refinement of a predictive model for early diagnosis of ankylosing spondylitis", 2019.
26. S.S. Gornale, P.U. Patravali, R.R. Manza,"Computer assisted analysis and systemization of knee osteoarthritis using digital x-ray images, 2019.