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Effective Prediction of Vertebral Column Pathologies Using Ensemble Classifiers

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Abstract

The medical diagnosis had a greater impact in the medical research domain. Accurate classification plays a vital role in medical diagnosis. It avoids the complexities and enables the treatment stage very effective. This study develops a prominent method that results in accurate recognition of the vertebral column pathologies. In our previous work, we developed a SPRINT algorithm which is a single classifier. Using single classifier counter parts, the possibility of poor selection. To overcome this and enhance the classification performance, we propose multiple-classifier techniques with multiple voting model. In this paper, we develop an Ensemble classifier for processing classification. The ensemble classifier applies to label the vertebral disorder image based on the similarity features. Ensemble classifier has a certain set of classifiers each classifier creates its model and combines response taken for achieving excellence in classification performance. The experimental work on this research is carried out with MATLAB and WEKA tools using UCI medical dataset. The performance evaluation based on the obtained results is achieved by undergoing several evaluation metrics. The efficiency of classification is measured by sensitivity, specificity, F-measure, and accuracy. The obtained result ensures our implementation of the ensemble classifier achieves better accuracy in classification and classifier speeds compared to others..

Keywords: Medical diagnosis, classification, Vertebral column pathologies, and ethical implications

1. Introduction

Recently, scientific inventions are exclusively improved in the medical domain. The medical diagnostic is known as a medical designed test for identifying infections, diseases, and conditions. In the medical diagnostic biological samples from human bodies like tissues and blood are taken for computing predictions. Most of the humans between the ages 35 – 45 are severely affected by back pain which results in an inability on doing their daily routine [1]. The main reason for this back pain is pathologies of the vertebral column. It is considered as the second neurological complaint after headaches. In the human body vertebral column is an important part that is responsible for protection, support, axis, and movements. The vertebral column is the series of 33 bones known as vertebrae separated by intervertebral discs. It has 24 articulating vertebras and 9 fused vertebras. These 33 vertebras are separated into five different groups including the cervical curve, thoracic curve, thoracic curve lumbar curve and sacral curve [2]. The commonly discussed vertebral disorders are disc hernia and spondylolisthesis. The pathologies including disc hernia and spondylolisthesis affect the stability and functionality of vertebral columns. Disc hernia is occurred during disc in the vertebral column get forced into the spinal canal results in a pressure on nearby nerves. It causes chronic or acute back pain. The spondylolisthesis is the slippage of the vertebra. Vertebrae segmentation and identification are vital for automatic spine analysis such as vertebral fractures [3]. The automatic spine analysis is achieved by processing various tomographic scans. In which image resolutions may vary, for this a robust generic vertebra segmentation algorithm is needed for covering different aspects of spines. The extraction does not include the visible vertebrae i.e about the section in which the spine belongs. This states that vertebra segmentation is important which solves instance segmentation problems as these instances are unique. The most prominent method used by radiologists for diagnosing vertebral column pathologies is computerized tomography (CT) and magnetic resonance imaging (MRI). In earlier days, image retrieval, image registration or image reconstruction techniques are popularly known methodologies for identifying vertebral column pathologies. Concerning interventional methods, medical imaging is essential but requires an expert physician to diagnose [4-7]. In addition to medical imaging, several computational methods including a computer-aided method for herniation diagnosis, Bayesian classifier with Gibbs distribution, k-means for estimating the degree of disc space narrowing and effect of the biomechanical measures along with orientation variables for detecting both normal and pathologic conditions are used [8-10]. In the technical era, the evolution of AI (Artificial Intelligence) is remarkable in designing machines for medical diagnosis. These are intelligent in observing the environment and taking decisions more than humans. The several AI-based techniques are Artificial Neural Network (ANN), Support Vector Machine (SVM), etc. ANN helps in learning of hidden pattern from the samples. There are two types of ANN such as a feed-forward neural network (FFNN) and a generalized regression neural network (GRNN). Whereas SVM is an advanced technique that divides the dataset into classes for reducing the generalization error. Our study is intended to enhance the diagnosis of Vertebral Column Disorders using Ensemble classifiers. For our research, we have taken the dataset from UCI for experimental purposes and applied it to the MatLab application. This paper is organized as follows; section 1 described the introduction. In section 2 related works were discussed and section 3 with our proposed contribution. Section 4 explains our proposed methodology and section 5 with experimental results. Finally, section 6 describes the conclusion part.

2. Literature Survey

K N Nithya et al [11] investigated the importance of improving the medical diagnosis system on vertebral column disorders. In this work, the author proposed sprint algorithm for enhancing the classification accuracy. The sprint algorithm is developed to establish excellence in identifying healthy and unhealthy spines. This sprint algorithm works with the principle of the decision tree algorithm. The experimental result using this sprint algorithm shows effectively in comparison to other traditional methods.

Fabio Galbusera et al [12] discussed artificial intelligence and machine learning in spine research. In this research, the author's described several techniques that are developed in recent days. They showed how AI and ML applications influences in localization of vertebrae and discs. In their work, they contribute the major ethical issues on using AI healthcare, namely, accountability especially on taking a decision, data privacy and security.

EsraMahsereciKarabulut et al [13] contribute their works in recognizing accurately the types of vertebral column pathologies. For this, they proposed a logistic model tree based automation system along with SMOTE Preprocessing. The work carried out with two phases, the first phase do preprocess of data using Synthetic Minority Over-sampling Technique (SMOTE). The second phase is the implementation of the Logistic Model Tree (LMT) classifiers. They describe a comparative study on vertebral column data with various machine learning algorithms. The experimental result based on the proposed methods shows better accuracy in identifying the vertebral column pathologies types.

Nikolas Lessmanna et al [14] developed an iterative instance segmentation approach for automatic vertebra segmentation and identification. The proposed method analyzes the image patches, based on the information gathered from image and memory the next vertebra is identified. The next vertebra is found to next each other which helps follow the vertebral column. The network model composite multiple tasks including segmentation of a vertebra, regression, and prediction with the visible images. The predicted images are labeled which results in effective prediction compared to others.

Sana Ansari et al [15] proposed machine learning classifiers for diagnosing Vertebral column disorders. The machine learning classifiers implemented in this work are Artificial Neural Network (ANN) and Support Vector Machine (SVM). The ANN is a combined approach of feed-forward back propagation neural network and generalized regression neural network. The dataset consisting of MRI images is taken for observation and classified into three different classes such as disk hernia, spondylolisthesis and normal. The classification results obtained and compared, the observation shows the excellence of the proposed method than the other methods.

3. Our contribution

Medical diagnosis plays a vital role in identifying the actual diseases. It avoids complexities during the treatment stages. Initially, based on the human samples an expert physician is required to diagnose the diseases. In the case of important diagnoses like vertebral column disorders the complexity is high and required more time as well as human inflection. The evolution of Artificial Intelligence (AI) and Machine Learning (ML) paves a way for modern diagnosis. The research work consists of two phases in the first phase we have implemented the SPRINT algorithm [11]. The implementation of the SPRINT algorithm to achieve better classification results. SPRINT algorithm is a one-way classifier work by the principle of decision tree mechanism. The problem of using a single-classifier is the possibility of poor selections [16]. This can be overcome by using multiple-classifier techniques. Our work is the extension of K N Nithya et al [11], where the Ensemble classifier is implemented to enhance the classification overall performance. Our proposed work Ensemble classifier consists of multiple-classifier techniques. The detailed mechanism of the Ensemble classifier is discussed in the upcoming section. The classification results using multiple-classifier techniques is more prominent than compared to the single-classifier. We use UCI datasets for observations and are applied in MatLab, then with the WEKA tool. The working mechanism of our proposed system is described below.

4. Proposed Works

4.1 Ensemble classifier & Working Principle

Ensemble classifiers is a set of classifiers applied for studying target functions. Their predictions are collected are used for classifying new samples. By combining several models it helps to improve the machine learning process. It improvises the generalization performance of certain classifiers set on a domain. Ensemble classifier works according to the features of similarity and classifies several stages. In our proposed work ensemble of classifiers are implemented for labeling vertebral disorder image either normal or abnormal as per its statistical features. In comparison to the individual classifier, the ensemble classifier combines a set of classifiers and achieving an enhanced classification performance.

Reason for implementing Ensemble methods; •Similar training performances onset of classifiers can exhibit several generalization performances

•The combining of several classifiers outputs would minimize the risk of poor selection in performing classifier

•On processing of a large amount of data a single classifier is not efficient to handle

•For too little data Ensemble systems can be used as resampling techniques How prediction with Ensemble classifier;

•The classifier output which has preeminent performance is taken as final output.

•The final decision is determined by combining the outputs of the individual classifiers.

•Precise predefined rules are applied for selecting the final class label

•The efficient rule combinations are weighted majority voting, the behavior of knowledge space common and Borda count

•The ensemble size i.e number of classifiers in the ensemble is estimated between the classifier speed and classifier accuracy.

•Larger ensembles, as well as over-trained classification, take more training time for prediction To enhance the prediction performance Ensemble learning combines various models which have various approaches such as;

Random subspace

The selection of the subset of features is taken randomly before functioning the training algorithms. Next, the models' outputs are chosen from the majority vote.

Bagging (Bootstrap Aggregation)

As per the random data, a set of models are created. The final prediction is taken by combining the model prediction using averaging.

Boosting

It works according to the averaging/voting of multiple models. These models are weighed and constructed according to their performance. In our proposed work we implement the majority voting rule through linear discriminant with the subspace ensemble.

Subspace discriminant

Ensemble Subspace learning techniques play a vital role in low-dimension data. It uses a linear discriminant analysis (LDA) scheme for dealing with those low-dimension data. In recent days various works are evolved with resampling, weighting and different sub spacing techniques. All the works are intended to improve the classification performance in the ensemble learning [16,17,18,19]. The most popular approach used is the random subspace method (RSM) [20]. To construct a model random sample of features is used to decrease the error rates. The major drawback of RSM is the possibility of poor discrimination due to random selection. To overcome this drawback majority voting (MV) method is implemented. By which ensemble is applied and each classifier provides new/ unknown instance. All the classifiers provide any new/ unknown instances which are collected and the majority vote is done to get the final classification result. In our proposed work, we applied discriminant learning. It uses the subspaces and classifies the fibrosis levels and the normal case respectively. This section is considered as an important component of the learning algorithm.

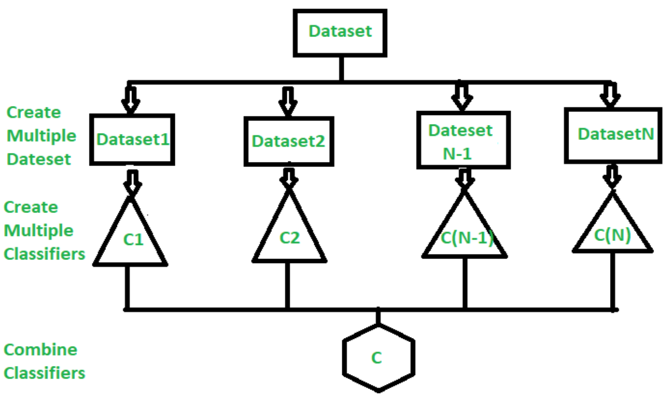

Fig-1 proposed architecture

As per fig1 the dataset is split into multiple datasets and creates multiple classifiers respectively. From the original dataset, several subsets are created with equal tuples. These subsets are the foundation for creating a base model. Each model analyzed parallel to form the training set and independent of each other. Each model shows its characteristic relationship in a tree form resulting in the dataset normal or abnormal. The resultant prediction involves several evaluation metrics which are discussed in the experimental work section. The prediction from all methods is collected and analyzed to get the final predictions. The model with higher accuracy is taken as final predictions.

5. Experimental Work

5.1 Dataset

In this research, we have taken the dataset from UCI. UCI has an enormous amount of medical datasets and data generators. UCI is one of the most popular sources for research work, especially in the medical domain. The UCI machine learning repository is the peculiar source where most of the machine learning communities considering their machine learning algorithms research works. In earlier, most of the medical required diagnostic parameters are provided by UCI which are considered to be best for students, educators, and researchers [21]. The dataset considers observation consist of 150 spondylolisthesis disorders, 100 healthy subjects, and 60 disk hernia disorders. At each of dataset, there are six attributes such as pelvic tilt, pelvic radius, pelvic incidence, sacral slope, lumbar lordosis angle and grade of spondylolisthesis. All these attributes are classified by the biomechanical feature vectors which are the important one of diagnosing vertebral column pathologies.

5.2 Tools

In this work, we took two frameworks such as MATLAB and WEKA for declaring classification outputs. MATLAB and WEKA are open source tools. MATLAB is the commonly used desktop environment for performing iterative analysis. It consists of programming languages that directly exploit matrix and array mathematics. It also facilitates Live Editor which enables creating scripts with a combination of code, output, and formatted text in an executable notebook. WEKA is another commonly used tool by the researchers which enables modification as per their needs. WEKA is best for re-implementing the multiple data mining algorithms.

5.3 Observations

The performance of our proposed is based on several evaluation matrices. In this section, we provide those matrices which are applied to the dataset and discussed the obtained results.

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5.4 Confusion Matrix

A confusion matrix is an instant report about the prediction results on a classification problem. The predictions are of two types such as correct and incorrect predictions. In each class, the number of correct and incorrect predictions are calculated with the count values and broken down. It not only states about the error made by a classifier but also states the kind of error thatmade.

	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Definition of the Terms

•Positive (P): Observation is positive

•Negative (N): Observation is not positive

•True Positive (TP): Observation is positive, and is predicted to be positive.

•False Negative (FN): Observation is positive, but is predicted negative.

•True Negative (TN): Observation is negative, and is predicted to be negative.

•False Positive (FP): Observation is negative, but is predicted positive.

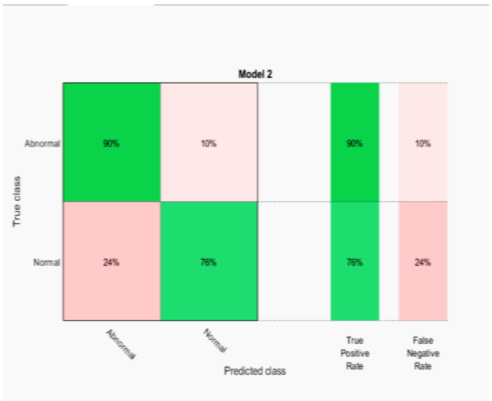

Fig 4: Confusion matrix on the dataset

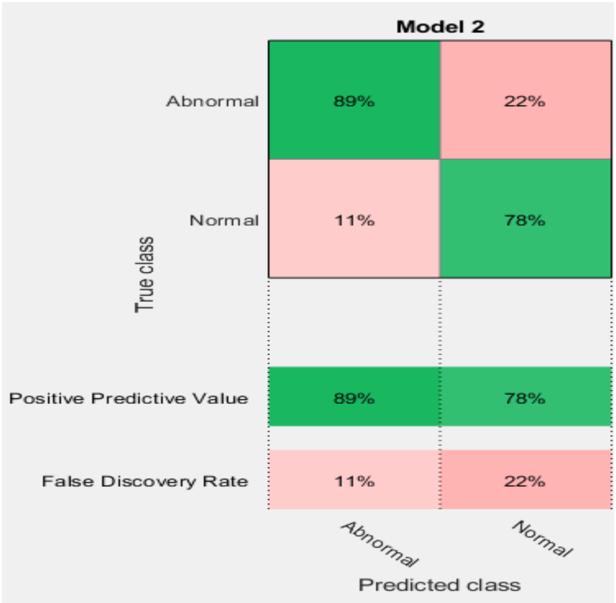

Fig 5: Confusion matrix on the dataset The above images 3,4& 5 show the implementation of the confusion matrix over the dataset. The output results are in the form of a true class with normal and abnormal predictions along with prediction classes with normal and abnormal predictions. Image 4 explicit the true positive rate and false-negative rate respectively. From which abnormal classes have 90% of true positive rate and 10% of the false-negative rate, whereas normal classes have 70% of true positive rate and 24% of the false-negative rate. Image 5 describes the positive predictive value and false discovery rate. From which abnormal classes obtain 89% positive predictive value with 11% of false discovery rate. In normal classes, the positive predictive value is about 78% and the false discovery rate is 22%.

5.5 Recall A recall is expressed as the total number of correctly classified positive examples divided by the total number of positive examples. They correctly recognized example is identified by the high recall values (a small number of FN). The recall can be expressed as below;

$$\text{Recall} = \frac{TP}{TP+FN}$$

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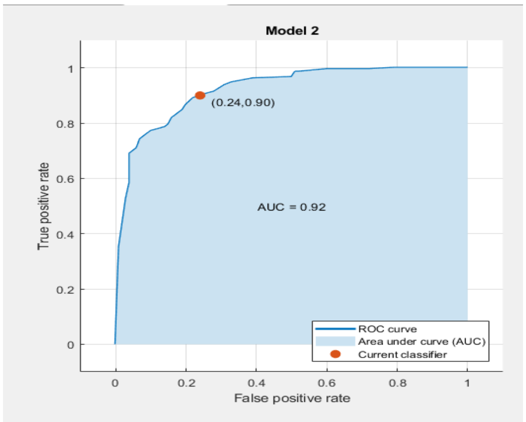

Fig 6: Recall observation on the dataset

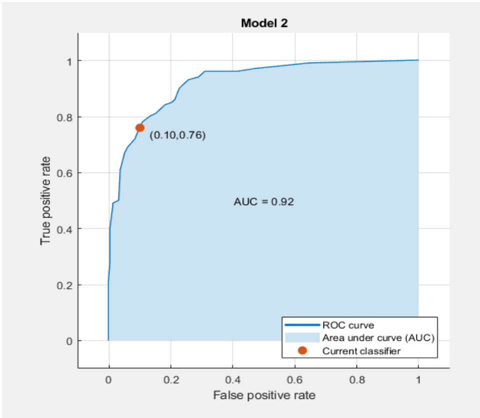

Fig 7: Recall observation on the dataset

The ROC is a receiver operating characteristic curve which determines with a graphical plot demonstrating the diagnosis ability of the classifier. In fig 6 & 7 the red point plotted determines the recall observation on two directions resulting at 0.92 respectively.

5.6 Precision

The precision value is obtained by dividing the total number of correctly classified positive examples with the total number of predicted positive examples. Herewith high precision is denoted by positive is indeed positive (a small number of FP). Precision is expressed as below;

$$\text{Precision} = \frac{TP}{TP+FP}$$

5.7 F-measure

F-Measure is calculated by measuring Precision and Recall. F-measure applies Harmonic Mean instead of Arithmetic Mean as it penalizes the extreme values widely. Consider the Precision or Recall, F-Measure will always smaller. Evaluation of F-measure is expressed as below;

$$\text{F-measure} = \frac{2*Recall*Precision}{Recall+Precision}$$

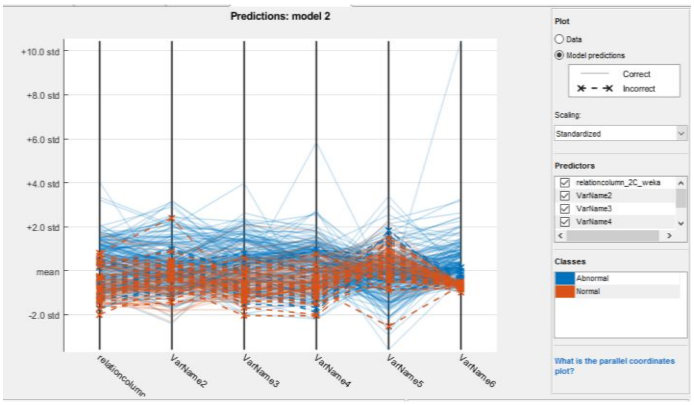

Fig 8: Prediction model using Ensemble classifier

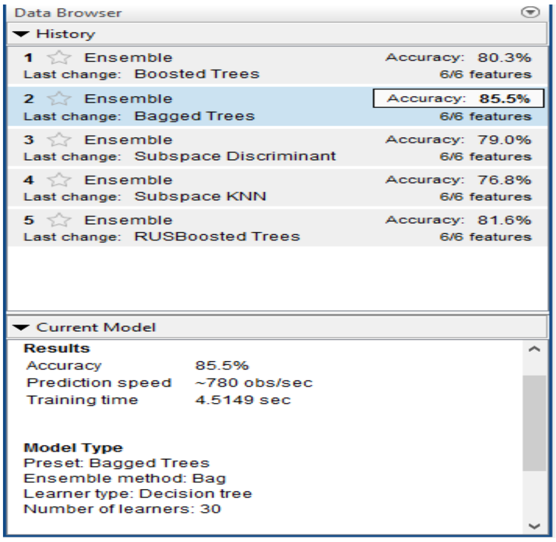

Fig 9: Prediction model using Ensemble classifier

The fig 8 & 9 show the result obtained using Ensemble classifier with MATLAB. Fig 8 is the pictorial representation of normal and abnormal model predictions. On which blue samples indicate abnormal stage and red samples indicates the normal stage. Fig 9 represents numerical accuracy obtained by Ensemble classifier with various models such as bagged trees, boosted trees, subspace discriminant, and RUS Boosted Trees. As per the features, the accuracy achieved by boosted trees is 80.3%, bagged trees with 85.5%, Subspace discriminant with 79.0%, Subspace KNN with 76.8% and RUS Boosted trees with 81.6% respectively. From which bagged trees achieve higher accuracy with 85.5% in comparison to others. The same dataset is applied to the WEKA tool. The obtained results are tabulated as follows based on TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, ROC, and PRC. To predict the class whether it's normal or abnormal.

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TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC	PRC	Class
0.886	0.220	0.894	0.886	0.890	0.622	0.922	0.953	Abnormal
0.780	0.114	0.765	0.780	0.772	0.622	0.922	0.865	normal
0.852	0.186	0.852	0.852	0.852	0.622	0.922	0.924	

Table 1. classification results

Based on the obtained values Sensitivity, specificity, F-measure and accuracy are calculated using the expression as mentioned above; Accuracy = 95 % Recall or specificity = 91% Sensitivity or Precision = 96 % F-measure = 91 % In our phase 1 work using the SPRINT algorithm, we achieve the classification performance of about 91%. Where the SPRINT algorithm is a single way classifier. To improvise the performance, we developed Ensemble classifier and predict the classification by calculating Sensitivity, specificity, and accuracy with multiple classifiers. In comparison with our Phase 1 work, Phase 2 shows excellence in classification on various attributes which makes predictions accurate and efficient.

6.Conclusion

This study analyzes the importance of medical diagnosis, especially in Vertebral column pathologies. Accurate classification and identification are more important in diagnosis. There are several approaches were evolved especially in the spine research field. We continued our Phase2 work in this study. Initially, in phase 1 we developed the SPRINT algorithm a single-classifier for classification. To avoid the possibility of poor selection, in the phase2 work we develop Ensemble classifier. It is multiple-classifier techniques that do the classification process according to the similarity features. On Ensemble classifier multiple models are developed and by multiple voting best classifier is taken for performance. The classifier with higher performance is evaluated using several evaluation matrices. Experimental results are carried out with UCI datasets on MATLAB and WEKA. Obtained results are discussed from which implementing of ensemble classifier states higher performance in both accuracy and speed of the classifier.

References

[1] Bigos, S. J., United States. Agency for Health Care Policy and Research., Acute low back problems in adults, U.S. Dept. of Health and Human Services, Public Health Service. Agency for Health Care Policy and Research, Rockville, 1994.

[2] Dana Andersen, Timothy Billiar, David Dunn, John Hunter, Jeffrey Mathews and RaphealE.PollockF.Brunicardi Schwartz's Principles of Surgery, 9th edition, Ed: McGraw Hill, 2009.

[3] Yao, J., Burns, J.E., Munoz, H., Summers, R.M., 2012. Detection of vertebral body fractures based on cortical shell unwrapping, in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer. volume 7512 of LNCS, pp. 509–516.

[4] Verdonck, B., Nijlunsing, R., Gerritsen, F. A., Cheung, J., Wever, D. J., Veldhuizen, A., Devillers, S., and Makram-Ebeid, S., Computer-assisted quantitative analysis of deformities of the human spine. In: Wells, W., Colchester, A., and Delp, S. (Eds.), Medical Image Computing and Computer-Assisted Intervention — MICCAI'98. Springer, Berlin, pp. 822–831, 1998.

[5] Herring, J. L., and Dawant, B. M., Automatic lumbar vertebral identification using surface-based registration. Journal of biomedical informatics 34(2):74–84, 2001.

[6] Whitmarsh, T., Humbert, L., Del Rio Barquero, L. M., Di Gregorio, S., and Frangi, A. F., 3D reconstruction of the lumbar vertebrae from anteroposterior and lateral dual-energy X-ray absorptiometry. Med. Image Anal. 17:475–487, 2013.

[7] Anitha, H., and Prabhu, G. K., Automatic Quantification of Spinal Curvature in Scoliotic Radiograph using Image Processing. J. Med. Syst. 36(3):1943–1951, 2012.

[8] Alomari, R. S., Corso, J. J., Chaudhary, V., and Dhillon, G., Toward a clinical lumbar CAD: herniation diagnosis. International journal of computer-assisted radiology and surgery 6(1):119–126, 2011.

[9] Chamarthy, P., Stanley, R. J., Cizek, G., Long, R., Antani, S., and Thoma, G., Image analysis techniques for characterizing disc space narrowing in cervical vertebrae interfaces. Comput. Med. Imaging Graph. 28:39–50, 2004.

[10] Berthonnaud, E., Dimnet, J., Roussouly, P., and Labelle, H., Analysis of the sagittal balance of the

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spine and pelvis using shape and orientation parameters. Journal of spinal disorders & techniques 18(1):40–47, 2005.

[11] K N Nithya, P. Suresh, “Diagnosis of Vertebral Column Disorders using A Novel Sprint Algorithm”, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, September 2019

[12] FabioGalbusera, Gloria Casaroli, and Tito Bassani, “Artificial intelligence and machine learning in spine research”, JOR Spine published by Wiley Periodicals, Inc. JOR Spine. 2019; https://doi.org/10.1002/jsp2.1044

[13] EsraMahsereciKarabulut&TurgayIbrikci, “Effective Automated Prediction of Vertebral Column Pathologies Based on Logistic Model Tree with SMOTE Preprocessing”, Springer Science+Business Media New York 2014, Med Syst (2014) 38:50 DOI 10.1007/s10916-014-0050-0

[14] NikolasLessmanna, Bram van Ginnekenb, Pim A. de Jongc,d and Ivana Išguma, “Iterative fully convolutional neural networks for automatic vertebra segmentation and identification”, 2019 Elsevier, Medical Image Analysis Volume 53, April 2019, Pages 142-155. https://doi.org/10.1016/j.media.2019.02.005

[15] Sana Ansari, FariaSajjad, Zia-ul-Qayyum, Nawazish Naveed and Imran Shafi, “Diagnosis of Vertebral Column Disorders Using Machine Learning Classifiers”, 2013 International Conference on Information Science and Applications (ICISA), Print ISSN: 2162-9048, DOI: 10.1109/ICISA.2013.6579446

[16] Tao D, Tang X, Li X, Wu X. Asymmetric bagging and random subspace for support vector machines-based relevance feedback in image retrieval. IEEE Trans Pattern Anal Mach Intell. 2006;28(7):1088–99.

[17] García-Pedrajas N, Ortiz-Boyer D. Boosting random subspace method. Neural Netw. 2008;21(9):1344–62.

[18] Kotsiantis S. Combining bagging, boosting, rotation forest and random subspace methods. ArtifIntell Rev. 2011;35(3):223–40.

[19] 16. Ho TK. The random subspace method for constructing decision forests. IEEE Trans Pattern Anal Mach Intell. 1998;20(8):832–44.

[20] Kuncheva LI, Rodríguez JJ, Plumpton CO, Linden DE, Johnston SJ. Random subspace ensembles for fMRI classification. IEEE Trans Med Imaging. 2010;29(2):531–42. [21]Hidayah I, Adhistya EP, Kristy MA. Application Of J48 And Bagging For Classification Of Vertebral Column Pathologies, In Information Technology And Multimedia (ICIMU), International Conference On IEEE 2014; 314-317.