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A TECHNICAL STUDY ON ABNORMALITIES DETECTION MACHINE LEARNING APPROACH FOR AUTOMATIC MUSCULAR

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ABSTRACT

Bones, ligaments, cartilage, tendons, and tissues are considered as the musculoskeletal system (MKS) in human body. Defects or abnormalities in MKS are identifies with the help of muscular radiographic images. Generally, the abnormal conditions are examined by the radiologist manually using the X-ray images. It requires export knowledge about the MKS systems, require lots of waiting time to complete the interpretations processes, and the timely interpretation is essential during emergency situation. It is essential to develop a cost effective automation tool to detect abnormalities in MKS. Therefore, this study is examining a methodology to perform the automation task in a cost effective manner. This methodology contains various stages such as image filtering, image enhancement, segmentation, edge detection, MKS's abnormality based features extraction and abnormality detection.

Keywords: ***Musculoskeletal system, Image processing, Clache equalization, Median filter, Morphological operations, Edge detection, KNN***

1. INTRODUCTION

Skeleton provides a framework for muscles and other soft tissues. Together, they support body's weight, maintain posture and help in movement. A wide range of disorders and conditions can lead to problems in the musculoskeletal system [1]. Aging [2], injuries, congenital anomalies (birth defects) and disease can cause pain and limit movement.Musculoskeletal conditions [3] affect more than 1.7 billion people worldwide, and are the most common cause of severe, long-term pain and disability, with 30 million emergency department visits annually and increasing. Significant advances in medical imaging technologies [4] which can diagnose at the level of experts, towards improving healthcare access in parts of the world where access to skilled radiologists is limited.So, it is essential to develop an artificial intelligent (AI) methods to perform the automatic abnormalities in MKS[5], to reduce interpretation cost and to save interpretation time of radiography image of various parts of MKS[6]. This research adopts a machine leaning based AI approach to perform this task. This automation process has been performed using various phases such as image enhancement phase using Clache equalization, image noise filtering phase using Median filter, image segmentation phase using Morphological operations, Feature extraction phase, Edge detection, shape detection. and finally abnormalities detection phase using K-

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Nearest Neighbor. The main objective of this research is to reduces the image examining cost and time. It contributes in increasing the accuracy rate of the automate detection process. Moreover, it mainly, focuses to automate the abnormalities detection process using X-ray images of human fingers. This research uses only X-ray images of finger, wrists to perform the detection task.

2. LITERATURE REVIEW

This paper [7] presents cost-efficient deep learning models based on ensembles of EfficientNet architectures to help automate the detection process. We investigate the transfer learning performance of ImageNet pre-trained checkpoints on the musculoskeletal radiograph (MURA) dataset which is very different from the ImageNet dataset. The experimental results show that, the ImageNet pre-trained checkpoints have to be retrained on the entire MURA training set, before being trained on a specific study type.

This study [8] introduces a new calibrated ensemble of deep learners for the task of identifying abnormal musculoskeletal radiographs. It leverages the strengths of three baseline deep neural networks (ConvNet, ResNet, and DenseNet), which are typically employed either directly or as the backbone architecture in the existing deep learning-based approaches in this domain.

This research [9] proposes the uses of deep learning techniques to detect musculoskeletal abnormalities in the MURA dataset, one of the largest collections of radiographic studies. In particular, it uses transfer learning techniques such as feature extraction and fine-tuning to well-known models for visual tasks such as InceptionV3, VGG and SqueezeNet, among others. Additionally, it presents a tool based on class activation mappings to aid in visualizing the decision of our models.

This study[10] investigates new model architectures and deep transfer learning to improve the performance in detecting abnormalities of upper extremities while training with limited data. DenseNet-169, DenseNet-201, and InceptionResNetV2 deep learning models were implemented and evaluated on the humerus and finger radiographs from MURA, a large public dataset of musculoskeletal radiographs.

In this study [11], analysis the effectiveness of various CNN-based pre-trained models such as such as Xception, Inception v3, VGG-19, DenseNet, and MobileNet models for detecting abnormalities in radiographic images and compare their performances using standard statistical measures.

In this study [12], a scoping review was conducted using seven literature databases to determine the applications of machine learning (ML) techniques used for the primary prevention of work-related musculoskeletal disorders (WMSDs). The study finds insight into the breadth of ML techniques used for primary WMSD prevention and can help identify areas for future research and development.

This study [13] was to investigate if interaction between individual predictors, using a decision tree model, could be used to develop a population-specific algorithm of lower-extremity injury (LEI) risk. In this, the CHAID approach can be a powerful tool to analyze population-specific risk factors for injury, along with how those factors may interact to enhance risk.

3. STAGES OF AUTOMATIC MUSCULAR ABNORMALITIES DETECTION

This section describes the various stages of the automatic muscular abnormalities detection process and their functionality.

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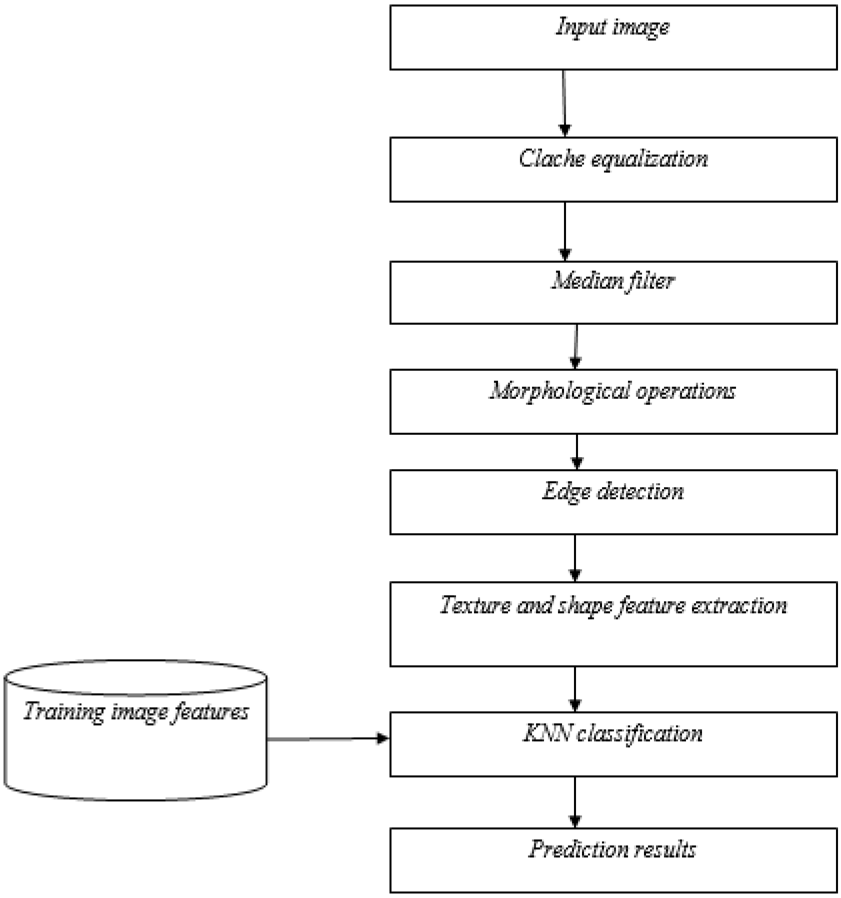

Fig 1: Work flow of the abnormality detection approach

This approach contains several stage, shown in figure 1 such as image acquisition, image filtering, image enhancement, segmentation, edge detection, shape feature extraction, and abnormality detection.

A. Image acquisition

In this study, the automation of abnormality detection has been made with a publicly available human finger X-ray images[14]. TheMURA [15], a large dataset of musculoskeletal radiographs containing 40,561 images from 14,863 studies, where each study is manually labeled by radiologists as either normal or abnormal. To evaluate the ML model robustly and to get an estimate of radiologist performance, it consists of additional labels from six board-certified Stanford radiologists on the test set, consisting of 207 musculoskeletal studies. It helps to identify the efficiency of the machine learning in detecting abnormalities.

Fig 2: Sample dataset image of finger's X-Ray

Fig 2 displays the sample input of the X-ray images. It is applied to perform the detection process using following methodologies**.**

B. Median filter

The median filter [16] is a non-linear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

Fig 3: Noise Filtered image

The figure 3 illustrates the efficiency of the median filter in filtering noisy pixels from the input images.

C. CLACHE equalization

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE)[17] prevents this by limiting the amplification.

Fig 4: contrast enhanced image

The fig 4 illustrates the output image of (CLAHE) equalization methods. It shows that the sample image's contrast has been adjusted to improve the prediction performance of the segmentation algorithms.

D. Morphological operations

Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation [18], the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries.

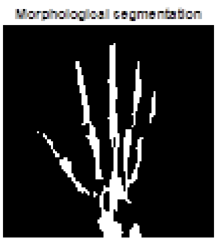

Fig5: Segmented image

Fig 5 illustrates the segmented bone region of fingers in this hand x-ray image using erosion method.

E. Edge Detection

Edge Detection is a method of segmenting an image into regions of discontinuity. It is a widely used technique in digital image processing like pattern recognition, image morphology, feature extraction. Edge detection allows users to observe the features of an image for a significant change in the gray level. This texture indicating the end of one region in the image and the beginning of another. It reduces the amount of data in an image and preserves the structural properties of an image.The edge detection method [19] determine the texture complexityby using the edge pixels in specified region, the edgelessper unit area is calculated as:

$$F_{edgeness} = \frac{I\{\{p|map\ (p)>T\}\}|\ I\{\{p|Dir\ (p)>T\}\}}{N} \quad (1)$$

Where N indicates region with N pixels, Mag(p) indicates gradient magnitude, and Dir(p) indicates gradient direction.

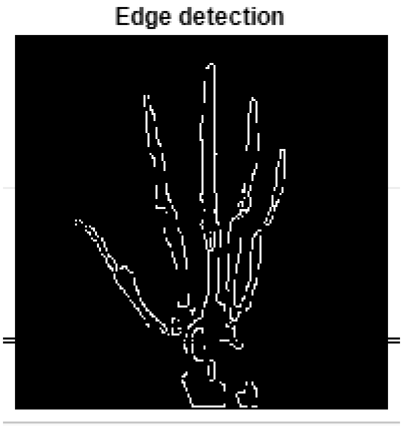

Fig 6: edge detected image

The fig 6 illustrates the edge detected bone regions from the segmented input images using canny edge detector.

***F.* Texture and shape Feature extraction**

1. Shape feature extraction methods using Binary image algorithm

Binary image algorithm convert image into two colorformat i.e. black and white color format, then traceexterior boundary region of image and by applying shapefactor shape of the image is recognized [19]:

$$shape\ factor = \frac{Area}{(Diameter)^2} \quad (2)$$

2. Texture feature extraction methods using Grey Level Co-occurrence Matrix

The Grey Level Co-occurrence Matrix is a statisticalapproach. Texture features [19] are calculated from thestatistical distribution. This method is a technique ofextracting subsequent order statistical texture features. The elements of matrix represent the relative frequency. This method describes texture by creating statistics of thedispersal of intensity values as well as location and orientation of similar valued pixel. Formula to calculate grey level co-occurrence (GLC) for single pixel:

$$GLC = \sum_{x=1}^{k} \sum_{y=1}^{k} \begin{cases} 1, & if\ I(x,y) = i\ and\ I(x+d_x, y+d_y) = j \\ 0, & otherwise \end{cases} \quad (3)$$

G. Detecting abnormalities using K-NN

The k-Nearest Neighbor classifier is by far the most simple machine learning/image classification algorithm. In fact, it's so simple that it doesn't actually "learn" anything.Inside, this algorithm simply relies on the distance between feature vectors, much like building an image search engine, only this time. The labels associated with each image. so,it can predict abnormality of input image.Simply put, the K-NN algorithm classifies unknown data points by finding the most common class among the k-closest examples. Each data point in the k closest examples casts a vote and the category with the most votes wins. It can see there are two categories of images such as normal bone abnormal/ affected bone image. In this, each of the data points within each respective category are grouped relatively close together in an n-dimensional space. This implies that the distance between two data points in the normal bone image is much smaller than the distance between a data point in the abnormal/injured boneimage.

In order to apply the k-nearest Neighbor classification [20], it is needed to define a distance metric or similarity function. Common choices include the Euclidean distance:

In the Euclidean plane, let point$p$ have Cartesian coordinates $\{p_1, p_2\}$ and let point q have coordinates(q_1, q_2). Then the distance between p and q is given by:

$$Euclidean\ distance, d(p, q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2} \quad (4)$$

This can be seen by applying the Pythagorean theorem to a right triangle with horizontal and vertical sides, having the line segment from p to q as its hypotenuse. The two squared formulas inside the square root give the areas of squares on the horizontal and vertical sides, and the outer square root converts the area of the square on the hypotenuse into the length of the hypotenuse.

4. CONCLUSION

Thus, the main objective of the study is performing the automatic detection of abnormal and normal bone from X-ray images. This research analysis the performance of deep learning, artificial intelligent based approach, and machine learning based approach in classifying the normal bone and injured bone from the input dataset images. The evaluation can be been made with various validity measure with relevant measures.

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