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RHEUMATOID ARTHRITIS DETECTION USING ARTIFICIAL NEURAL NETWORKS

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Abstract: **Rheumatoid Arthritis (RA) is a prevalent disease characterized by joint inflammation, discomfort, tenderness, and potential involvement of other body organs in severe cases. Elevated vascular disorder is often observed in the vicinity of inflamed tissue, and autoimmune lesions in joints are associated with heightened fever. Traditional RA detection primarily relies on blood sample tests. However, this work introduces an innovative approach for RA detection utilizing Convolutional Neural Network (CNN) classification applied to X-ray images.**

This work need clear X-ray images as input, and following preprocessing and segmentation and Convolutional Neural Network (CNN) classifier for accurate discrimination between abnormal and normal images. Various evaluation metrics are employed to gauge the performance of the model. Through the utilization of an optimized Convolutional Neural Network (CNN) architecture, substantial enhancements in the accuracy of image classification are achieved. The proposed Convolutional Neural Network (CNN)-based model exhibits high effectiveness in precisely distinguishing between RA-positive and RA-negative samples.

***IndexTerms* – Rheumatoid Arthritis (RA), Convolutional Neural Networks (CNN).**

I. INTRODUCTION

Rheumatoid Arthritis (RA) is different from other forms of arthritis, such as osteoarthritis, because it is an autoimmune disease. The immune system mistakenly attacks healthy joint tissue, leading to inflammation, pain, and joint deformity. Rheumatoid Arthritis (RA) is a progressive disease, which means that without appropriate treatment, it can lead to permanent joint damage and disability. Early detection and diagnosis of Rheumatoid Arthritis (RA) is necessary for many reasons. Best of all, early intervention can slow the progression of the disease and reduce the severity of symptoms. Second, it can prevent irreversible joint damage, while maintaining joint function and mobility. Ultimately, early diagnosis allows healthcare professionals to tailor treatment plans to each patient's needs, increasing the likelihood of a positive outcome. Diagnosing Rheumatoid Arthritis (RA) can be difficult due to a number of factors. Its symptoms, which include joint pain, swelling and fatigue, can be nonspecific and overlap with other conditions. In recent years, the field of medical image processing, particularly using Convolutional Neural Networks (CNN), has shown remarkable promise in the early and precise detection of various medical conditions, including Rheumatoid Arthritis (RA). Convolutional Neural Network (CNN) has demonstrated their ability to analyze and interpret complex patterns and features within medical images, leading to more objective and accurate diagnostic results.

This work focuses on the application of image processing techniques with Convolutional Neural Network (CNN) classifier for the detection of Rheumatoid Arthritis and also covers the key steps involved in the image processing, including image acquisition, image pre-processing, image segmentation feature extraction, classification and results. Additionally, this will explore the implications and potential benefits of this technology in the field of rheumatology, including early diagnosis and disease monitoring. By harnessing the power of image processing and Convolutional Neural Network (CNN) classifiers, this research aims to contribute to the development of more effective and efficient tools for Rheumatoid Arthritis (RA) detection and management. The work proposed is aimed that this documentation will serve as a valuable resource for clinicians, researchers, and technologists alike, as it strives to improve the lives of individuals affected by Rheumatoid Arthritis through early and accurate diagnosis.

II. LITERATURE REVIEW

[1] **Ahmed A. Elngar, Mohamed Arafa, Amar Fathy,Basma Moustafa, Omar Mahmoud and Mohamed Shaban, Nehal Fawzy [1]** have trained image classifier model using a dataset called CIFAR-10 in Python. This dataset is about 163 GB in size and contains 60,000 color images. These images are small, each measuring 32x32 pixels, and they belong to one of 10 categories: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, or truck. There are 6,000 images for each category, split into 50,000 images for training and 10,000 images for testing.

[2] **Gitanjali S. Mate [3]** has performed tests on hand radiography for monitoring the progression of rheumatoid arthritis (RA) in human joints. This work introduces a CNN capable of learning features automatically and predicting the class of hand radiographs from a large dataset. The CNN's intermediate layers, which illustrate the network's dynamics, are also simulated. The model is trained using a dataset of 290 radiography images. The results indicate that hand X-rays are classified with an accuracy of 94.46% using the proposed methodology. This experiment reveals a sensitivity of 0.95 and a specificity of 0.82 for the network.

[3] **Sankar K. Pal and Robert A. King. [4]** Prior enhancement of variation between regions (with minor variations in gray levels) using intensification (INT) efficiency and shifting on a non-slip material plane before gaining its edges are used in the algorithm. Using the functions S,π and (1 -π), as well as fuzzifiers, the cargo plane was ejected from the local domain. A maximum or minimum operator is employed to identify the ultimate endpoint. A radiograph of the wrist is used to demonstrate the accuracy of a device with several parameters.

[4] **P. Thangam, K. Thanushkodi, and Thushika Mahendiran [5]** have created a curriculum that includes endocrinological disorders in children that are seen in many countries worldwide and vary in diameter and severity in various age ranges and races. Changes in diet and eating habits also correlate to endocrine disorders, necessitating the development of a device that can predict those issues ahead of time. In the treatment and diagnosis of endocrine diseases, osteoporosis is a popular technique. It might also be interpreted as indicative of a therapeutic impact, particularly in pediatric medicine where it holds significance in detecting growth hormone deficiencies or genetic abnormalities. The left-hand connector was used to determine bone age, which was then applied to time. The inconsistency between the two illustrates the disparity.

[5] **S Yoon and T Lee [6]** have developed sequencing software aimed at excising non-transcribed regions from pre-messenger ribonucleic acid (RNA) copies. Finding target sequences is a crucial machine learning activity that aids in the identification of basic genes as well as the understanding of how various proteins are made. Existing prediction repetition approaches have shown good results, but they are also moderately stable and inaccurate. This article presents a comprehensive theory outlining a mechanism based on a predictive network of computational splice junctions. The idea involves a novel method of training Boltzmann's equipment collection for horizontal inequality prediction. The method proposed here addresses the limitations of individual variants and enables the creation of datasets with diverse features. Using individual social data sets, this approach was shown to have greatly increased accuracy and decreased running time as compared to other methods. The suggested approach is more efficient at handling false interaction signals and is less vulnerable to the duration of the input chain.

[6] Jenny Ann Verghese, D.Pamela, Prawin Angel Michael , R.Meenal [7] discusses about the Rheumatoid Arthritis (RA) detection with x-ray images, after pre-processing and segmentation using Support Vector Machine. Separation tasks were assessed using various output parameters. The accuracy of the model section has improved to use of an optimized SVM network. This model was effective in accurately separating the samples.

[7] Jun Fukae and others [8] studied to explore how deep learning can help diagnose rheumatoid arthritis (RA), as there are no definitive criteria for diagnosing RA. Rheumatologists typically diagnose RA based on a combination of evidence and experience. They came up with a new idea: turning various patient clinical information into simple images and using them to train a convolutional neural network (CNN) to distinguish between RA and non-RA cases. They converted different types of patient clinical data into colored square images and combined them into one image per patient. These images were then used to train a CNN with transfer learning, using 1037 images (252 RA, 785 non-RA). A rheumatologist adjusted each patient's data slightly to create more training examples. We also tested the CNN's performance on separate clinical data (10 RA, 40 non-RA) that weren't used in training, comparing its performance to three expert rheumatologists. Their system showed potential in supporting RA diagnosis, suggesting it could be valuable in screening for RA in both specialized hospitals and general clinics. This study opens up the possibility of using deep learning in RA diagnosis.

[8] Üreten, Erbay, and Maraş [10] developed a computer program to help doctors diagnose rheumatoid arthritis using hand X-rays. They used a type of artificial intelligence called convolutional neural networks (CNN), which learn patterns from images. The program was trained on 135 X-rays, including 61 normal ones and 74 showing rheumatoid arthritis. Then, it was tested on 45 X-rays, with 20 normal and 25 showing rheumatoid arthritis. The program analyzes the X-ray images pixel by pixel and can detect signs of rheumatoid arthritis with good accuracy, sensitivity, and specificity. This method shows promise in assisting doctors with diagnosing this condition.

[9] Khurram ejaz [11] have introduced a new method for accurately detecting tumors in MRI images is introduced. The process involves two main steps. Firstly, the Resultant Biggest Blob (RBB) is identified in the Confidence Region of the MRI image, aiding in the localization of tumors. In the second step, a deterministic feature selection method is proposed to identify highly accurate features in the dataset. These features contribute to defining a good region of interest. The chosen features are applied to the image, and feature-based segmentation is accomplished using a combination of Fuzzy C-Means (FCM) for comprehensive tumor detection.

[10] Prof G.S. Mate [14] developed an intelligent system to detect rheumatoid arthritis of the hand using image processing techniques and a neural network of convolution. The system comprises of two main phases. The initial stage of the process involves image processing, where images undergo techniques such as pre-processing, segmentation, and feature extraction using the Gabor filter. In the subsequent phase, these extracted features serve as inputs for the convolutional neural network (CNN), which categorizes hand images as either normal or abnormal (arthritic). This classification is executed through the CNN algorithm, which entails training the network with both normal and abnormal hand images.

[11] Y. Lecun, L. Bottou, Y. Bengio, and no P. Haffner [15] have created a software that exhibits several neural networks trained using a back-distribution algorithm, demonstrating an efficient gradient learning technique. Gradient-based learning algorithms can be used to implement dynamic decision-making environments that can discern high-quality symbols, such as handwritten characters, with limited computation if the network layout is sufficient.

III. METHODOLOGY

In Existing method [7], Fuzzy C-Means (FCM) segmentation and SVM Classifier are used. In the context of Rheumatoid Arthritis (RA) detection through image processing, Fuzzy C-Means (FCM) segmentation stands as a well-established and effective technique. Fuzzy C-Means (FCM) segmentation has emerged as a critical component in the precise delineation of the regions of interest within medical images, supporting the identification and characterization of Rheumatoid Arthritis (RA) related anomalies and structural changes. The dataset of X-Ray images have been used for identifying the Rheumatoid Arthritis (RA). The X-Ray images are taken as input followed by preprocessing and then by FCM Segmentation and the relevant features are extracted from segmented image and further selected for classification by using SVM classifier and the evaluation metrics is calculated to assess the performance of model. As it have some drawbacks like Over-Segmentation, Lack of Coherent Regions, Limited Handling of Complex Structures, Ineffective Noise Reduction, Manual Feature Engineering Requirement, Limited Hierarchical Feature Learning and Robustness to Noise. So to overcome these drawbacks we use CNN classification with Hybrid Segmentation.

In proposed method, Hybrid segmentation with Fuzzy C-Means (FCM) and Region based segmentation is used for segmentation of images and Convolutional Neural Network (CNN) classifier for classification of images. The steps involved in this method are Image acquisition, Image Preprocessing, Image segmentation, GLCM feature Extraction, GLCM Feature Selection and Convolutional Neural Network (CNN) Classification.

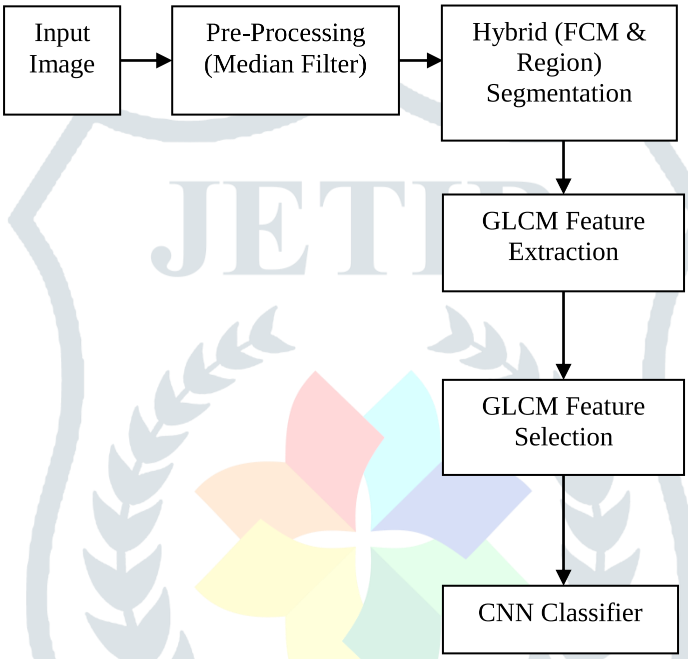

Figure-1: Block Diagram

IMAGE ACQUISITION [9]:

- The first step is to acquire medical images of the affected joint.
- These images are typically obtained using medical imaging modalities, such as X-rays, magnetic resonance imaging (MRI), ultrasound, or other specialized imaging techniques

IMAGE PREPROCESSING:

- Preprocessing involves the application of various filters and techniques to improve the suitability of these images for further analysis and diagnosis.
- Different filters are used to address issues like noise and image quality. After applying different filters in preprocessing SSI values are calculated for preprocessed images. Among the different filters used in preprocessing, the median filter demonstrated remarkable efficacy in improving the quality of images.

IMAGE SEGMENTATION:

- Hybrid Segmentation [11] with FCM and Region based is used for segmentation of images.
- FCM identifies clusters of pixels within the image, while region-based segmentation refines the identified regions of interest (ROIs) associated with RA-affected areas.
- FCM can help identify regions with similar intensity characteristics, which may correspond to affected areas in joint and separate different tissue types within the joint, including bone, cartilage, synovium and inflammation.

- In addition to FCM, region-based segmentation techniques are employed to further refine the segmentation results. These techniques consider spatial information and connectivity among pixels to delineate distinct regions within the image.
- This method unifying FCM with region-based segmentation, offers a promising solution to Rheumatoid Arthritis (RA) detection.

FEATURE EXTRACTION:

- Once the joint area is segmented, relevant features can be extracted from the images.
- GLCM is a statistical method used to analyze spatial relationships between pixels in an image.
- GLCM Calculation:

  The GLCM is computed by counting the number of occurrences of pixel pairs with specific intensity values and spatial relationships within a defined neighbourhood.

  - P (i,j,d,θ) = $\frac{\text{Number of occurrences of (i,j) at distance d and angle } \theta}{\text{Total Number of valid pairs at distance d and angle } \theta}$

- GLCM Features:

  Once the GLCM is computed, various statistical measures can be derived from it to characterize texture. These features can include Contrast, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Entropy, Homogeneity and Variance.

1. Contrast [5]: Contrast measures the local variations in the GLCM.

   Contrast = $\sum_{i,j}(i-j)^2 . G(i,j)$

2. Correlation [5]: Correlation measures the linear dependency between the gray levels in the GLCM.

   Correlation = $\sum_{i,j} \frac{(i-\mu)(j-\mu).G(i,j)}{\sigma^2}$

3. Cluster Prominence [5]: Cluster Prominence captures the skewness and asymmetry of the GLCM.

   Cluster Prominence = $\sum_{i,j}(i+j-\mu)^4 . G(i,j)$

4. Cluster Shade [5]: Cluster Shade quantifies the asymmetry of the GLCM.

   Cluster shade = $\sum_{i,j}(i+j-\mu)^3 . G(i,j)$

5. Entropy [5]: Entropy characterizes the randomness or complexity of the image texture.

   Entropy = -$\sum_{i,j} G(i,j). \log(G(i,j)+\epsilon)$

6. Variance [5]: Variance measures the spread or dispersion of pixel intensity values.

   Variance = $\sum_{i,j}(i-\mu)^2 . G(i,j)$

7. Energy [12]: Energy measures the local homogeneity of an image.

   Energy = $\sum_{i,j} G(i,j)^2$

8. Homogeneity [12]: Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

   Homogeneity = $\sum_{i,j} \frac{G(i,j)}{1+|i-j|}$

9. Dissimilarity [12]: Dissimilarity measures the average absolute difference between pixel intensities.

   Dissimilarity=$\sum_{i,j}|i-j|. G(i,j)$

   Where:

- i and j represent the intensity values of two pixels in the image.
- G (i,j) represents the element at row i and column j of the GLCM matrix.
- N represents the quantity of distinct gray levels within the image.
- ∈ is a small positive constant to prevent the logarithm of zero.
- μ is the mean of the GLCM. $\left(\mu = \frac{\sum_{i,j} G(i,j)}{N^2}\right)$

- σ^2 is the variance of the GLCM. $\left(\sigma^2 = \frac{\sum_{i,j}(G(i,j)-\mu)^2}{N^2}\right)$

FEATURE SELECTION:

- The extracted GLCM features will be selected for classifying.

CNN CLASSIFIER:

The Convolutional Neural Network (CNN) takes the segmented and feature-extracted images as input and outputs a prediction regarding the type of tumor in the joint (normal or Rheumatoid Arthritis). Key components of the CNN include convolutional layers, pooling layers, fully connected layers, and activation functions, all of which work together to extract features from input images and make predictions. The CNN model is trained on a labeled dataset comprising medical images of joints affected by RA, as well as healthy joints. The model consisted of multiple convolutional layers with varying filter sizes, followed by pooling layers to reduce spatial dimensions. Batch normalization and dropout layers were incorporated to enhance training stability and prevent over fitting. The final layers included fully connected layers leading to the output layer with a softmax activation function for classification. Following this classification process, various evaluation metrics such as such as accuracy, sensitivity, specificity and F1-score are calculated to assess the performance of the Convolutional Neural Network (CNN) model.

IV. RESULTS

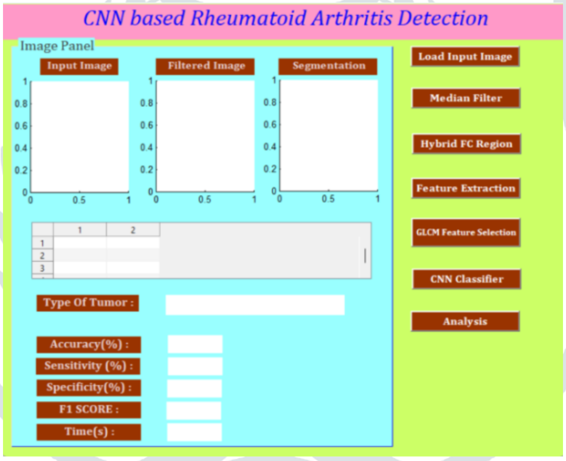

Figure-2 Output GUI

The above figure is the output GUI after running the code. This interface allows us to interact with the program, providing a convenient way to input data, make selections, and view results.

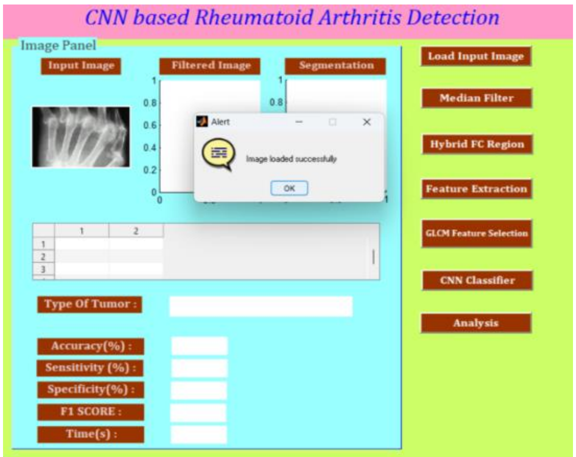

Figure-3 Image Loaded

The above figure is the loading of MRI image in GUI and after loading MRI image an alert message will be displayed like Image loaded successfully.

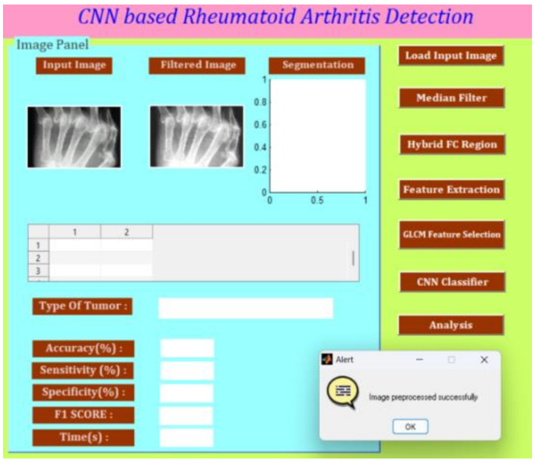

Figure-4 Pre-processing

The above figure depicts the image that is pre-processed and an alert message will be displayed like Image preprocessed successfully.

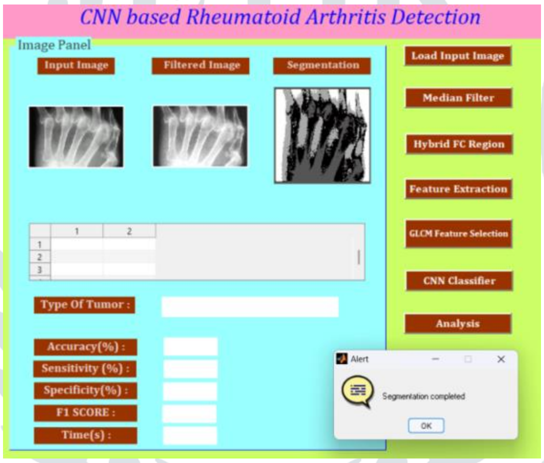

Figure-5 Segmentation

The above figure depicts the image that is segmented and an alert message will be displayed like Image pre-processed successfully along with the segmented images.

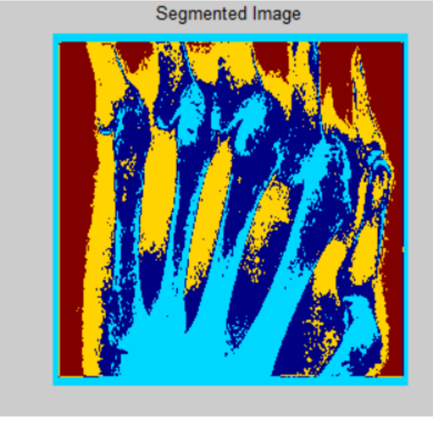

Figure-6 segmented image of FCM

The above figure is the segmented image after applying FCM segmentation. FCM identify regions with similar intensity characteristics, which may correspond to affected areas in joint.

Figure-7 segmented image of region based

The above figure is the segmented image after applying Region Based segmentation. Region-based segmentation techniques are employed to further refine the segmentation results. This technique considers spatial information and connectivity among pixels to delineate distinct regions within the image.

Figure- 8 segmented image of FCM and Region based

The above figure is the segmented image after combining both segmentation techniques.

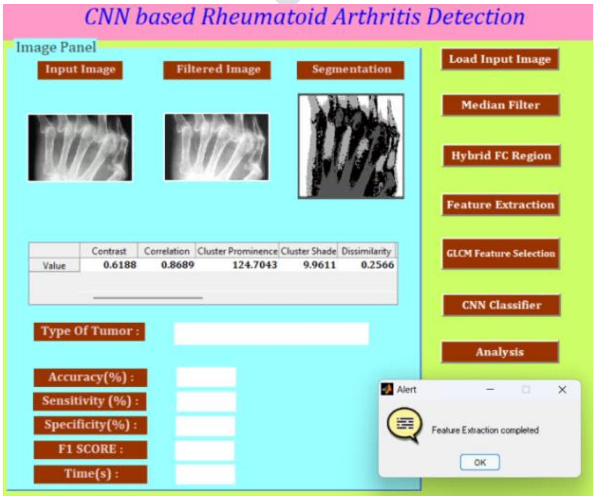

Figure-9 GLCM Feature extraction

The above figure depicts the feature extraction, after segmentation the GLCM features will be extracted.

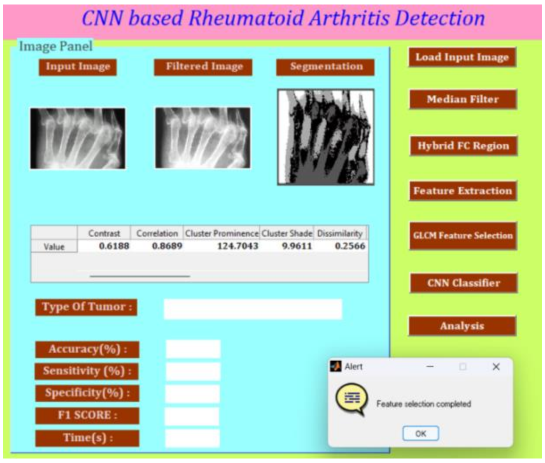

Figure-10 GLCM Feature Selection

The above figure depicts the feature selection, after feature extraction the extracted GLCM Features will be selected for classification.

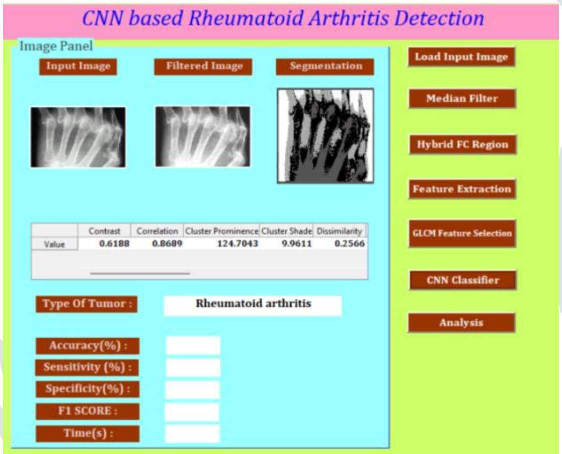

Figure-11 Classification

The above depicts the classification of image by CNN Classifier. The CNN classifier takes the selected features of segmented image as input and predicts the output as Rheumatoid Arthritis or Normal based on the features selected.

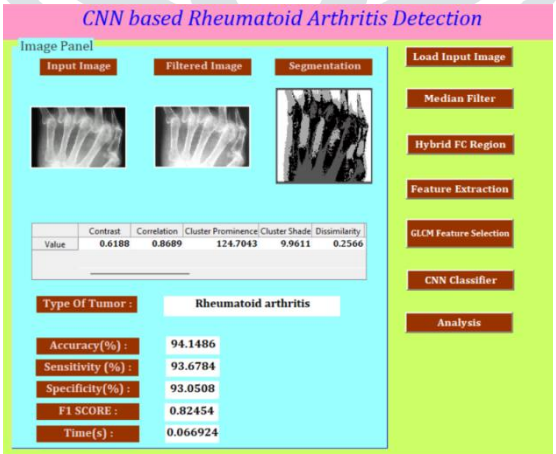

Figure-12 Analysis

The above figure is the analysis of Rheumatoid Arthritis hand fingers, after classifying the performance metrics will be calculated and displayed.

Table-1 Comparison of performances of both methods

Images	Accuracy		Sensitivity		Specificity		F1 Score	
Images	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
Images	91.2247	85.4689	91.7136	84.3146	93.8474	90.5518	0.74835	0.6511
2	89.8553	87.5511	88.1162	87.3276	88.3225	87.4185	0.74814	0.64857
3	85.1792	93.1702	86.4109	91.4726	84.5236	94.6558	0.54759	0.86305
4	89.2789	86.8918	91.8523	90.4308	91.4954	90.3967	0.74572	0.66316
5	88.9235	87.8844	91.2311	87.1397	86.0782	83.9055	0.74346	0.6475
6	88.9299	84.3893	87.0933	82.8699	90.6349	89.5635	0.75015	0.6571
7	82.4474	95.8888	79.9866	92.7485	84.6167	95.1399	0.54528	0.8497
8	87.3611	94.5426	83.3106	92.1035	82.3307	96.1658	0.54868	0.89635
9	91.7879	89.4729	88.5292	87.7945	88.6817	85.3148	0.74888	0.65741
10	90.5943	87.6956	92.4127	89.1024	91.471	90.9214	0.74858	0.61969
11	86.8271	98.4024	81.868	94.5347	83.2203	92.4453	0.55104	0.8787
12	87.2897	96.2102	79.8202	96.3709	82.213	94.9814	0.54705	0.86999
13	85.8639	94.1486	78.3012	93.6784	82.6459	93.0508	0.5456	0.82454
14	85.0738	95.8867	84.683	91.2243	81.1644	96.101	0.55656	0.88197
15	81.8559	94.2324	79.6787	96.8107	78.1895	96.3623	0.54614	0.81825
16	91.0173	87.1567	92.3991	83.5337	86.1168	83.7901	0.74935	0.6145
17	85.8302	94.8769	86.1085	95.8322	79.4884	93.0328	0.54724	0.86694
18	83.5004	93.1066	83.0755	93.0631	83.9045	96.6167	0.54804	0.87255
19	78.8171	97.0415	81.9398	93.6942	82.2807	95.9829	0.5505	0.90558
20	84.6918	96.4496	80.6892	95.2921	77.9043	92.5359	0.54835	0.83745
21	80.108	96.3015	83.0957	92.8625	82.0523	92.7834	0.54353	0.8788
22	84.2307	95.8045	80.7576	96.966	80.7188	93.3439	0.54696	0.86818
23	84.9804	95.0523	82.5528	91.6486	78.9884	96.4429	0.55277	0.85523
24	88.0266	86.0699	87.5108	87.2571	87.7429	87.3866	0.75029	0.64933
25	88.9859	84.1056	85.8785	81.4831	86.1352	82.0509	0.75261	0.65605
26	90.269	89.2255	85.1994	82.936	90.37	86.7452	0.7475	0.6568
27	80.1778	94.7554	86.1378	93.4779	77.4193	92.1807	0.55195	0.85538
28	82.7717	94.5973	79.9178	95.3474	77.6992	95.1985	0.54805	0.88399
29	78.589	92.1356	84.1014	95.173	82.6612	94.6632	0.54911	0.80421

30	79.8746	95.2734	84.9783	95.3763	78.6618	96.4528	0.5465	0.84115
31	82.2451	93.856	78.4252	91.8601	81.6348	95.2048	0.56183	0.88998
32	88.2144	85.9308	88.3343	83.1919	87.5934	88.6841	0.7524	0.63988
33	89.5412	87.886	87.3666	84.0879	91.8045	85.3551	0.74961	0.61868
34	79.2677	94.1079	80.2776	93.3634	79.2679	94.791	0.55527	0.85125
35	82.6847	96.8439	78.0401	94.373	85.1213	92.7066	0.54607	0.83393
36	89.0266	87.4331	89.2649	87.484	89.9141	89.0526	0.74626	0.65598
37	90.0753	87.0506	91.8132	90.2721	88.5087	86.6987	0.75215	0.61772
38	89.2087	86.2893	90.4361	81.2719	89.4663	88.0924	0.75666	0.64086
39	79.2308	98.5561	78.4651	95.6575	78.0549	94.1099	0.55604	0.80903
40	81.1104	92.2106	79.5556	93.9438	79.9698	92.7613	0.55642	0.79068
41	79.094	96.0019	79.9234	93.7821	83.5137	96.1054	0.55083	0.88345
42	84.3791	92.3749	78.3122	93.8248	78.1065	94.7893	0.55259	0.83601
43	87.3154	85.4013	90.5451	87.5383	86.7822	85.7669	0.75678	0.70156
44	86.0832	84.6506	84.527	81.4157	88.1335	85.3586	0.74802	0.65802
45	83.9229	93.867	79.8841	95.9232	78.2049	92.4173	0.54681	0.85818
46	87.3181	83.2501	82.2495	80.3423	85.5789	82.6696	0.75036	0.62019
47	88.0021	87.6355	90.7087	86.4416	92.6824	91.2608	0.74726	0.65926
48	79.2052	96.4662	83.8169	91.9289	81.1671	92.1068	0.5469	0.85329
49	86.4358	93.7489	82.8013	93.9282	80.3406	95.5358	0.54397	0.85623
50	89.3055	92.573	79.8303	93.0006	76.0803	94.0389	0.55403	0.82575

V. CONCLUSION AND FUTURE SCOPE

CONCLUSION:

Our study demonstrates the superior performance of the proposed method in detecting Rheumatoid Arthritis (RA) compared to Existing method [7]. We conducted an evaluation using a dataset containing 50 images to assess the efficacy of both methodologies. Among the 50 images analyzed, our method outperformed in detecting RA in 30 images, achieving a significant success rate of 60% when compared to the Existing method [7]. The efficacy and reliability of our proposed methodology lie in its ability to accurately identify RA-affected regions within the images.

FUTURE SCOPE:

In the future, we can focus on:

- Advancing CNN classifier with advanced optimization techniques.
- Integrating additional imaging modalities for improved accuracy.
- Implementing real-time diagnosis and telemedicine integration.
- Exploring longitudinal monitoring and outcome prediction.
- Enhancing interpretability and collaboration with healthcare professionals.

- Expanding to detect other autoimmune diseases with similar characteristics.

VI. Acknowledgment

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