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Decision Support System Using Fuzzy Image Classification for Diagnosis of Knee Injuries

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Abstract: Manual analysis of medical images is quite complicated and time consuming process and its outcomes highly depend over the experience of practitioners. Improper analysis of the patient's data may lead to false diagnosis. In order to overcome from this issue, a fuzzy based decision support system will be presented in this paper. Injury will be detected on the basis of weighted classification and finally, this data will be provided to multi-agent-fuzzy interference engine for final decision making and diagnosis recommendation.

Keywords: *Multi-Agent, Fuzzy Logic, Image Processing, Knee Injury, MRI*

1. Introduction

Medical imaging plays an important role for the timely detection and diagnosis of the diseases/injuries but accurate interpretation of the input images depends over the experience of the medical experts and assessment of these images at very large scale is very time consuming thus causes delay in diagnosis as well as it also increase the overall treatment cost. The diagnosis process can be automated using computer assistance as given in figure:

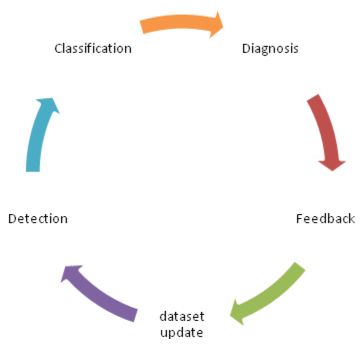

Fig.1. Process of Automated Diagnosis system

Fig.1 shows the steps of automated diagnosis process in which symptoms of disease/injury are detected using medical imaging followed by classification method that is used to extract the different features from input image to assist the diagnosis process. Timely progress of patient health's recovery is recorded using a dataset for future reference but it has the following barriers:

a) **Accuracy of Symptom recognition:** A medical image may contain different attributes, so system must be able to recognize the relevant data only. Accuracy of outcomes highly depends over the validation of testing/training datasets. Without dataset validation, prediction accuracy cannot be achieved.

b) **Standards used for Dataset Sampling:** Practitioners must use some standards to ensure proper sampling using medical imaging otherwise it can produce the incorrect medical dataset thus may affect the accuracy of the entire system [1-5].

2. Traditional Image classification Techniques

Image classification is a process that is used to classify the input image by recognizing its visual attributes. Following are the basic image classification methods:

1. Object detection: A specific object can be detected in a given image using its unique attributes
2. Feature Extraction: Different features can be extracted from a image for analysis.
3. Object classification: This goal can be achieved by comparing the extracted features with predefined feature classes/patterns.

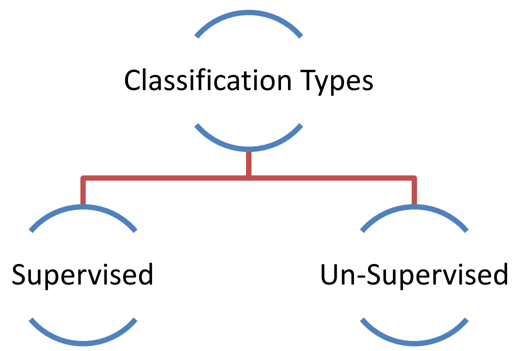

Fig.2. Classification Types

Classification may be: supervised, in which predefined data is used for training/modeling and in case of un-supervised classification, process can obtain the knowledge

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from its experience.

3. Automated disease detection and diagnosis support

Following are the various solutions presented by different researchers in the relevant field:

S. Zahiaet al. [6] did a survey for the diagnosis of pressure injuries using deep learning schemes. It deals with theclassification of skin tissues/wond segmentation/lesion type etc. and highlights the various solutions for the same using neural network (NN), support vector machine (SVM)/K-means clustering /Gaussian process regression etc. Outcomes show that this study can be further used for the development of automated diagnosis techniques.

A, Tolba et al. [7] introduced a fuzzy based assistant to improve the performance of players. It provides feedback using different sensors and it can be further used to enhance the accuracy of sportsman. Analysis shows its performance in terms of prediction accuracy/ratio of decision time/minimal decision errors etc.

N. Sharma et al. [8] developed a fuzzy logic based framework to identify the disease using sensors outcomes that are used to define the member function and rules are defined for different age groups for increase the prediction accuracy. Analysis shows its performance in terms of optimal RMS error/prediction accuracy etc. However, these parameters vary w.r.t. age group (Adults/children).

G. Nanda et al. [9] investigated the role of various machine learning approaches (SVM/Linear regression (LR)/, Recurrent Neural Network (RNN)) etc. for the detection/surveillance of the injury. Study found that this goal can be achieved by assigning a unique code to each injury type/cause. A threshold based filtering approach is further used to optimize these codes w.r.t. their categories but analysis shows the inconsistency in coding along with less prediction accuracy. This study can be used to develop the training sets to overcome these limitations.

Y. Liua et al. [10] developed a framework for the automatic detection and diagnosis of liver disease. It uses fuzzy sets to recognize the region in given ultrasound images and then classification is performed for perdition purpose and outcomes are compared with normal liver stages. Experimental results show its accuracy in terms of accuracy of disease perdition/stage recognition /classification etc. as compared to existing schemes and it can be further enhanced for the diagnosis of other liver diseases also.

K. N.Kunze et al. [11] analyzed the role of Artificial intelligence to detect/diagnose the different knee injuries (Anterior Cruciate Ligament and Meniscus Tears). Comparison shows that AI based schemes fully depend over various factors i.e. knowledgebase/training/testing sets and these are less accurate as compared to medical practitioners.

D. T. Fernando et al. [12] introduced a mortality prediction model for hospitals. It uses various indexes, age groups, injury/disease types to form prediction model. Experiments show that its accuracy varies w.r.t. above discussed parameters.

E. B. Monroya et al. [13] presented a fuzzy based scheme to manage postural changes for pressure ulcers. Wearable sensors collects the data about different body parts and SVM classifiers are applied to identify the sensitive regions over body and finally, suitable body postures are recommended to avoid the pressure over marked regions. Experimental results show its performance in terms of fast health recovery and it can be further extended for gait speed analysis.

G. W. Fuller et al. [14] investigated the injury assessment tool for sports. It establishes a relationship between participants, end results, injury impact over individual player and there are several parameters (i.e. sample size, population, data collection methods) that affect accuracy of diagnosis. Experimental results show that prediction accuracy can be achieved by applying threshold values.

D. Joshi et al. [15] investigated the AI based methods for the diagnosis of bone fractures and found that the higher accuracy of detection/diagnosis can be achieved using correct testing/training datasets. Experimental results show it outperforms as compared to traditional schemes. However, its classification model can be further improved using labeling and it can also be extended for the diagnosis of other injuries

4. Fuzzy Based Knee Injury Classification

Fuzzy logic can be used for injury classification which is explained below:

Fr: feature

Inp: Input Image of knee injury

Tinp: Input image used for training

Cl: class of a given feature Fr

Fset: Feature Set

Define Cl->fset{Fr0, Fr1,……Fni}

If (exists(Inp-Fni, Cli->fset{}) then

Cli->Th++

Update (Th_List)

End if

If exists(Inp->Fri, Cli->fset{}&&Inp->Fri,, ClnCli-

>fset{})

Add(Fri, Idleset{}

ElseIf exists(Inp->Fri, Cli,)

Add(Fri, Cliset{}

ElseIf exists(Inp->Fri, Cln,)

Add(Fri, Clnset{}

End if

As per the above steps, first of all, a training set is used to define standard features and their classes for the classification process and later on, for each input image, feature set is matched against existing feature set and finally, a decision is made for classification category.

If a feature set belongs to several classes, then input image is marked as idle case and so on. Following rules are used for diagnosis:

Rule: If (Fri, Idleset{}, True) then Inpcategory is idle

Rule:If (Fri, Cliset{}, True) then Inp category is Cli

Rule:If (Fri, Cliset{}, True) then Inp category is Cln

For each (Inp, Idle)

Rule:No diagnose rule is defined for this category

End for

For each (Inp, Cli)

Rule: Agent->Recommendation(Inp, Diagnosis)

End for

For each (Inp, Cln)

Rule: Agent->Recommendation(Inp, Diagnosis)

End for

5. Automated decision making for knee injuries

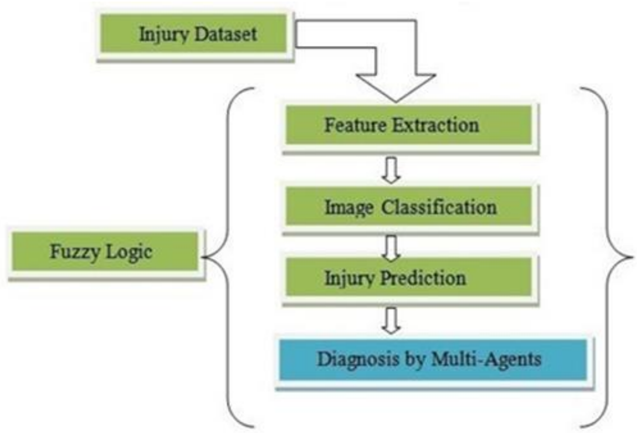

Fig.3. Fuzzy Logic based injury diagnosis

Figure 3: above shows the various steps of the fuzzy based knee injury classification method. Mrnet knee injury dataset was used for experiment purpose.

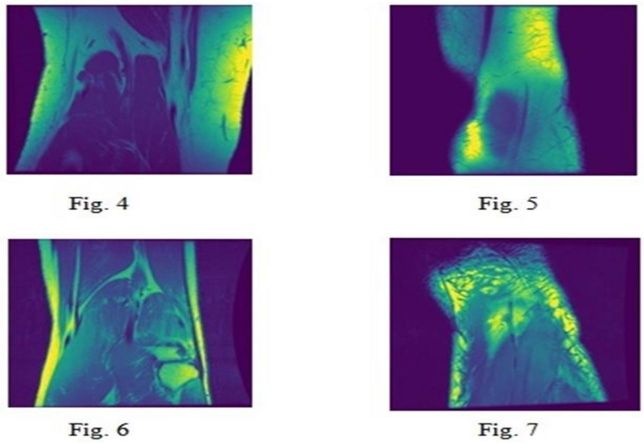

Fig.4. sample image of Non-ACL injury type, Fig.5. sample image of ACL injury type, Fig.6. sample image of Non-MNL injury type, Fig.7. sample image of MNL injury type

Following are its steps:

1 First of all knee injury types are categorized in to different cases i.e. Anterior Cruciate Ligament (ACL) and Meniscal Tears (MNL) etc.

2 A training set is prepared for each injury type

3 Features of input images are extracted using following methods :

a) Scale-Invariant Feature Transform (SIFT): This method builds key points, called features and which are independent from the image orientation can be utilized for object detection/classification etc.

b) Speeded-Up Robust Features (SURF): It is upgraded version of SIFT method. It uses wavelets to locate the features on the basis of pixel attributes (i.e. contrast/brightness etc.). Identical features are marked as matched and vice versa.

4 On the basis of extracted features a fuzzy logic based image classification process is initiated to identify the type of injury and finally a decision list is produced for the prediction of injury type.

5 As per the detected injury type, multi-agent can generate the treatment plan

Table 1: Configuration for Analysis

Open Knee Injury Dataset	**MRnet**
Training Samples	ACL: 100 MNL: 100
Input samples for experiments	1130
Environment	Linux Platform, Python OpenCV4.x, JADE

Knee Injury Type: ACL/Non-ACL

Table 2: Fuzzy Values for image classification using SURF method

SURF	CLASSIFICATION-I	CLASSIFICATION-II
1	0.49	0.51
2	0.55	0.45
3	0.56	0.44
4	0.52	0.48
5	0.51	0.49
6	0.51	0.49
7	0.5	0.5
8	0.58	0.42
9	0.54	0.46
10	0.5	0.5

Table 3: Fuzzy Values for image classification using SIFT method

SIFT	Classification-I	Classification-II
1	0.5	0.5
2	0.5	0.5
3	0.54	0.46
4	0.51	0.49
5	0.5	0.5
6	0.5	0.5
7	0.5	0.5
8	0.53	0.47
9	0.51	0.49
10	0.5	0.5

Table(s) shows some sample output generated by fuzzy logic using SURF/SIFT methods. Higher value in columns shows that image falls in specific category i.e. for S.No. 1, input image falls in classification-II

Knee Injury Type: ACL/Non- Meniscal Tears (MNL)

Table 4: Fuzzy Values for image classification using SURF method

SURF	CLASSIFICATION-I	CLASSIFICATION-II
1	0.49	0.51
2	0.55	0.45
3	0.56	0.44
4	0.52	0.48
5	0.51	0.49
6	0.51	0.49
7	0.5	0.5
8	0.58	0.42
9	0.54	0.46
10	0.5	0.5

Table 5: Fuzzy Values for image classification using SIFT method

SIFT	Classification-I	Classification-II
1	0.5	0.5
2	0.5	0.5
3	0.54	0.46
4	0.51	0.49
5	0.5	0.5
6	0.5	0.5
7	0.5	0.5
8	0.53	0.47
9	0.51	0.49
10	0.5	0.5

Table(s) shows some sample output generated by fuzzy logic using SURF/SIFT methods. Higher value in columns shows that image falls in specific category i.e. for S.No. 1, input image falls in classification-II

Knee Injury Type: ACL/Non-ACL

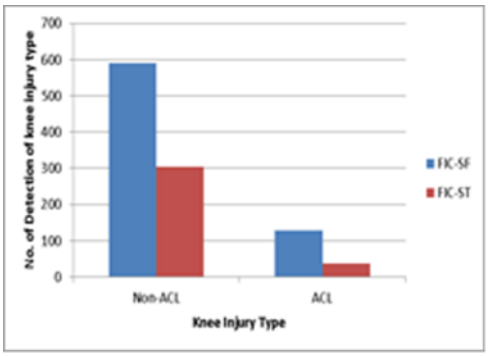

Fig.8. No. of detections of knee injury type: ACL

As shown in Figure:, in case of FIC-SF, Non-ACL injury cases are 590 whereas ACL cases are only 128 where as in case of FIC-ST, 304 are Non-ACL injury cases and 38 are ACL injury cases.

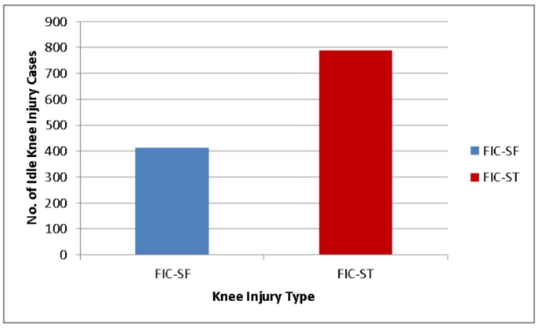

Fig.9. No. of idle knee injury cases

Figure shows that out of 1130 injury cases, 412 cases fall in idle category using FIC-SF where as it is 788 using FIC-ST.

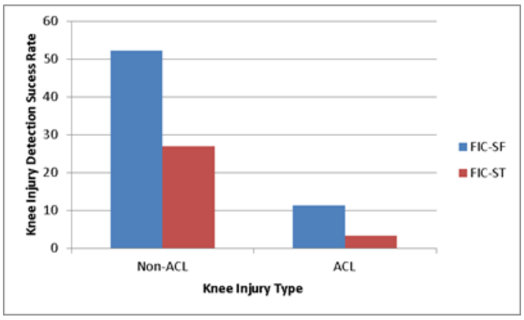

Fig.10. Success rate of Knee injury detection (ACL)

As shown in Figure, In case of FIC-SF, success rate of Non-ACL injury detection is 52.21238938 and it is 11.32743363 for ACL injury detection (outof 1130 total cases).

In case of FIC-ST, it is 26.90265487 for Non-ACL injuryand 3.362831858 for ACL injury.

Knee Injury Type: ACL/Non- Meniscal Tears (MNL)

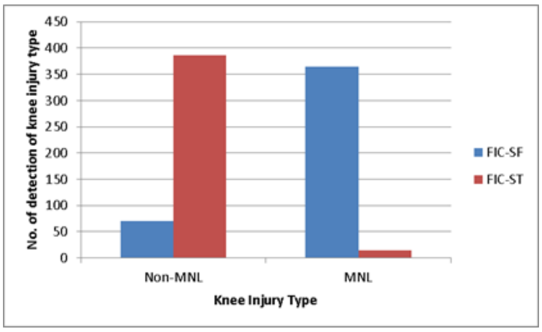

Fig.11. No. of detections of knee injury type: MNL

As shown in Figure:, in case of FIC-SF, Non-MNL injury cases are 70 whereas MNL cases are only 364 where as in case of FIC-ST, 386 are Non-MNL injury cases and 14 are MNL injury cases.

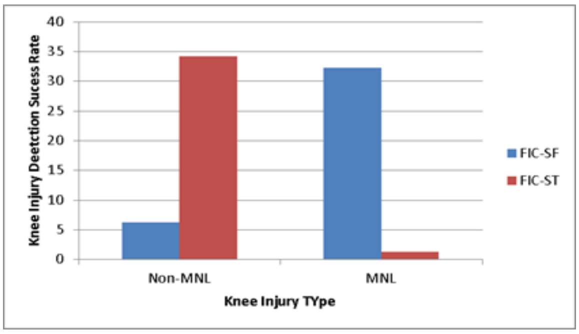

Fig.12. Success rate of Knee injury detection (MNL)

As shown in Figure, In case of FIC-SF, success rate of Non-MNL injury detection is 6.19469 and it is 32.21239 for MNL injury detection (out of 1130 total cases).In case of FIC-ST, it is 34.15929 for Non-MNL injury and 1.238938 for MNL injury.

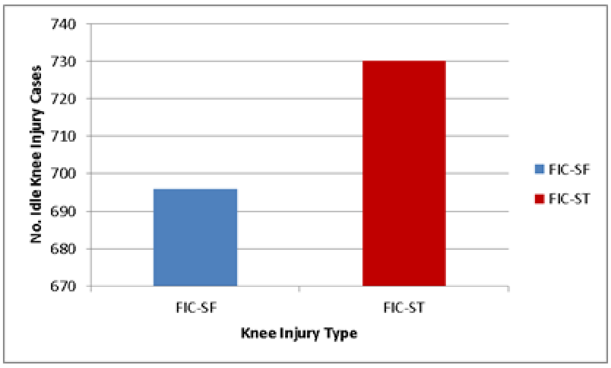

Fig.13. No. of idle knee injury cases

Figure shows that out of 1130 injury cases, 696 cases fall in idle category using FIC-SF where as it is 730 using FIC-ST

6. Conclusion

In this paper, issues and solutions related to the automated disease detection and diagnosis are explored and a fuzzy based knee injury classification method is presented. It utilizes the feature detection methods (SURF/SIFT) and finally, output data is used for the knee injury classification of the input sample.

Performance of FIC-SF and FIC-ST was compared using different parameters i.e. number of detection of knee injury type. Results show that in case of ACL, FIC-SF outperforms as compared to FIC-ST.

FIC-SF also offers higher success rate for both categories (Non-ACL/ACL) whereas it is lowest for FIC-ST.

There are few idle knee injury cases using FIC-SF where as it is highest for FIC-ST.

In case of MNL, FIC-ST has the higher detection/success rate of Non-MNL cases as compared to FIC-SF but it is lowest for MNL cases. However, number of idle cases is higher as compared to FIC-SF.

Finally, it can be concluded that comparison study shows that if fuzzy logic is compatible with SURF than better results can be obtained in contrast of SIFT method. However, it can also be observed that performance feature extraction method varies with each knee injury type and it may affect the decision making of diagnosis agents.

In future, contribution made in this paper can be further extended for other injury types as well as for disease detection and automated diagnosis process.

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