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TEXTURE FEATURE EXTRACTION WITH MEDICAL IMAGE USING GLCM AND MACHINE LEARNING TECHNIQUES

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Abstract

Bones are a vital component of the human body. Bone provides the capacity to move the body. Humans have a high rate of bone fractures. The X-ray image is used by the doctors to identify the fractured bone. The manual fracture identification technique takes a long time and has a high risk of mistake. Machine learning and artificial intelligence are critical in resolving difficult difficulties in clinical imaging. Both medical practitioners and patients benefit from machine learning and artificial intelligence. Nowadays, an automatic system is built to detect abnormalities in bone X-ray pictures with great accuracy. To achieve high accuracy with limited resources, image pre-processing methods are employed to improve the quality of medical images. Image pre-processing entails steps such as noise removal and contrast enhancement, resulting in an instantaneous abnormality detection system. In image classification challenges, the Gray Level Co-occurrence Matrix (GLCM) texture features are commonly utilised. The second order statistical information about grey levels between nearby pixels in an image is represented by GLCM. In this work, we used various machine learning algorithms to categorise the MURA (musculoskeletal radiographs) dataset's bone X-ray images into fractures and no fracture categories. For anomaly detection, the four different classifiers SVM (support vector machine), Random Forest, Logistic Regression, and Decision tree are utilised. The aforementioned abnormality detection in X-ray pictures is evaluated using five statistical criteria, including Sensitivity, Specificity, Precision, Accuracy, and F1 Score, all of which indicate considerable improvement.

Keywords:

Machine Learning, GLCM, SVM, Random Forest, Logistic Regression, Decision Tree, MURA, Bone Fractures

1. INTRODUCTION

In the human body, bones occur in a range of forms and sizes. Bone fractures are most commonly caused by a car accident or a bad fall. The risk of bone fractures is higher in older adults because their bones are weaker. [1]. When the patient receives proper treatment, the fracture bone heals. The fractured bone is diagnosed using an x-ray or an MRI (Magnetic Resonance Imaging) imaging. [2]. The doctor will have a difficult time analysing the small fracture in the bone. The manual technique for diagnosing a broken bone takes a long time and has a high chance of inaccuracy. As a result, developing a computer-based method to reduce the time and risk of error in fracture bone detection is essential. [2]. Machine learning techniques that have recently emerged are frequently used in medical imaging and power electronics. The computer-based approach uses an x-ray or MRI image to accomplish the fracture bone diagnosis. [3]. There is noise in the bone image. To eliminate noise and edges from the image, a suitable pre-processing technique is utilised. Then, from the bone image, features are retrieved. Finally, the model was trained with the features, and the ML (machine learning) algorithms do the classification.

Medical image analysis is a difficult process for physicians to complete since it requires them to employ all of their skills, knowledge, and imaging techniques. The automatic detection of abnormalities in clinical X-ray images is a difficult topic in the field of machine learning. Each patient has a wide range of anatomical variations. As a result, one of the most essential challenges in the projection of radiographs with superimposed structures is this. The radiologist uses their ability and experience to examine an X-ray image with the purpose of detecting a fracture in the bone. The clinical image acquired via the image capture tool is of poor quality, making it difficult for the medical practitioner to spot the anomaly. To address this issue, an effective automatic computer-aided detection method is being developed. As a result, the radiologist can diagnose a variety of clinical concerns such as arthritis, tooth decay, bone cancer, osteoporosis, fracture, and infection using the automatic anomaly detection of X-ray images.

A musculoskeletal radiograph (MURA) is a large collection of X-rays of the bones. It is up to the computations to determine whether Xray images are normal or abnormal. Musculoskeletal disorders affect more than two billion people worldwide and are the most widely recognised cause of serious, long-term pain and incapacity, with 30 million crisis division visits each year. The MURA dataset could lead to significant advances in medical imaging, such as analysing the dimensions of specialists in the context of changing social insurance. MURA is one of the greatest significant open radiography normal and abnormal X-ray datasets, with a whole of 36770 images, 20828 of which are normal and 15942 of which are abnormal, with a ratio of 56.64 percent normal and 43.36 percent abnormal.

In this paper texture features are extracted using Gray Level Co-occurrence Matrix (GLCM) and shape features are extracted using linked regions. The planned method for feature extraction is described in section 3. Results found by most changed effort images are given is section 4. Finally, conclusion is provided in section 5.

2. RELATED WORK

Naveed Iqbal [4] From the underlying grey scale photos gathered by the drone, grey level co-occurrence matrix (GLCM) based characteristics are retrieved. ML methods such as Random Forest (RF), Naive Bayes (NB), Neural Network (NN), and Support Vector Machine (SVM) are used to classify different types of crops. The results showed that ML algorithms performed substantially better on GLCM features than grey scale photos, with an overall accuracy margin of 13.65%.

Leonardo Rundo [5] proposed CHASM, a new method that combines two CUDA-based computationally efficient methodologies capable of harnessing the power of contemporary GPUs: (i) HaraliCU, which is used for Haralick features extraction and allows for GLCM computation to be accelerated while maintaining the full dynamic range in medical images; (ii) CUDA-SOM, which is used for unsupervised image pixel clustering and reduces running time by leveraging the parallelization of the network's learning process. A dataset of ovarian cancer CT scans was used to evaluate their system. On their dataset, they achieved speedups of up to 19.50 with HaraliCU and up to 37 with CUDA-SOM using the GPU during the two most computationally demanding steps of the pipeline, compared to the CPU version coded in C++.

The Gray Level Co-occurrence Matrix (GLCM) was proposed by Mireille Pouyap [6] in texture analysis and applied to the vibration signal recorded in images. To acquire the most relevant features, a grouping of the PCA (Principal Component Analysis) and SFE (Sequential Features Extraction) methods is used to choose features. The proposed approach is put to the test using a multiclass-Naive Bayes classifier. This classification has a success percentage of 98.27 percent. The relevant properties discovered produce promising outcomes and are more efficient than existing methods.

Dian Li [7] offer a unique iris anti-counterfeit detection approach based on a binary classification neural network and an upgraded Gray Level Cooccurrence Matrix (Modified-GLCM). The experimental findings reveal that the suggested method outperforms the best result of LivDet-Iris2017 and the traditional texture analysis methods employing feature statistical features. Furthermore, using iris texture extraction, they analyse and evaluate the possible threat of the iris adversarial sample on the iris performance spell finding system.

Padmavathi [8] seeks to extract textural features from brain tumour instances and classify them as benign or malignant. Segmentation, feature extraction, and classification are the stages involved. For segmentation and selection of the appropriate region of interest, the K-means clustering method is preferred. GLCM, HOG, and LBP patterns are used to gather textural information from a region of interest. The performance accuracy of ANN, SVM, and k-NN classifiers in classifying tumour data into kind and hateful states in brain MR images is investigated. By successfully combining a combination of GLCM, LBP, and HOG feature extraction processes, ANN with LM training algorithm gives high accuracy and best performance compared to other two classifiers in recognising benign and malignant states of tumours.

Barburiceanu [9] offer a texture feature extraction technique with increased discrimination power for volumetric pictures. The technique could be used to classify textured volumetric data. They do so by combining two complimentary types of data: feature vectors obtained from Local Binary Patterns (LBP) and Gray-Level Cooccurrence Matrix-based techniques. The Support Vector Machine, k-Nearest Neighbours, and Random Forest classifiers were utilised. Their method outperforms traditional deep-learning networks and other custom 3D or 2D texture feature extraction methods. Even with a modest number of photos per class, the proposed technique improves discrimination power and yields encouraging results.

Priyanka [10] Followed that, GLCM is used to generate a number of second order statistical texture features such as energy, entropy, homogeneity, correlation, contrast, and dissimilarity. Using principal component analysis, the resulting characteristics are finally reduced to an ideal subset (PCA). When utilising Artificial Neural Networks to categorise images, the results reveal that GLCM combined with PCA for feature reduction yields good classification accuracy (ANN).

3. PROPOSED METHOD

The X-ray/CT scans are collected from the hospital and include images of normal and fractured bones. The first stage involves using pre-processing techniques like RGB to grayscale conversion and improving them with a filtering algorithm to remove noise from the image. It transforms each image into a set of features using some feature extraction approach after pre-processing. The classification method is then built using the extracted features. Finally, the suggested system's performance and accuracy are assessed.

MURA is a large dataset of radiographs that contains 14,863 upper extremity musculoskeletal studies. Each research has one or more views (images) that are manually labelled as normal or abnormal by radiologists.

An important radiological task is determining whether a radiographic examination is normal or abnormal: a study assessed as normal rules out disease and can save patients from having to undergo additional diagnostic tests or treatments. The problem of detecting musculoskeletal abnormalities is especially important because musculoskeletal diseases impact over 1.7 billion people globally. With 30 million emergency department visits every year and rising, these illnesses are the most common cause of acute, long-term pain and impairment. The MURA dataset includes 9,045 normal and 5,818 aberrant musculoskeletal radiography investigations of the shoulder, humerus, elbow, forearm, wrist, hand, and finger. MURA is one of the greatest comprehensive public radiography image databases available.

On a holdout test set of 207 trials, we obtained six more labels from board-certified radiologists to evaluate models robustly and derive an estimate of radiologist performance. On MURA, we trained a baseline model for abnormality detection. One or more opinions for an upper extremity study are fed into the model. A 169-layer convolutional neural network expects the chance of abnormality for each view, and the per-view probabilities are then averaged to produce the study's probability of abnormality.

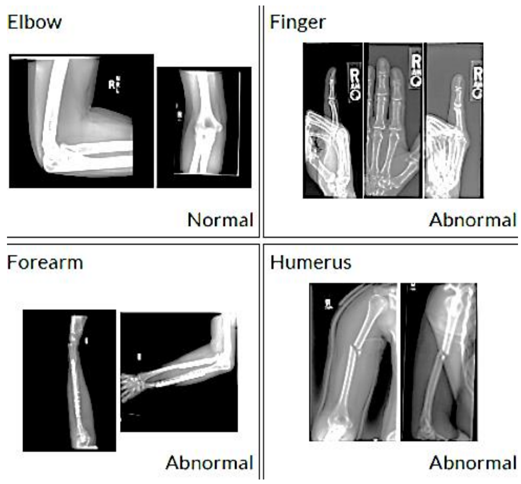

Fig.1. MURA dataset

The Fig.1 contains 14,863 upper extremity musculoskeletal investigations, each of which contains one or more views and is manually categorised as normal or abnormal by radiologists. A normal elbow study (left), an abnormal finger study with degenerative alterations (middle left), an abnormal forearm study (middle right) displaying operative plate and screw repair of radial and ulnar fractures, and an abnormal humerus study with a fracture are shown in these cases (right)

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The model's ability to detect anomalies on finger and wrist tests is on par with the top radiologist. Model performance in detecting abnormalities on elbow, forearm, hand, humerus, and shoulder investigations, on the other hand, falls short of that of the best radiologist. We made our dataset openly available to encourage breakthroughs in medical imaging models.

3.1 SHORTCOMINGS OF GLCM ON FEATURE EXTRACTION

This paper takes the gray level co-occurrence matrix as the research basis for feature extraction. GLCM was first proposed by Haralick [17] and is a statistical method to describe the texture characteristics of images. It calculates the statistical characteristics of the image texture by studying the gray-level relationship between the pixel unit in the gray image and its neighborhood pixels, that is, it uses the statistical gray-level relationship between adjacent elements to represent the texture. And it's often used for studying the texture features by calculating its own statistical features.

It is a two-dimensional matrix of $H\times H$, where H is the largest gray level in the gray-level image. GLCM has four calculation instructions (horizontal, vertical, left diagonal, right diagonal). The calculation direction selected in the Fig.is the horizontal direction, namely GLCM (i,j) represents the occurrence frequency of a pair of element pairs with pixel values i and j that satisfy the horizontal adjacent relationship in the gray-level image.

From the calculation process of GLCM, it can be seen that the calculation of GLCM is very simple. Meanwhile, it also has statistical features that relevantly describe the thickness, size, and sharpness of the texture. All above these advantages make GLCM a simple and efficient method to describe the texture of the image. However, the limitations of GLCM are also obvious.

First of all, from the calculation principle of GLCM, GLCM is obtained by calculating the gray-level changes of adjacent elements, which can only represent the gray-level relationship of adjacent areas. So, the direction of scale of the features is single and the range is short. In terms of iris texture, it's likely that feature information such as the high-level texture features under the large scale and the correlation between detailed textures will not be extracted. Besides, it uses several statistical features of the matrix obtained by GLCM represent some texture features of the image, separately. These textures are often just surface features that have explainable physical meaning. And more useful texture information is often not completely retained. In this way, some highly distinguished high-level image content is likely to be ignored.

3.2 MODIFIED-GLCM

As mentioned above, there is a big difference between the local iris spot of colored contact lenses and real iris. A real iris is composed of small iris spots with different sizes and shapes, while colored contact lenses are printed by combining small iris spots with very high similarity.

Therefore, if the texture features in the large scale in the image can be extracted, more combined correlation information between spot and spot can be obtained. This will be of great help for authentic iris recognition. Taking countermeasures against the existing shortcomings of GLCM and the texture characteristics of colored contact lenses, this paper proposes a modified method based on GLCM. We call it Modified-GLCM. This method can expand the texture feature scale of GLCM.

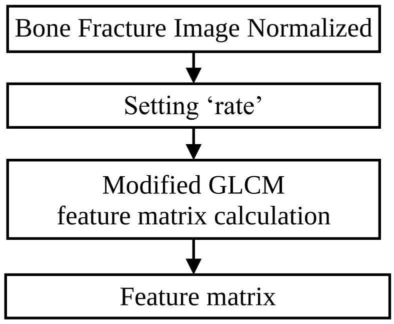
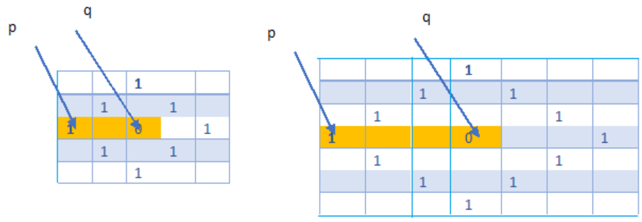


Fig.2. Calculation process of Modified-GLCM algorithm



rate $=|p_i-q_i|+|p_j-q_j| = 2$ rate $=|p_i-q_i|+|p_j-q_j|=3$

(a) rate=2 (b) rate =3

Fig.3. Distance Measurement

The Modified-GLCM algorithm is shown in Fig.2, including setting rate and Modified-GLCM feature matrix calculation. We introduce a parameter called rate to represent the scale of the features of Modified-GLCM, shown in Fig.3 rate represents the Manhattan distance [18] between two elements with gray value p and q in the gray image. The distance is expressed in L1 norm, as below:

$$\text{rate} = |p_i-q_i|+|p_j-q_j| = 2 \quad (1)$$

where i and j represent the number of rows and columns of the two elements whose gray level is p and q.

Here Modified-GLCM is no longer calculated in thesingle direction, but all element pairs that meet the scale of the features conditions are calculated. The Fig.4(a) and Fig.4(b) respectively indicate the spatial positional relationship that an element with a gray level of 1 paired with an element with a gray level of 0 when the scale of the features are 2 and 3 respectively.

The calculation of Modified-GLCM is expressed as follows.

$$\text{Modified GLCM}(p,q)=\sum_{p,q\in G}\begin{cases}1 & \begin{array}{l} if\left(\left|p_i-q_i\right|+\left|p_j-q_j\right|=rate\right) \\ \cap\left(\left|p_i-q_i\right|-\left|p_j-q_j\right|\leq 0\right)\end{array} \\ 0 & otherwise\end{cases}$$

where G means the gray level map with size of $m\times n$, p and q are the elements in the gray level map, $p\in G(G(i,j)=p, i\in(1,m), j\in(1,n))$ means the gray level of the element in G is p, $|p_i-q_i|+|p_j-q_j|$ = rate means that the elements with gray levels p and q meet the given rate.

If $|p_i-q_i|+|p_j-q_j|\leq 0$ it means that the element with gray level p is at the upper left of the element with gray level q.

An example of the calculation process of Modified-GLCM is shown in Fig.5. The occurrence frequency of element pairs that meet the scale of the features conditions is calculated statistically: for instance, Modified-GLCM (1, 1) represents the number of (1, 1) element pairs in the gray level image when rate = 2. By comparing the Modified-GLCM and GLCM obtained from the same gray level image in Fig.2 and Fig.5, it can be drawn that Modified-GLCM has a larger neighbourhood and more calculation directions than GLCM. Modified-GLCM extracts more spatial information about image textures than GLCM, and also filters out some redundant statistical values, for example, band textures in a small area with the same gray level. It can be found that (1, 1) element pairs in the horizontal direction do not participate in the calculation in Fig.5. Note that we are more concerned about the edge, shape and size information of the texture. In this way, the calculation of the internal of the band texture can be reduced.

From the calculation principle of the above algorithm, it can be drawn that Modified-GLCM has another advantage, that it has more comprehensive statistical texture information than GLCM. When rate is 3, Modified-GLCM can extract texture information in 12 directions equally divided by 360 degrees in a more balanced manner, while GLCM can only calculate one direction once. This is very favorable for complete extraction of iris texture.

4. RESULTS AND DISCUSSION

The results of the proposed methodology are categorized into three major parts: image reprocessing, feature extraction and classification. All three-parts image pre-processing, feature extraction and classification has been performed using R Studio. For RasterLayer objects in *R*, the GLCM package provides an easy-to-use method to determine such textural characteristics.

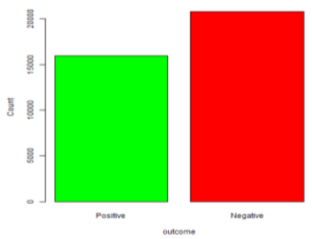


Fig.4. Total number of count positive and negative records

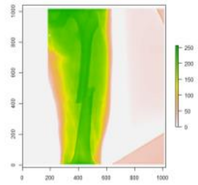


Fig.5. Most repeated value of each feature extracted

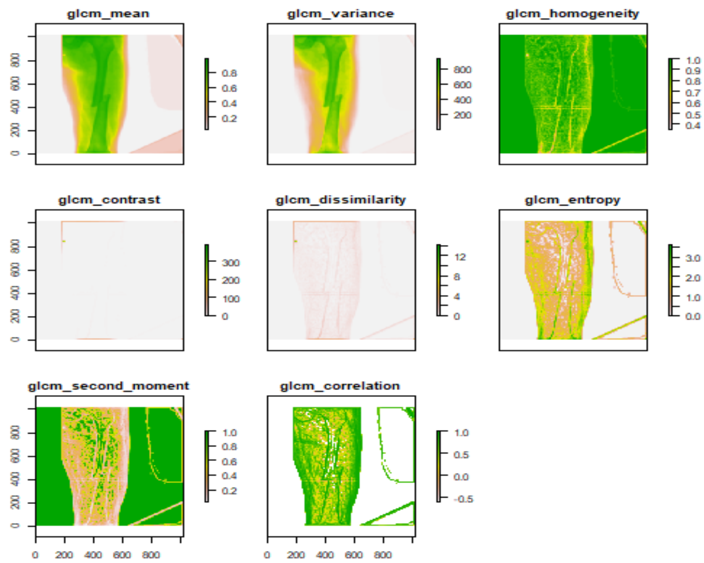


Fig.6. Graphical representation of co-occurrence matrix

The Fig.4 indicates the total number of positive and negative records of the MURA database, which contains total no of 36770 X-ray pictures out of which 15942 positive images and 20828 negative images. The proposed methodology is implemented using it. In the proposed method total, twelve number of features were extracted from an X-ray image of MURA dataset using a GLCM, above histograms (Fig.5) displays the most repeated value of each feature extracted. Features like autocorrelation, contrast, cluster prominence, cluster shade, sum of squares variance and sum average values are same less dispersed, about other features like correlation, dissimilarity, entropy, energy, maximum probability and homogeneity values are highly scattered. Heat map of 10 GLCM texture features displayed in (Fig.6) is the graphical representation of co-occurrence matrix using colour code, dark green color represents highly co-related feature and red color represent features with less co-relation direction once. This is very favourable for complete extraction of iris texture.

Through GLCM, following textural features are extracted autocorrelation, contrast, correlation, cluster importance, cluster gloom, dissimilarity, energy, entropy, homogeneity, extreme probability, sum of squares variance, and sum average is used for the classification of the X-ray images as the number of textural features increases, the performance of classifier becomes better, but it increases the computational complexity. By analysing the statistical parameters, Sensitivity, Specificity, Precision, Accuracy, and F1 Score, the classifier's performance can be evaluated. Through the proposed work, a radiologist could better identify the fractures of bone X-ray. The main objective of our proposed work is performance evaluation through different classifier algorithms with the outcomes of different textural features obtained from GLCM. One of the important steps is training the classification algorithm for which 67 % of MURA dataset and the remaining 33% dataset are used for testing purpose.

The performance evaluation of this abnormality detection in X-ray images is done using five statistical parameters such as sensitivity, specificity, precision, Negative Predictive Value, False Positive Rate, False Discovery Rate, False Negative Rate, accuracy, and F1 score.

$$\text{Sensitivity } TPR = TP / (TP + FN) \tag{13}$$

$$\text{Specificity } SPC = TN / (FP + TN) \tag{14}$$

$$\text{Precision } PPV = TP / (TP + FP) \tag{15}$$

$$\text{Negative Predictive Value } NPV = TN / (TN + FN) \tag{16}$$

$$\text{False Positive Rate } FPR = \text{FP} / (FP + TN) \tag{17}$$

$$\text{False Negative Rate } FNR = \text{FN} / (FN + TP) \tag{18}$$

$$\text{Accuracy } ACC = (TP + TN) / \text{Total Number} \tag{19}$$

$$F1 = 2TP / (2TP + FP + FN) \tag{20}$$

where true positive (*TP*) is devoted to individuals X-ray images that are positively labelled as fractured and classified as same, true negative (*TN*) is devoted to those X-ray images that are positively considered as non-fractured and classified as similar. False positive (*FP*) is devoted to the X-ray images that are considered as non-fractured but classified as fracture image. False-negative (*FN*) is referred to those X-ray images that are considered as fractured but classified as non-fracture image. For the classification of abnormality of the fracture X-ray image, several machines learning algorithm were applied such as SVM, logistic regression, Random Forest and decision tree. Above statistical performance, the measure is considered to evaluate machine learning algorithm. Sensitivity commonly known as true positive rate, specificity is the measurement of false positive rate, precision is the prediction of positive observation, accuracy correct prediction observation to the total observations, F1 Score is the measurement of a weighted average of precision and sensitivity. These five statistical presentation values were assessed using a confusion matrix (Table 1) and several machine learning techniques, with the results displayed in Table 2.

Table.1. Performance evaluation of various machine learning technique (GLCM)

Measure	**SVM**	**Random Forest**	**Logistic regression**	**Decision tree**
TPR	0.9310	0.9308	0.9029	0.7796
SPC	0.9540	0.9336	0.7960	0.8954
PPV	0.9549	0.9382	0.7793	0.8839
NPV	0.9297	0.9256	0.9113	0.7990
FPR	0.0460	0.0664	0.2040	0.1046
False Discovery Rate	0.0451	0.0618	0.2207	0.1161
FNR	0.0690	0.0692	0.0971	0.2204
ACC	0.9422	0.9321	0.8434	0.8368
*F*1	0.9428	0.9345	0.8366	0.8285

Table.2. Performance evaluation of various machine learning technique (Modified GLCM)

Measure	**SVM**	**Random Forest**	**Logistic regression**	**Decision tree**
TPR	0.9506	0.9375	0.9240	0.8270
SPC	0.9538	0.9463	0.8133	0.8884
PPV	0.9549	0.9548	0.7793	0.8839
NPV	0.9494	0.9259	0.9375	0.8333
FPR	0.0462	0.0537	0.1867	0.1116
False Discovery Rate	0.0451	0.0452	0.2207	0.1161
FNR	0.0494	0.0625	0.0760	0.1730
ACC	0.9522	0.9415	0.8594	0.8573
*F*1	0.9527	0.9461	0.8455	0.8545

Based on the confusion matrix of various classification algorithms, we have designed the performance measures, shown in Table.1 and Table.2; Modified GLCM in Table.2 the SVM classifier achieved a classification accuracy of 95.22% with sensitivity of 95.06%, specificity of 95.38%, precision of 95.49% and F1 score of 95.27, Random Forest classifier achieved a classification accuracy of 94.15% with sensitivity of 93.75%, specificity of 94.63%, precision of 95.48% and F1 score of 94.61; Logistic Regression classifier achieved a classification accuracy of 85.94% with sensitivity of 92.40%, specificity of 81.33%, precision of 77.93% and F1 score of 84.55; Decision tree classifier achieved a classification accuracy of 85.73% with sensitivity of 82.70%, specificity of 88.84%, precision of 88.39% and F1 score of 85.45%. However, among the four models measured; so, due to the visual challenges of MURA database facture detection modified GLCM with SVM shows significant development in terms of performance is encouraging.

5. CONCLUSION

The goal of this paper is to detect abnormalities in X-ray images of bone fractures. http://stanfordmlgroup.github.io/competitions/mura presented us with the MURA dataset of musculoskeletal radiographs. The fully automatic detection method is employed for the classification of fractures from the standpoint of medical practitioners and patients. The MURA dataset contains a huge number of X-ray images of poor quality and clarity, making categorization a difficult task. The method executed to solve this issue, modified GLCM texture features are extracted and further used for image abnormality detection in the X-ray image. Several machine learning algorithms considered for the evaluation of automatic detection system is as follow SVM, Random Forest, logistic regression and decision tree. Above performance, evaluation is considered to evaluate machine learning algorithm. SVM with an accuracy of 95.22%, gives the best result among the other machine learning algorithm. The experimental outcomes approve that the proposed GLCM method achieved an acccuracy of advanced than the basic GLCM method, representative over 95.22% success in texture feature. However, experimenting with alternative feature sets still has the potential to enhance performance.

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