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Classification of Long Bone X-ray Images using New features and Support Vector Machine

Amani Al-Ghraibah[1], Mohammad Algharibeh[2], Waseem AlMohtasib[3], Muneera Altayeb[4]
[1]Al-Ahliyya Amman University, Jordan, a.ghraibah@ammanu.edu.jo
[2]Private Orthopedic Surgery, Jordan, mmgh1990@gmail.com
[3]Medical Engineering Private Sector, Jordan, was2015eem@gmail.com
[4]Al-Ahliyya Amman University, Jordan, m.altayeb@ammanu.edu.jo

ABSTRACT

Bones are protecting many organs in the human body such as the lungs, brain, heart and other internal organs. Bone fracture is a common problem in human beings and may occur due to the high pressure that is applied to the bones as a result of an accident or any other reasons. X-ray (radiograph) is the noninvasive medical experiment that helps doctors diagnose and present medical conditions. X-rays represent the oldest and most often used kind of medical imagery. Medical image processing attempts to enhance the bone fracture diagnosis processes by creating an automated system that can go through a large database of the X-ray images and identify the required diagnosis faster and with high accuracy than the regular diagnosis processes. In this paper, the lower leg bone (Tibia) fracture is studied and many novel features are extracted using various image processing techniques. The purpose of this research is to use new investigated features and classify the X-ray bone images as a fractured and non-fractured bone and make the system more applicable and closer to the user using the Graphical User Interface (GUI). The Tibia bone fracture detection system was developed in three main steps: the preprocessing step, feature extraction using wavelet analysis, gradient analysis, principal components (PCA), and edge detection methods and classification using Support Vector Machine (SVM). The results were produced using four possible outcomes from the confusion matrix which are TP, TN, FP, and FN. The classification process was repeated using different feature groups at a time and the resultant accuracies were ranged between 70%-80%.

Key words: Bone fracture detection, Classification of bone fracture, Features extraction, Support Vector Machine (SVM), Tibia bone X-ray images.

1. INTRODUCTION

Tibia fractures are the most common long bone fracture accounting for more than 20% occupancy of hospital wards. On average 26 tibia fractures occur per 100,000 populations per year. Several accidents require health care experts to analyze a huge number of X-ray images and diagnose patients with the right decision. So, cases of false diagnosis may occur, where a false diagnosis is defined as either failure to see a significant fading or attaching the incorrect diagnosis that is readily seen. A higher false diagnosis rate will result in weak quality in healthcare and time-delayed treatment [1].

In 2015, Anu et al [3] extracted features using the Gray-Level Co-occurrence Matrix (GLCM) from X-ray bone images. Then, the extracted features were used to calculate the segmented image and based on these features the bone is classified whether it has a fracture or not. The presented methods in [3] work have been tested on a data set with 40 X-ray and CT images containing fractured and non-fractured (normal) images. In the feature extraction process, the GLCM features were extracted and the images were classified depending on that into normal and fractured images. The performance of their work reached 85% accuracy. The limitation of the presented method was in using CT, and some cases of X-ray images, as it was very problematic to find the area of the fracture [3].

Al-Ayyoub and his colleagues (2013) [4] considered the binary classification problem to investigate the existence of the fracture in the hand X-ray images. The dataset consisted of 98 X-ray images. They focused on Decision Tree (DT), Bayesian Network (BN), Naive Bayes (NB) and Neural Networks (NN) methods. Furthermore, as three sets of features were computed in their work, separate experiments were conducted to evaluate which set is more useful by using each set of features individually in the classification process. But the results were far from perfect and they found that one way to improve the performance of base classifiers is to combine all features and use them in classification, also they tried to use two-level meta-classifiers as it turned out that it gave the best classification results. In the final stages, different sets of features were used in the classification process, but the maximum accuracy level was 91.8% which was obtained by applying boosting and then bagging on the

Bayesian Network classifiers with the feature set that included: Wavelets, Curvelets and GLCM features [4].
In Umadevi and Geethalakshmi work [5], twelve features of two groups; the shape features and texture features were used. The texture features that were extracted from long bones X-ray images are Gray Level Co-Occurrence Matrix (GLCM) features. While the shape features were extracted using a Fast Hough Transformation algorithm. The accuracy of a single classification was evaluated using 10-fold cross-validation technique. Three binary classifiers, SVM, BPNN, and KNN were presented to build ensemble classification models. The classifiers were built with different feature sets and the presented experiments proved that a group of models can significantly improve the quality of fracture identification [5].

In 2012, Mahendran and his colleagues [6], focused on their research to build an automated system that detect fractures in long bones from diagnostic X-rays using a series of progressive steps. Three classifiers were considered which are: Back Propagation Neural Networks, Support Vector Machine (SVM) and Naïve Bayes. Also, two feature classes were collected and extracted from X-ray images, namely: texture and shape features, with a total of 11 features. In the classification part, four classifiers were merged and used to classify the X-ray images as fractured or non-fractured images. The results proved that fusion classifiers were efficient for fracture detection and reached a maximum accuracy. One difficulty encountered with fusion classification was on detecting which classifier produces the best accuracy. The researchers considered only simple fractures and the experimental results showed that the performance reduces if the fractures were parallel or perpendicular to the bone edge [6].

Mahendran et al [7] used the texture features in bone fracture detection research. Fused classifiers were proposed for fracture detection where some specific classifiers were established and work as a binary classifier, which can report if a bone fracture is detected or not. If detected, the location of the fracture is highlighted. There are mainly three classifiers: Feed Forward Back Propagation Neural Networks (BPNN), Naïve Bayes (NB) and Support Vector Machine (SVM) classifier. The fusion classifiers built from base classifiers which are (1) Texture features with BPNN, (2) Texture features with SVM, (3) Texture features with NB and (4) Texture features with BPNN, SVM, and NB. The basic fusion rule used was that if more than 2 classifiers report fracture then the image is said to have a fracture. Many experimental works were accompanied to analyze the performance of the proposed fusion classifier-based detection system concerning its efficiency in terms of correct detection and speed of the algorithm. After comparing the performance with the traditional single classification system, the suggested unification of techniques revealed that the results were improved in terms of accuracy in detecting fractures and in the speed of the detection [7].

In Myint et al (2018) work [8], suggested a Computer-Aided Diagnosis (CAD) technique to automatically recognize and localize the leg bone fracture. Many image processing techniques were used in their paper, they recognized that Harris corner detection was an effective tool to catch the broken points of the leg bone. Decision Tree (DT) was used as a simple classification for fracture and non-fracture bones. KNN was also used as it is suitable for pattern recognition and supports to classify fracture types. Fracture types such as Transverse, Oblique, Comminuted and Normal were classified by the system too. The performance accuracy concerning fracture and non-fracture were calculated and the accuracy assessment was also evaluated. Kappa accuracy assessment was used to consider the error results when calculating the performance and classifying the types of fractures. However, the system produces the output results with accurate and reliable performance and less processing time based on the contributed methods. According to the result, best accuracy achieved was 83 % using the Kappa accuracy assessment [8].

In this paper, new features were extracted from the long bone X-ray images that were discussed in our previous work [2]. An automated predicting system is built here to predict the existence of the bone fracture automatically and faster than the regular diagnosis processes. So, the motivations of our project are to reduce human errors and reduce the time and effort associated during the bone injury diagnostic process which is usually done manually by physicians. Ultimately, this system can be integrated within the software of the x-ray imaging devices to allow users to produce a rapid and highly accurate diagnosis while generating the image. So, a Graphical User Interface (GUI) is designed which enables the user to perform interactive tasks.

The novelty of this work covers two main things: using a large number of Tibia bone X-ray images and classifying the images based on new features which were investigated in our previous work depends on the physical properties of the bone images [2]. Also, Graphical User Interface (GUI) is built to enable the user to perform interactive tasks easily. Many classification processes are presented depending on the feature group used each time and a comparison between the results is also performed.

This paper is presented as follows: Section 2 explains briefly the methodology of feature extraction and image's classification. Section 3 shows the results of the classification using different feature groups and summarizes the graphical user interface (GUI) and Section 4 is the summary of this work.

2. METHODOLOGY

2.1 Feature Extraction

Recent work has analyzed and extracted new features from Tibia bone X-ray images depending on the physical properties of the bone which detects the changes of these features in the presence and absence of a fracture. Al-Ghraibah et al produced a novel method to examine whether these features are efficient in detecting bone fracture or not. They used the X-ray images of both legs of the patient (the left and right Tibia bones), taking advantage of human body symmetry, to study the performance of the extracted features in detecting bone fracture instead of directly using the classification methods [2]. Here, we extend the work in [2] and use the most significant features to build an automated classification system that classify any X-ray Tibia bone image as a fractured or non-fractured image.

Four different methods and techniques were used to describe the physical properties of the bones. These methods are: 1. wavelet analysis, 2. gradient analysis, 3. Principle Component Analysis (PCA) and 4. bone edge detection method. The efficacy of the methods was presented, and the results showed that, depending on the features changes in the presence of the fracture, the most significant features extracted from each method were summarized. Here, a brief description of each method and the most significant features are presented.

2.1.1 Wavelet features

Two-Dimensional Discrete Wavelet Transform (2D DWT) was used in image processing as a powerful tool solving to image analysis, denoising, image segmentation and other. 2D DWT is computed when the original image is convolved along x and y directions by low pass and high pass filters. The images obtained are downsampled by half the size of the original image. The resultant images are convolved again with high pass and low pass filters. The four sub-band images generated contain the approximation coefficient (which contain the maximum information of the image), horizontal, diagonal, and vertical information of the image [9,10].

The three detailed images were used to evaluate the energies of each decomposition level by adding the absolute values of the wavelet coefficients (the highpass images). Then a sum of these energies was calculated including the three highpass images as we are interested in the edge structure. From that, five energy values were extracted which are related to each of the five levels of decomposition namely: Energy level 1, Energy level 2, Energy level 3, Energy level 4, and Energy level 5. The results show that all the wavelet energies can detect the existence of bone fracture in a good way and these features can be used in further bone classification processes [2].

2.1.2 Gradient features

From the general image processing science, the spatial gradient is equivalent to the first derivative of the processed image. Gradient of the image will highlight fragments and edges that may not be noticeable in the original image. The image is filtered (convolved) with the known Sobel filters, Gx and Gy which are given by: $Gx = hx*f$ and $Gy=hy*f$ respectively, where * is the two-dimensional convolution operator, h is the filter and f is the image. To abbreviate this gradient information into single descriptors for each image, the following features were computed from the resultant gradients from each image: mean, standard deviation, maximum, minimum, skewness and kurtosis [10-12].

From the results in [2], a summary was made that the gradient features were efficient in detecting bone fracture and could be used in further bone classification processes. But it was recommended to exclude: the mean, standard deviation and minimum features, as they were less significant in detecting the bone fracture. The remaining and effective features are the maximum, skewness and kurtosis and will be used in this research.

2.1.3 Bone edge features

Edge detection defines a set of mathematical procedures that aim to recognize points in a digital image where the brightness varies sharply or has discontinuities. One of the second-order derivative operators that is used for edge detection is the Laplacian edge detector. It is from the zero-crossing category of the edge detection technique and it gives better edge detection results than the first-order derivative detection techniques, but it is somehow sensitive to noise [13]. In the previous work [2], the Tibia bone X-ray images were preprocessed using a smoothing (average) filter to remove the unwanted signals, the image then was converted to a binary image and the canny edge detection method was used to detect the bone edges. From the resultant image, two features were extracted, which are related to the edges of the bone; the sum of the on (white) pixels and the number of the 8-connected pixels in the binary image. It was found that both features are effective in detecting bone fracture and could be used in further bone classification processes.

2.1.4 Principal component features

From a mathematical view, PCA is a statistical process that uses an orthogonal transformation to convert a set of observations of probably correlated variables into a set of values of linearly uncorrelated variables called Principal Components (PCs). This transformation is defined in such a way that the first PC has the largest possible variance, which measures for as much of the variability in the data as possible. Then, each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components [14]. Six features were extracted from the highest variance PCA which are: mean, standard deviation, minimum value, maximum value, skewness, and kurtosis. These six features can detect the bone fracture effectively depending on the previous work results [2].

2.2 Classification

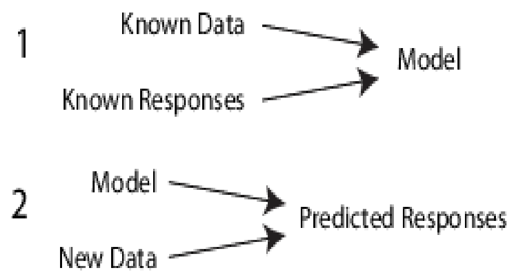

Figure 1: General description of SVM

The purpose of supervised, machine learning is to build a model that makes predictions based on evidence in the presence of uncertainty. The machine learns from the results when adaptive algorithms classify data patterns. The computer improves its prediction performance when exposed to more observations. Specifically, a supervised learning algorithm uses a known set of input data and known responses of the data (classes) and trains a model to generate reasonable predictions for the response to new data. In this work, the input X-ray image that has a fractured bone addressed class 1 and the image without a fractured bone addressed class 0. Figure 1 shows a simple description of SVM.

The whole set of input data can be called a heterogeneous matrix as the matrix rows are called observations or instances and each of them includes several measurements for a subject. Matrix columns are denoted to as predictors or features and each of them represents a measurement of each subject [15]. In this research, the observations are the X-ray images of the Tibia bones where the features of each image are set in columns. The data matrix contains one row of features extracted from each image as given in (1).

$$\begin{bmatrix} f1,1 & \cdots & f1,n \\ \vdots & \ddots & \vdots \\ fm,1 & \cdots & fmn \end{bmatrix} \quad (1)$$

where n is the number of features extracted and m is the number of images.All supervised learning methods start with an input data matrix. The data were prepared as each row in the feature matrix represents one observation and each column represents one variable or predictor. In this step the features were extracted from each X-ray image in the data set and arranged in one matrix for each image and called a data matrix. Each row has ten features related to the ten features described before.

Cross-validation is a statistical method of calculating and comparing learning algorithms by dividing data into two segments: the first segment used to train a model and the other one is to validate the model. The basic form of cross-validation is k-fold cross-validation, while other forms of cross-validation are special cases of k-fold cross-validation or involve repeated rounds of them [16]. A 10-fold cross-validation method is used in this work where the MATLAB

Table 1: Confusion matrix

	Fractured	Non-fractured
Fractured	TP	FP
Non-fractured	FN	TN

software completes these steps by randomly partition the data into 10 sets of equal size and train the SVM classifier on the remaining nine sets. The previous steps were repeated 10 times and at the end, the system combines generalization statistics from each fold.

2.3 Performance evaluation

A connection between our university and King Abdullah University Hospital (KAUH) was settled and the data were collected from the orthopedic department there. The total number of Tibia bone images used in this work are 100 images for the evaluation purpose of which 50 are with a fracture while the rest are normal images. The terms used in the confusion matrix (shown in Table 1) can briefly be described as: **True Positive (TP)**: true decisive system classified as true, **True Negative (TN)**: false event detected as false, **False Positive (FP):** the event is false and discriminated as true and **False Negative (FN):** true event classified as false [17].

Also, **Accuracy (AC)** is defined as the probability that the classification by the system is correct and it is given by (2) [20]:

$$AC = \frac{TP + TN}{TP + FP + TN + FN} * 100 \quad (2)$$

The Sensitivity **(True Positive Rate (TPR))** and Specificity **(True Negative Rate (TNR))** are also calculated from the confusion matrix using (3), and (4) respectively [20]:

$$TPR = \frac{TP}{TP + FN} \quad (3)$$

$$TNR = \frac{TN}{TN + FP} \quad (4)$$

3. RESULTS

In this section, the results are presented for the following experiments: classification using one feature analysis at a time, classification using all feature analyses, classification using two or three feature analyses each time. Also, a Graphical User Interface (GUI) is presented which was built to classify any new Tibia bone X-ray image into a fractured or non-fractured image automatically using any of the existence features group of the user choice.

3.1 Classification using one feature analysis at a time

Table 2: Confusion matrix using gradient features

	Fractured	Non-fractured
Fractured	45	5
Non-fractured	23	27

Table 3: Confusion matrix using wavelet features

	Fractured	Non-fractured
Fractured	46	4
Non-fractured	16	34

The result confusion matrix of gradient analysis is shown in table 2, where the accuracy (AC) is equal to 72%, TPR is 66.2% and TNR is 84.4%. While the confusion matrix of the wavelet analysis is presented in table 3 and the resultant AC is 80%, TPR is 74.2% and TNR is 89.5%. From these results, the wavelet features are more effective than the gradient features in detecting the bone fracture.

The confusion matrix results after using the edge features is presented in table 4, where the calculated accuracy AC is equal to 72%, TPR is 73.8% and TNR is 67.2%. Also, the confusion matrix of using the PCA features is shown in table 5; the AC is 71%, TPR is 68.3% and TNR is 77.5%. From the previous results, the accuracy of detecting the bone fracture using the wavelet analysis is higher than using the other features: gradient, edge and PCA features. Table 6 presents a summary of the classification results while using each analysis alone in the classification process. As mentioned above the wavelet analysis gives the best classification accuracy (80%) and it shows the best TPR and TNR results too.

3.2 Classification using all features

The result confusion matrix using all features is shown in table 7. Where the accuracy (AC) is equal to 73%. While the TPR and TNR are equal to 71.7% and 74.5%, respectively.

Table 4: Confusion matrix using edge features

	Fractured	Non-fractured
Fractured	41	9
Non-fractured	19	31

Table 5: Confusion matrix using PCA features

	Fractured	Non-fractured
Fractured	35	15
Non-fractured	14	36

Table 6: Summary of classification results using each analysis alone

	Gradient	Wavelet	Edge	PCA
Accuracy (AC)	72%	80%	72%	71%
TPR	66.2%	74.2%	73.8%	68.3%
TNR	84.4%	89.5%	67.2%	77.5%

Table 7: Confusion matrix using all features

	Fractured	Non-fractured
Fractured	38	12
Non-fractured	15	35

3.3 Classification using group of three or two analyses

Other groups of features are used to build the classification model and classify the images as a fractured and non-fractured image. Table 8 shows the features groups which are used in each process which contains a collection of the features that are extracted using three analyses out of the four presented analyses. The reason behind using different features groups is to find the best collection of the extracted features that could give better classification accuracy. From table 8 the results show that the best feature group in detecting the bone fracture is the group of Wavelet, Edge and PCA features, which means all features except the gradient features. While the group who gives a balance accuracy (AC) with TPR and TNR is the group of Gradient, Wavelet and PCA features (all features except the edge features). So, the later feature group can detect the fractured and non-fractured images with the same accuracy.

Table 9 presents the results while using a group of two feature analyses one of them is the wavelet analysis. In general, the resultant accuracies are somehow close to each other with maximum accuracy (AC) is reached using wavelet and edge features together with high TNR result ~ 90%.

3.4 Graphical User Interface (GUI)

The classification system can be integrated within the software of the X-ray imaging devices so the users can diagnose the images quickly and accurately during image generation. Graphical User Interface (GUI) is a graphical display in one or more windows containing components, that enable the user to perform interactive tasks. The reason behind designing an application using a graphical interface is to make the system more applicable and friendly interface [18]. In this work, the designed GUI lets physicians to choo-

Table 8: Summary of classification results using three analysis each time

	Gradient, Wavelet & Edge	Gradient, Wavelet & PCA	Gradient, Edge & PCA	Wavelet, Edge & PCA
Accuracy (AC)	73%	76%	71%	77%
TPR	68.3 %	76%	69.8%	74.5%
TNR	81.1%	76%	72.3%	80%

Table 9: Summary of classification results using two analysis each time

	Gradient & Wavelet	Edge & Wavelet	PCA & Wavelet
Accuracy (AC)	77%	80%	77%
TPR	70.7%	74.2%	73.7%
TNR	88.5%	89.5%	81.4%

-se the feature extraction method and then show the resultant features after using the selected feature method and finally classify the image into a fractured or non-fractured. Figure 2 shows an example of classifying an X-ray Tibia bone image using the wavelet analysis method, the image on the left is the original image selected randomly from the data, the bar next to the image shows an options for the available feature extraction methods where the user can select the type of the method by click on the method name.

The images next to the feature methods bar represent the image at the last step of image processing which then used to extract the wanted features. The last bar on the right is the features that were extracted and used in the classification process. The image class (fractured or non-fractured) is presented at the bottom.

4. CONCLUSION

Recent work of Al-Ghraibah et al has analyzed new features from Tibia bone X-ray images depending on the physical properties of the bone which detects the changes of these features in the presence or absence of a fracture. They produced a novel method to examine whether the extracted features are efficient in detecting bone fracture or not. In this work, an extension to the work in [2] is presented and is used the most significant features to build an automated classification system that classifies any X-ray Tibia bone image as a fractured or non-fractured image. Four different methods were used, namely: wavelet analysis, gradient analysis, Principle Component Analysis (PCA) and bone edge detection method. Classification process was repeated using each feature analysis group alone, using all feature analyses groups together and using two or three feature analyses groups at a time. Also, a Graphical User Interface (GUI) was presented to classify any new Tibia bone X-ray image into a fractured or non-fractured image automatically using any of the existence features group of the user choice. The maximum accuracy result was reached when the wavelet features are used alone in the classification process or if they were used along with the edge features too.

Figure 2: GUI example; classifying the input image using wavelet analysis.

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