Fuzzy-Based X-RAYClassificationSystem using GLCM Feature Extraction

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Abstract— In recent research, high-precision monitoring, big data, and medical diagnosis continue to face issues caused by transit delays. To assist in addressing this issue, we designed and developed a novel fuzzy logic-based algorithm. Currently, a high-accuracy automated method is built to detect abnormalities in X-ray images. Order to obtain high accuracy while using a limited amount of system resources, pre-processing image methods are employed to improve the quality of medical images. Among the processes involved in image pre-processing are noise reduction and contrast enhancement, both of which contribute to the provision of an immediate anomaly diagnostic system.In this research, we have proposed a Fuzzy-BasedClassification System using GLCM Feature Extraction. This approach classifies the X-ray images.The musculoskeletal radiographs (MURA) dataset is divided into two categories normal and abnormal.We also investigated evaluation metrics and also loss over epochs, evaluated using a confusion matrix, and presented graphs of the membership functions trained by the model.

Keywords—FuzzySystem; GLCM, MURA, Bone Fractures

I. INTRODUCTION

In today's world, these models have undergone extensive training and have acquired remarkable levels of accuracy. However, a characteristic used for classification cannot be an exact match to a crisp value, i.e., there is some degree of fuzziness in the data[1]. The GLCM (Gray Level Co-occurrence Matrix) texture characteristics are commonly employed in image classification challenges because of their high dimensionality and low cost. The grey level GLCM provides the second-order statistical data about grey levels between adjacent pixels in the image[2]. Some of the sophisticated characteristics are used to detect things that people are incapable of detecting on their own without the assistance of the automatic system. When it comes to machine intelligence, the new coming age of intelligent machines offers radiologists tremendous assistance in their clinical processes.

A. Intelligent (IS) systems

An intelligentsystem, often known as image interpretation software, is a vital tool for supporting radiologists in the image interpretation process. Since the 1980s, it has gained in prominence and has developed into a significant field of computer science study, resulting in a large number of published articles as well as several software systems[3]. There are many anatomical variations for each unique patient; as a result, one of the essential issues in radiograph projection is the presence of superimposed structures, which is one of the most serious problems.

While using conventional X-ray equipment that has poor service and maintenance with increased availability of digital X-ray imaging technology, producing higher diagnostic is becoming simpler. The emergence of fuzzy-based computer-aided detection (CAD) technologies for interpreting has addressed not just intra and inter-reader variability among radiologists but also the issues that arise when they are not present. Thus, automated anomaly identification in X-ray images aids the radiologist in the diagnosis of a variety of clinical conditions such as lung cancer, tooth decay, etc.

II. RELATED WORK

In[4], the authors have focused onGLCM texture features in 1973. Most researchers widely use it formedical image classification.The goal of this [5] study is to look into using the GLCM approach as an absolute picture quality assessment. The fundamental concept is that picture quality may be established via a comparison procedure in which a series of photos are compared to each other to find the point of diminishing returns. In [6], authors have focused on the femur's bone fracture detectionusing GLCM features. In [7],authors have proposed a fusion-classification approach to detecttiba bones fracture in the year 2011. In [8],the authors have designed a pelvic fracture classification using hierarchy. In [9],authors have designed edge recognitionin X-ray data using canny and Sobel filters. In [10],the authors have designed the fuzzy and AHP methodologies in the construction of a medical diagnostic system, which includes the fundamental symptom of malaria patients.In [11],the research seeks to diagnose breast cancer using three distinct forms of Fuzzy based Decision Trees (Stable, ordered, and non-ordered). In [12] this paper, the author proposes iFCM (intuitionistic fuzzy cognitive map), which extends the current fuzzy cognitive map (FCM) to decide medical decision-making.In [13] authors have design a viable Decision Support System framework based on Multi Agent System and Intuitionistic Fuzzy Logic that may be used in the healthcare field.The authors of [14] have designed a fuzzy-based expert system for lung disease identification.

III. PROPOSED WORK

The suggestedresearch methodology consists of three major phaseslisted below:

1) X-ray image-Preprocessing,
2) GLCM Features Extraction,
3) Fuzzy-basedClassification Model.
The block-digramfor the suggested modelis in Figure.1.

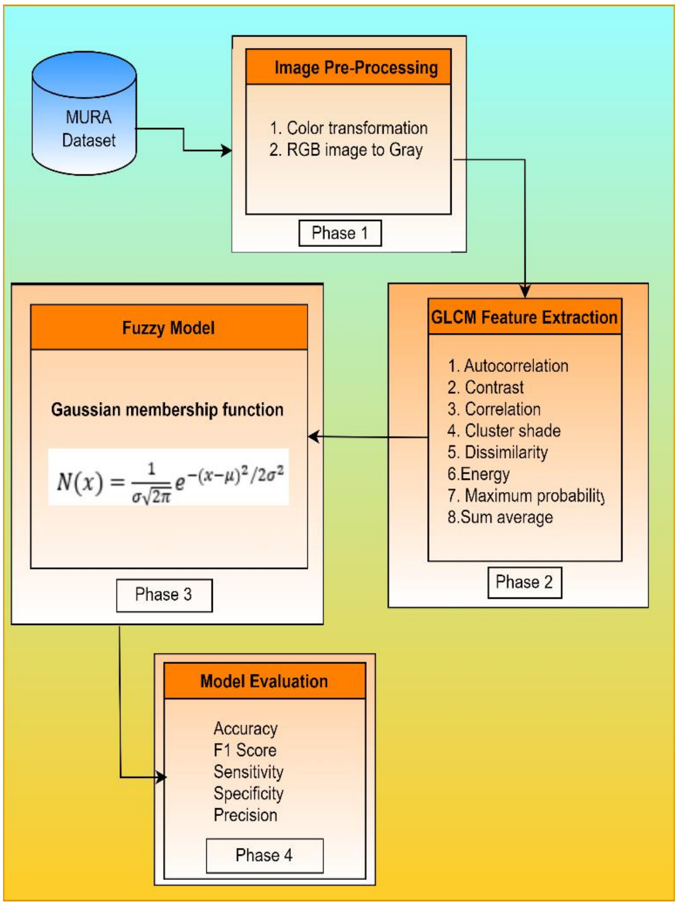

Figure 1: The blockdiagramfor the suggested model

A. *Image Pre-processing*

- The medical image is essentially treated during the pre-processing phase to reduce distortion caused by noise and to improve the vital details in the original x-ray data. The primary goal is to integrate color transformation techniques such as converting RGB images into Grayscale, using red layer details, and improving image contrast level, among other things.

- *Color transformation*:The luminosity technique is used in which blue layer 0%,green layer 0%, red layer 100% portion is used.

- *Contrast Enhancements:*The most crucial step of pre-processing is to remove undesirable distortion signal (noise) and improve image contrast. The CLAHE (contrast limited adaptive histogram equalization) approach improves the contrast quality of X-ray images.

Figures 2 and 3 show the original and enhanced X-ray images.

Figure: 2 Orignal Image

B. *Feature Extration*

The feature extraction from X-ray data is a critical component of our suggested model. The GLCM-based texture features the phenomenon of neighbouring grey level co-occurrence matrix and its frequencies in the X-ray data. These featuresare computed using a matrix evaluation on the selected dimensions of grey levels in the X-ray data. In the current work, eight characteristicsfeatures were retrieved; a description of featuresis provided below.

Figure: 3 CLAHE based enhancement

Let C bethe co-occurrence data-matrix of the Z dimension,and x, y are the coordinates of the object.

*Autocorrelation (AC):*The ACdefines the fitness and roughness of the texture features in the picture. The autocorrelation approach displays valleys and peaks in X-ray images with smooth or normal surfaces.Equation 1 provides the description of the "AC"feature.

$$P(x,y)=\frac{\sum_{a=0}^{N}\sum_{b=0}^{N} I(a,b)I(a+x,b+y)}{\sum_{a=0}^{N_g-1}\sum_{b=0}^{N_g-1} I^2(a,b)} \quad (1)$$

*Contrast (Con):*The Con measures the intensity of each pixel and its neighbours throughout the image. It also determines the number of regional differences present in the picture.Equation 2 provides the description of the "Con"feature.

$$Con=\sum_a\sum_b|a-b|^2 p(a,b) \quad (2)$$

- Correlation (CR): An image's correlation measures, how a pixel is associated with its adjacent pixels across the entire picture. The correlation value ranges from -1 or 1.Equation 3 provides the description of the "CR"feature.

$$CR = \sum_a \sum_b \quad (3)$$

- Cluster shade (CS): The CS feature assesses the skewness of the GLCM matrix and is a notion of picture homogeneity. A higher value suggests that there is asymmetry.Equation 4describesthe "CS"feature.

$$Sha = \sum_{a=0}^{N_g-1} \sum_{b=0}^{N_g-1} (a + b - u_x - u_y)^3 \quad (4)$$

- Dissimilarity (DS):It calculates the grey level average variance in the image distribution. A higher value indicates a more considerable discrepancy in intensity levels between neighbouring pixels. Equation 5 provides the description of the "DS"feature.

$$DS = \sum_a \quad (5)$$

- *Energy (Ene):*The Ene is the degree of pixels pair repetitions. It is the measuring of irregularity in texture in input data.Equation 6 provides the description of the "Ene"feature.

(6)

- *Maximum probability (MP)*: The MP measures the maximum probabilityfor generating the pixels of interest. Equation 7describesthe "MP"feature.

$$MP = max.p(a, b) for \quad (7)$$

- *Sum average (SA):*The SA feature computes the average of the X-ray grey Scale sum distribution. Equation 8 provides the description of the "SA"feature.

(8)

*C. Fuzzy Classification Model:*The term "membership function" refers to a mathematical function that determines the degree to which an element is included in a fuzzy collection of elements. Rather than describing difficulties in terms of correlations between exact numerical values, this theory provides a more natural representation of problems using language concepts. The Gaussian membership function is the most extensively utilised of the membership functions available today.Other membership functions, such as the Generalized Bell membership function, the Triangular fuzzy number, the Trapezoidal fuzzy number, and others, may be used in addition to the one described above.

$$N(x) = \quad (9)$$

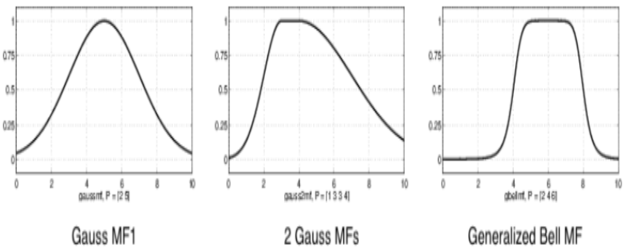

Figure 4: Membership function

IV. RESULTS

Simulation of the suggested approach is divided into three primary phases: data pre-processing, featureextraction, and the fuzzy-classificationmodel, which is all shown in Figure 1.The first two phases, image pre-processing and feature-extraction, were carried out in the MATLAB R2017 environment, while the last portion, fuzzy classification, was carried out in the Python 3.0 environment.

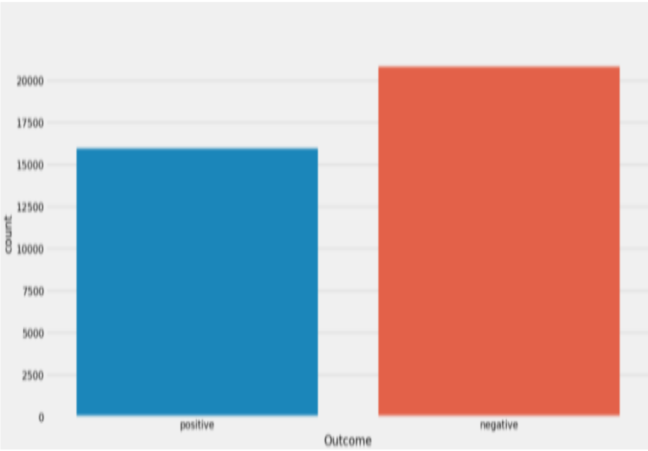

Figure 5: Dataset positive and negative count

The above Figure 5showsboth negative (20828) and positive (15942) records count from MURA[15] database in a total of 36770 records.The next step proposed model is to split the dataset into train set (67%) and test (33%). In the suggestedapproach total seven number of (GLCM)features were extracted from the inputdata. Features like autocorrelation, contrast,correlation, dissimilarity, Energy,cluster shade,and Maximum probability.

The fuzzy layer contains ab nodes (where a is the number of fuzzy rules and b is the number of input features). For every input feature x (x = 1, 2, . . . , n) there are nodes any wherey= 1, 2, . . . , m. The Gaussian membership function (8) is used in the proposed model.µ is trainable parameters, and σ 2 is variance; both are applied to the input features to generate the output. The weights of µ, σ were randomly assignedfor normal distribution. A total of 14 rule sets are generated.The model was trained and tested for 1000 epochs. Table 1 shows the confusion matrix for both trained and tested.

Table 1: Confusion matrix (i) Train (ii) Test

n=24635	Predicted Yes	Predicted No
Actual Yes	9235	1446
Actual	2251	11703

n=12135	Predicted Yes	Predicted No
Actual Yes	3575	1686
Actual	666	6208

No		

(i)

No		

(ii)

Using five statistical metrics, such as accuracy[16](ACC), precision (PPV), sensitivity (TPR), specificity (SPC), and F1 score (F1) is consider for X-ray abnormality detection.

$$TPR = \alpha / (\alpha + \beta) \quad (9)$$

$$SPC = \gamma / (\lambda + \gamma) \quad (10)$$

$$PPV = \alpha / (\alpha + \lambda) \quad (11)$$

$$ACC = (\alpha + \gamma) / \text{Total Number} \quad (12)$$

$$F1 = 2\alpha / (2\alpha + \lambda + \beta) \quad (13)$$

Where $\alpha$is referredto as true positive means, X-ray data that are labeledpositive and model predicts as same. $\gamma$is referred to as true negative means, X-ray data that are labeled negative and model predicts as same.$\lambda$is referredto as false positive X-ray data that are labeled positive, but the model predicts the opposite.$\beta$is referred to as false-negative means, X-ray data that are labeled positive and model predicts as same. Figures 5 and 6 represent the accuracy and loss over epochs.

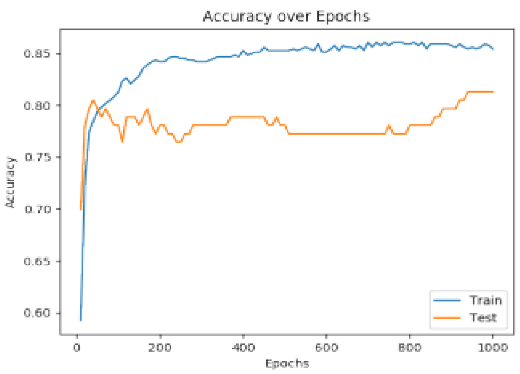

Figure 6 Accuracy over epochs

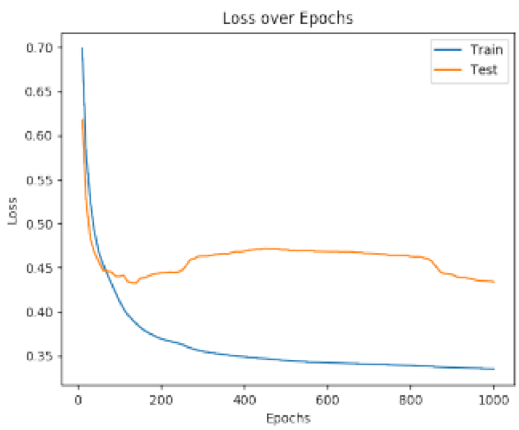

Figure 7 Loss over epochs

Table 2:Compraisionof previous research work.

Measure	Yadav et.al [17]	Proposed		Improvement
		Train	Test	
ACC	0.62	0.8499	0.8062	+30.03%
F1	0.4472	0.8332	0.7525	+68.26%
PPV	0.6055	0.8646	0.6796	+12.23%
TPR	0.3545	0.8040	0.8430	+137.79%
SPC	0.8232	0.8900	0.7864	-4.47%

We estimated the performance metrics in Table 2 based on the confusion matrix of the suggested model.The suggested modelattained a trainingaccuracy of 0.8499 and test accuracy of 0.8062,train F1 score 0.8332 and test F1 score 0.7525, train precision 0.8646 and test precision 0.6796, trainsensitivity 0.8040 and test sensitivity 0.8430, and train specificity 0.8900 and test specificity 0.7864. Table 2 shows the improvement from the previous research work done.In [17] author has demonstrated the result based on the test set; we have compared our result with the same. The improvement achieved accuracy by +30.03%, F1 score by, precision by +68.26%, sensitivityby 137.79%,and specificity by -4.47%.

V. CONCLUSION AND FUTURE SCOPE

The problem undertaken in this paper is abnormality detection of the Bone fracture X-ray image. A three-part solution is proposed for the issue, which includes pre-processing, feature extraction, and fuzzy classification. A totalof eight GLCM texture features are extracted and further used for the evaluation of the proposed model. It was observed that the proposed model had a training accuracy of 0.8499 and a test accuracy of 0.8062, a train F1 score of 0.8332 and a test F1 score of 0.7525, a train precision of 0.8646 and a test precision of 0.6796, a trained sensitivity of 0.8040 and a test sensitivity of 0.8430, and a train specificity of 0.8900 and a test specificity of 0.7864. Overall the proposed model shows significant improvement.However, by experimenting with alternative feature sets, there is still the possibility of improving performance.

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