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ADVANCED DIAGNOSTIC FRAMEWORK FOR RHEUMATOID ARTHRITIS THROUGH DEEP LEARNING ANALYSIS

Bhavani M[1], Prithi Samuel[2]

[1]*Research scholar, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai.*

[2]*Assistant Professor, Department of Computational Intelligence, School of Computing, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai.*

[1]*bm6010@srmist.edu.in*, [2]*drprithisamuel@gmail.com*

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Rheumatoid Arthritis, Deep Learning Decision- Support System (DLDSS), Convolutional neural network (CNN), neural networks

ABSTRACT

Rheumatoid Arthritis (RA) is characterised by joint abnormalities, swelling, and pain. Effective treatment and the prevention of irreparable joint injury depend on early and correct diagnosis.Strategies using convolutional neural networks and a dedicated deep-learning decision-support system are two examples of DL approaches (DLDSS). Automatic detection of key features indicative of Rheumatoid Arthritis (RA) is achieved by training on medical imaging data such as magnetic resonance imaging (MRI) and computed tomography (CT) scans using well-established convolutional neural network-based models. The convolutional neural network (CNN) model learns to identify complicated patterns linked to RA progression through rigorous training on a big database of labelled photos. When it comes to detecting and classifying anomalies in joints impacted by RA, the fine-tuned model is lightning fast and very specific. The Decision Learning Support Systems for Deep Learning's (DLSS) primary objective is to improve the deep learning model's interpretability and provide treatment-related insights. The outcome of the convolutional neural network (CNN) model is integrated with clinical data, previous patient medical history, and other related biomarkers to generate a thorough decision-support framework (OC-1). In addition, this holistic method confirms accurate diagnosis, which permits a well-informed assessment of RA severity and therapy options for afflicted individuals. The proposed Decision Methodology underwent a comprehensive analysis utilising many datasets to assess its effectiveness in diagnosing rheumatoid arthritis, hence illustrating the applicability of our proposed system. In order to make better decisions, the CNN and DLDSS work together to leverage the context information. In order to accomplish this, it processes images using deep learning frameworks. Finally, RA Predictive Diagnosis shows significant improvement in medical intensive-care unit analysis. With the help of cutting-edge CNN algorithms and a brand new DLDSS, the system can enhance RA diagnosis accuracy and efficacy, which in turn improves patient outcomes and allows for more personalised treatment plans.

1. INTRODUCTION

Patients are increasingly seeking out rheumatology services, despite a steady decline in the overall number of rheumatologists [1]. Long delays between the onset of problems and the visit, the diagnosis, and beginning of treatment are caused by the shortage of rheumatologists. To limit the irreparable damage that unmanaged inflammatory disease causes, rheumatologists must triage patients. Multiple triage and screening methods have been developed, however the overwhelming majority of patients treated by rheumatologists do not develop inflammatory rheumatic diseases (the IRD) [2]. The quality of treatment is diminished due to inadequately standardised triage decisions in rheumatology as, unlike emergency medicine, there have been no objective triage standards in this field.

New recommendations from the European Union of Rheumatology (EULAR) stress the additional value of telehealth patients pre-assessment in enhancing referrals to rheumatology and in helping to prioritise patients suspected of having IRD [3]. Report is an automated rheumatology system for referrals that sorts incoming referrals for patients according to the probability of each visit; it is now operational in Germany. An end goal, weighted total score is used to compute the likelihood of each particular IRD.

Patients or those who refer them to doctors can use the tool. New research shows that patients appreciated and found Report easy to use, but that it only had a moderate impact on their diagnoses. In many areas artificial intelligence (or AI) has been proven to be an invaluable tool for improving the precision of diagnoses [4]. Recently, rheumatology radiographs have shown expert-level accuracy in diagnosis due to sophisticated deep learning algorithms. Furthermore, it has been accurately predicted that RA flare-ups will occur in patients using advanced machine learning algorithms [5]. The use of machine learning to categorise rheumatic facility patients into different groups has not been investigated in any research that we are aware of. It was the hope of the researchers that machine learning may make the digital RA self-referral system Reports more accurate and faster in the diagnosis of inflammatory rheumatic disorders.

2. LITERATURE REVIEW

Personalised biologic therapy provides rapid relief for the majority of patients with rheumatoid arthritis (RA), a chronic inflammatory disorder that damages and paralyses joints. However, refractoriness worsens quality of life for those who do not improve with treatment. Additionally, biotech treatments might be quite pricey [6]. The 144 patients with RA who were prepared to begin anti-tumor nuclear factors (anti-TNF) medication provided us with plasma samples. Studies utilised four screens containing an entire collection of 92 proteins for close proximity extension at Olink Proteomics in the Swedish city of Uppsala, using the samples that were delivered. Out of the 89 patient samples included in the data set for anti-TNF treatment responders, it was passed [7]. With an accuracy of 81%, sensitivity of 75%, and specificity of 86%, the machine learning-based model, ATRPred (anti-TNF responses to treatment prediction), can inform a RA patient about the efficacy of anti-TNF treatment. By guiding physicians to treat patients most likely to gain benefits from anti-TNF medication, ATRPred has the potential to reduce healthcare costs and improve outcomes for patients who do not react. The building blocks of ATRPred are R.

A considerably improved prognosis is shown for patients with rheumatoid arthritis (RA) who were diagnosed within the previous ten years compared to those who were diagnosed twenty years ago [8]. The long-term outlook of the ailment has improved due to changes in treatment based on disease activity, the availability of new, efficient drugs, and the early starting of therapy. But present therapeutic methods are still based on populations rather than individual patients. In order to make decisions about providing personalised treatment, accurate prognostication on multiple factors is required. This article covers the strategies for evaluating prediction models [9]. When to begin disease-modifying antirheumatic drug (DMARD) treatment for patients just starting treatment, the right dose to start treatment at, and the probability that a patient will react to a particular therapy. Except for a model that may foretell when RA will develop, most prognostic tools derived from RA and arthritis are either unvalidated or incorrect. This means that decisions about tailored treatment for Rheumatoid and arthritis will take a long time to reach the bedside.

Rheumatoid arthritis (RA) is an autoimmune disorder that damages the system of joints and generates long-lasting, systemic flare-ups [10]. The progressive nature of rheumatoid arthritis (RA) makes it more difficult to engage in physically demanding pursuits without experiencing fatigue and joint pain. Joint and muscle cartilage is typically damaged or destroyed by RA, which weakens and eventually destroys the joints themselves. In this study, medical illnesses are grouped according to RA using ensemble methods. Classification issues with large amounts of numerical data are present in this dataset. In this study, three group algorithms—Support Vector Machine, Ada-boosting, and random subspace—were employed. In order to determine the classifier's baseline measures, ensemble classifiers use Random Forest and k-NN. To sort the data into groups, we utilise tenfold cross-validation. To analyse the outcomes, we employ performance metrics like ROC, accuracy, and precision. Comparisons with baseline approaches and different ensemble classifications showed intriguing results for these metrics [11]. A significant improvement is described by this optimality, which pertains to the performance of beginning classifiers in the context of ensemble classifiers.

The importance of explain ability in deep learning-based techniques is growing, especially in fields like medical image analysis where rapid choices are crucial. This survey provides information about the function of explainable artificial intelligence (XAI) in medical image analysis that is powered by deep learning [12]. We offer a set of XAI criteria to classify deep learning-based medical image analysis methods. After that, articles about XAI methods in medical image processing are surveyed and categorised according to their anatomical locations. In the latter section of the article, we survey some of the possible uses of XAI in medical picture analysis.

Rheumatoid arthritis (RA) affects 700,000 Japanese people, and that figure increases by 30,000 annually. Early and appropriate treatment on the basis of the course of RA can enhance the patient's prognosis. A frequently used technique for evaluating the progression of rheumatoid arthritis, the Total Sharp (MTS) that has been previously modified. In order to get the MTS rating, you have to undergo a long series of X-ray exams on your feet and hands. Multiple times throughout the year, this rating must be attained [13]. The automated mTS score calculation system must be utilised. The article suggests two methods for estimating mTS scores: one that uses support vector machines to identify finger joints, and another that uses the same approach. The proposed method was determined to have an accuracy of 81.4% in identifying finger joints, 64.3% in estimating the JSN score, and 50.9% in estimating erosion, according to X-ray images from 45 RA patients.

As an element of a clinical decision-support system, deep neural network models can be used to make predictions about future disease activity by learning from historical data on a large scale. One cutting-edge neural network that has been trained on the incomplete and variable nature of clinical data is Adaptive Net. Repetitive connections have been established [14]. This method utilises a one-of-a-kind neural network that has been trained to forecast the course of disease in patients with rheumatoid arthritis (RA), using data from a registry. Information such as demographics, medical history, physical exams, test findings, medication information, clinical evaluation outcomes, outcomes reported by patients, and data about patients are all part of this. This information was gathered via the Swiss Clinical Quality Management in Ra Diseases (SCQM) database, which includes around 9500 patients and 65,000 recorded visits; this database was developed through well-structured instruction and examination [15]. The network can recognise the presence of active RA disease and utilise its forecasting ability to forecast the frequency of future disease activity. The DAS28-BSR serves as the main endpoint for this process, which involves regression analysis as well as classification algorithms.

Rheumatoid arthritis, an autoimmune joint disease, is the most common autoimmune illness in the world. Tumour necrosis factor inhibitors are among the second-line agents that are used most frequently. Some patients may find relief from TNFi, but it has the potential to weaken the immune system, which increases the risk of infection and other side effects. Consequently, the capacity to foretell how patients will react to TNFi is critical for selecting the most effective treatment plan. The purpose of this study was to determine, one year after treatment began, if patients were still receiving TNFi by training a procedural neural networks structure called Variational Auto encoder (VAE). Supervisor VAE (SVAE) is a supervised learning algorithm that integrates a VAE with a classifier neural network. It was built using two versions of a tabular dataset that were trained using Swedish register data [16]. The datasets consist of 7,341 patient records, and our SVAE achieved a validation AUROC grade of 0.615. Nevertheless, SVAE fared better than elastic net and choice trees, but worse than randomised woods and gradient-boosted trees of choice, when compared to previous machine learning models used for the same prediction task. In spite of the regularisation influence that VAEs provide during classification training, the results achieved by the SVAEs evaluated for this thesis fell below the acceptable discriminatory level.

A state-of-the-art RA diagnostic tool that makes use of deep learning analysis is the subject of this study. For a more precise and time-saving RA diagnosis, the system makes use of state-of-the-art Deep Machine Learning Decision-Supported Systems (DLDSS) and Convolutional Neural Networks [17]. By employing complex image-processing techniques to uncover precise patterns from medical pictures, specific joints abnormalities that correlate with RA have been identified using CNN technology and machine learning. To conclude, the DLDSS uses a variety of patient information systems (e.g., genetics and clinical records) as "inputs" to produce a more thorough and precise "composite health function" assessment. In order to facilitate personalised consideration during treatment decisions and to streamline the diagnosis process for personalised RA treatment, our system integrates data from several technologies. In the long run, the proposed method might reduce the risks associated with rheumatoid arthritis and represents a big step towards a data-driven, all-encompassing approach for rheumatology management of the disease.

The term "over diagnosis" was coined by cancer screening doctors to characterize the discovery of benign tumours during screenings that would never have caused any symptoms anyhow. Worry, costs, and the necessity for unnecessary medical treatment (overtreatment) are all increases due to over diagnosis. Over diagnosis and overtreatment are topical issues in rheumatology, although seldom addressed [18]. Over diagnosis and overtreatment of inflammatory rheumatic diseases are discussed from this perspective, which also looks at our current ideas about how to manage these conditions. Precision medicine, evidence-based rheumatology, early diagnosis, rigorous treatment, remission, and prognosis and assessment of risk will be the six cornerstones of contemporary rheumatology that will be the subject of the next debate. Despite the great advances that have been made, it has been concluded that all paradigms carry the danger of over diagnosis and overtreatment. Hence, exercise caution [19].

Medical outcomes for rheumatoid arthritis (RA) patients have changed dramatically in the past 30 years due to innovations in the treatment of inflammation with disease-modifying anti-rheumatic medications (DMARDs), both biologic and conventional synthetic. We need to figure out how to best manage this subset of patients because some of them may have permanent remission while on the current medication. Especially for patients whose RA has been fully managed with DMARD treatment, the idea of gradually reducing or discontinuing DMARD use appears to be a promising one at the moment, as it would allow for a more personalized and dynamic approach to RA management [20]. This review article covers the most current improvements in DMARD tapering methods. Using a review of prior studies, the paper delves into new ways to attain remission without drugs. We also talk about some ideas on how to figure out who can get off DMARDs, and some ways to use biomarkers to predict when a disease relapse will happen after DMARD tapering starts. These outcomes are ultimately measured against the objective of assisting RA patients in achieving complete inflammatory control and curing their disease.

Table 1: Detailed literature synthesis

Reference	**Technology**	**Focus**	**Pros**	**Cons**	**Potential Applications**
[1]	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]	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]	Clinical Evidence Review	Analyze existing studies	Optimizing medication use in RA	- Evaluates strategies for safely	- Lacks discussion on future research directions for

				reducing medication dosage	tapering strategies
[4]	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]	Machine Learning	Analyze existing research	Predicting cardiovascular disease	- Demonstrates potential of machine learning for disease prediction in general	-Not specific to Rheumatoid Arthritis
[6]	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]	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]	Deep Learning	Forecast clinical outcomes	Predicting long-term disease course	- Investigates using deep learning to predict	- Relies on specific electronic health record data format, limiting generalizability

				future health outcomes in RA patients	
[9]	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]	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]	ICML2020	Machine Learning	Address missing data in deep learning	Techniques for handling missing data in deep learning models	- Improves the robustness and generalizability of deep learning models in healthcare applications
[12]	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

Improving images, segmenting them, extracting features, preprocessing them, capturing them, and classifying them are some of the steps taken to process any image at the moment. What follows is a flow diagram depicting the standard procedure that the researchers followed. Figure 1.

Data preprocessing is a subset of enhancing images in image processing that, in preparation for subsequent processing, enhances certain features of the image or eliminates undesirable distortions. Below, a novel approach is used to noise reduction using convolutional neural network (CNN) networks, which they call sparse aware noise reduction (SANR CNN) [21]. After that, the author used the Euclidean transform to precisely position a slice about a previously chosen, cropped, and scaled templates in order to build model training images for every knee [22].

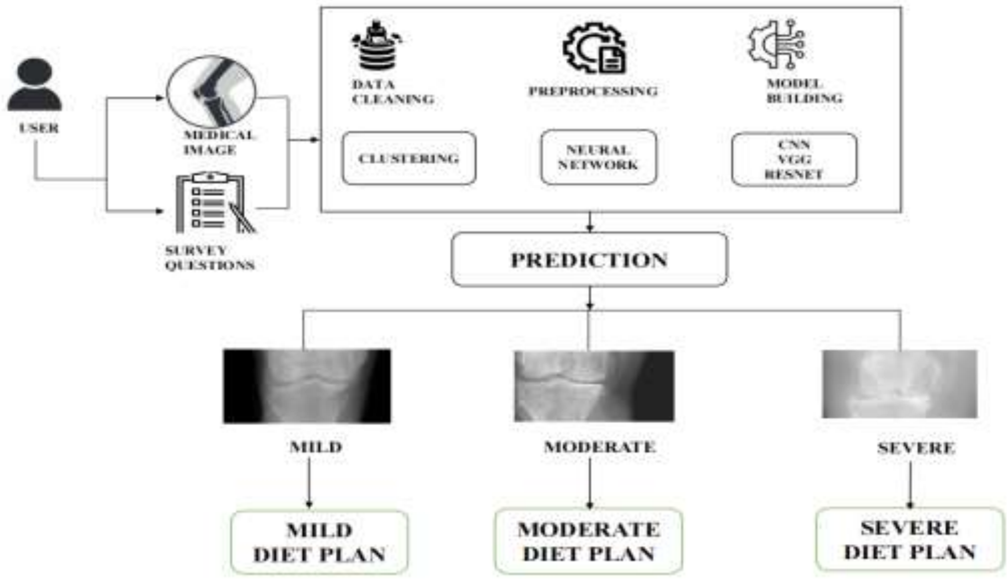

Fig.3.1 Advanced Diagnostic Framework

Afterwards, images were selected for the purpose of training models for every knee from the center slice, eleven adjacent slice on the far left side of the centre slice, and eleven near the center on the medial side.
The DLDSS procedure is elucidated in the following algorithm for diagnostic framework.

CNN
When it comes to handling time series data, CNN models have proven to be very good at extracting features. Convolutional neural networks (CNNs) are able to successfully detect important local features and trends in diagnosis of rheumatoid arthitiritis. Important information, such as seasonal variations, periodic fluctuations, peaks, and troughs, may be included in runoff data by means of these local features. To have a better grasp of the data's evolving patterns, the model is able to correctly extract these local features due to the convolutional kernel's sliding activity over various time periods [23]. A classic convolutional neural network (CNN) model consists of five layers: input, convolutional,

pooling, fully connected, and output. A key component of these is the convolutional layer, which houses the convolutional kernel that is responsible for extracting the data's intrinsic features. The following equation describes how the convolution kernel works:

$$c_i = f(w \otimes x_{i:i+h-1} + b) \qquad (1)$$

indicates the feature data obtained by the above convolution; denotes the convolution operation i from i+h-1 data; and denotes the convolution operation ⊏. In this context, W stands for the parameters of the convolution kernel, b for the bias matrix, and h for the height of the convolution kernel.
Using the Inception framework, CNN is able to decrease computation while extracting more effective features from raw data. The Inception structure uses parallel applications of 1x1, 3x3, and 5x5 convolutional kernels to capture features at various scales. While 3x3 and 5x5 convolution capture both local and broader global characteristics, 1x1 convolution reduces the complexity and processing. All of the characteristics of runoff data can be captured by this multi-scale feature extraction method. Furthermore, the convolution operation's parameter sharing property aids in decreasing computational and storage needs while enhancing model efficiency.

VGG:

Two fully linked layers follow a chain of sixteen convolutional layers in the VGG16 architecture. The network is able to produce intricate and detailed feature representations of the input image through the use of convolutional layers, which employ tiny filters (3x3) and a stride of 1 [24]. The architecture is easy to grasp and put into practice because of its straightforward design. It works well for tasks that involve classifying images. Because it has been trained on several popular deep-learning frameworks, its simplicity is a result of that. VGG16 has some restrictions: Due of its size and computing expense, the model is prohibitive. Making a change to the hyperparameters can change the outcome. Compared to more recent CNN models, it is not as robust against noise and occlusions.

ResNet:
Picture classification is a typical use case for ResNet50. This model's main novelty is its use of residual blocks [25]. A key component, it reduces the likelihood of overfitting while letting the network learn more complex features. A ResNet50 architecture consists of a stack of residual blocks. Instead of depending only on the input, it can acquire the input residual via the shortcut connection. The network's efficiency and resistance to overfitting are both enhanced as a result.

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 is a method for dividing a digital picture into multiple separate areas. Using a FLIR cameras connected to a computer, thermal photos were taken of the subjects' knees on both sides of their bodies [26]. While getting the data ready, the researcher used a segmentation mask to transform the annotations for the joint centers. Some pixels are associated with the joint center of their respective joints, whereas others are associated with a distinct backdrop class. They used the fuzzy c-means method to segment the images in this study. Subregions were created inside the region of greatest interest using this kind of segmentation method based on the item's clusters. We use the MATLAB software to segment the photos. Canned operators were brought in to aid in the search for edges. When it comes to finding edges and segmenting images, this is the method that everyone uses. Among the best edge detectors on the market, the incredible edge detector stands out for its remarkable noise immunity and edge-finding capabilities.

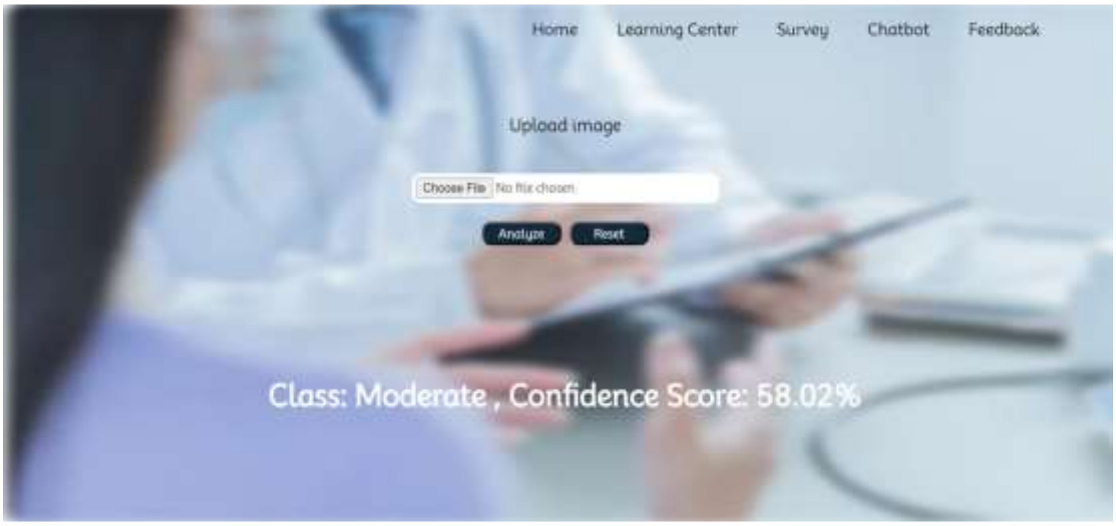

Fig.3.2 User access gateway-login

3.3 Diet and Exercise Methodologies

Individualized Dietary Guidance: Set up a system that takes into account patient information, such as food allergies, preferences, and medical history. Make use of this data to furnish individualized dietary recommendations for the alleviation of RA-related inflammation. Irritating Foods to Watch Out For:We trained convolutional neural networks (CNNs) to recognize inflammatory foods by analyzing images and text. Give them immediate comments and suggestions based on the foods they select.

Exercise Programs Tailored to Each Individual Patient: Take into account each patient's unique physical characteristics, pain tolerance, and mobility limitations to develop individualized exercise programs using deep learning techniques. Since the system constantly tracks the patient's development, it may gradually modify and improve the training programs. Analyze the patient's motions in real time as they exercise by combining computer vision methods with the convolutional neural network (CNN). Make sure to provide prompt feedback on correct technique to avoid overstretching joints, and make any necessary adjustments to the training plan. Fig. 3.3 illustrates the patient's questionnaire that was utilized for disease analysis and to provide dietary and exercise recommendations. Example is displayed in Fig. 3.4. Diet and exercise regimens recommended.

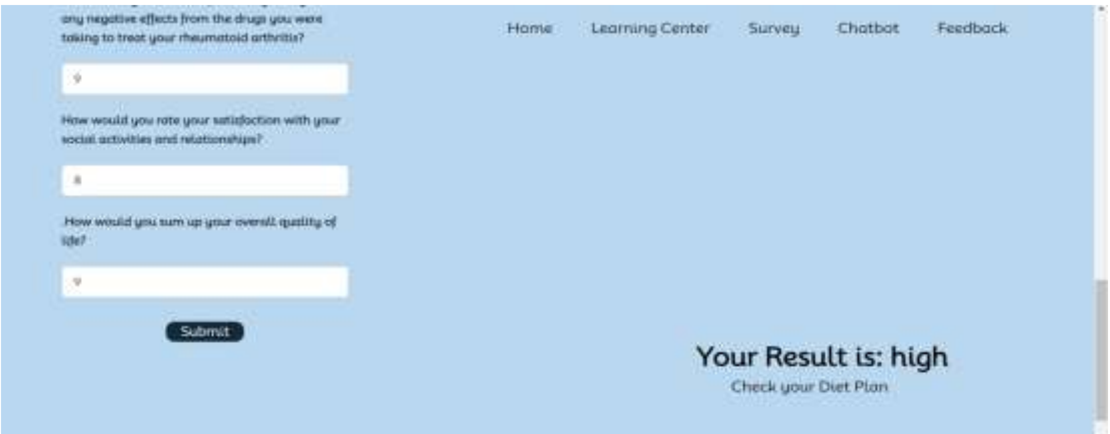

Fig.3.3 sample questionnaire

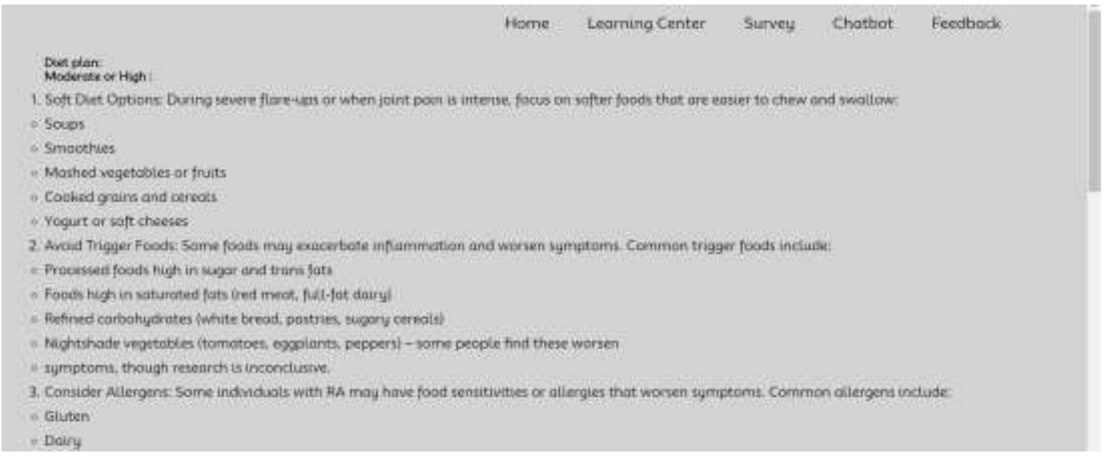

Fig.3.4 Suggested Diet Plan

3. 4 Chatbot Methodologies

Problem Tracking and Reporting: Design a chatbot interface that allows users to log their symptoms, medication adherence, and overall health every day. The chatbot is capable of updating the DLDSS with appropriate information after interpreting user input using the processing of natural languages. To aid in education, create a chatbot that talks about RA, its treatments, and how to change your lifestyle to manage the disease. It can provide proactive recommendations and prompts to take medications as prescribed, schedule checkups, and maintain healthy habits. The discussion platform that facilitates communication and connection development between different doctors and patients is depicted in Figure 3.5.

Fig.3.5 Discussion Forum

3.5 Classification

Now that the features have been retrieved from the input photos, the classifiers may be trained with them. Classifiers produce output by comparing parameters with the record set. In order to categorize the results, the researchers employed a mix of classifiers from machine learning as well as image processing. The results of the research project show that several simple methods of classification were employed.

4. RESULT AND DISCUSSION

The literature on deep learning algorithms for RA identification has some good answers to fill in the gaps in our knowledge, but it also has some major drawbacks and some areas that need to be improved. Firstly, researchers should consider data augmentation approaches to enhance the amount of training information and to make their models more resilient, since high-quality data is not always easy to come by. Secondly, although it is possible to reduce the training duration of the models by using various cross-validation approaches, doing so carries the risk of over fitting and poor generalizability. Researchers should avoid sacrificing computational economy for the sake of poor generalization performance when choosing a cross validation method.

Tables 4.1, 4.2, 4.3, 4.4, and 4.5 display the results of comparing different model parameters with the produced DLDSS. Likewise, picture 4.1, 4.2, 4.3, 4.4, and 4.5 show a comparison plot of several models. Inception V3, ResNet-50, VGG-16, and MobileNetV2 are some of the models. All of the metrics related to training and validation, including accuracy and loss, may be seen in table 4.6. The plot for the same is shown in Figure 4.6..

Table 4.1: Model vs Execution time

Model	Execution time(sec)
ResNet-50	0.5
VGG-16	0.6
InceptionV3	0.4
MobileNetV2	0.7
DLDSS	0.3

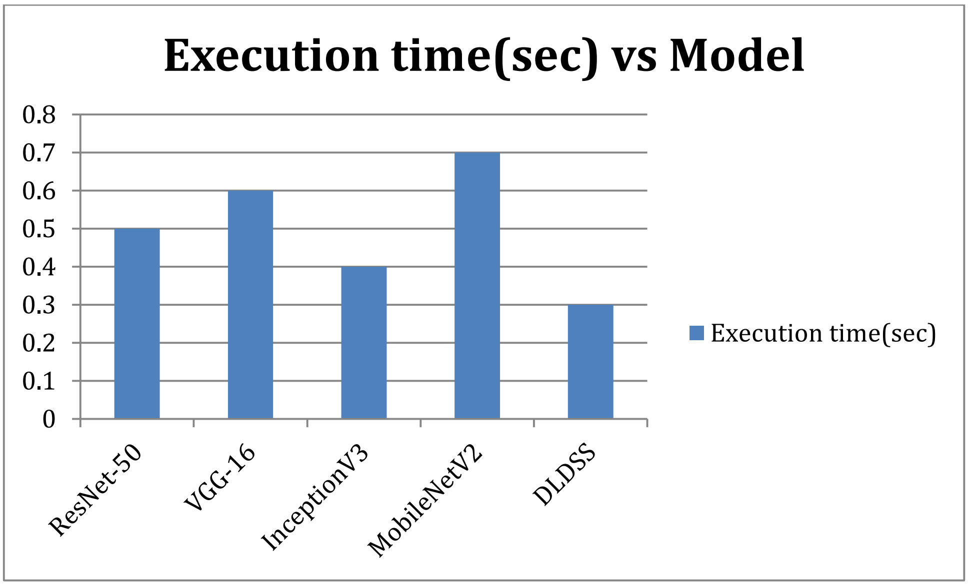

Fig.4.1 Execution time plot of various algorithm

Table 4.2: Model vs Precision value

Model	Precision value
ResNet-50	86
VGG-16	84
InceptionV3	88
MobileNetV2	82
DLDSS	89

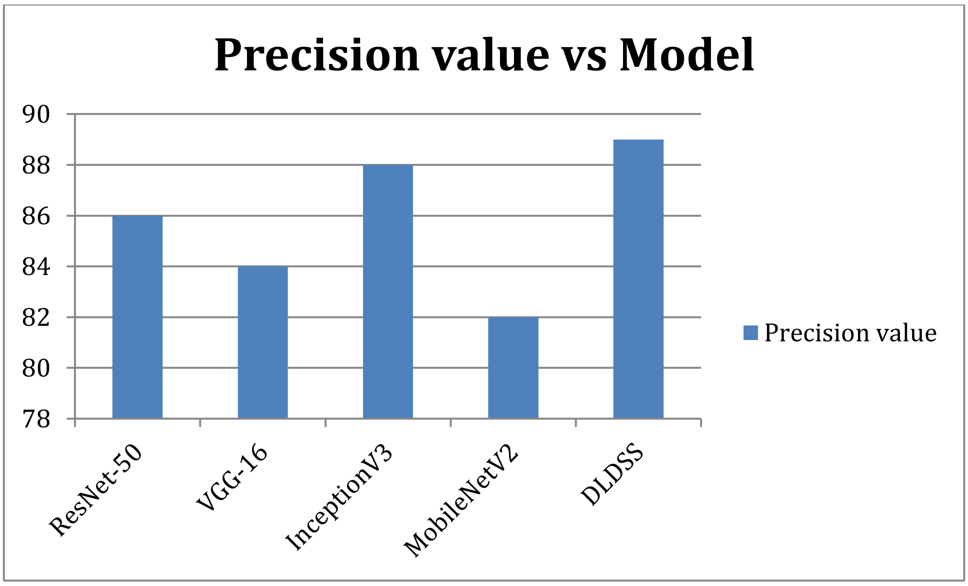

Fig.4.2 Precision value plot of various algorithm

Table 4.3: Model vs Recall value

Model	Recall value
ResNet-50	91
VGG-16	89
InceptionV3	93
MobileNetV2	87
DLDSS	95

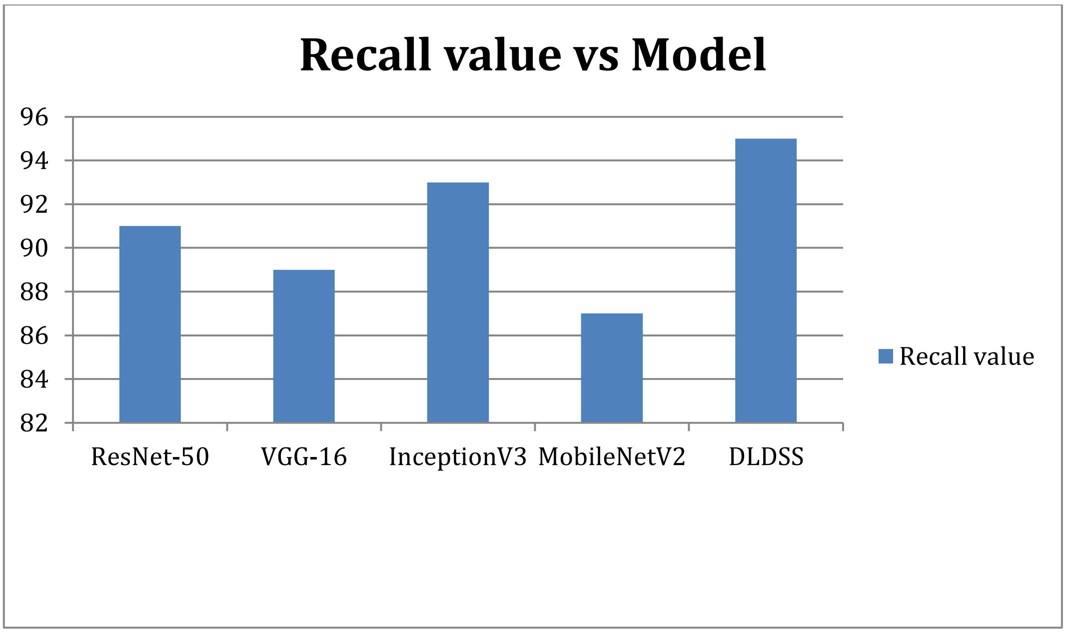

Fig.4.3 Recall value plot of various algorithm

Table 4.4: Model vs F1 Score

Model	F1 score
ResNet-50	88
VGG-16	86
InceptionV3	90
MobileNetV2	84
DLDSS	91

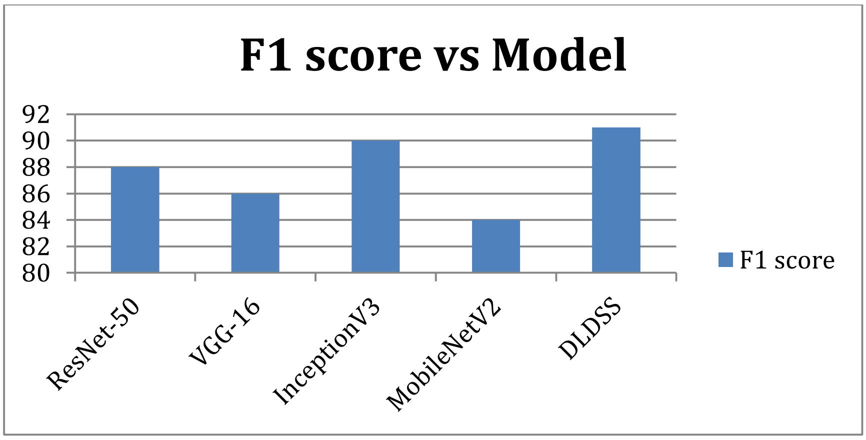

Fig.4.4 F1 Score plot of various algorithm

Table 4.5: Model vs Accuracy value

Model	Accuracy
ResNet-50	93
VGG-16	91
InceptionV3	93
MobileNetV2	90
DLDSS	95

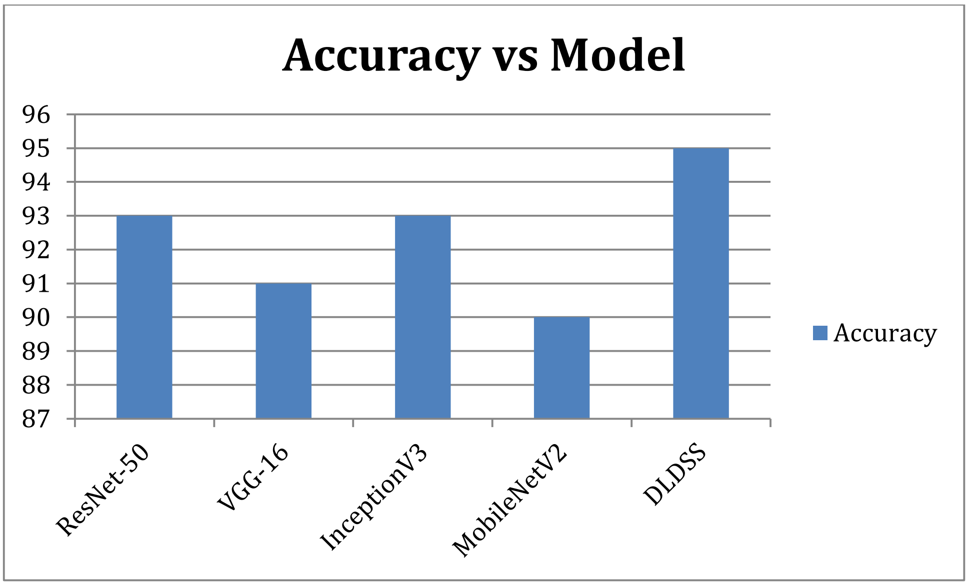

Fig.4.5 F1 Accuracy value plot of various algorithm

Table 4.6: Discrimation of various model.

Parameter	ResNet-50	VGG-16	InceptionV3	MobileNetV2	DLDSS
Final training loss	0.21	0.23	0.19	0.29	0.17
Final validation loss	0.31	0.26	0.22	0.29	0.21
Final training accuracy	0.96	0.94	0.93	0.93	0.97
Final validation accuracy	0.91	0.89	0.93	0.88	0.95

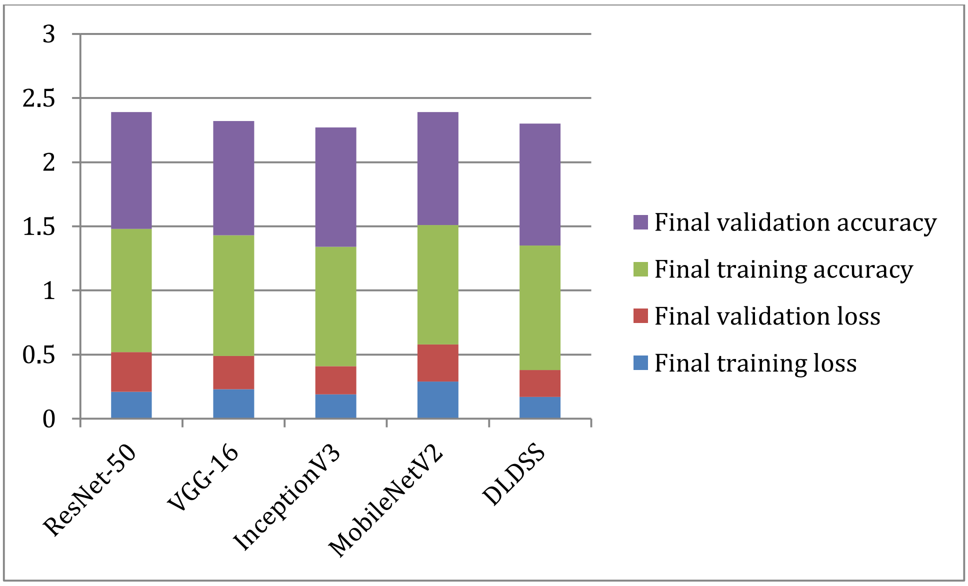

Fig.4.6 Discrimation plot of various model.

4.CONCLUSION

The present study processes a number of medical datasets based on RA using three distinct ensemble classifiers, each of which uses a unique baseline method. The Rheumatology center provided the real-time dataset that this query is based on. We use three of the most popular ensemble classifiers such as Support Vector Machines (SVM, or Support), AdaBoosting, and Random Subspace—to accomplish our prediction rate and compare it to the expected technique. Baseline classifiers are Random Forest (RF) as well as k-Nearest Neighbors (k-NN). There is a correlation between the data type and the particular combination of data used to train an ensemble classifier, according to the experimental results. Nevertheless, this study has been selected, and these datasets will need to be used to train the classifiers. Excluding some performance characteristics allowed us to find classification methods that put efficiency first. Prediction accuracy, precision, and receiver operating characteristic (ROC) are some of these metrics. In order to find out how much more accurate the model is, this research used the 10-fold cross-validation evaluation method. Among the ensemble classifiers tested, SVM with KNN outperformed the competition when it came to properly predicting outcomes using the real-time dataset. Improving the accuracy of diagnoses and perhaps improving indicators of health in the future has motivated the exploration of various methodologies and applications in the model of ensembles.

Future work

There are some encouraging solutions to fill in the study gaps in the literature on algorithms employing deep learning for RA identification, however there are also substantial limitations and a need for development. To begin, increasing the accuracy of the models may not always be possible, even if doing so would increase the number of the samples of datasets, due to the difficulty in obtaining high-quality data. Therefore, researchers can consider using data augmentation techniques to enhance the models' robustness by increasing the amount of information used as training data sets. Secondly, although it is possible to reduce the training duration of the models by using various cross-validation approaches, doing so carries the risk of overfitting and poor generalizability. To extract more meaningful data from images, it is necessary to improve the existing image processing and machine learning techniques. Research efforts should center on developing a product that combines software and hardware into a single package. Thus, numerous ethical the processing of images and machine learning algorithms have been thoroughly examined for the aim of RA and OA classification and identification.

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