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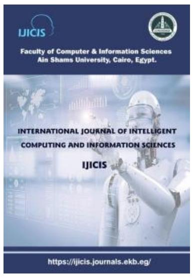

Bone X-Rays Classification and Abnormality Detection using Xception Network

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Abstract: *Computer aided diagnosis (CAD) has a vital role and becomes an urgent demand nowadays. Bone fractures cases are considered from the most frequently occured dieases among individuals. Moreover, the incorrect diagnosis of the bone fractures cases may cause disability for the patient. Hence, CAD system for bone fractures has become a must. This paper proposes a two-stage classifcation method for bone type classification and bone abnormality detection. Xception pre-trained model is considered for all experiments. Two different approaches are utilized for the testing phase: 1) Singl-view and 2) Multi-view approachs. The enhanced images are fed into the first stage to be classified into one of the seven classes: shoulder, humerus, forearm, elbow, wrist, hand and finger. Thereafter, the classified bones are fed into the second stage to detect whether the bone is normal or*

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abnormal. MURA dataset has been utilized for all experiments. Moreover, the last layer of the utilized model is replaced by Support Vector Machine (SVM) layer. The results reveal the superiority of the SVM layer.

Keywords: *Computer Aided Diagnosis (CAD), X-ray, Medical Imaging, Convolution Neural Network (CNN), MURA Dataset.*

1. Introduction

Musculoskeletal cases are considered from the most common conditions that affect the people worldwide. Musculoskeletal cases can lead to disability or severe, long-term pain. The accurate diagnosis of such cases is very critical as incorrect diagnosis can lead to unnecessary diagnostic procedures, extending the duration of treatment, and to distortion of bones, resulting in patient disability in the worst cases. Hence, correct diagnosis and appropriate treatment of such cases is considered a critical issue [1]. On the other hand, the performance of the clinicians is affected by their physical and psychological status [2] which may result in wrong diagnosis. Hence, Computer-aided diagnosis (CAD) system can assist clinicians by saving human error, time, and effort. In addition, it provides accurate, fast diagnosis to get the best treatment.

X-ray medical imaging is considered from the most frequently used techniques for the detection of the bone's abnormality, especially the fractures. X-ray images are utilized by the clinicians to be able to give the appropriate diagnosis and treatment [3] [4]. Moreover, progress in image processing and machine learning techniques has facilitated the emergence of X-ray-based CAD systems that can help clinicians in diagnosis with promising results [5] [6] [2] [7] [8] [9] [10] [11].

Recently due to the high need for CAD systems, many studies have been emerged to detect bones abnormality, especially the fractures [5] [6] [2] [7] [8] [9] [10] [11]. However, most of the studies [5] [6] [2] [7] [8] [9] [10] [11] consider only one bone for the following reasons: 1) lack of public datasets; 2) the high variability in bones types; and 3) the huge differences in bones shapes. Hence, to cover all the human body bones, huge number of systems with huge computations is a must which is not realistic at all.

In this paper, a two-stage classification method is proposed to detect bone abnormality in the seven bones of upper extremity (shoulder, humerus, forearm, elbow, wrist, hand, and finger). The enhanced x-ray images are fed into the first stage to be classified into one of the seven classes. Subsequently, the classified bones are fed into the second stage to detect whether the bone is normal or not. Hence, the proposed method encompasses eight different classifiers: one for stage 1 and seven for stage 2. Xception pre-trained model is utilized for the eight classifiers and the last layer is replaced by Support Vector Machine (SVM) layer. Moreover, two different approaches are examined for the testing phase: 1) single-view and 2) multi-view approaches. MURA dataset has been examined for testing and training purposes.

The remainder of this paper is organized as follows: Section 2 presents a literature review for the previous studies; Section 3 discusses the utilized dataset and the proposed method; Section 4 provides the conducted experiments and the achieved results; Finally, section 5 presents the conclusion and future work.

2. Literature Work

Recently, there is a trend to develop Computer-aided diagnosis (CAD) system to assist clinicians [12] [13] [14] [15] [16] . Many studies have been emerged to detect bone abnormality using x-rays. Due to the high variability in the human body bones, there are not many studies for the task in hand. Recently, deep learning has been utilized to handle the task in hand due to its efficacy. In this section, a brief survey on the previous studies is provided.

2.1. Traditional Approaches

A computer aided diagnosis method to detect the abnormalities of long bones was proposed by M. Al-ayyoub, et al [5]. A set of filters were applied on the x-ray images to reduce darkness, brightness, blurring, Poisson, and Gaussian noise. Subsequently, the features were extracted by utilizing edge detection, corner detection, peak detection, texture features and fracture lines. Thereafter, four different classifiers 1) Support Vector Machine (SVM); 2) Decision Tree;3) Nave Bayes; and 4) Neural Network (NN) were utilized to detect the presence / absence of the fracture(s) and the fracture(s) type. Two classification problems were addressed in this study: binary classification (presence / absence of a fracture) and fracture type (five classes). The best accuracy had been achieved using SVM classifier, which was above 85% by utilizing 300 x-ray images collected from hospitals and websites.

Y. Cao, et al [6] proposed a generalized Stacked Random Forests Feature Fusion method to detect multiple bone fracture types and multiple bone structures throughout the body. The proposed method had achieved an accuracy of 81.2% using 145 x-ray images as a performance dataset.

A hand fracture detection method was proposed by I. Hmeidi, et al [2]. The raw images were filtered and sobel operator was utilized to detect the edges. Thereafter, the edge detected images were preprocessed by utilizing wavelet transform and curvelet transform. On the other hand, the features were extracted only from the filtered images by utilizing Gray Level Co-occurrence Matrix (GLCM). The extracted features were then fed into four different classifiers: 1) Bayesian Networks; 2) Naive Bayes; 3) NN and 4) Decision Tree. The proposed method achieved an accuracy of 98.1% using 98 x-ray images as a performance dataset.

A computer aided diagnosis method to detect fracture in long bones of legs called Tibia was proposed by S. Mahendran, et al [8]. Simultaneous Automatic Contrast adjustment, Edge Enhancement and Noise Removal (SACEN) algorithm were utilized to preprocess the raw x-ray images. The preprocessed images were fed into two different segmentation algorithms to segment the bone image from the x-ray image and identify the diaphysis region of the bone image. GLCM was utilized to extract the textural features. Thereafter, the extracted features were fed into three classifiers: 1) BPNN; 2) SVM and 3) Naïve Bayes. Moreover, the results of the three classifiers were combined to get the final decision by applying a majority voting approach. The proposed method achieved an accuracy of 90% using 1000 images gathered for training & testing purposes.

A. Akter, et al [9] introduced a method to detect the fractures of hand fingers. X-ray images were preprocessed and converted into binary images. GLCM features, moments, entropy, major axis length, minor axis length, orientation, eccentricity, area, convex area, filled area, equivalent diameter, solidity, extent, mean, standard deviation, perimeter, correlation coefficient, median, variance, width, height, pixel count and Euclidian distance were extracted as 32 features from the preprocessed images. Thereafter, the extracted features were then fed into two different classifiers: 1) Support Vector Machine (SVM) and 2) Artificial Neural Network (ANN). 92.24% was the best accuracy achieved by utilizing ANN classifier.

2.2. Deep learning models

S. Chung, et al [10] considered Normal and four proximal humerous fracture types (greater tuberosity, surgical neck, 3-part, and 4-part) using plain antero-posterior shoulder radiographs. The images were preprocessed by resizing the images to be 256 x 256. Thereafter, the preprocessed images were then fed into Convolutional Neural Network (CNN) classifier. Accuracy, sensitivity, and specificity of 96%, 99% and 97% were achieved by utilizing 1891 images as a benchmark dataset.

A two-stage classification method was proposed by M. Tantawi, et al [17] to detect the abnormality in the seven extremity upper bones (shoulder, humerus, forearm, elbow, wrist, hand, and finger) using deep learning models. Enhanced X-ray image was fed into two stage classification method to detect bone type and abnormality in the bone. Two convolution neural network (CNN) models namely ResNet-50 and Inception-v3 were utilized for both classification stages. MURA dataset was utilized as a performance dataset. The best accuracy was 73.71% for fracture detection after merging the two classification stages and it was achieved by utilizing Inception model.

P. Rajpurkar, et al [11] proposed a method to detect and localize the abnormality in upper extremity bones which include shoulder, forearm, humerus, elbow, wrist, hand, and finger. The images were preprocessed and resized to be 320 x 320. Then, the preprocessed images were fed into 169-layer densely connected convolutional network to predict the abnormality in each bone separately. MURA dataset which contains more than 40,000 images and each bone has more than one view had been utilized for the training and testing purposes. 70.5% was the best average accuracy achieved for all seven bones.

2.3. Comparative Analysis

Table 1 presents a brief comparison between the previous studies. The main criteria for comparison are: 1) The study considers deep learning classification model or traditional one; 2) Bones considered in the classification; 3) The study considers the fracture type or just presence / absence of fracture; 4) The study utilizes a public benchmark dataset or not; 5) The study considers the bone type in the classification step or not; and 6) The achieved accuracy. Generally speaking, the following observations can be drawn: 1) lack of available public benchmark datasets and this is due to the difficulty of collecting data from the hospitals; 2) most of the studies consider only one bone and this is due to the high variability in the bones types and shapes; 3) few studies only consider the fracture type due to the difficulty of the task in hand; 4) few studies utilize deep learning classification methods compared to the studies that utilized traditional methods and this is due to the lack of public benchmark datasets.

Table 1. Comparsion between the previuos studies

Research study	Deep learning or traditional methods	Bones considered	Fracture type is considered?	Public dataset?	Bone type is considered?	Accuracy
M. Al-ayyoub, et al [5]	Traditional	Long bones	No	No	No	85.00%
I. Hmeidi, et al [2]	Traditional	Hand bone	No	No	No	98.10%
S. Mahendran, et al [8]	Traditional	Tibia bone	No	No	No	90.00%

A. Akter, et al [9]	Traditional	Hand fingers	No	No	No	92.24%
S. Chung, et al [10]	Deep learning	Shoulder bones	Yes	No	No	96.00%
M. Tantawi, et al [17]	Deep learning	Upper extremity bones	No	Yes	Yes	73.71%
P. Rajpurkar, et al [11]	Deep learning	Upper extremity bones	No	Yes	No	70.50%

3. Proposed Method

In this paper, a two-stage classification method is proposed to detect the abnormality in the upper extremity bone which include: shoulder, humerus, elbow, forearm, wrist, hand, and finger. The first stage is to classify the bone type into one of the different seven classes. Thereafter, the correctly classified images from stage 1 are fed into the second stage to detect the abnormality in the bone. Xception CNN model is utilized for the two stages. Moreover, the last layer in the second stage is replaced by SVM layer to enhance the results. In addition, the proposed method is tested using two different approaches: 1) single-view approach where only one x-ray image is fed into the two-stage classification method; and 2) multi-view approach where for each study more than one image are fed into the two-stage classification method and thereafter a majority voting technique is utilized to get the final decision. In the next subsections, a detailed description for the utilized dataset and the steps of the proposed method is presented.

3.1. Dataset

After investigating the utilized datasets in the previous studies, the only public benchmark dataset is the MURA dataset [11]. Mura data is considered the largest public dataset for x-ray bone abnormality. It contains 40,561 images from 14,863 studies, where each study is labeled as either normal or abnormal. There are 9,045 normal studies and 5,818 abnormal studies. The studies encompass the upper extremity bones which include shoulder, humerus, elbow, forearm, wrist, hand, and finger. Moreover, each study includes more than one view. MURA dataset [11] contains many types of bones abnormality: 1) fractures; 2) with hardware; 3) with degenerative joint diseases; and 4) with other miscellaneous abnormalities, including lesions and subluxations.

3.2. Preprocessing

The main propose of this step is to enhance the raw x-ray images. The difference between the bone and the background should be maximized to increase the prominence of the bones in the images. Hence, adaptive histogram equalization is utilized in this study as it changes the intensity of the image to uniform intensity. Adaptive histogram equalization divides the image into four quarters and applies the histogram equalization on each quarter separately to enhance the local contrast [18].

Hence in this study, the preprocessing step consists of four main steps: 1) to enhance the contrast in the images, adaptive histogram equalization is utilized; 2) the intensity values of the RGB are rescaled to be from 0 to 1 instead of from 0 to 255; and 3) data normalization. Figure 1 shows samples from the dataset before and after the preprocessing step.

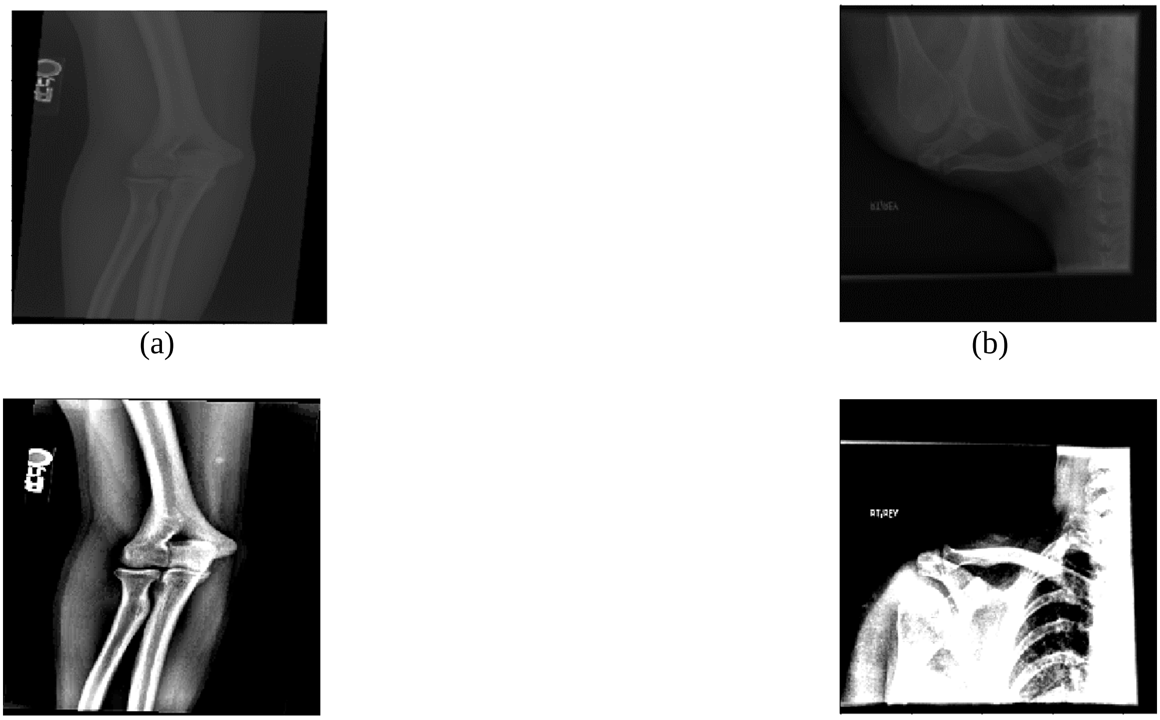

Figure 1. Image preprocessing: a, b original images and c, d images after the preprocessing step

3.3. Features Extraction and Classification

In the proposed method, a two-stage classification is utilized. Xception pre-trained model is utilized for the two stages. The initial weights for the networks are those of the ImageNet dataset [19]. Moreover, the last layer is replaced by SVM layer to enhance the results of the classification as the second stage is a binary classification problem.

Xception model [20] is a deep architecture that is mainly inspired by Inception model where depthwise separable convolutions are utilized instead of the inception modules. Xception is considered as interpretation of Inception modules in CNN. It acts as an intermediate step between both the regular and depthwise separable convolutions. Thus, in this case, depthwise separable convolution is like an inception module with large number of towers. Figure 2 and Figure 3 present the detailed architecture for the models utilized for stage 1 and stage 2, respectively.

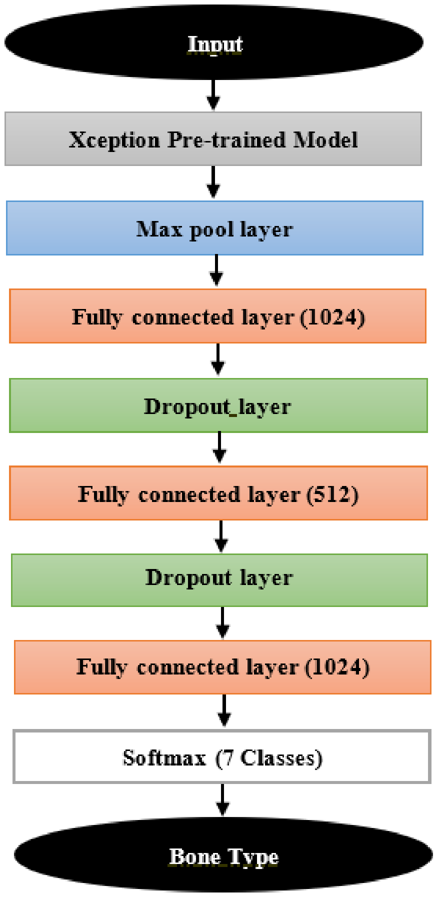

Figure 2. Xception model for the first stage

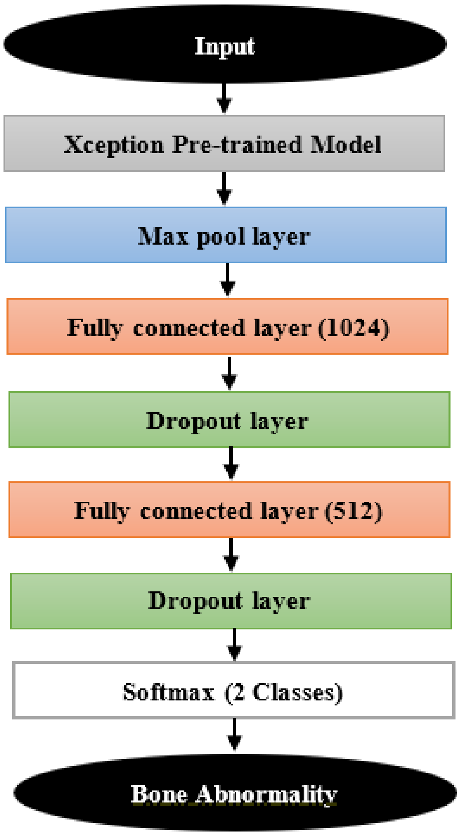

Figure 3. Xception model for the second stage

4. Experimental Results

MURA dataset is utilized for training and testing in the proposed method. X-ray images are preprocessed using adaptive histogram equalization. Thereafter, the preprocessed images are fed into two-stage classification method. The images are first fed into the first stage to be classified into one of the seven bone types: shoulder, humerus, elbow, forearm, wrist, hand, and finger. Subsequently, the corrected classified images are fed into the second stage to be classified as normal or abnormal bone. Xception pre-trained CNN model is utilized for both stages. The next subsections provide all the needed details about the 1) evaluation metrics; and 2) the achieved results.

4.1. Evaluation Metrics

In this paper, two evaluation metrics are utilized to measure the performance of the proposed method: 1) Sensitivity; and 2) Specificity. The evaluation metrics have been computed based on the confusion matrices using these four main parameters: 1) False Negative (FN); 2) False Positive (FP); 3) True Negative (TN); and 4) True Positive. The equations are as follows:

$$\mathbf{Sensitivity\%} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} * \mathbf{100} \tag{1}$$

$$\mathbf{Specificity}\% = \frac{\mathbf{TP}}{\mathbf{TP+FP}} * \mathbf{100} \qquad (\mathbf{2})$$

4.2. Experiments and Results

This section presents the results achieved by the proposed method. The experiments were conducted on an Intel Core (TM) i7-8700K desktop processor 6 cores up to 3.2 GHz Turbo 300 series with 16 GB RAM and GIGABYTE GeForce GTX 1080 Ti overclocked 11G graphics card. The next subsections present details about the conducted experiments.

4.2.1. Experiment I – Xception Model using Single View X-ray Images

In this experiment, Xception pre-trained model is utilized for the eight classifiers using single-view x-ray image. First, the raw images are fed into one classifier to classify the enhanced images into seven classes namely shoulder, humerus, elbow, forearm, wrist, hand, and finger. Then, according to the bone type, each correctly classified image is fed to one of the seven classifiers in the second stage to detect the abnormality, if exists. Table 2 and Table 3 show the results of the first and second stages. In addition, Table 4 presents the results after the integration step.

Table 2. Sensitivity and Specificity results by utilizing Xception model in stage 1 – Single view

Bone Type	Sensitivity	Specificity
SHOULDER	99.82%	99.50%
HUMERUS	92.01%	99.90%
FINGER	97.18%	99.64%
ELBOW	98.50%	98.98%
WRIST	98.18%	99.54%
FOREARM	86.05%	99.62%
HAND	98.70%	99.45%
Average Accuracy	**95.78%**	**99.45%**

Table 3. Sensitivity and Specificity results by utilizing Xception model in stage 2 – Single view

Bone Type	Sensitivity	Specificity
SHOULDER	82.01%	80.70%
HUMERUS	75.00%	71.62%
FINGER	76.92%	60.47%
ELBOW	69.87%	68.09%
WRIST	76.97%	86.83%
FOREARM	53.42%	56.67%
HAND	68.78%	79.34%
Average Accuracy	**71.85%**	**71.96%**

Table 4. Sensitivity and Specificity results by utilizing Xception Model after integrating the two stages – Single view

Bone Type	Sensitivity	Specificity
SHOULDER	81.83%	80.20%
HUMERUS	67.01%	71.52%
FINGER	74.10%	60.11%

ELBOW	68.37%	67.07%
WRIST	75.15%	86.37%
FOREARM	39.47%	56.29%
HAND	67.48%	78.79%
Average Accuracy	**67.63%**	**71.41%**

4.2.2. Experiment II – Xception Model using Multi View X-ray Images

In this experiment, Xception pre-trained model is utilized for the eight classifiers using multi-view x-ray image. First, the raw images are fed into one classifier to classify the enhanced images into seven classes namely shoulder, humerus, elbow, forearm, wrist, hand, and finger. Then, according to the bone type, each correctly classified image is fed to one of the seven classifiers in the second stage to detect the abnormality, if exists. Table 5 and Table 6 show the results of the first and second stages. In addition, Table 7 presents the results after the integration step.

Table 5. Sensitivity and Specificity results by utilizing Xception model in stage 1 – Multi view

Bone Type	Sensitivity	Specificity
SHOULDER	99.40%	99.48%
HUMERUS	99.91%	90.37%
FINGER	99.71%	96.57%
ELBOW	99.23%	98.73%
WRIST	99.48%	98.73%
FOREARM	99.34%	93.98%
HAND	99.42%	98.20%
Average Accuracy	**99.50%**	**96.58%**

Table 6. Sensitivity and Specificity results by utilizing Xception model in stage 2 – Multi view

Bone Type	Sensitivity	Specificity
SHOULDER	84.85%	72.63%
HUMERUS	85.30%	95.52%
FINGER	70.09%	62.65%
ELBOW	96.74%	75.76%
WRIST	88.57%	83.51%
FOREARM	95.65%	68.75%
HAND	89.11%	71.21%
Average Accuracy	**88.04%**	**75.72%**

Table 7. Sensitivity and Specificity results after integrating the two stages – Multi view

Bone Type	Sensitivity	Specificity
SHOULDER	84.25%	72.12%
HUMERUS	85.20%	85.89%
FINGER	75.79%	59.22%
ELBOW	95.97%	74.49%
WRIST	88.05%	82.24%
FOREARM	94.00%	62.73%
HAND	88.53%	69.42%
Average Accuracy	**87.54%**	**72.30%**

4.2.3. Experiment III – Xception – SVM Model using Single View X-ray Images

In this experiment, due to the binary nature of the second stage classification (normal/abnormal), the last layer of the utilized model in Experiment I is replaced by SVM. Table 8 show the results of the second stage after adding the SVM layer. On the other hand, Table 9 presents the results after the integration step.

Table 8. Sensitivity and Specificity results by utilizing SVM in the last layer in stage 2 – Single view

Bone Type	Sensitivity	Specificity
SHOULDER	88.13%	84.56%
HUMERUS	75.00%	72.97%
FINGER	79.76%	66.05%
ELBOW	69.87%	74.47%
WRIST	81.25%	91.02%
FOREARM	55.28%	61.74%
HAND	74.60%	84.50%
Average Accuracy	**74.84%**	**76.47%**

Table 9. Sensitivity and Specificity results by utilizing SVM layer after integrating the two stages – Single view

Bone Type	Sensitivity	Specificity
SHOULDER	87.95%	84.06%
HUMERUS	67.01%	72.87%
FINGER	76.94%	65.69%
ELBOW	68.37%	73.45%
WRIST	79.43%	90.56%
FOREARM	41.33%	61.36%
HAND	73.30%	83.95%
Average Accuracy	**70.62%**	**75.92%**

4.2.4. Experiment IV – Xception – SVM Model using Multi View X-ray Images

In this experiment, the last layer of the utilized model in Experiment II is replaced by SVM. Table 9 show the results of the second stage after adding the SVM layer. On the other hand, Table 10 presents the results after the integration step.

Table 9. Sensitivity and Specificity results by utilizing SVM in the last layer in stage 2 – Multi view

Bone Type	Sensitivity	Specificity
SHOULDER	90.96%	76.49%
HUMERUS	85.29%	96.87%
FINGER	78.52%	68.37%
ELBOW	96.74%	82.14%
WRIST	92.65%	86.80%
FOREARM	97.64%	73.42%
HAND	94.93%	76.38%
Average Accuracy	**90.96%**	**80.07%**

Table 10. Sensitivity and Specificity results by utilizing SVM layer after integrating the two stages – Multi view

Bone Type	Sensitivity	Specificity
SHOULDER	90.37%	75.98%
HUMERUS	85.20%	87.24%
FINGER	78.22%	64.94%
ELBOW	95.97%	80.87%
WRIST	92.13%	85.54%
FOREARM	96.98%	67.40%
HAND	94.35%	74.58%
Average Accuracy	**90.46%**	**76.65%**

4.2.4. Analysis and Discussion

Analyzing the results without and with the SVM layer proves its significance in both testing approaches (Single-View and Multi-View approaches) since the average sensitivity and specificity results has been increased by approximately 3% and 4% respectively after utilizing the SVM layer due to the binary nature of the classification task in stage 2 (Normal/Abnormal). Moreover, it is unfair to compare the results of the experiments utilized single-view images by the experiments utilized multi-view ones as the number of the testing samples are not equal. Figure 4 shows the final proposed hybrid two-stage classification scheme where the input differs according to the approach whether single-view image or multi-view images.

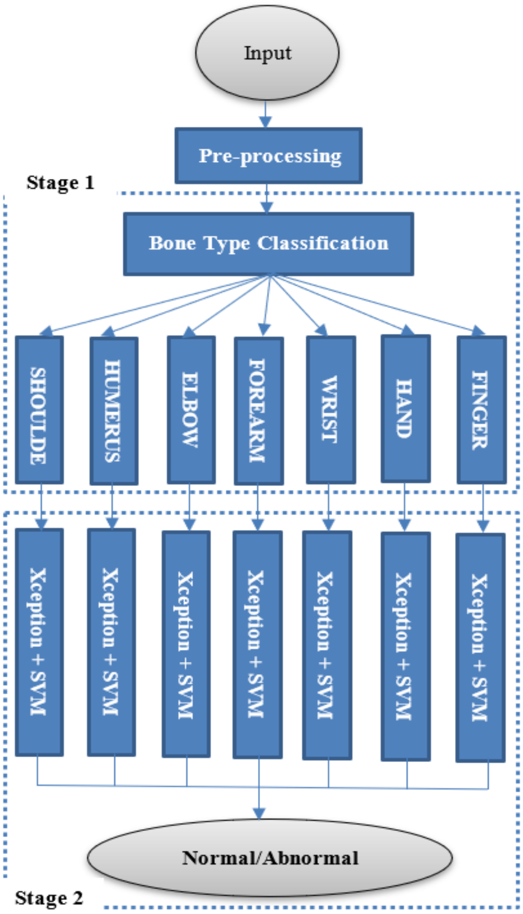

Figure 4. The final hybrid two-stage classification method

5. Conclusion

To conclude, this paper proposes a two-stage classification method for abnormality detection of extremity upper bones including shoulder, humerus, forearm, elbow, wrist, hand, and finger. MURA dataset has been utilized for training and testing purpose. Raw x-ray images are enhanced by utilizing adaptive histogram equalization. The enhanced images are fed into two-stage classification method. Xception pre-trained CNN model was utilized for the two stages. In the first stage, the bone is classified into one of the seven classes. Thereafter, the second stage detects the abnormality of the bone, if exists. Moreover, the two-stage classification method has been tested using two different approaches: 1) single-view approach where only one x-ray image is fed into the two-stage classification stage; and 2) multi-view approach where multi view images for the same study are fed into the classification stage and a majority voting approach is applied to get the final decision. Moreover, the last layer of the utilized model is replaced by SVM layer. The results reveal the superiority of the SVM layer. The advantages of the proposed method can be summarized as follows: 1) two problems are considered: bone type classification, and abnormality detection; 2) the proposed method considers the extremity upper bones which include seven different bones instead of only one bone as in the literature; 3) due to the two-stage classification approach, the proposed method is scalable. In future, we are looking forward to 1) adding more bones; 2) considering the abnormality type; and 3) testing the proposed method on different datasets.

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