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Study of Anatomical Variations of Para nasal sinus (PNS) using Multislice Computed Tomography (CT) in Rhinosinusitis

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Abstract: ***The study aimed to characterize anatomical variations of Para nasal sinus (PNS) in Rhino sinusitis depending on the classification processes of CT Brain using Interactive Data Language(IDL) program as platform for the generated codes. This retrospective study included* 392 *patients,* 272 *males,* 120 *females; Their ages ranged from* 18 *to* 68 *years, the majority of cases were found in age group from 28 to less than 38 years 154 Patients (39.3%) , referred for CT brain at Riyadh Hospitals, Saudi Arabia, mostly from Consultant Radiologists Diagnostic Center selected randomly. The results of the classification showed that incidence of PNS diseases was more in males (69.4%) as compared to females (30.6%). The predominant clinical presentations were headache 276 Patients (70.4%), and the most the sinuses areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissues. Several texture features are introduced from the first order statistics and the classifications score matrix was generated by linear discriminate analysis and overall classifications accuracy of sinuses regions found was 94.3%, and the classification accuracy of normal sinuses 100%, the classification accuracy of abnormal sinuses measured as 89.7%, and for spine as 86.9 %, While the bone showed a classification accuracy of 100%. These relationships are stored in a Texture index that can be later used to automatically annotate new CT with the appropriate characterizedanatomical variations of PNS, which will help defining Rhino-sinusitis.***

Keywords: MSCT, PNS, Anatomical Variations, Rhinosinusitis

1. Introduction

Sinonasal diseases, especially rhino-sinusitis, are commonly encountered health problems in otorhinolaryngology practice. Variations in sinonasal anatomy such as deviated nasal septum, enlarge turbinates,etc are common in the population [1]. Chronic rhinosinusitis is a common condition in which the paranasal sinuses (PNS) become inflamed and swollen for at least eight weeks despite treatment attempts [2]. It is also known that chronic rhinosinusitis interferes with drainage and causes mucus to build up. It is one of the most common illnesses of our times, and it is increasing in epidemic proportions throughout the world [3]. Chronic or recurrent sinusitis has been known to negatively impact health-related quality of life [4].

Its patho-physiology seems to be multi -factorial. The approach to patients with chronic rhino-sinusitis has changed after Messerklinger published the first comprehensive account of technique of nasal endoscopy and its application to the diagnosis and treatment of sinonasal diseases [5].

The prevalence of these variations differs in various ethnic populations [6]. Role of sinonasal anatomical variations in the causation of chronic rhinosinusitis is still debated though it cannot be ruled out altogether [7,8]. Although sinusitis is a clinically diagnosed condition, imaging studies are used to assess the disease and demonstrate the sinonasal anatomy [9].

Computed tomography (CT) scan plays a fundamental role in the diagnosis of anatomical variations as well as of sinonasal diseases for a better guidance in the decision making about clinical, therapeutic and surgical approaches. Spiral CT provides axial and coronalimages that facilitate good appreciation of the size and relationship of the paranasal sinuses. It is currently the gold standard to study the imaging modality of choice for evaluating paranasal sinuses and adjacent structures [10,11]. MSCT with its capability of displaying bone and soft tissues is the current diagnostic modality of choice for evaluating the ostiomeatal complex. MSCT is used both as a diagnostic tool to identify anatomical anomalies and mucosal pathology and as a preoperative map to guide the surgeon through the challengingly convoluted and variable anatomy of the area [12,13].

2. Material and Methods

Subjects

This retrospective study included 392 patients, 272 males, 120 females; their ages ranged from 18 to 68 years referred for CT brain at Riyadh Hospitals, Saudi Arabia, mostly from Consultant Radiologists Diagnose Center selected randomly.

Data acquisition and measurement protocol

Statistical Methods

The study depends on the Interactive Data Language (IDL) as a high-level language for datamanipulation, visualization and analysis. IDL has strong signal and image processing capabilities and extensive math and statistical functions, First Order Statistics: FOS can be used as the mostbasic texture feature extraction methods, which are based on the probability of pixel intensityvalues occurring in digital images. The parameters in the following statistical formulas are xi, the Intensity value of pixel i, N, the total number of pixels, max V, the maximum intensity valuewithin a patch and Hi, the histogram of an image patch.

Mean: Calculates the mean intensity value of all pixels. In Mat lab the function μ= mean2(IP) can be used to compute this feature.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Standard Deviation

The standard deviation (STD) of all the intensity values of a patch is used as a texture feature. The corresponding Mat lab function is σ= std2(IP).

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Coefficient of variation

The coefficient of variation can be seen as the relative standard deviation. It is calculated by dividing the standard deviation with the mean value.

$$c_v = \frac{\sigma}{\mu}$$

Entropy

The entropy of a gray-scale image is a measure of intensity value randomness. It is calculated from the histogram counts of an image giving a probability p of certain pixel values occurring in the image.

$$s = -\sum(p. * log2(p))$$

3. Results

In this paper were features extracted from CT images using first order statistic and All these features were calculated for all images and then the data were ready for discrimination which was performed using step-wise technique in order to select the most significant feature that can be used to classify the brain CT imaging for Para nasal sinuses and the results show that:

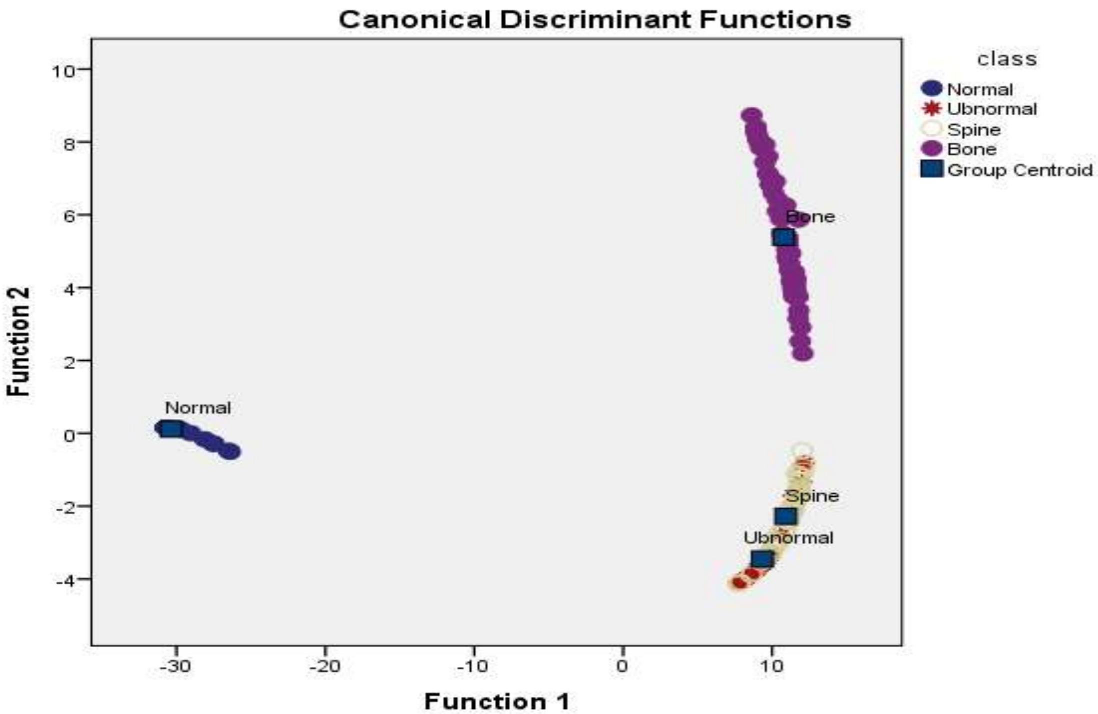

Figure 1: Classification Map that created using linear discriminant analysis function.

Fig. 1. Scatter plot generated using discriminate analysis function for three classes represents: normal, abnormal, spine and bone the classification showed that the sinuses were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Table 1: Showed the classification accuracy of the sinuses regions using linear discriminant analysis:

Classes		*Predicted Group Membership*				Total
		Normal	Abnormal	Spine	Bone	
Original	*Normal*	*100.0*	*.0*	*.0*	*.0*	*100.0*
	Abnormal	*.0*	*89.7*	*10.3*	*.0*	*100.0*
	Spine	*.0*	*13.1*	*86.9*	*.0*	*100.0*
	Bone	*.0*	*.0*	*.0*	*100.0*	*100.0*

a. 94.3% of original grouped cases correctly classified

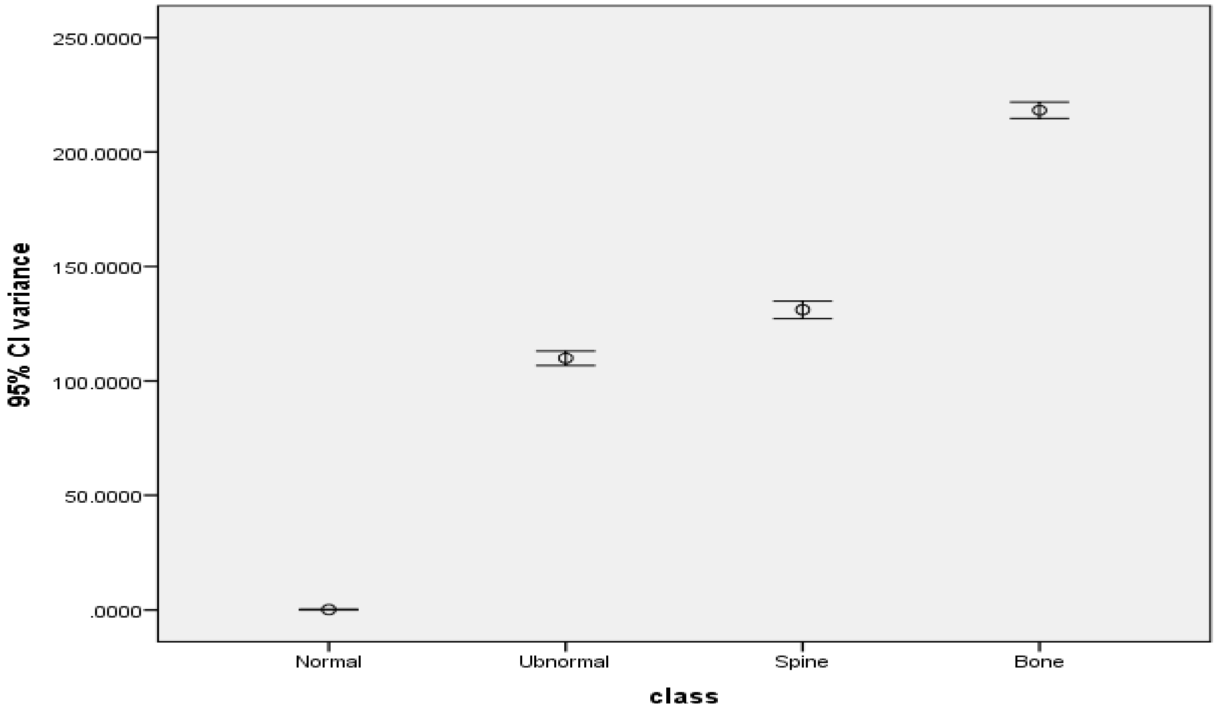

Figure 2: Show error bar plot for confidence interval (CI) variance textural features

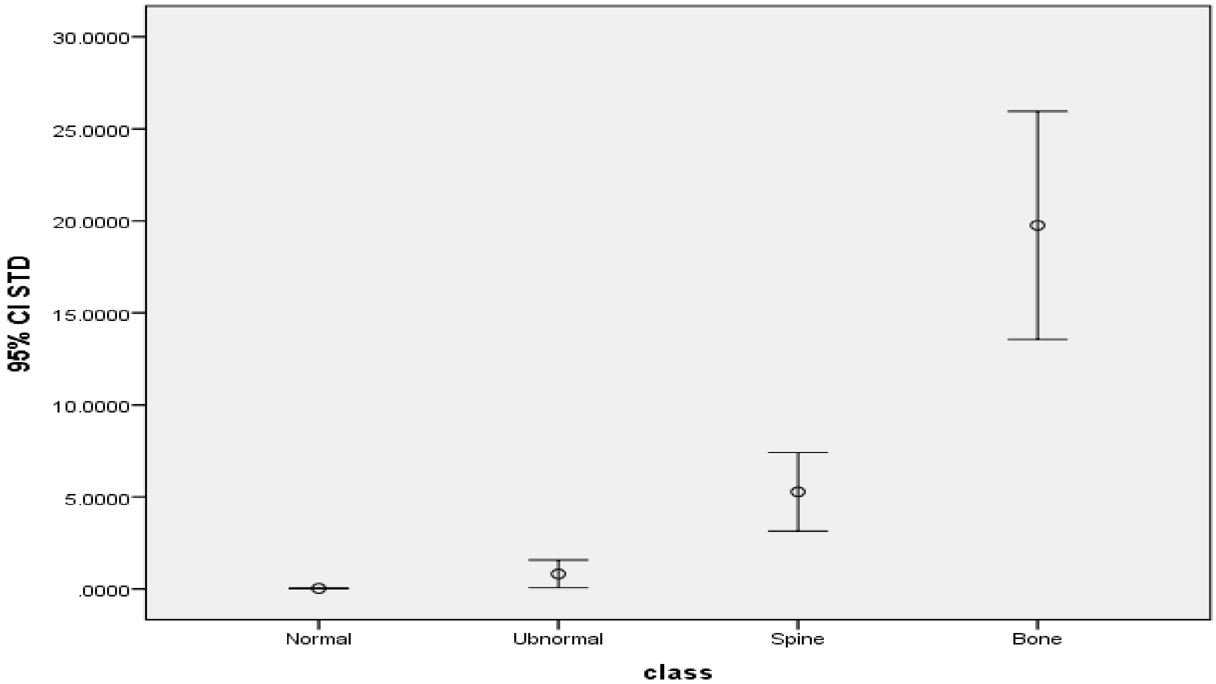

Figure 3: Show error bar plot for the CI STD textural features

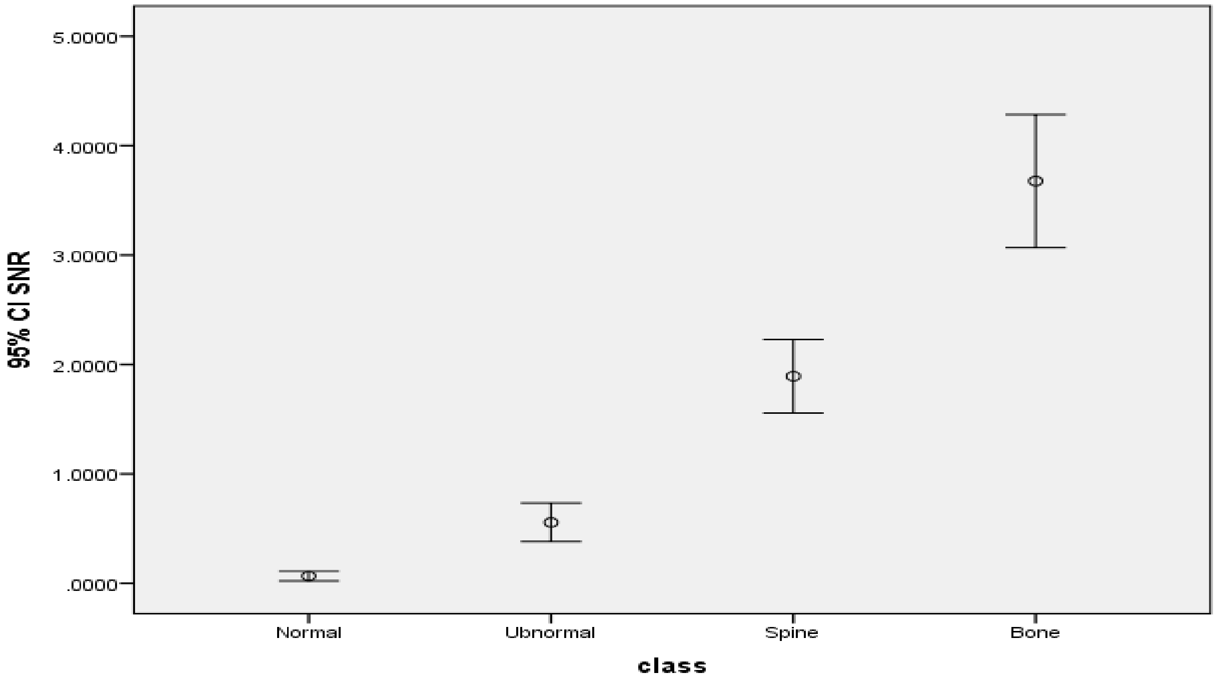

Figure 4: Show error bar plot for the CI SNR (signal to noise ratio) textural features

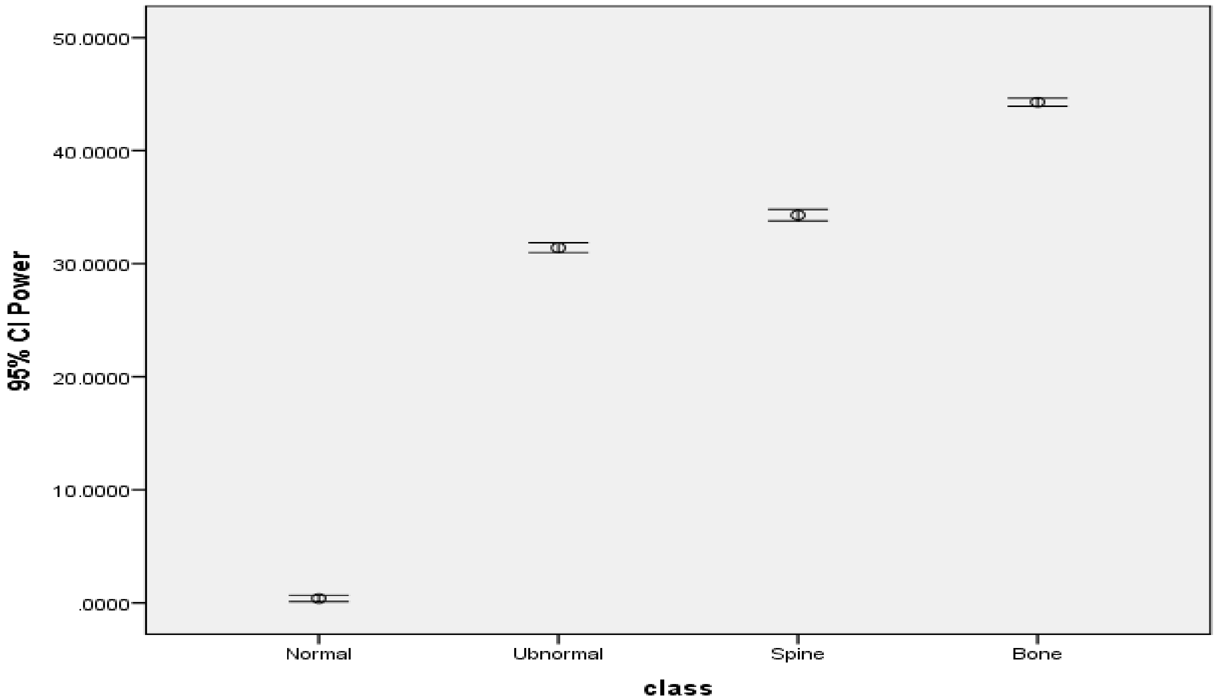

Figure 5: Show error bar plot for the CI power textural features

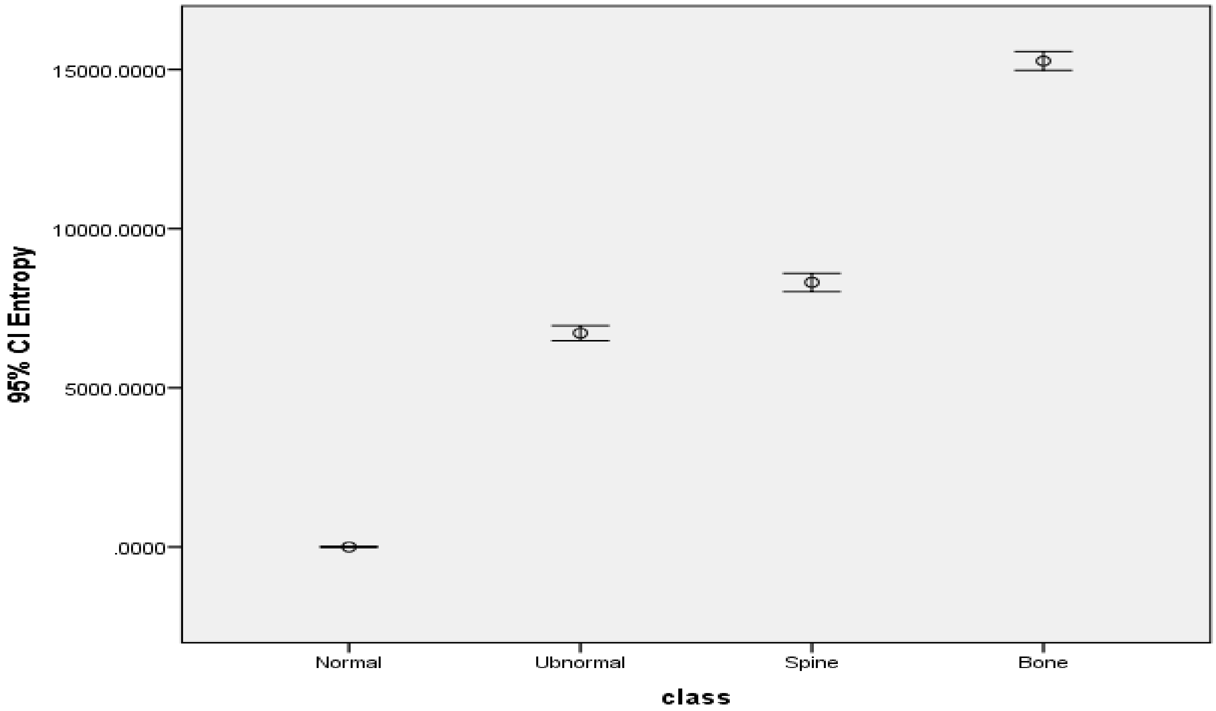

Figure 6: Show error bar plot for CI entropy textural features

4. Discussion

This study included 392 patients, 272 males, 120 females; incidence of PNS diseases was more in males (69.4%) as compared to females (30.6%). Their ages ranged from 18 to 68 years, the majority of cases were found in age group from 28 to less than 38 years 154 Patients (39.3%). The predominant clinical presentations were headache 276 Patients (70.4%), and the most affected site is inferior nasal turbinate hypertrophy (94.1%).Most anatomic variants and common pathological findings were detected in this study that could be incidental or causative by the Sino-nasal inflammatory disease.incidence of PNS diseases was more in males similar of Study Kushwah etal.[14].

In this study 70.4% patients presented with headache similar findings Study Kushwah etal.[14].in their study.91.3% patient had deviation of the nasal septum (DNS) as observed by Mohammad Adeel etal.[15].and Ibrahim Sumaily etal.[16].in their study.

In this study features extracted from MSCT images using First Order Statistic and All these characters were calculated for all images and then the data were ready for discrimination, which was performed using Step-wise technique in order to select the most significant character that can be used to classify the brain CT imaging for Paranasal sinuses.

Fig.1. Scatter plot generated using discriminate analysis function for three classes represents: normal, abnormal, spine and bone the classification showed that the sinuses were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Table (1) show classification score matrix generated by linear discriminate analysis and the overall classification Accuracy of normal sinuses 100%, were the classification accuracy of abnormal sinuses 89.7%, spine 86.9 %, While the bone showed a classification accuracy of 100%.

Fig .2 show error bar plot for CI variance textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features. From the discriminate power point of view in respect to the applied features the variance can differentiate between all the classes successfully.

Fig .3 show error bar plot for the CI STD textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

Fig .4 shows error bar plot for the CI SNR textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

Fig .5 shows error bar plot for the CI power textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features.

Fig .6 show error bar plot for CI entropy textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminates between all features. From the discriminate power point of view in respect to the applied features the entropy can differentiate between all the classes successfully.No previous studies regarding the texture analysis of PNS CT scan were found.

Using Linear discrimination analysis generated a classification function which can be used to classify other image into the mention classes as using the following multi regression equation;

Normal = variance * (-0.750) + STD * (-0.001) + SNR * 0.011 + power * 1.492 + entropy * 0.007 - 1.662
Abnormal = variance * 50.353 + STD * 0.664 + SNR * -7.026 + power * 16.037 + entropy * -0.658 - 808.978
Spine = variance * 53.718 + STD * 0.448 + SNR * -4.657 + power * 14.354 + entropy * -0.697 - 869.328
Bone = variance * 48.531 + STD * 0.710 + SNR * -6.755 + power * 16.403 + entropy * -0.626 - 873.853

5. Conclusion

The classification processes of CT Brain were defining the sinuses regions to normal, abnormal, spine and bonewere carried out using Interactive Data Language (IDL) program as platform for the generated codes. The result of the classification showed that the sinuses areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue. Several texture features are introduced from first order statistic and the classification score matrix generated by linear discriminate analysis and the overall classification accuracy of sinuses regions 94.3%, and the classification accuracy of normal sinuses 100%, and the classification accuracy of abnormal sinuses 89.7%, spine 86.9 %, While the bone showed a classification accuracy of 100%.

References

[1] Gebrim ES. Relevance of sinonasalanatomical variations in the preoperative evaluation bycomputed tomography for endonasalsurger. Radiol Bras. 2008;41:5-6
[2] Fadda GL, Rosso S, Aversa S et al: Multiparametric statistical correlations between paranasal sinus anatomic variations and chronic rhinosinusitis. ActaOtorhinolaryngol Ital, 2012; 32(4):244–51
[3] Shpilberg KA, Daniel SC, Doshi AH: CT of anatomic variants of the paranasal sinuses and nasal cavity: Poor correlation with radiologically significant rhinosinusitis but importance in surgical planning. Am J Roentgenol, 2015; 204(6): 1255–60
[4] Alkire BC, Bhattacharyya N: An assessment of sinonasal anatomic variants potentially associated with recurrent acute rhinosinusitis. Laryngoscope, 2010; 120: 631–34
[5] MesserklingerW.Endoscopy of the nose. Baltimore.MD:Urban& Schwarzenberg:1978.
[6] Badia L, Lund VJ, Wei W, Ho WK. Ethnic variation in sinonasal anatomy on CT-scanning. Rhinology. 2005;43:210-4.
[7] Gebrim ES. Relevance of sinonasalanatomical variations in the preoperative evaluation bycomputed tomography for endonasalsurger. Radiol Bras. 2008;41:5-6
[8] Jones NS. CT of the paranasal sinuses: a review of the correlation with clinical, surgical andhistopathological findings. ClinOtolaryngol Allied Sci. 2002;27:11-7.
[9] Kaygusuz A, Haksever M, Akduman D, Aslan S, Sayar Z. Sinonasal Anatomical Variations: Their Relationship with Chronic Rhinosinusitis and Effect on the Severity of Disease—A Computerized Tomography Assisted Anatomical and Clinical Study. Indian J Otolaryngol Head Neck Surg. 2014;6:260–6.
[10] AhmetKaygusuz, Mehmet Haksever, DavutAkduman, Sundus, Aslan, ZeynepSayar. Sinonasal Anatomical variations: Their Relationship with Chronic Rhinosinusitis and Effect on the Severity of Disease-A Computerized Tomography Assisted Anatomical and Clinical Study. Indian J Otolaryngol Head Neck Surg. 2014; 66(3):260–266.
[11] H. Mamatha, N.M. Shamasundar, M.B. Bharathi, L.C. Prasanna. Variations of ostiomeatal complex and its applied anatomy: a CT scan study. Indian journal of science and technology. 2010; 3 (8):904-907.
[12] Shpilberg KA, Daniel SC, Doshi AH: CT of anatomic variants of the paranasal sinuses and nasal cavity: Poor correlation with radiologically significant rhinosinusitis but importance in surgical planning. Am J Roentgenol, 2015; 204(6): 1255–60
[13] Alkire BC, Bhattacharyya N: An assessment of sinonasal anatomic variants potentially associated with recurrent acute rhinosinusitis. Laryngoscope, 2010; 120: 631–34
[14] Kushwah APS, Bhalse R, Pande S. CT evaluation of diseases of Paranasal sinuses & histopathological studies. Int J Med Res Rev 2015;3(11):1306-1310. doi: 10.17511/ijmrr.2015.i11.237
[15] Mohammad Adeel, Muhammad Shaheryar Ahmed Rajput, Shabbir Akhter, MubasherIkram, Asif Arain (Department of Otolaryngology and Head and Neck Surgery, Aga Khan University Hospital, Karachi, Pakistan. Yasir Jameel Khattak (Department of Radiology, Aga Khan University Hospital, Karachi, Pakistan.) Anatomical variations of nose and para-nasal sinuses; CT scan review march 2013.
[16] Ibrahim S, Saud A, Jibril H. Anatomical Variations of Paranasal Sinuses Gender and Age Impact. Glob J Oto 2018; 14(1): 555877. DOI: 10.19080/GJO.2018.14.555877.