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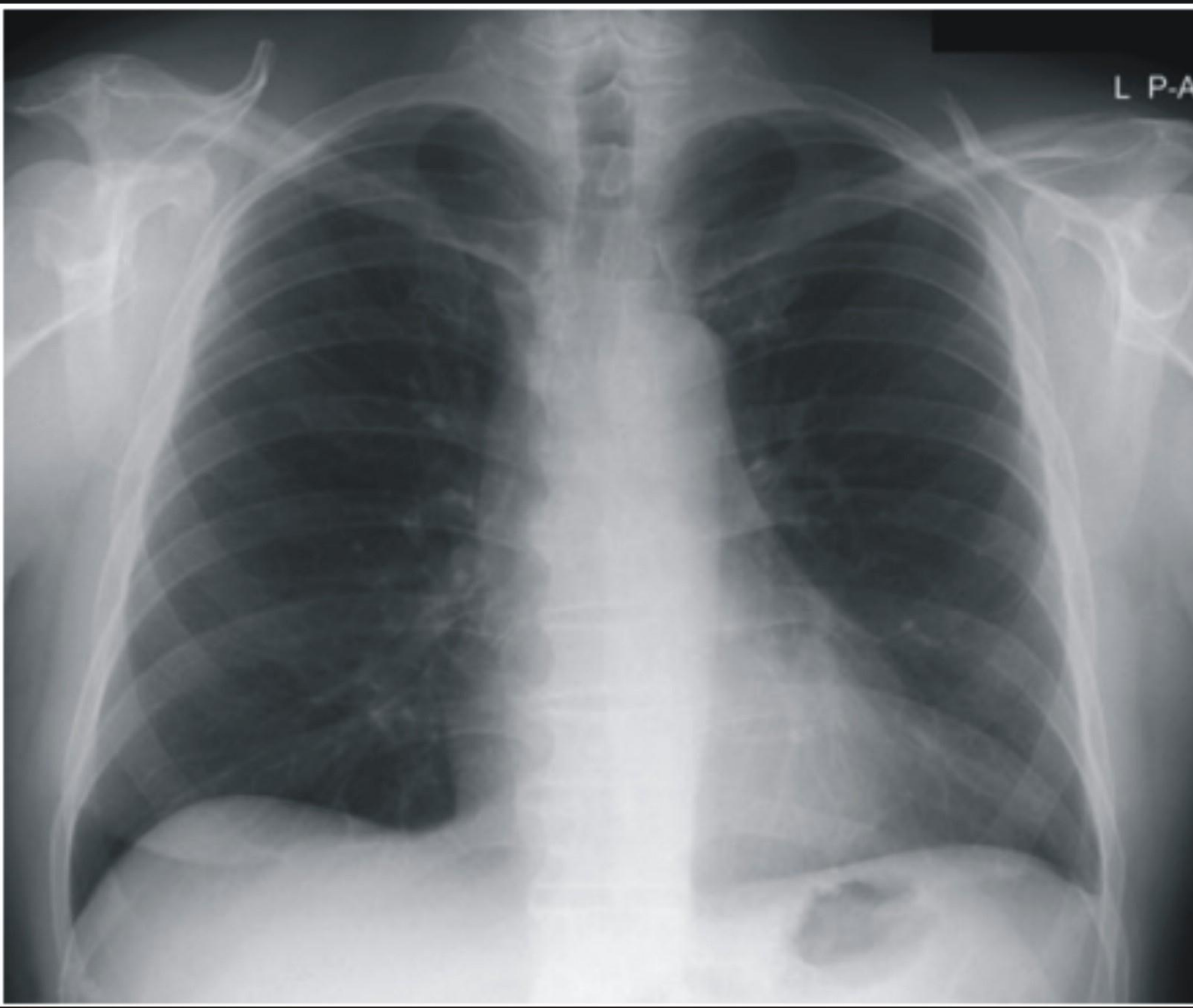

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Characterization and Classification of Brain Tissue and Stroke Lesions in Non-Contrast Computed Tomography Images of Stroke Patients Using Statistical Texture Descriptors and Artificial Neural Network

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ABSTRACT

Aim: To characterize and classify stroke lesions and normal brain tissue in computed tomography (CT) images using statistical texture descriptors.

Patients and methods: Two experienced radiologists blinded to each other inspected CT images of 164 stroke patients to identify and categorize stroke lesions into ischaemic and haemorrhagic subtypes. Four regions of interest (ROIs) in each CT slice that demonstrated the lesion; two each representing the lesion and normal tissue were selected. Statistical texture descriptors namely, co-occurrence matrix, run-length matrix, absolute gradient and histogram were calculated for them. Raw data analysis was performed to identify the parameters that best discriminate between normal brain tissue and stroke lesions. Artificial neural network (ANN) was used to classify the ROIs into normal tissue, ischaemic and haemorrhagic lesions using the radiologists' identification and categorization as the gold standard, and further analyzed using the receiver operating characteristic curve.

Results: Three parameters in each texture class discriminated between normal tissue, ischaemic and haemorrhagic stroke lesions. The discriminating co-occurrence matrix parameters were sum average parameters namely S1-1 SumAverg, S1-0 SumAverg and S0-1 SumAverg. For the run-length matrix, short run emphasis in horizontal, 135^0 and 45^0 directions were the discriminating features. The discriminating absolute gradient parameters were gradient non-zeros, gradient variance and gradient mean. For the histogram class, the mean, 90th and 99th percentiles were the discriminating parameters. The ANN achieved a sensitivity of 0.637, specificity 0.753, false positive rate (FPR) 0.247, and false negative rate (FNR) 0.363 with co-occurrence matrix. With run-length matrix the sensitivity was 0.544, specificity 0.607, FPR 0.393, and FNR 0.456 while with absolute gradient the sensitivity was 0.546, specificity 0.586, FPR 0.414, FNR 0.454. With histogram, the sensitivity was 0.947, specificity 0.962, FPR 0.038, and FNR 0.053.

Conclusion: The histogram texture features showed the highest sensitivity and specificity in the classification of brain tissue and stroke lesions using the artificial neural network.

Keywords: Texture analysis, Characterization, Classification, Brain tissue, Stroke, Computed tomography

Introduction

The clinical diagnosis of stroke and its subtyping is often inaccurate [1], and neuroimaging is essential for accurate diagnosis. Non-contrast computed tomography (NCCT) is considered the mainstay for early stroke diagnosis because computed tomography (CT) scanners are sensitive to the detection of early stroke lesions [2]. Computed tomography scanners are more widely available in the communities and may be accessed much more easily and faster [3]. Computed tomography examinations are cheaper and faster to perform than magnetic resonance imaging (MRI). Thus, taking the time-critical nature of early stroke diagnosis into consideration, NCCT is the preferred first-line imaging tool.

The occurrence of a stroke is always an emergency. Computed tomography is considered to be very sensitive to early stroke and often provide information necessary to make decisions during an emergency. Ischaemic stroke diagnosis is time-critical. Ischaemic stroke has a narrow therapeutic window in the first few hours following stroke ictus and a dramatic rise in haemorrhage complications thereafter putting the patient at a serious risk of increased neurological damage.

Computed tomography and other neuroimaging procedures are beneficial to the patient only after the images have been accurately interpreted. For visual analysis and interpretation of stroke CT images, the radiologist seeks to identify affected areas by examining the dissimilarity between the left and right cerebral hemispheres. This is a challenging and error-prone task and can be improved upon by texture analysis.

Texture analysis makes it possible for an automated computer-aided approach to be used by clinicians as a second opinion especially in equivocal cases. Automatic method of stroke detection follows the same pattern as visual analysis and interpretation used by radiologists [2]. Some clinical applications of automatic detection and classification of stroke on CT images using texture analysis have been proposed [4, 5]. The proposed methods were based on data from a small number of patients and images, focused mainly on ischaemic stroke and employed only one or two classes of texture features.

Image texture analysis is a stage in medical image processing which enables a computer-aided diagnosis to be carried out. Texture analysis of a medical image is the measurement of quantitative parameters such as grey level distributions and their patterns that constitute the image of a supposed lesion or normal tissue. Computed tomography images being monochromatic and digital in nature, the texture is considered as the distribution of grey-level values among the pixels of a given region of interest in the image. There are four methods of texture analysis namely structural, statistical, model-based and transform methods [6, 7].

The statistical method describes texture in terms of the spatial distribution of grey levels and their patterns in the images [6]. Statistical texture descriptors include parameters in co-occurrence matrix, run-length matrix, absolute gradient and histogram classes [8]. Co-occurrence matrix describes the relative positions of pairs of pixels with the same grey-level intensity as illustrated in Figure 1, while run-length matrix describes the consecutive occurrence of pixels with the same grey-level intensity in particular directions as illustrated in Figure 2.

Absolute gradient calculates parameters related to the variation of pixel grey-level values across an image as illustrated in figure 3. The histogram calculates the frequencies of grey-levels in an image. It is a very familiar simple concept learnt in lower level mathematics. There are complex mathematical formulae for calculating parameters that make up the statistical texture descriptors but these are outside the intended scope of this article.

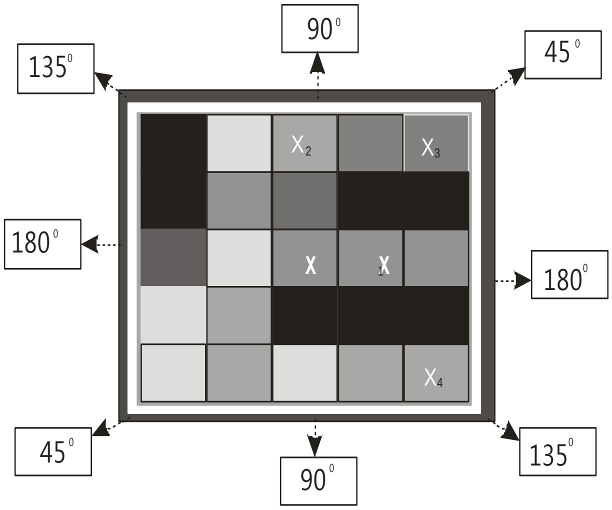

Figure 1: An illustration of the grey level co-occurrence matrix concept of texture computation

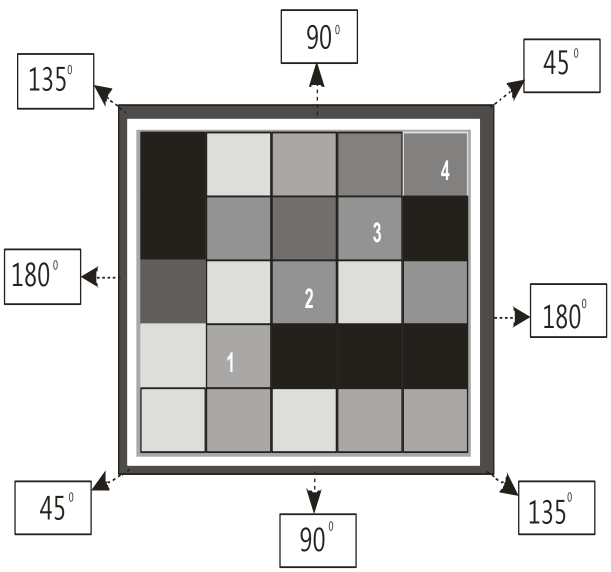

Figure 2: An illustration of the grey level run-length matrix concept of texture computation

Figure 3: An illustration of the gradient concept of texture computation

Stroke may pose a diagnostic challenge to clinicians in locations with dearth of neuroradiologists and delays in obtaining fast, accurate and reliable diagnosis have led to increased mortality. The time-critical nature of stroke diagnosis, therefore, necessitates a simple, fast and reliable computer-aided automated process. Previous attempts to produce automatic detection and classification system of stroke lesions and normal brain tissue in CT images did not utilize all the classes of statistical texture features [4, 5]. Therefore, a comparison of the performances of these statistical texture descriptors in the classification of stroke lesions and normal brain tissue has not been undertaken. The aim of this study was to classify stroke lesions and normal brain tissue on non-contrast CT images using the four groups of statistical texture descriptors and cross-validate the classification with the radiologists' visual interpretation.

Patients and methods

A prospective, cross-sectional study approved by the Research Ethics Committee of Nnamdi Azikiwe University Teaching Hospital, Nnewi, Anambra State, Nigeria was conducted. The study targeted patients that were clinically diagnosed with stroke in the hospitals and were referred to undergo NCCT of the head. The data for the study were collected in two locations namely Onitsha metropolis, Anambra State and Ibadan Metropolis, Oyo State, between May 2012 and April 2013.

The required CT images were those of 164 patients; composed of 58.6% (n= 96) and 41.4% (n = 68), and aged between 32 and 85 years (mean 60 ± 12.4 years). The patients were those diagnosed with stroke at CT in the two centres and who consented to participate in the study. The CT machines used for this study were a 4-slice *Toshiba Asteion*™ and a 2-slice *Philips MX8000 Dual*™ CT scanner. Non-contrast CT images of the brain were obtained in contiguous sections from the base of the skull to the vertex. The image acquisition parameters were those chosen by the attending radiographers.

The CT images obtained were independently visually inspected and reported upon by a team of two radiologists with experiences in CT diagnosis of stroke. Images included in the study were those which radiological reports from the two radiologists were in agreement that it was stroke and the identified stroke subtype. The affected parts of the brain were identified and classified into ischaemic or haemorrhagic lesions by the two radiologists. The images were then transferred from the CT archive to a *Datamax*™ DVD and then loaded into a *Toshiba*™ satellite A200 laptop computer for viewing using *Medysynapse*™ and *Microdom*™ DICOM viewing software.

Texture analysis carried out using the *MaZda*® texture analysis software version 4.7 (Institute of Electronics, Technical University of Lodz, Poland; www.eletel.p.lodz.pl). All the images in which the lesion appeared were selected for analysis and loaded into the computer program. Four regions of interest (ROIs) were defined for each image; two for lesioned tissues and two for normal brain tissues as shown in Figure 4.

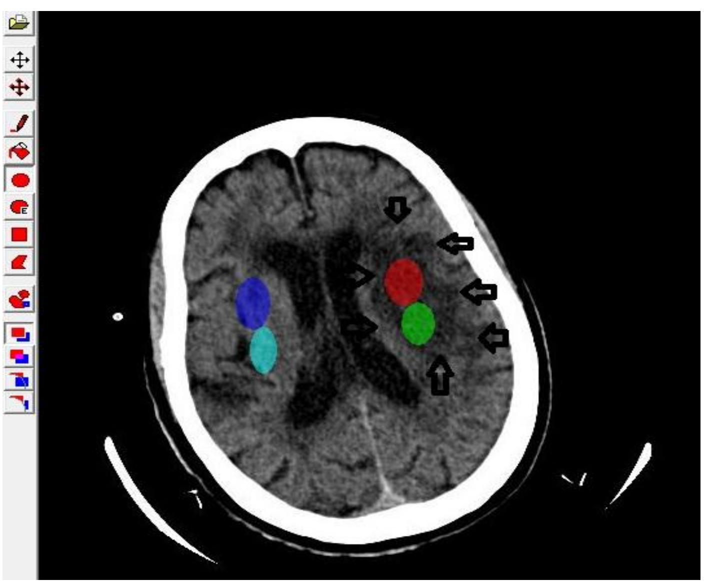

Figure 4: Illustration of the method of selection of a region of interest (ROI). Note that ROI 1 (red) and ROI 2 (green) are on ischaemic tissues on the left cerebral hemisphere while ROIs 3 and 4 (blue and sky blue) are on normal tissues on right cerebral hemisphere

The lesioned brain tissue contained ROI 1 and 2 while the non-lesioned brain tissue in the contra lateral or neighbouring part contained ROI 3 and 4. Statistical texture parameters in the classes of grey level co-occurrence matrix, run-length matrix, absolute gradient and histogram were computed for the four ROIs. Grey level co-occurrence matrices were computed for inter-pixel distances; d = 1, 2, 3, 4, 5 pixels and in the directions; $\theta = 0^0$, 45^0, 90^0, and 135^0 for a total of 20 matrices for each ROI. Run-length matrix was computed for each of the ROI in four directions, namely horizontal, vertical and two diagonals. Absolute gradient and histogram features were computed as well. The output of each class of descriptors computed for each CT image was saved as comma-separated-value (CSV) file in *Microsoft Excel* for further analysis.

Prior to texture analysis precaution was taken to ensure that machines settings which differed between cases did not affect the result of texture analysis. This was achieved by normalizing the image using the ±3 sigma method selected from the program functions. Normalization process literally changes the range of pixel grey-level values of different images so that they appear to have been obtained with the same machine settings. This is called image consistency.

Data analysis

Statistical analysis was carried out in three stages. The first stage was raw data analysis in which data points from text analysis of the ROIs were categorized into ischemic, haemorrhagic and normal tissues. This was to identify the parameters in each class of statistical texture descriptors that best distinguish these tissues from one another. In the second stage, the brain tissues for which texture parameters were calculated were categorized as normal, ischaemic or haemorrhagic. In the third stage, the brain tissues from which statistical texture parameters were computed were then classified by the artificial neural network into normal tissue, haemorrhagic and ischaemic brain tissues.

The classification of stroke lesions and brain tissue using the artificial neural network (ANN) algorithm and cross-validation with the radiologists' classification was done using with *WEKA* 3.6.11 (University of Waikato, New Zealand). Receiver operating characteristic (ROC) curve parameters were calculated for the classifications. Statistical significance was considered at $p < 0.05$.

Results

The results of the raw data analysis which discriminated between the various ROIs as normal brain tissue, ischaemic stroke lesion or haemorrhagic stroke lesions are shown in figures 5-8. The classifications of the ROIs obtained in the discrimination are shown in the following 3D feature space diagrams. In the diagrams, the ischaemic lesion is represented by 1, haemorrhage by 2 and normal brain tissue by 3. The discriminating co-occurrence matrix parameter were sum average parameters namely S1-1 SumAverg with the feature value of -3.54 to 4.35, S1-0 SumAverg -4.19 to 4.39 and S0-1 SumAverg -3.87 to 4.30, as shown Figure 5. For the run-length matrix, short run emphasis in horizontal, 135^0 and 45^0 directions with feature values of -9.08 to 2.27, -9.61 to 2.13 and -9.13 to 2.16 respectively were the discriminating parameters as shown Figure 6.

The discriminating absolute gradient-derived parameters were gradient non-zeros with the feature value of -14.33 to 0.83, gradient variance -2.71 to 4.00 and gradient mean -3.96 t0 2.58 as shown in figure 7. For the histogram class, the mean with feature values of -1.77 to 2.59, 90 percentile -1.83 to 2.19 and 99 percentile -1.99 to 1.91 were the discriminating parameters as shown in figure 8. The result of the raw data analysis shows that histogram class of statistical descriptors was the most accurate in discriminating between normal brain tissue, ischaemic lesion and haemorrhagic lesions as shown in Figure 8.

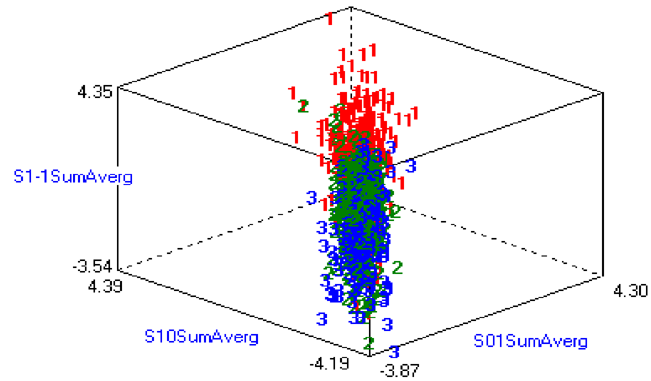

Figure 5: Distribution of the ROIs in 3D feature space using data obtained from the co-occurrence matrix parameters

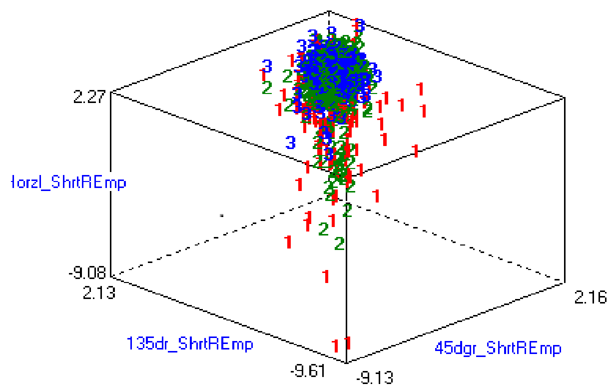

Figure 6: Distribution of the ROIs in 3D feature space using data obtained from the run length matrix parameters

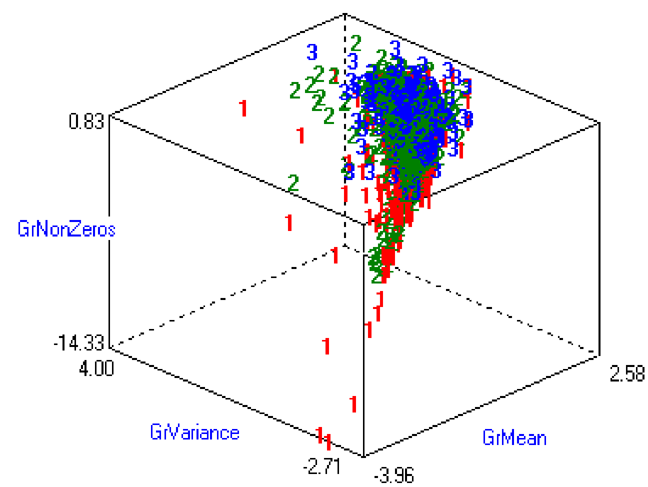

Figure 7: Distribution of the ROIs in 3D feature space using data obtained from the absolute gradient parameters.

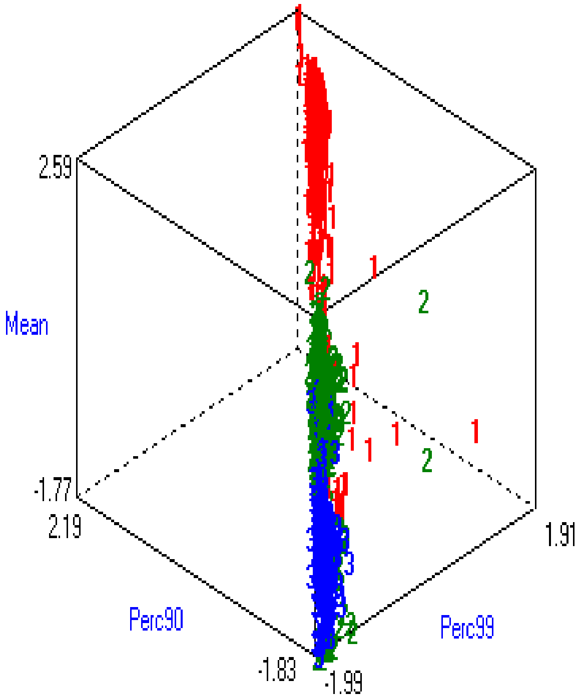

Figure 8: Distribution of the ROIs in 3D feature space using data obtained from the histogram parameters

Table 1 shows the performance co-occurrence matrix parameters in classifying stroke lesions according to type and normal brain tissue using ANN algorithm.

Table 2 shows the performance of run-length matrix (RLM) parameters classifying stroke lesions according to type as well as normal brain tissue using ANN algorithm.

The statistics shown in Table 3 indicate the performance of absolute gradient parameters in the classification of normal brain tissue and stroke lesions according to type using the artificial neural network. The statistics in Table 4 show the performance of histogram-based texture features in the classification of stroke lesions according to type and normal brain tissue using the artificial neural network algorithm. The accuracy of detection was 94.68% while sensitivity, positive predictive value, and area under ROC curve all exceeded 0.9 for normal brain tissue, haemorrhagic and ischaemic stroke lesions.

The histogram-based artificial neural network classification achieved significantly higher weighted sensitivity, specificity and larger area under the ROC curve than the other three classes of texture descriptors ($p < 0.05$) as shown in Table 5. The false positive rate for histogram-based classification was also significantly lower than that for the other three classes of texture descriptors ($p < 0.05$) as shown in Table 5.

Table 1: ROC analysis of artificial neural network classification of brain tissue based on co-occurrence matrix parameters

Evaluation Parameters	Tissue/Lesion Type			
	Normal	Haemorrhage	Ischaemia	Weighted Average
Sensitivity or true positive rate (TPR) or *Recall*	0.708	0.648	0.450	0.637
True negative rate (TNR) or Specificity	0.613	0.905	0.872	0.753
False positive rate (FPR) or ***Fall- out***	0.387	0.095	0.128	0.247
False negative rate (FNR)	0.292	0.352	0.550	0.363
Positive predictive value (PPV) or *Precision*	0.645	0.741	0.477	0.639
Negative predictive value (NPV)	0.830	0.828	0.106	0.721
Area under ROC curve (AUROCC)	0.710	0.831	0.784	0.761

Table 2: ROC analysis of artificial neural network classification of brain tissue based on run-length matrix parameters

Evaluation Parameters	Tissue/Lesion Type			
	Normal	Haemorrhage	Ischaemia	Weighted Average
Sensitivity or true positive rate (TPR) or *Recall*	0.889	0.321	0.057	0.544
True negative rate (TNR) or Specificity	0.277	0.902	0.973	0.607
False positive rate (FPR) or *Fall- out*	0.723	0.098	0.027	0.393
False negative rate (FNR)	0.111	0.679	0.943	0.456
Positive predictive value (PPV) or *Precision*	0.547	0.565	0.372	0.514
Negative predictive value (NPV)	0.514	0.836	0.937	0.694
Area under ROC curve (AUROCC)	0.632	0.663	0.652	0.646

Table 3: ROC analysis of artificial neural network classification of brain tissue based on absolute gradient parameters

Evaluation Parameters	Tissue/Lesion Type			
	Normal	Haemorrhage	Ischaemia	Weighted Average
Sensitivity or true positive rate (TPR) or *Recall*	0.888	0.347	0.021	0.546
True negative rate (TNR) or Specificity	0.221	0.917	0.994	0.586
False positive rate (FPR) or *Fall- out*	0.779	0.083	0.006	0.414
False negative rate (FNR)	0.112	0.653	0.979	0.454
Positive predictive value (PPV) or *Precision*	0.533	0.619	0.500	0.550
Negative predictive value (NPV)	0.446	0.940	0.978	0.694
Area under ROC curve (AUROCC)	0.551	0.714	0.660	0.621

Table 4: ROC analysis of artificial neural network classification of brain tissue based on histogram parameters

Evaluation Parameters	Tissue/Lesion Type			
	Normal	Haemorrhage	Ischaemia	Weighted Average
Sensitivity or true positive rate (TPR) or *Recall*	0.971	0.949	0.888	0.947
True negative rate (TNR) or Specificity	0.937	0.989	0.983	0.962
False positive rate (FPR) or *Fall- out*	0.063	0.011	0.017	0.038
False negative rate (FNR)	0.029	0.051	0.112	0.053
Positive predictive value (PPV) or *Precision*	0.938	0.971	0.936	0.947
Negative predictive value (NPV)	0.953	0.857	0.050	0.693
Area under ROC curve (AUROCC)	0.979	0.986	0.977	0.980

Table 5: Comparison of performance of the texture descriptors in artificial neural network classification

Class of Texture Descriptors	Weighted ROC Analysis Parameters			
	Sensitivity	Specificity	FPR	AUROCC
Co-occurrence matrix	0.637	0.753	0.247	0.761
Run-length matrix	0.544	0.607	0.393	0.646
Absolute gradient	0.546	0.586	0.414	0.621
Histogram	0.947	0.962	0.038	0.980
Remark	$p < 0.05$	$p < 0.05$	$p <0.05$	$p < 0.05$

Discussion

Stroke remains a leading neurological cause of morbidity and mortality, and as such is a public health concern in Nigeria and globally. In view of its outstanding importance, a great deal of effort is being made to automate its CT diagnosis. This is in tandem with the future direction of radiology which is the computer-aided diagnosis.

In this study, we attempted to automatically identify normal brain tissue, ischaemic and haemorrhagic stroke lesions on non-contrast CT images using a combination of statistical texture parameters and artificial neural network. In computer-aided diagnosis in radiology, the image has to be analyzed and translated into a machine readable form. The image analysis carried out in this study was texture analysis in which statistical texture parameters were calculated for selected ROIs in the image. The selected ROIs were then classified as normal brain tissue, ischaemic stroke lesion or haemorrhagic stroke lesion.

This classification which was based on texture features of the ROIs is referred to as discriminant analysis. In this way the best discriminating parameters in each class of statistical texture were deduced. For the co-occurrence matrix the identified best discriminating parameter between normal brain tissue and haemorrhagic and ischaemic stroke lesions was sum average (SumAverg).

In a previous study [5], non-contrast brain CT images of 5 acute ischaemic patients and 5 normal subjects were evaluated. Four co-occurrence matrix parameters, namely; angular second moment (ASM), sum of squares (SS), contrast (C), and sum variance (SV) for lesioned and non-lesioned tissues. The researchers found that the ASM was best at discriminating between lesioned and non-lesioned brain tissues and between brain tissues of patients and normal subjects [5]. This is not in agreement with the result of our study.

Aside co-occurrence matrix parameters, other statistical texture features were computed and evaluated in the present study. The best feature to discriminate between normal, ischaemic and haemorrhagic brain tissues was short run emphasis (ShrtREmp in 45^0, 135^0 and horizontal directions). For the absolute gradient features, gradient non-zeros, gradient variance and gradient mean were best discrimination while for histogram-derived parameters the mean, percentile 90 and percentile 99 were the best features for discrimination. These findings regarding these statistical texture features could not be compared with previous reports as no similar study in the subject area was found.

In computer-aided diagnosis, the computer tries to emulate the radiologist's visual inspection and interpretation of CT images or any other image it has been presented with depending on the case under investigation. Classification is typically accomplished by using a decision or discriminant function [9]. In this study supervised classification was carried using the artificial neural network, which simulates the working of the human brain [10, 11].

The classification of ROIs into normal brain tissue, ischaemic and haemorrhagic stroke lesions was carried out this study using a data mining software. This was to take care of the large volume of data generated by texture analysis. The artificial neural network algorithm was used in the classification and its performance in carrying out this task was evaluated using the receiver-operating characteristic (ROC) curves.

The ROC curve is popularly used in biomedicine to compare the diagnostic performance of two or more laboratory or diagnostic tests [12] and also to discriminate between a diseased case and a normal case [13]. The results of ROC curve analysis of performance of artificial neural network classification of brain tissues based data obtained from statistical methods of texture analysis show that histogram-based parameters were by far better than the co-occurrence matrix, run-length matrix and gradient parameters.

A classification accuracy of over 90% was achieved, and the weighted average sensitivity, specificity and area under ROC curve of almost unity were recorded for both artificial neural network. Correspondingly the false positive rate and false negative rate in both methods were very low. A diagnostic test with high sensitivity is useful in ruling out a disease condition when the test result is negative. Correspondingly, a diagnostic test with high specificity is useful in ruling in a disease condition when the test result is positive [13].

Similar studies have been carried out in the past with quite promising outcomes. There was an attempt to classify stroke lesions into acute infarct, chronic infarct and haemorrhage on non-contrast brain CT using histogram-based comparison and wavelet energy-based texture information [3]. Another study also showed that texture analysis can possibly help in detection of acute ischaemic stroke lesions and thus identify potentially affected areas even if they are not visually perceptible [5].

Texture analysis is an important step in building computer-aided schemes which has been demonstrated in previous studies. Chen et. al. [14] extracted texture features from sonograms of solid breast nodules. With artificial neural network classification they reported 95% accuracy, in classification of nodules as malignant or benign. The sensitivity was 98%, specificity 93%, positive predictive value 89% and negative predictive value 99%. In another study, co-occurrence matrix texture features from ultrasound images of breast lesions were extracted and linear Bayesian classifier was used for classification [15]. The results of both studies indicate that texture analysis may reduce the number of biopsies done for benign lesions.

Although the sensitivity and specificity levels in this study were high, they were not 100% implying that a computer-aided scheme can make mistakes. This study recognizes this fact but it did not consider how the mistaken cases may be identified. A caveat that readily comes to mind is: "sensitivity is rarely 100% especially because of the wide variability in lesion and background appearance" [16]. It may be the case that majority of the computer-aided detection schemes may never be trained with enough cases to "see" all possible variations of a given target lesion. Even for those scheme that use artificial neural networks and continue to learn with each successive case they analyze, sensitivity of 100% may not be achieved [16].

Thus, computer-aided detection systems should be used with caution and it ideally should not completely replace visual inspection and interpretation. Such systems are meant to complement visual inspection and interpretation. Heavy reliance on computer-aided detection system to detect and classify lesions may alter the normal search and decision-making processes [17].

It is important to note that only stroke cases confirmed at CT were evaluated in this study. Clinical mimics of stroke were not included and therefore it is not possible to tell if this method can distinguish stroke from its clinical mimics. Also, post-ictal intervals before CT imaging were not captured and thus the result of this study cannot be used to explain the changes in CT appearance of stroke lesions with time.

Conclusions

The results of previous attempts to deploy texture analysis in building automatic abnormality detection system are quite similar to the result of this study. The classification accuracy, sensitivity, and specificity levels are about the same with that of previous studies. The histogram texture features showed the highest sensitivity and specificity in the classification of brain tissue and stroke lesions using the artificial neural network. Therefore, histogram texture features are very suitable for computer-aided diagnosis of stroke. This may help in fast CT diagnosis of stroke where a radiologist is not available and also resolve equivocal cases.

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