Journal of Positive School Psychology
2022, Vol. 6, No. 3, 8407–8414
http://journalppw.com

Improving the Classification of Scoliosis on Radiographic Image using the AdaBoost Ensemble Model

Raseeda Hamzah[1], Nurbaity Sabri[2], Siti Khatijah Nor Abdul Rahim3,
Nursuriati Jamil[4], Zaidah Ibrahim[5]

[1,3]Senior Lecturer, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
[2]Lecturer, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Melaka Kampus Jasin, Melaka, Malaysia
[4]Professor, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
[5]Associate Professor, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
Email: [1]raseeda@uitm.edu.my, [2]nurbaity_sabri@uitm.edu.my, [3]sitikhatijahnor@uitm.edu.my, [4]liza@uitm.edu.my, [5]zaidah@uitm.edu.my

Abstract
Scoliosis is a disorder in which the spine bends to one side or the other. Surgeons, physiatrists, and academicians can be confused when facing situations involving certain types of scoliosis that resemble the normal spine. Manually detecting scoliosis requires a lot of time and effort. The need for a method that can speed up the process by using an approach that surgeons, physiatrists, and academicians understand would undoubtedly solve the issues. To overcome this issue, a machine learning using image processing is introduced. A Grey-Level Co-Occurrence Matrix (GLCM) was implemented with an ensemble classification, which is AdaBoost, to classify between normal and scoliosis radiographic images. Based on the results, this method achieved an accuracy of 86.67%. The study would aid in the identification of more types of scoliosis by providing more data for future studies. Furthermore, it is hoped that it would be able to assist orthopaedics in making decisions.
Keywords: Scoliosis, Grey-Level Co-Occurrence Matrix (GLCM), Ensemble Models, AdaBoost, Radiographic

I. INTRODUCTION

Scoliosis (pronounced sko-lee-oh-sis) is derived from the Greek word skolosis, which means "curve." Scoliosis is a condition in which a person's spine curves sideways, most often in the form of a "S" or "C" (Siddiqui, 2016). A Cobb angle from a radiograph can be used to determine the degree of scoliosis. This calculation will assist in determining the stage of the deformity and tracking the curve's progression. The Cobb angle, which is the angle between two lines perpendicular to the upper end of the vertebra and the lower end of the lower vertebra, is used in the current clinical practice to quantify the curvature. Manually estimating spine curvature, on the other hand, takes a lot of time and effort, particularly when dealing with issues like inter-observer and intra-observer variations (Horng et al., 2019). Furthermore, obtaining a curvature measurement of the cobb angles from x-ray images is challenging. Besides, by using the Cobb method, humans may make mistakes by determining the top or end vertebrae of the scoliotic curve incorrectly (Yildiz, 2016).

Over the past few years, there are many radiographic base systems that have been proposed for scoliosis detection. Random Forest (RF) is another machine learning that has been used in many scoliosis researches. RF that is used to detect vertebral corners on sagittal x-ray promotes a minimal initialization, fast, and precise individual vertebrae on sagittal radiographs on normal and pathological cases. In this research, Haar-like features and contextual features based on patch intensity and contrast are used as visual features (Ebrahimi et al., 2019). A comparison between Support Vector Machine (SVM) and Random Forest (RF) has been done to detect the changes of spine and stress from the adolescence from the Magnetic Resonance Imaging (MRI) images. It shows that RF outperforms SVM when the training parameter changes (Mikulka et al., 2019). Another comparison work was done between SVM and RF to predict a patient with adult spinal deformity who needed to go through an operation or non-operation based on radiographic and the patient's data. From this research, SVM outperformed RF with 86% of accuracy achieved (Durand et al., 2020). SVM has a lower computing complexity and is capable of handling features of several dimensions. However, training the dataset takes longer, and SVM cannot accommodate independent attributes (Lashari & Ibrahim, 2013). With its flexibility and high precision, RF can be used for both classification and regression problems. The complexity of RF is its biggest drawback. Furthermore, they are much more difficult and time-consuming to construct. It therefore necessitates more computational capabilities and less intuitive understanding of the input data's relationship(Negandhi et al., 2019).

To achieve a superior performance, ensemble machine learning algorithms incorporate multiple different learners' model. Theoretically, ensemble classifiers outperform single classifiers performance (Subasi et al., 2018). Due to this advantage, this model has been implemented in many image analysis applications (Iwendi et al., 2020). One of the ensemble algorithms is Adaboost. This algorithm is a combination of different types of algorithm and by combining these algorithms, the performance will be improved. To enhance the basic boosting algorithm, this well-known ensemble algorithm uses an iterative approach. AdaBoost increases the weights on the observations that cannot be modelled correctly using the previous predictors of each iteration (Chu et al., 2020). This algorithm has been successfully extended to a variety of medical (Y. Zhang & Zhao, 2018) and non-medical (Iwendi et al., 2020) applications. It has been used in (L. Zhang et al., 2018) to recognized unlabeled spine CT scoliosis by cascade gentle Adaboost and distance regularized level set evolution (DRLSE). The combination of CGA and DRLSE has reduced the labor work of data labeling that is crucial to achieve higher performance of scoliosis recognition rate. The same algorithm has been implemented on measuring the spinal curvature. In this research, AdaBoost classifier is used to detect automatically and localize vertebral bodies from computer tomography (CT) spinal image(L. Zhang et al., 2019). It able to achieve 98.3% accuracy. Due to this success, the present research introduced ensemble classifier to classify the scoliosis radiographic images.

Feature extraction is an important step before conducting further classification operation. In this research, two most common features used in radiographic research are Gabor filter and GLCM. The Gabor filter, also known as a linear filter, is a two-dimensional filter (2D) which is often used for better dimensional localization. In medical field, this algorithm detects a bone fracture from radiographic images (Mungona, S. S., & Sawarkar, 2018). However, the Gabor filter's output, on the other hand, is not orthogonal between texture features and high cost (Al-Falluji et al., 2017). GLCM is a mathematical tool for extracting any characteristic from an image by using co-occurrence greyscale matrices. It also entails determining the distance between pixels and obtaining orientation data (P.S & V.S, 2016). GLCM is applied on osteoporosis research where the detection of osteoporosis on radiographic image takes place (Hwang et al., 2017). This algorithm is able to achieve a promising result. The implementation of GLCM also has been done on prediction of fragility of bone density (Gomes et al., 2020). In this research, the GLMC method was used to determine the spatial relationship between the pixels in a diagnostic image. This algorithm shows a reliability to determine the bone density based on a specific texture parameter. GLCM also has widely been used in medical x-ray image classifications where this algorithm is used to detect abnormality in x-ray images (Mall et al., 2019). In this research, twelve (12) features extracted to further classifications in machine learning algorithm were used. It showed a remarkable result and more improvement can be done using the combination of different features. From the literature, the advantages of GLCM that showed reliability features were precisely measured, and it was found that there was less complication, and the calculation was easier (P.S & V.S, 2016). Due to GLCM's capability, it is suitable to be used with scoliosis detection research.

The main objectives of this research is to create a high-accuracy scoliosis detection system. In addition, this study also sets out to: 1) develop earning algorithms for the scoliosis detection system; and 2) employ scoliosis datasets to implement and validate the proposed approach.

The rest of the paper is structured as follows. A brief introduction to feature extraction and machine learning algorithms will be covered in Section 2. The execution and flow of this research is explained in Section 3. The result and discussion will be carried out in Section 4, where the proposed algorithm will also be evaluated. Section 5 concludes the study.

II. METHODOLOGY

This section will discuss the methodology used in this research consist of features extraction algorithm and machine learning algorithm.

Feature Extraction

Feature extraction is a technique for determining the properties needed to describe an object's characteristics (Ganesan et al., 2019). This is a crucial step in the image processing process, since it will be used in the classification process. One of the most well-known texture features, GLCM, was used to define the quality of the radiographic image in this study.

Grey-Level Co-Occurrence Matrices (GLCM)

GLCM is applied to produce information about the distance between two pixels (i, j) as well as their orientation (Yang et al., 2017). The size of M x N of 2D images is represented with *f (a, b).* The θ and d are the angle and distance between (a1, b1) and (a2, b2). Meanwhile, N is the number of pixels of an image. The features extracted from an image with a total of 12 features are shown below (Isah et al., 2017) (Vamsidhar, E., Rani, P. J., & Babu, 2019).

a) Contrast

The measurement of intensity and contrast between a pixel and its neighbour are calculated. The contrast value is represented with 0 in an image, while non-contrast as 1.

$$\sum_{i=1}^{N-1}\sum_{j=1}^{N-1}(i-j)^2\, P(i,j,d,\theta)^2 \quad (1)$$

b) Correlation

It consists of the correlation pixel's and its neighbours' measurements in relation to the entire image. For both positive and negative correlated images, the correlation value is in the range of 1 to -1.

$$\frac{\sum_{i=1}^{N-1}\sum_{j=1}^{N-1} i*j*P(i,j,d,\theta)-\mu_x-\mu_y}{\sigma_x-\sigma_y} \quad (2)$$

c) Energy

Calculating the number of squared elements may be used to refer to energy as a second angular moment or uniformity. This is represented by a range between 0 and 1 on an image.

$$\sum_{i=1}^{N-1}\sum_{j=1}^{N-1}[P(i,j,d,\theta)]^2 \quad (3)$$

d) Homogeneity

Homogeneity of an image calculated by returning the closes value of the GLCM distribution element to with the image diagonal. The value consists of range between 0 to 1 where homogeneity is indicated as 1.

$$\sum_{i=1}^{N-1}\sum_{j=1}^{N-1}\frac{P(i,j,d,\theta)}{1+|i-j|}$$
(4)

e) Entropy

On a grey level, entropy measures how random a distribution is. If the grey rates are evenly distributed across the picture, it is expected to be strong.

$$-\sum_{i}^{m}\sum_{j}^{n}P[i,j]logP[i,j]$$
(5)

f) Dissimilarity

Dissimilarity is a pixel-based estimated of the distance between two object's pixels.

$$\sum_{i,j=0}^{N-1}P_{i,j}|i-j|$$
(6)

g) Cluster Shade

The propensity of the pixels in the region of interest to cluster is represented by cluster shade and cluster prominence.

$$\sum_{i}\sum_{j}\left(i+j-\mu_i-\mu_j\right)^3 p(i,j)$$
(7)

h) Sum Variance

Analyses the distribution of the sum of grey level of an image in mean

$$\sum_{i=2}^{2N_k}\left(i-\left[\sum_{i=2}^{2N_k}ip_{x+y}(i)\right]\right)^2$$
(8)

i) Sum Entropy

Analyses the condition associated with an image's total distribution of grey levels.

$$-\sum_{i=2}^{2N_k}P_{x+y}(i)\log\{P_{x+y}(i)\}$$
(9)

j) Sum Average

The grey level image distribution's total average was measured in this equation.

$$\sum_{i=2}^{2N_k}ip_{x+y}(i)$$
(10)

k) Difference Variance

In relation to the mean, the total dispersion of the grey level variance distribution of the image.

$$\sum_{i=2}^{2N_k}\left(i-\left[\sum_{i=2}^{2N_k}ip_{x-y}(i)\right]\right)^2$$
(11)

l) Difference Entropy

To measure the condition relating to the grey level difference distribution in the image.

$$-\sum_{i=0}^{N_{k-1}}P_{x+y}(i)\log\{P_{x+y}(i)\}$$
(12)

Machine Learning

Machine learning is the process of improving a result by learning from previous training data (Das, K., & Behera, 2017). It can be divided into two types: supervised and unsupervised. The ability to predict data by having labels on a dataset is known as supervised learning. Unsupervised learning, on the other hand, is when the label is not provided to the dataset. In this research, the supervised learning algorithm was used where machine learning that learns the function from the labelled data of the radiographic image. This research focuses on two label data name scoliosis and normal.

AdaBoost Algorithm

AdaBoost, also known as Adaptive Boosting, was introduced by (Freund & Schapire, 1997). Boosting is a general term for a collection of iterative methods for generating accurate prediction rules by combining weak classifiers. A training set $(a_1,b_1)\ldots.(a_m,b_n)$ is used as an argument in boosting algorithms. Each a_i belongs to domain a and each label b_i with $\{-1,1\}$. A classifier is constructed on training *train* set according to the distribution of weights C_{train} at each iteration. The algorithm begins by setting all weights to the same value, but as each round progress, the weights of incorrectly classified examples are increased, forcing the slow learner to concentrate on the most

Given $(a_1,b_2)\ldots.(a_m,b_n), a_i\epsilon a, b_i\epsilon b=\{-1,1\}$

Initialize $C_1(i)={}^1/_m$

For $train=1\ldots..n$

1. Train weak classifier of C_{train}
2. Get weak hypothesis $hyp_{train}: a\rightarrow\{-1,1\}$ with error $\varepsilon_{train}=\sum_{i:hyp_{train(a_i)}\neq y_i}C_{train}(a_i)$
3. Choose $\alpha_{train}=\frac{1}{2}\log\left(\frac{1-\varepsilon_{train}}{\varepsilon_{train}}\right)$
4. Update

$$C_{train+1}(i)=\frac{C_{train}(i)}{X_{train}}.=\begin{cases}e^{-\alpha_{train}} & if\ instance\ i\ is\ true\\ e^{\alpha_{train}} & if\ instance\ i\ is\ false\end{cases}$$

complicated as a result to classify. Figure 1 shows the pseudocode of AdaBoost algorithm.

Figure 1. Pseudocode for AdaBoost algorithm

III. EXPERIMENT AND TESTING

MATLAB R2018a was used to implement the proposed method with i7- 4770CPU and NVIDIA Quadro K2000 GPU.

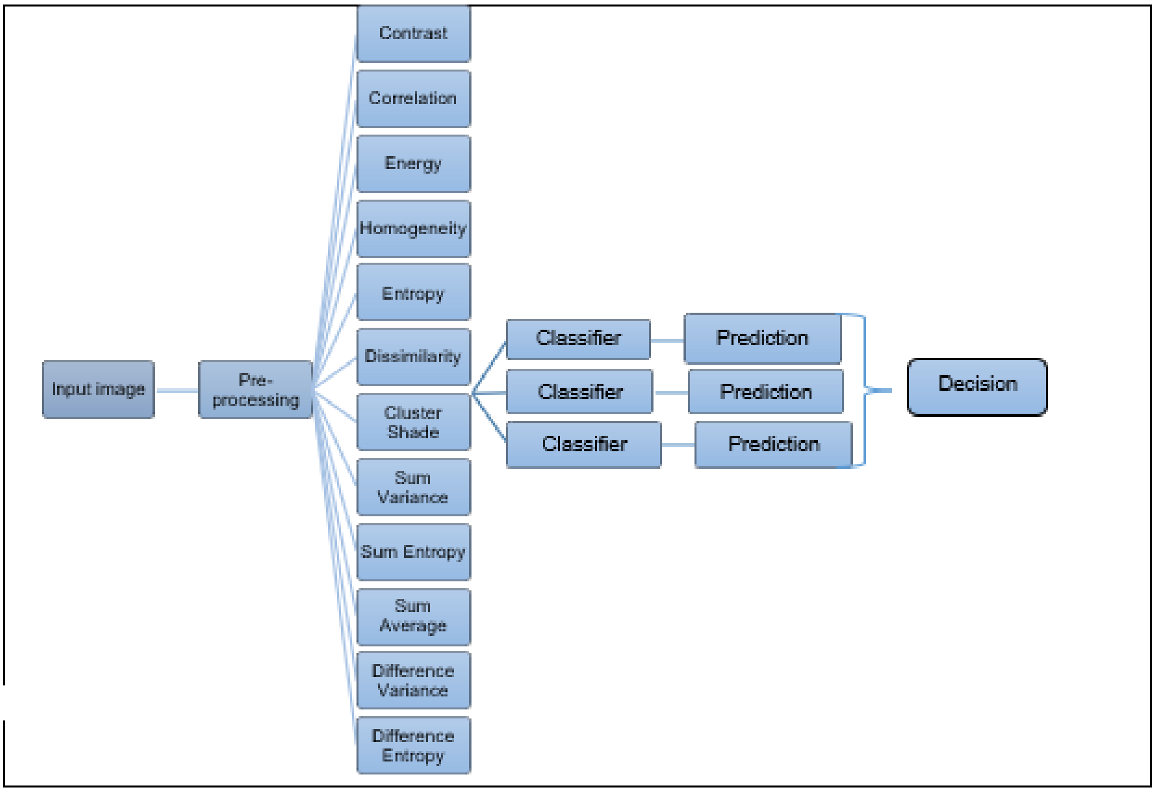

Figure 2. Diagram of scoliosis detection from radiographic images

Figure 2 shows the diagram of scoliosis detection using GLCM and ensemble classifier. As mentioned in the methodology (subtopic 2), the diagram of this research, starting from input image, pre-processing, the GLCM features extraction (a total of fourteen (14) features) is shown below. Next is the ensemble model of AdaBoost to perform a classification operation. In this research, classification on normal and scoliosis radiographic image was performed.

In this research, 30 radiographic images of scoliosis, including mild scoliosis (Cobb angle of 20 degrees), moderate scoliosis (Cobb angle of 25 degrees and below 45 degrees), and severe scoliosis (Cobb angle of 45 degrees), as well as 30 normal spines were used. The images for scoliosis radiographic images were taken from the shoulder to the pelvis. Normal radiographic images, on the other hand, begin at the shoulder and end at the rib cage. The dataset was divided into 80% for training, while the rest was used for testing. Before performing feature extraction, the image was resized to 300 x 350 pixels. Then, a pre-processing was performed on each 60 images where the simple enhancement created the image. This was done to emphasize the bone structure by improving the blur produced during the image acquisition process.

The GLCM performed in this stage involved 12 features extracted from the images according to the equation 1 until equation 12. From the operation, contrast, correlation, energy, homogeneity, entropy, dissimilarity, cluster shade, sum variance, sum entropy, sum average, difference variance and entropy were used for further classification operation. The observation on the 5 types of features was done due to its significance compared to other features. Figure 3 shows the extracted value of contrast, correlation, energy, homogeneity, and entropy.

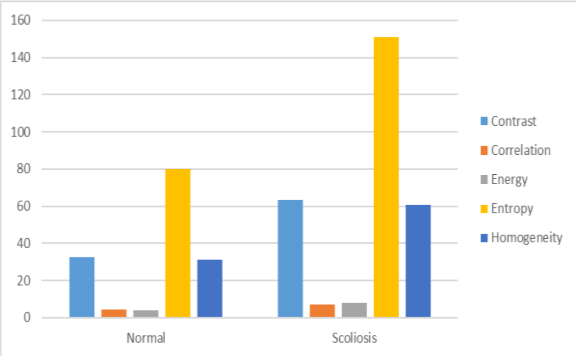

Figure 3. Five (5) GLCM features extracted from the dataset label

From the Figure 3, it is shown that entropy is the most prominent among the features due to the high number of grey level distribution for scoliosis compared to normal.

IV. PERFORMANCE EVALUATION AND RESULT

The ensemble algorithm, which is AdaBoost, was performed in this stage where it used all the features from the extracted features to classify them into binary classes, which are scoliosis and normal. To determine the model's accuracy, an evaluation was done using the confusion matrix. The following shows the equation used to obtain the accuracy of the developed model.

$$Accuracy(\%) = (Total\ correctly\ predicted) \Big/ (Total\ image\ testing) \times 100 \quad (13)$$

An evaluation of ensemble algorithm was made using the GLCM features on the radiographic image of scoliosis. Table 1 shows that the correctly predicted radiographic image is twenty-four (24) for normal and twenty-eight (28) for scoliosis. Meanwhile, only two (2) images are incorrectly predicted as normal and six (6) images are incorrectly predicted as scoliosis. By implementing equation 13, a comparison among SVM, RF, and ensemble classifier is shown in Table2 where ensemble model was able to achieve the accuracy of 86.67% on the total of 60 images.

Table 1 Confusion matrix evaluation of AdaBoost algorithm

		Prediction Value	
		Normal	Scoliosis
Reality Value	Normal	24	6
	Scoliosis	2	28

Table 2 Comparison result (%)

Model	Accuracy
SVM+GLCM	81.4433
RF+GLCM	74.2268
Ensemble+GLCM	86.67

V. CONCLUSION

Improving the classification of scoliosis on the radiographic image using AdaBoost ensemble models was proposed in this research. In this research, the binary classification of scoliosis and normal radiographic image was used as the dataset. Using a total of sixty (60) images (consisting of 30 images of scoliosis and 30 images of normal radiographic images), the experiment showed that this model achieved 86.67% of accuracy using twelve (12) features of GLCM. It proved that the Grey-Level Co-Occurrence Matrix (GLCM) method can be used to extract features to distinguish normal and scoliosis images using twelve (12) features. However, more features analysis is recommended to identify the suitable features to be used in this research. Therefore, from the result achieve, the proposed method can be applied in clinical diagnoses to assist orthopaedics on making decision based on radiographic images. It can be inferred that this research, which employed GLCM and AdaBoost ensemble models, can be used to improve current practices in scoliosis research. In the future, more data collection on scoliosis images based on Lenke Classification System and tested using other advance algorithms should be done.

BIBLIOGRAPHY

1. Al-Falluji, R., Adeeb, R., & Al-Falluji, A. (2017). MRI based Techniques for Detection of Alzheimer: A Survey MRI Based Techniques For Detection Of Alzheimer: A Survey View project Super Resolution View project MRI based Techniques for Detection of Alzheimer: A Survey. Article in International Journal of Computer Applications, 159(5), 975–8887
2. Chu, J., Lee, T. H., & Ullah, A. (2020). Component-wise AdaBoost algorithms for high-dimensional binary classification and class probability prediction. In Handbook of Statistics (Vol. 42, pp. 81–114). Elsevier
3. Das, K., & Behera, R. N. (2017). A Survey on Machine Learning: Concept, Algorithms and Applications. Article in International Journal of Innovative Research in Computer and Communication Engineering.
4. Durand, W. M., Daniels, A. H., Hamilton, D. K., Passias, P., Kim, H. J., Protopsaltis, T., LaFage, V., Smith, J. S., Shaffrey, C., Gupta, M., Klineberg, E., Schwab, F., Burton, D., Bess, S., Ames, C., & Hart, R. (2020). Artificial Intelligence Models Predict Operative Versus Nonoperative Management of Patients with Adult Spinal Deformity with 86% Accuracy. World Neurosurgery, 141.
5. Ebrahimi, S., Gajny, L., Vergari, C., Angelini, E. D., Skalli, W., Vertebral, W. S., & Gajny, • Laurent. (2019). Vertebral rotation estimation from frontal X-rays using a quasi-automated pedicle detection method. European Spine Journal, 28.
6. Freund, Y., & Schapire, R. E. (1997). A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. Journal of Computer and System Sciences, 55(1), 119–139
7. Ganesan, T., Jothi, R. A., Thenmozhi, G., Anandha Jothi, R., & Palanisamy, V. (2019). Comparative Analysis of Finger Vein Pattern Feature Extraction Techniques: An Overview. Article in International Journal Of Computer Sciences And Engineering.
8. Gomes, J., de Araújo, I. M., Trazzi, L. C., de Azevedo-Marques, P. M., Salmon, C. E. G., de Paula, F. J. A., & Nogueira-Barbosa, M. H. (2020). Association of bone mineral density with bone texture attributes extracted using routine magnetic resonance imaging. Clinics, 75, 1–5.
9. Horng, M. H., Kuok, C. P., Fu, M. J., Lin, C. J., & Sun, Y. N. (2019). Cobb angle measurement of spine from x-ray images using convolutional neural network. Computational and Mathematical Methods in Medicine.
10. Hwang, J. J., Lee, J.-H., Han, S.-S., Kim, Y. H., Jeong, H.-G., Choi, Y. J., & Park, W. (2017). strut analysis for osteoporosis detection model using dental panoramic radiography. Dentomaxillofacial Radiology, 46(7).
11. Isah, O. R., Usman, A. D., & Tekanyi, A. M. S. (2017). A Hybrid Model of PSO Algorithm and Artificial Neural Network for Automatic Follicle Classification. In Int. J. Bioautomation (Vol. 21, Issue 1).
12. Iwendi, C., Khan, S., Anajemba, J. H., Mittal, M., Alenezi, M., & Alazab, M. (2020). The Use of Ensemble Models for Multiple Class and Binary Class Classification for Improving Intrusion Detection Systems. Sensors, 20(9), 2559.
13. Lashari, S. A., & Ibrahim, R. (2013). A Framework for Medical Images Classification Using Soft Set. Procedia Technology, 11, 548–556.
14. Mall, P. K., Singh, P. K., & Yadav, D. (2019, December 1). GLCM based feature extraction and medical X-RAY image classification using machine

learning techniques. 2019 IEEE Conference on Information and Communication Technology, CICT 2019.

15. Mikulka, J., Chalupa, D., Říha, K., Filipovič, M., & Dostál, M. (2019). Pediatric Spine Segmentation and Modeling Using Machine Learning. International Congress on Ultra Modern Telecommunications and Control Systems and Workshops, 2019-October.
16. Mungona, S. S., & Sawarkar, M. N. M. (2018). Diagnosis of X-Ray Using Gabor Wavelet Transform.
17. Negandhi, P., Trivedi, Y., & Mangrulkar, R. (2019). Intrusion detection system using random forest on the NSL-KDD dataset. Advances in Intelligent Systems and Computing, 906, 519–531.
18. P.S, S. K., & V.S, D. (2016). Extraction of Texture Features using GLCM and Shape Features using Connected Regions. International Journal of Engineering and Technology, 8(6), 2926–2930.
19. Siddiqui, O. S. (2016). Heavy School Bags and Their Effect on the Growth of. In Children in Karachi.JICTRA (Vol. 7).
20. Subasi, A., Dammas, D. H., Alghamdi, R. D., Makawi, R. A., Albiety, E. A., Brahimi, T., & Sarirete, A. (2018). Sensor based human activity recognition using adaboost ensemble classifier. Procedia Computer Science, 140, 104–111.
21. Vamsidhar, E., Rani, P. J., & Babu, K. R. (2019). Plant Disease Identification and Classification using Image Processing. In International Journal of Engineering and Advanced Technology (IJEAT) (Issue 8).
22. Yang, F., Hamit, M., Yan, C. B., Yao, J., Kutluk, A., Kong, X. M., & Zhang, S. X. (2017). Feature extraction and classification on esophageal x-ray images of xinjiang kazak nationality. Journal of Healthcare Engineering, 2017.
23. Yildiz, I. (2016). Computer-assisted Cobb angle measurement from posteroanterior radiographs by a curve fitting method. Turkish Journal Of Electrical Engineering & Computer Sciences, 24(6), 4604–4610.
24. Zhang, L., Zhao, J., Jiang, Z., & Yang, H. (2019). Intelligent measurement of spinal curvature using cascade gentle adaBoost classifier and region-based DRLsE. Journal of Advanced Computational Intelligence and Intelligent Informatics, 23(3), 502–511.
25. Zhang, L., Zhao, J., Yang, H., Jiang, Z., & Li, Q. (2018). Unsupervised Scoliosis Diagnosis via a Joint Recognition Method with Multifeature Descriptors and Centroids Extraction.
26. Zhang, Y., & Zhao, Z. (2018). Fetal state assessment based on cardiotocography parameters using PCA and AdaBoost. Proceedings - 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI 2017, 2018-January, 1–6.