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Lateral Cephalogram Analysis Using Wighted Rough Neural Network for Sex Determination

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Abstract: Cephalometric investigation in forensic science, concerned with the recognition, identification, individualization and assessment of physical confirmation. This study portrays the different soft computing algorithms for horizontal cephalogram picture based sexual orientation classification. In this study, we proposed another classification strategy called Weighted Rough Neural Network (WRNN). The Weiner filter has been utilized for preprocessing to lessen clamor in a picture. Programmed landmark identification for cephalogram pictures utilizing single fixed appearance model. The fifty one landmark points are extracted from skull image. Then principal component analysis and Daubechies wavelets are applied for feature selection. At the end chosen features are ordered according to the sexual orientation by applying Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), Back Propagation Neural Network (BPN) with proposed Weighted Rough Neural Network (WRNN) strategies. The comparative examination is performed among these techniques by utilizing the quantitative measures. From the after effects of the present investigation, it might be concluded that parallel cephalogram examination utilizing WRNN can be utilized as a dependable instrument in sex assurance.

Key words: Gender classification, feature extraction, feature selection, PCA, Daubechies, SVM, K-NN, BPN and WRNN

INTRODUCTION

Forensic humanities is a train, for the most part centers around human distinguishing proof to recognize natural profile, for example, age, sex and race of an unknown human from the skeletal remains. Additionally, forensic human sciences is one of the quickest developing orders which require observational procedures, for example, discriminant function analysis and soft computing systems to get more exact outcomes. Sex assurance is considered as essential angle for the distinguishing proof of people in anthropological research context (Arulselvi *et al*., 2011). Forensic specialists took after manual strategy utilizing vernier caliper, to distinguish cephalometric landmarks which is considered as the most established technique and tedious in process. After computer period, digitized strategy as advanced cephalogram and computed radiography for land marking. Be that as it may, both the above strategies required forensic master's knowledge and some uncommon equipment prerequisites.

Later self-loader land marking tools have been discovered which additionally needs master's knowledge for preparing the framework or Graphical User Interface (GUI) based manual explanation method (Zayed and Elnemr, 2015). Habitual land marking of cephalogram can be accomplished by assortment of algorithms like active shape model (Zayed and Elnemr, 2015), fuzzy logic (Stanojevich, 2012) in view of picture division, neural networks (Vanitha and Venmathi, 2011) and Genetic algorithm (Jangam *et al*., 2014). Sometimes comes about are unacceptable because of expansive varieties in biological shapes and dark level varieties between pictures. Subsequently, it is required an adaptable strategy to extend the landmark features preceding further classification.

Literature review: A few specialists have presented distinctive methodologies for sexual orientation arrangement. Arulselvi *et al.* (2011) exhibited cephalometric analysis for dimension decrease with order utilizing PCA and SVM strategies. Lakkshmanan (2013) exhibited cephalometric examination for discovering facial development anomalies utilizing BPN and SVM strategies, for the reproduction comes about BPN (96.7%) and SVM (99.8%) exactness. Vanitha and Venmathi (2011) achieved 93.3% precision rate used SVM strategy for restorative picture characterization. The order proficiency of 97.5% amid preparing stage and 93.33% productivity amid testing stage. A few researchers have explained various methodologies with different data (Jaswante *et al*., 2013; Khan *et al*., 2011).

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Table 1: Feature selection and feature extraction

Input	Feature selection stage 1	Feature extraction stage 2
The 83 images	Active Appearance Model	PCA Wavelet

Materials used: The 83 ample data is collected from American Association of Orthodontists Foundation, AAOF from age limit of 13-55 years. The sample data consists of 39 male and 44 female images. The images are preprocessed with various filtering methods (Saravanan and Lakshmi, 2013). The standard algorithm AAM is used for feature extraction. In active appearance model, single fixed view appearance algorithm is used to extract 51 land marks automatically for each image Saravanan and Lakshmi (2018). Principal component analysis and wavelets are used for feature selection from the fifty one land mark points of an each image (Saravanan and Lakshmi, 2018). The preliminary stages of sex determination are given in Table 1.

Gender classification: Classification is a machine learning system used to anticipate aggregate enrollment for information occasions. Classification implies assessing a function which relegates a class name to an information thing. After the features have been extricated the pictures are characterized in light of the sexual orientation. Sex identification alludes to individual distinguishing proof with a specific sexual orientation. So, it will decrease the hunt time once the pictures are characterized in view of the sexual orientation. Here, the pictures are characterized utilizing different classification techniques. That is support vector machine, k-nearest neighbor, back propagation neural network and proposed weighted rough neural network.

K-Nearest Neighbor algorithm (K-NN): K-NN is non-parametric technique utilized for classification. This case, the information consists of the k-nearest preparing cases in the facet space. k-nearest neighbor algorithm is amid the slightest thorny of the entire the machine learning algorithms. Regularly the question is grouped in light of the names of k nearest neighbors by greater part vote. In the event that, $k = 1$, the protest is just named the group of question bordering to it. At the point whilst nearby just 2 clustering classes, k ought to be an odd number.

Nonetheless, there can be tranquil knot whilst k is an odd number whilst achieving multiclass cataloging. Behind we renovate every picture to a vector of the flat length with factual numbers, we utilized the mainly widespread separation utility for LKNN.

Back Propagation Neural network (BPN): Back-propagation neural networks are the essentially widespread neural network formations as they are basic, successful with helpful in assortment of utilizations. Back propagation neural system is a group of the hub organized in players. The first layer of system is participation stratum, preceding stratum of the system is yield layer land staying every single moderate layer are shrouded layers. Three layered structure of the back propagation neural group having info, yield and concealed layer has been utilized for categorization (Lakkshmanan, 2013). Every hubs starting one stratum are associated to the entire hubs in the subsequent stratum. Every correlation is related with its weight which speaks to quality of the specific correlation. Prior to the preparation procedure, the weight for the hubs is measured as arbitrary.

Any network must be prepared so as to play out a specific task. In preparing process, preparing informational index is exhibited to the network and network's weights are refreshed keeping in mind the end goal to limit blunders in the yield of the network. Back propagation neural network utilizes back propagation algorithm for preparing the network. The primary points of interest of back propagation are effortlessness and sensible speed. Back propagation is a common strategy for preparing a neural network, the objective of back propagation is to enhance the weights with the goal that the neural network can figure out how to correctly outline contributions to yields.

Support Vector Machine (SVM): Support Vector Machine (SVM) is a learning framework which the classification utilizing hypothesis space as straight functions in a feature space high measurement, prepared with the learning algorithm in light of the hypothesis of advancement by actualizing learning predisposition got from factual learning hypothesis. SVM has demonstrated its effectiveness over the neural networks and RBF classifiers. Unlike neural networks, this model forms does not require speculating the quantity of neurons in the center layer or characterizing the focal point of Gaussian functions in RBF. SVM utilizes an ideal straight isolating hyper plane to isolate two arrangements of information in a feature space. This ideal hyper plane is delivered by augmenting least edge between two sets. In this way, the subsequent hyper plane may be relied upon outskirt preparing designs called support vectors.

MATERIALS AND METHODS

Proposed method Weighted Neural Network using rough set (WRNN): A novel method Weighted Rough Neural

Network (WRNN) is proposed to handle inconsistent, uncertain and class imbalance dataset. The unbalanced distribution of data leads to poor performance of existing classification techniques. To overcome these disadvantages and improve the performance of BPN, a novel weighted rough neural network has been proposed (Own and Abraham, 2014; Satishkumar *et al*., 2016). In this algorithm, rough set is associated with back propagation network to classify the gender. The algorithm is given as:

Enhanced Weighted Neural Network using Rough set (EWNR):

Algorithm 1; EWNR (F, C):

Input: IM = (U, A, F, C) be a decision system of image data
U-Universal set, A-attributes (feature with decision), F-Extracted image features
C-Class of image
Output: Predicted class labels
Step 1: Set, WIM←[ ], NC←[ ]
Step 2: Do
Step 3: For every $a_i \in A$
Step 4: For every $c_j \in C$
Step 5: If $a_i \in c_j$ then
Step 6: $w_j \leftarrow 1(n(C) \times n(A_j))$
where, n(C)-No. of classes in image dataset
$n(A_j)$-No. of samples classified as image c_j
Step 7: Form weighted image matrix features
$WIM \leftarrow a_i \times w_i$ here, $WIM = (U, A_w, F_w, C)$
end
end
Step 8: Compute the upper approximation
${}^{R}X_w \leftarrow \{x \in U | [x]_{Fw} \cap X \neq \Phi\}$
Step 9: Compute the lower approximation
${}^{R}x_w \leftarrow \{x \in U / [x]_{Fw} \subseteq X\}$
Step 10: Compute the boundary region
$wB_F(x) \leftarrow U^{R} X_w - U^{R} X_w$
Step 11: $wC_C(x) \leftarrow$ Mean $({}^{R} X_w)$
Step 12: For every $wB_F(x)$
Step 13: For every $wC_C(x)$
Step 14: $C_{ij} \leftarrow Dist(wC_C(x), wB_F(x))$
End
Step 15: $Temp \leftarrow index(min(C_{ij}, wC_C(x)))$
End
Step 16: Update C←Temp
Step 17: Call BPN(F, C)

In the above algorithm, $wB_F(x)$ values are considered as uncertain values and inference decision making is done based on the similarity measure. The similarity measure is evaluated for every element of $wB_F(x)$ with the centroid of each class lower approximation $wC_C(x)$ and the decision value is updated according to the closest centroid.

RESULTS AND DISCUSSION

The following steps have to follow: filtering images by using various filtering technique, namely, unshorp filter and average filter, median filter, Gaussian filter and Wiener filter. For all the above methods, mean square error, root mean square error and poison signal to noise ratio statistical measurements are used to calculate the enhancement performance. The experiment result shows that the Weiner filter performs better than the other methods (Saravanan and Lakshmi, 2013).

Apply single view appearance algorithm in AAM to extract fifty one landmark points automatically from each image. Then two feature selection tests: namely, principal component analysis and Db4 wavelet decomposition method conducted to select the principal points (Saravanan and Lakshmi, 2018).

The 83 images are divided into two sets. One set is training set with 90% of images. The other set is test data with 10% of images. Every time, we will change the training set and test set, so, we use all the images are training and test set. Tenfold cross validation test is conducted for each classification.

Four gender classification test, namely, K N back propagation, support vector machine, neural network and weighted neural network methods are applied to fifty one extracted landmark points, PCA and Daubechies 4 wavelet.

Gender classification test applied to 51 extracted landmark points: The 51 landmark points are extracted by using AAM method for each image. Four gender classification methods applied to 51 landmark points of each of 83 images by using Tenfold test. The results of the test and the graph of comparison result are given in Table 2 and Fig. 1, respectively. The test result shows that the proposed method, WRNN average accuracy is 0.6511 which is better than the other methods test results.

Gender classification test applied to principal component analysis: The principal component analysis is applied to 51 points and reduced to one principal value for each image. Four gender classification methods applied to principal values of 83 images by using Tenfold test. The results of the test and the graph of comparison results are given in Table 3 and Fig. 2, respectively. The test result shows that the proposed method, WRNN average accuracy is 0.9625. WRNN test result is the best among the four test results.

Gender classification test applied to Daubechies 4 wavelet: The Daubechies 4 wavelet is applied to 51 points and reduced to one principal value for each image. Four gender classification methods applied to principal values of 83 images by using Tenfold test. The results of the test and the graph of comparison result are given in Table 4 and Fig. 3, respectively. The test result shows that, the proposed method, WRNN average accuracy (0.8125) is the best one compare to the other methods.

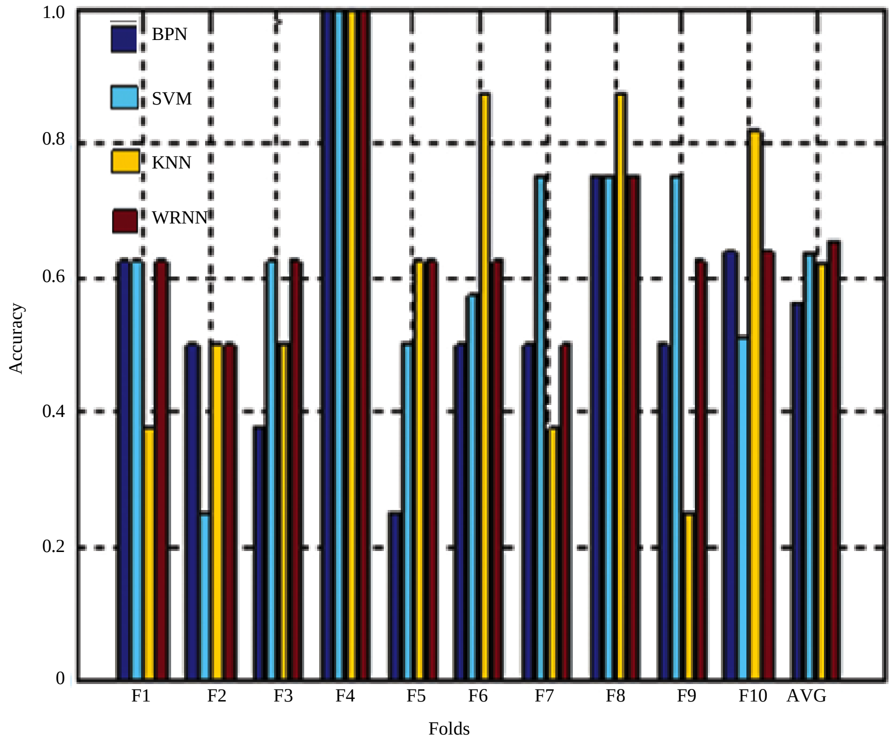

Fig. 1: Comparison of accuracy analysis of four gender test with AAM

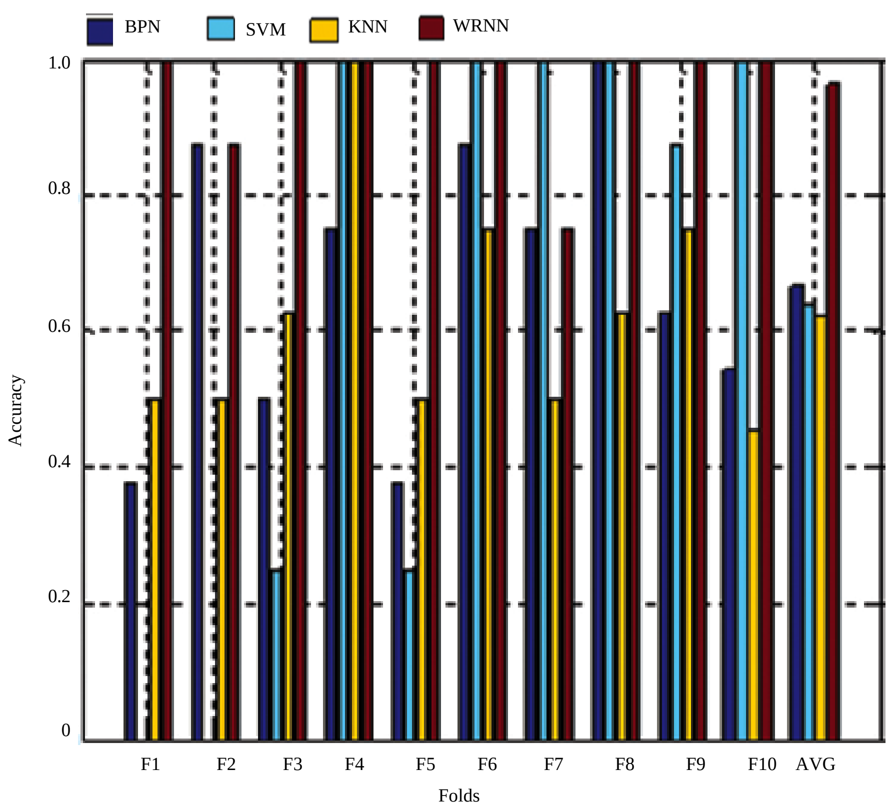

Fig. 2: Comparison of accuracy analysis of four gender test with PCA

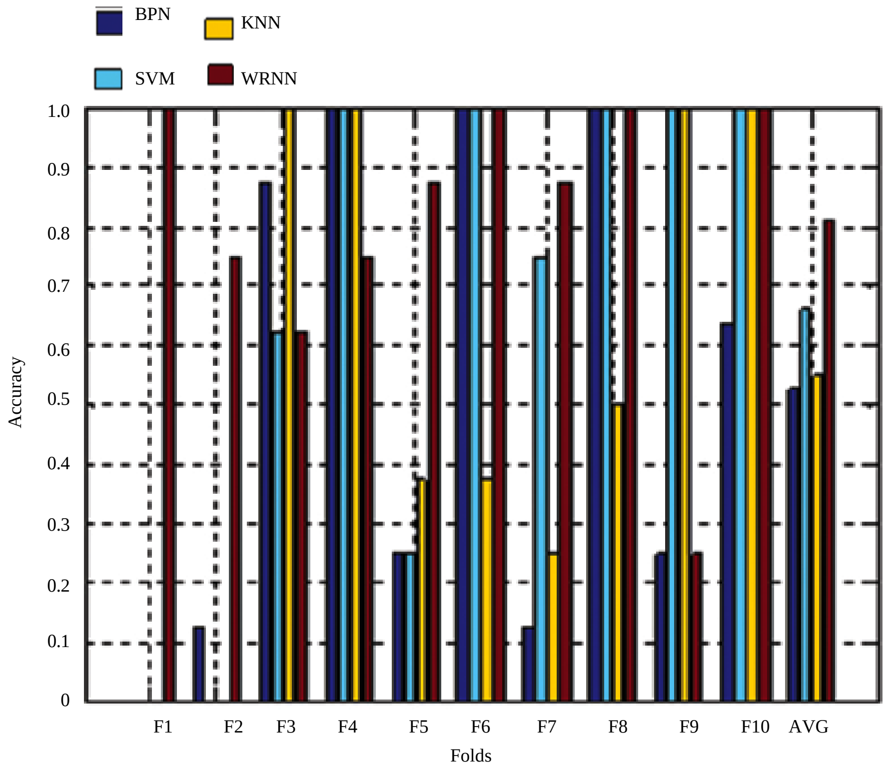

Fig. 3: Comparison of accuracy analysis of four methods with Daubechies 4 wavelet

Table 2: Four gender classification test results with fifty one land mark points (original data classification [83 images*102 values])

Ten Folds	BPN	SVM	KNN	WRNN
F1				
Tr: 9-83				
Test:1-8	0.6250	0.6250	0.3750	0.6250
F2				
Tr: 1-8,17-83				
Test:9-16	0.5000	0.2500	0.5000	0.5000
F3				
Tr: 9-83				
Test:1-8	0.3750	0.6250	0.5000	0.6250
F4				
Tr: 1-24,33-83				
Test:25-32	1.0000	1.0000	1.0000	1.0000
F5				
Tr: 1-32,41-83				
Test:33-40	0.2500	0.5000	0.6250	0.6250
F6				
Tr: 1-40,49-83				
Test:41-48	0.5000	0.5750	0.8750	0.6250
F7				
Tr: 1-48,57-83				
Test:49-56	0.5000	0.7500	0.3750	0.5000
F8				
Tr: 1-56,65-83				
Test:57-64	0.7500	0.7500	0.8750	0.7500
F9				
Tr: 1-64,73-83				
Test:65-72	0.5000	0.7500	0.2500	0.6250
F10				
Tr: 1-72				
Test:73-83	0.6364	0.5091	0.8182	0.6364
Avg	0.5636	0.6334	0.6193	0.6511

Tr: Training images, test: test images

Table 3: Four gender classification test results with PCA (original data classification+PCA [83 images*2 values])

Ten folds	PBN+PCA	SVM+PCA	KNN+PCA	WRNN+PCA
F1				
Tr: 9-83				
Test:1-8	0.3750	0.0000	0.5000	1.0000
F2				
Tr: 1-8,17-83				
Test: 9-16	0.8750	0.0000	0.5000	0.8750
F3				
Tr: 9-83				
Test:1-8	0.5000	0.2500	0.6250	1.0000
F4				
Tr: 1-24,33-83				
Test:25-32	0.7500	1.0000	1.0000	1.0000
F5				
Tr: 1-32,41-83				
Test:33-40	0.3750	0.2500	0.5000	1.0000
F6				
Tr: 1-40,49-83				
Test:41-48	0.8750	1.0000	0.7500	1.0000
F7				
Tr: 1-48,57-83				
Test:49-56	0.7500	1.0000	0.5000	0.7500
F8				
Tr: 1-56,65-83				
Test:57-64	1.0000	1.0000	0.6250	1.0000
F9				
Tr: 1-64,73-83				
Test:65-72	0.6250	0.8750	0.7500	1.0000
F10				
Tr: 1-72				
Test:73-83	0.5455	1.0000	0.4545	1.0000
Avg	0.6671	0.6375	0.6205	0.9625

Tr: Training images, test: test images

Table 4: Four gender classification test results with wavelet (original data classification+DB4 wavelets [83 images*2 values])

Ten folds	DB4+BPN	DB4+SVM	DB4+KNN	DB4+WRNN
F1				
Tr: 9-83				
Test:1-8	0.0000	0.0000	0.0000	1.0000
F2				
Tr: 1-8,17-83				
Test: 9-16	0.1250	0.0000	0.0000	0.7500
F3				
Tr: 1-16,25-83				
Test:17-24	0.8750	0.6250	1.0000	0.6250
F4				
Tr: 1-24,33-83				
Test:25-32	1.0000	1.0000	1.0000	0.7500
F5				
Tr: 1-32,41-83				
Test:33-40	0.2500	0.2500	0.3750	0.8750
F6				
Tr: 1-40,49-83				
Test:41-48	1.0000	1.0000	0.3750	1.0000
F7				
Tr: 1-48,57-83				
Test:49-56	0.1250	0.7500	0.2500	0.8750
F8				
Tr: 1-56,65-83				
Test:57-64	1.0000	1.0000	0.5000	1.0000
F9				
Tr: 1-64,73-83				
Test:65-72	0.2500	1.0000	1.0000	0.2500
F10				
Tr: 1-72				
Test:73-83	0.6364	1.0000	1.0000	1.0000
Avg	0.5261	0.6625	0.5500	0.8125

Tr: training images, test: test images

CONCLUSION

This study has reviewed four gender classification methods and proposed weighted rough neural network method to identify the gender by handling dataset which is inconsistent and imbalance. The four gender classification methods are applied to 51 land mark points, principal component analysis and Daubechies 4 wavelet. The test result shows that weighted rough neural network method with principal component analysis has highest average accuracy.

REFERENCES

Arulselvi, M., V. Ramalingam and S. Palanivel, 2011. Cephalometric analysis using PCA and SVM. Intl. J. Comput. Appl., 30: 39-47.

Jangam, D.K., K. Priyanka and F. Sana, 2014. Age determination using lateral cephalogram and orthopantomograph: A comparative study. Scholars J. Appl. Med. Sci., 2: 526-528.

Jaswante, A., A. Khan and B. Gour, 2013. Gender classification technique based on facial features using neural network. Intl. J. Comput. Sci. Inf. Technol., 4: 839-843.

Khan, S.A., M. Nazir, N. Naveed and N. Riaz, 2011. Efficient gender classification methodology using DWT and PCA. Proceedings of the 14th International Conference on Multitopic (INMIC), December 22-24 2011, IEEE, Karachi, Pakistan, ISBN:978-1-4577-0654-7, pp: 155-158.

Lakkshmanan, A., 2013. Cephalometric analysis for finding facial growth abnormalities. Intl. J. Comput. Sci. Eng. Technol., 4: 680-684.

Own, H.S. and A. Abraham, 2014. A novel-weighted rough set-based meta learning for ozone day prediction. Acta Polytech. Hungarica, 11: 59-78.

Saravanan, P. and M. Lakshmi, 2013. An optimal noise removal approach for lateral skull images. Intl. J. Innovative Technol. Res., 1: 182-186.

Saravanan, P. and M. Lakshmi, 2018. Advanced classification of gender based cephalometric radiograph using advanced active appearance model in combination with principle component analysis and wavelet. Hellenic Eur. Res. Intl. J. Comput. Math. Appl., 2641: 485-492.

Satishkumar, E.N., K. Thangavel and P.S. Raja, 2016. Weighted rough classification for imbalanced gene expression data. Intl. J. Comput. Inf., 6: 220-232.

Stanojevich, V., 2012. The role of a forensic anthropologist in death investigation. J. Forensic Res., 3: 1-2.

Vanitha, L. and A.R. Venmathi, 2011. Classification of medical images using support vector machine. Intl. Conf. Inf. Netw. Technol., 4: 63-67.

Zayed, N. and H.A. Elnemr, 2015. Statistical analysis of Haralick texture features to discriminate lung abnormalities. J. Biomed. Imaging, 2015: 12-12.