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AUTOMATED DIAGNOSIS OF NORMAL AND PATHOLOGICAL CT BRAIN IMAGES FOR TISSUE CHARACTERIZATION USING DEEP LEARNING TECHNIQUES

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ABSTRACT

Introduction: The mortality rate attributed to brain abnormalities has shown a significant upward trend in recent years. Early diagnosis is essential in decreasing mortality rates and to provide effective treatment. Texture analysis, consisting of a variety of mathematical techniques plays an important role in analyzing the spatial organization of different tissues and organs.

Objectives: The primary objective of the study was to systematically categorize and analyze brain abnormalities via quantitative texture analysis using computed tomography scans as a computer-aided diagnosis system

Methods: 138 diseased and 20 normal CT scan images of brain were used to make a comparison between normal and diseased brain. Classification of brain tissue was achieved through the ANN (one-training class) method with POE+ACC feature selection method and LDA, NDA and PCA feature reduction methods.

Results: ANN-1class shows accuracy of 92.37% to separate data into different groups. It was observed that PCA yields the best classification results while NDA have higher misclassification rates.

Conclusion: These findings suggest that integrating machine learning techniques offers a promising pathway for improving diagnostic accuracy and patient care in radiology. MaZda software successfully classifies different diseases into distinct clusters; differentiate them from each other as well as from the normal individual brain.

Key words: Texture analysis, computed tomography (CT) scans, tissue characterization, CT imaging, artificial neural network (ANN), PCA, LDA, NDA and POE+ACC.

1. INTRODUCTION

Detecting early brain disorder is a great challenge for radiologists. Mortality rate is not decreasing over the last decades, despite of significant advancement in medical images research. It could be

reduced by early detection of abnormalities of brain. According to medical literature, certain drugs have side effects that can lead to brain diseases. Genetics, lifestyle, bacterial infection and exposure to chemicals can cause a number of damages, including direct or indirect neural disorders. The most common ones include senile brain atrophy, Meningitis, Hypoplasia, Infarct, Sinusitis, Tumor and Brain Cyst.
One effective diagnostic tool for the diagnosis and detection of brain abnormalities is computed tomography (CT) imaging. Less distortion is the primary advantage of using computed tomography images. The CT images are used by the radiologist to examine and diagnose the brain tissues but without the aid of an additional tool called the Computed Aided Diagnosis (CAD) System 1], it could be challenging for the radiologist to make an accurate diagnosis in many cases. Septal Thickening, Ground Glass pattern, Cystic pattern, Mosaic pattern of brain attenuation, Nodular pattern and Tree-in-bud [2] pattern are among the most popular and valuable signs and patterns in CT images of brain diseases [3].
Texture analysis, consisting of a variety of mathematical techniques that can describe the grey-level patterns of an image [4], plays an important role in analyzing the spatial organization of different tissues and organs. For these reasons, the potentiality of texture analysis in the context of radiotherapy has been widely investigated in several studies, especially for the prediction of the treatment response of infectious and normal tissues [5]. There are three primary categories of methods that can be used to compute textural features: Statistical methods, Model-based methods and Transform-based methods [6]. Using advanced imaging technologies and analyzing textures in a detailed way can really change how we diagnose lung problems.
In image analysis, a comprehensive exploration of image texture involves the computation of various textural features within selected 3D regions of interest (ROIs). These features extend beyond simple perceptual properties, encompassing aspects like coarseness, granulation, regularity, and more. The quantitative description of image texture is achieved through the use of local statistics, primarily parameters derived from the co-occurrence matrix, collectively known as texture features. The analytical process further involves the estimation of the data covariance matrix, followed by the computation of its eigenvalues and eigenvectors. Techniques such as Principal Component Analysis, Linear Discriminant Analysis, and Nonlinear Discriminant Analysis are employed for feature reduction. This reduction can be achieved through feature selection, where a subset of features is chosen based on specific mathematical criteria. The resulting texture parameters include mean, variance, skewness, kurtosis, percentiles, and various statistical measures reflecting the image's texture [7].

2. METHODS AND MATERIALS

This is a Retrospective study where CT images of the brain are used as experimental data, and deep learning methods applied to classify normal and pathological brain. Total 138 patient's data are including in study. Additionally, 20 CT scan images of normal brain data are also obtained to make a comparison between normal and diseased brain. The data for brain study is collected from Sir Sadiq Hospital Bahawalpur a leading medical Hospital renowned for its expertise in radiology department and the research is conducted from September 2023 to October 2024. CT images of patients suffering from different brain diseases were selected and marked by radiologist while; Inclusion criteria: Among many of brain diseases Senile Brain Atrophy, Meningitis, Infarct and Sinusitis are selected. Other imaging techniques are excluded only CT images of brain diseases were included. These images for analysis are obtained using a 160-slice scanner with a 12-bit depth. CT images of each patient were uploaded in MaZda software for texture analysis. Following steps are involved in the analysis of these brain CT images.

2.1 Region of interest

With the approval of a qualified radiology specialist, areas of interest are marked with different colors. By using drawing tools RIO shape are drawn on surface of the image. MaZda software is used in this study. After uploading the image in MaZda software, region of interest is selected (shown in figure 1). In this software maximum 16 regions of interest with different colors and shapes can be selected.

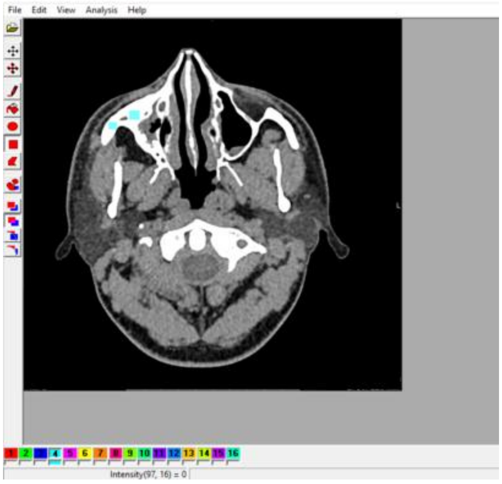


Figure 1: Selection of ROI in MaZda

2.3 Feature Extraction

After proper selection of ROL features for identification, categorization, analysis, grouping, assembling, recognition, and detection are extracted to process images. Extraction of maximum information from an image is the aim of feature extraction techniques. The variety and effectiveness of characteristics and their selection currently pose a main problem. MaZda software calculates about 300 texture features. These features include histogram- based feature, co-occurrence features, run length matrix, absolute gradient matrix, autoregressive based features and wavelet features.

2.3.1 Histogram based features

A two-dimensional representation of the image's gray level distribution is called an image histogram. A histogram is only a graphic representation. It displays the image's visual content. The amount of light and darkness in an image is what is meant by optical content. Utilizing statistical torques connected to an image or region's intensity histogram is one of the simplest ways to characterize a texture. These features may include:

$$\text{Mean} = \sum_{i=0}^{L-1} z_i p(z_i)$$

$$\sigma^2 = \sum_{i=0}^{L-1} (z_i - m)^2 \, p(z_i)$$

$$Skewness = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$

$$\text{Entropy} = -\sum_{i=0}^{L-1} p(z_i) \, log_2 p(z_i)$$

2.3.2 Absolute Gradient

The gradient of an image examines the spatial variance of grey-level values. Consequently, a low gradient value occurs where grey level gradually transitions from dark grey to lighter grey, while a high gradient value is observed where grey level changes abruptly from black to white. Mean and

variance of the texture can be calculated from the absolute gradient as examples of texture parameters. Hence, mean grey-level variation throughout image will be measured by the absolute gradient mean, and the variance will indicate how much these variations deviate from the mean.
Mean absolute gradient:

$$GrMean = \frac{1}{M}\sum\nolimits_{ij_{e\in ROI}} ABSV(i,j)$$

Variance of absolute gradient:

$$GrVarience = \frac{1}{M}\sum\nolimits_{ij_{eROI}} (ABSV(i,j) - GrMean)^2$$

Skewness of absolute gradient:

$$GrSkewness = \frac{1}{\left(\sqrt{Gr\,Variance}\right)^3}\frac{1}{M}\sum\nolimits_{ij_{eROI}} (ABSV(i,j) - GrMean)^3$$

Kurtosis of absolute gradient:

$$GrKurtosos = \frac{1}{\left(\sqrt{Gr\,Variance}\right)^4}\frac{1}{M}\sum\nolimits_{ij_{eROI}} (ABSV(i,j) - GrMean)^3 - 3$$

2.3.3 Run-length Matrix

The run-length matrix records the number of runs of consecutive pixels (e.g., two pixels) with the same value for each allowed grey-level value, given a specific direction such as the horizontal direction. Two parameters that can be computed from run-length matrix are short-run focus and the percentage of image in runs.

ShrtR Emph= $\frac{\left(\sum_{i=1}^{N_e}\sum_{j=1}^{N_r}\frac{p(i,j)}{j^2}\right)}{C}$

Long run highlights moments

$$LngREmph = \frac{\left(\sum_{i=1}^{N_e}\sum_{j=1}^{N_r} j^2 p(i,j)\right)}{C}$$

Grey level non-uniformity

$$GLevNonUni = \frac{\left(\sum_{i=1}^{N_e}\sum_{j=1}^{N_r} p(i,j)^2\right)}{C}$$

Run length non-uniformity

$$RLNonUni = \frac{\sum_{i=1}^{N_e}\sum_{j=1}^{N_r} p(i,j)}{\left(\sum_{i=1}^{N_e}\sum_{j=1}^{N_r} jp(i,j)\right)}$$

The coefficient c is given as

$$C = \sum_{i=1}^{N_e}\sum_{j=1}^{N_r} p(i,j)$$

2.3.4 Co-Occurrence Matrix

The correlations between image pixels form the basis of an image's co-occurrence matrix. For example, the co-occurrence matrix can be used to derive six statistical properties: contrast, correlation, energy, homogeneity, entropy and maximum probability.

$$Contrast = \sum_{i,j} |i - i|^2 p_{i,j}$$

$$Correlation = \sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)p_{i,j}}{\sigma_i\sigma_j}$$

$$Energy = \sum_{i,j} p_{i,j^2}$$

$$Homogeneity = \sum_{i,j} \frac{p_{i,j}}{1 + |i - j|}$$

$$Entropy = -\sum_{i,j} p_{i,j} log_2 p_{i,j}$$

Maximum probability = $max(p_{i,j})$

2.3.5 Autoregressive Model

Assuming a local interaction between picture pixels, the autoregressive (AR) model calculates pixel intensity as the weighted sum of adjacent pixel intensities. If f is a random field with zero mean, an AR causal model is described as

$$f_s = \sum_{r \in N_s} \theta_r f_r + e_s$$

Where $f_s$image intensity at site s, e_s denotes an independent and identically distributed noise, N_s is a neighborhood of s, and □ is a vector of model parameters.

2.4 Feature Selection

Higher dimension data tends to contain noisier, irrelevant, and redundant data [8]. This raises the error rate of learning method and causes the model to be over fit to address these problems. The most common applications of dimensionality reduction techniques are in feature extraction (FE) and feature selection (FS). FS employs to eliminate redundant, noisy and irrelevant data. So, after extraction of features feature selection is done because it chooses a subset of features from the initial feature collection based on feature redundancy and relevancy. Normally basic methods are used for feature selection in MaZda software, are POE+ACC (probability of error and average correlation co-efficient) Fisher co-efficient and mutual information. In this research we have use POE+ACC feature selection method using MaZda software for selection and analysis of these features.

- **POE+ACC (Probability of Error and Average Correlation Coefficient):** This method focuses on minimizing both the classification error probability (POE) and the average correlation coefficients (ACC) among selected features. It is calculated as the ratio of misclassified samples to the total number of samples in the dataset when only feature (f_j) is used. The POE for this feature is determined as follows:

$$POE(f_j) = \frac{number\ of\ misclassified\ samples}{total\ number\ of\ samples}$$

2.5 Feature reduction

Selecting the most relevant features from a dataset is a vital part of the machine learning process, further is feature reduction, which enables the reduction of data complexity, enhances model accuracy, and decreases computational requirements, ultimately leading to more efficient and effective model building. MaZda software helps in minimizing the dimension of features by apply various techniques, includes

- **Principal Component Analysis (PCA)**

One method for reducing dimensionality without supervision is Principal Component Analysis (PCA). PCA is a statistical technique that employs an orthogonal transformation. The steps involved in doing a Principal Components Analysis on data include [9].

1. Get image data: Suppose x_1 , x_2 ... x_M are shown as N×1 vectors
2. Calculate average of vector: $\bar{x} = \frac{1}{M} \sum_{i=1}^{M} x_i$
3. Deduct the mean: $\emptyset_i = x_i - \underline{x}$

1. Compute covariance matrix: $Matrix A = [\emptyset_1, \emptyset_{2 ....} \emptyset_M]$ (N×M matrix) from this compute $C = \frac{1}{M}\sum_{n=1}^{M} \emptyset_N {\emptyset_N}^T = AA$

4. Calculate eigenvalues and eigenvectors of covariance matrix

$$C = \lambda_1 > \lambda_2 > \cdots > \lambda_N \qquad (eigenvalues)$$

$$C = u_1, u_2 \ldots u_N \qquad (eigenvectors)$$

5. Compute a feature vector: The eigenvectors are arranged from highest to lowest eigenvalue, indicating the components in order of their importance [9]. The primary component of a dataset is eigenvector with highest eigenvalue. The largest eigenvalue is used to form the feature vector.

6. Deriving new dataset: By selecting the major components (eigenvectors) to retain, we create a feature vector. Then multiply this feature vector's transpose by the original dataset.

Final data = row data adjust× row feature vector

- **Linear Discriminant Analysis (LDA)**

Linear Discriminant Analysis (LDA) is a supervised dimensionality reduction technique that projects data from a high-dimensional space to a lower-dimensional space, aiming to maximize between-class dispersion while minimizing within-class scatter. Establish two measures in LDA for every sample across all classes:

1. within-class scatter matrix

$$S_W = \sum_{i=1}^{c} \sum_{i=1}^{N_j} \left(x_i^j - \mu_j\right)\left(x_i^j - \mu_j\right)^T,$$

Where μ_j is the mean of class j, x (i) ^j is the ith sample of class j, N_j the number of samples in class j and c is number of classes.

2. between class scatter matrix

$$S_b = \sum_{j=1}^{c} \left(\mu_j - \mu\right)\left(\mu_j - \mu_j\right)^T,$$

- **Nonlinear Discriminant Analysis (NDA)**

These methods depend on linear transformations, but sometimes function data cannot be grouped using these techniques; in this situation, nonlinear discriminant analysis (NDA) is used. This NDA method uses a nonlinear classification algorithm to create highlighted data after transforming the data in a nonlinear manner [10, 11]. Further, main purpose of NDA is to find a nonlinear change in the feature vectors in a region where they are linearly separable.

2.6 Classification

The data is classified based on selected feature by classification techniques. Classification is the process of grouping related classes of input patterns. Unsupervised classification is a process of identifying structures or natural groups in multi-spectral data. Supervised classification involves using samples with known identities to classify samples with unknown identities. Here Artificial Neural Networks (ANNs) are utilized as tissue classifier[12]. Figure 2 is the graphical representation of the presented research work.

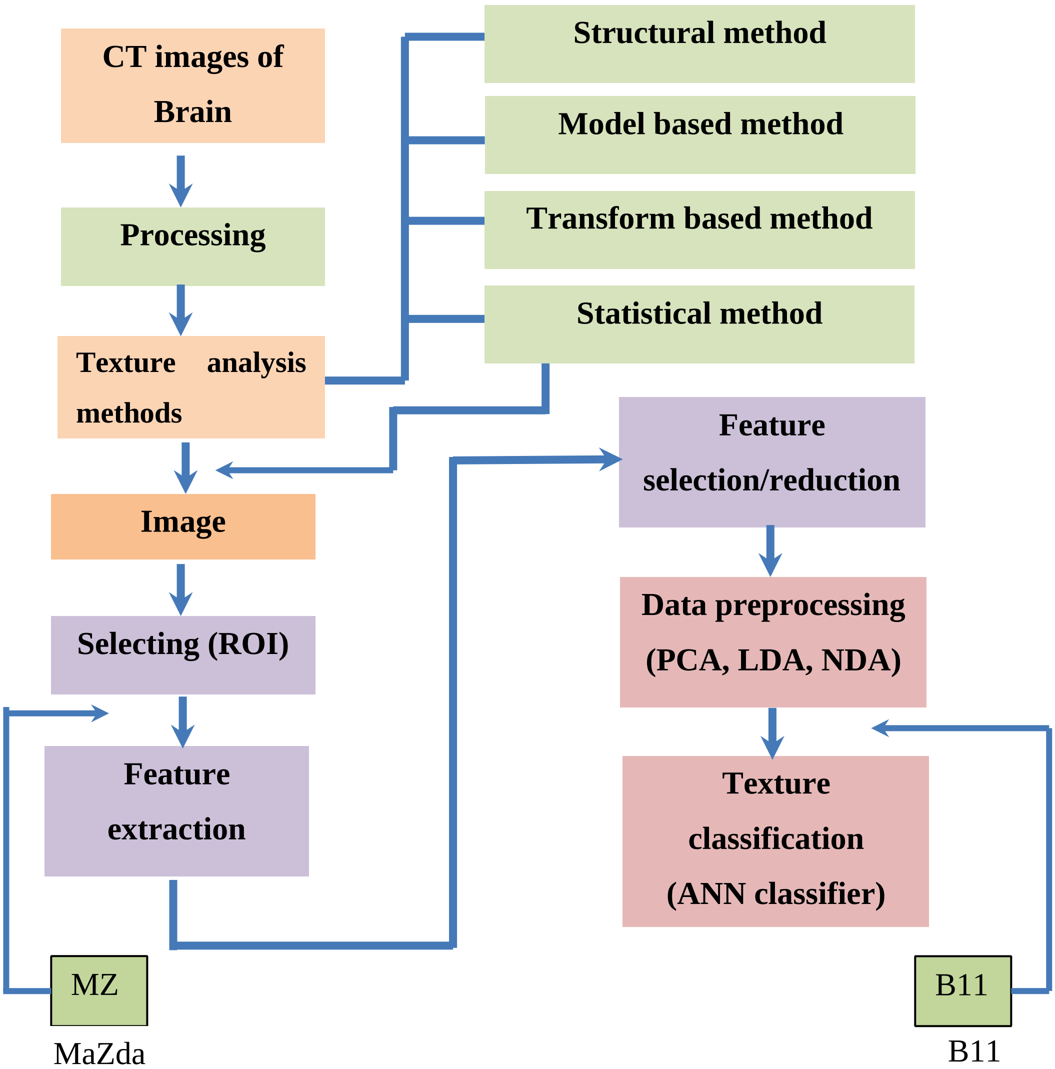


Figure 2: Summary of the work flow

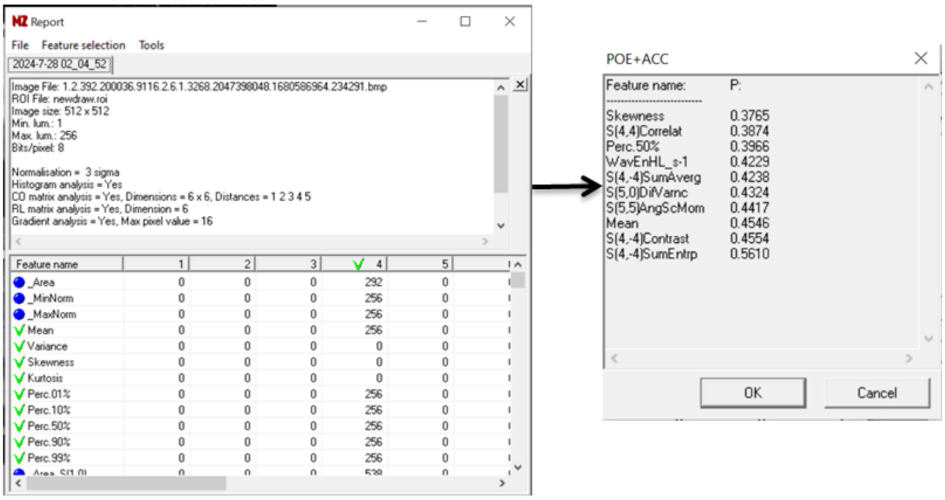
3. RESULT

Different texture feature extraction methods are used to evaluate the proposed research methodology. The CT brain image collected from a patient have approximately 160 slices. The slices which are clearly focusing the brain disease, are selected from the available slices of a CT brain image. They are in DICOM format. The slices were converted to BMP images, which are an acceptable format for medical image processing. Following Table 1 shows the demographic data and clinical characteristics of patients of different diseases along their gender.

Table 1 Imaging Data of different brain diseases collected from Hospital

Disease	Number of Patients	Gender	Figure
Senile brain Atrophy	12	M=7,F=5	
Meningitis	12	M=8,F=4	
Infarct	6	M=4,F=2	
Sinusitis	4	M=2,F=3	

The primary objective of this research is to classify or differentiate between the normal brain tissues from the pathologic tissues of brain by using different techniques. Software called MaZda provides a ranges of classification methods and selection process from which we analyzed the texture feature from these brain CT images. Features selected by MaZda software are shown in figure 3. By uploading the images in MaZda, software different regions of interest with different colors and shapes can select. After selecting region of interest, a normalization condition of $\mu \pm 3\sigma$ using the POE+ACC approach were applied. After that different classification technique, PCA, LDA and NDA are being utilizing from which PCA gives the best result. Accuracy rate of our research is 92.37%. Medical image analysis techniques play very important role in several radiological interpretations. In general, the application involve the automatic extraction of texture features from images which are then used for a variety of classification tasks, such as distinguishing normal tissue from abnormal tissues.



Feature name	1	2	3	4	5
_Area	0	0	0	292	0
_MinNorm	0	0	0	256	0
_MaxNorm	0	0	0	256	0
Mean	0	0	0	256	0
Variance	0	0	0	0	0
Skewness	0	0	0	0	0
Kurtosis	0	0	0	0	0
Perc.01%	0	0	0	256	0
Perc.10%	0	0	0	256	0
Perc.50%	0	0	0	256	0
Perc.90%	0	0	0	256	0
Perc.99%	0	0	0	256	0

Figure 3: feature selected by MaZda software

After selection and extraction of features using MaZda software, analysis is performed using B11 analysis tool.

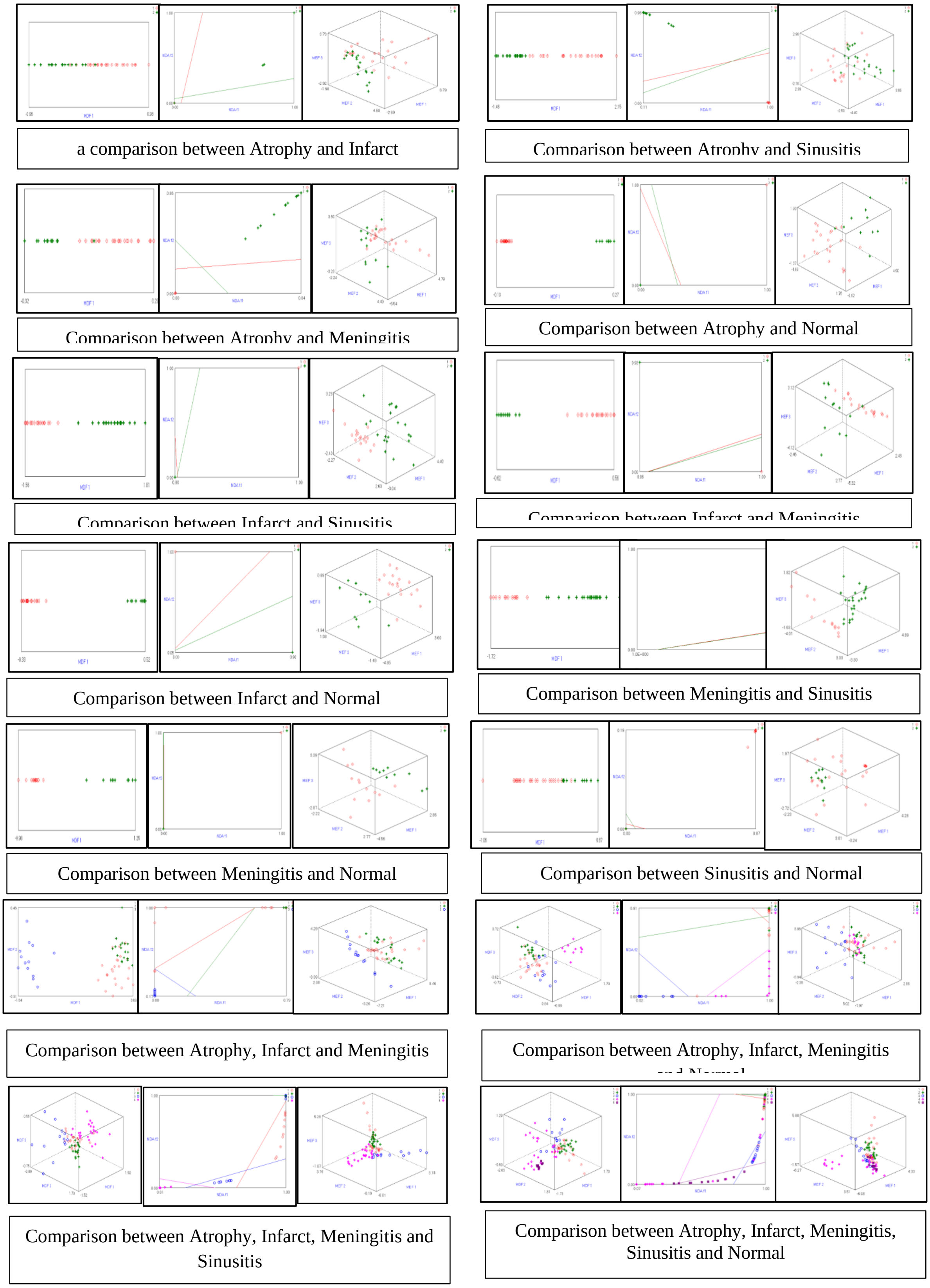


Figure 4: Comparison graphs (a)LDA (b)NDA (c)PCA

The above-mentioned figure 4 shows the comparison graphs between different diseases of brain and diseases with normal individual too. This shows a proper cluster formation of different diseases that are properly discriminated from each other demonstrating the efficiency of classifier.

Table 2: Comparison of classification results using different classification approaches

Normalization	Comparison b/w	Classification Rate		
		LDA	NDA	PCA
$\mu \pm 3\sigma$	Atrophy and infarct	85.37%	97.56%	82.93%
	Atrophy and sinusitis	100%	100%	91.49%
	Atrophy and meningitis	94.44%	94.44%	88.89%
	Atrophy and normal	100%	100%	100%
	Infarct and sinusitis	100%	100%	97.62%
	Infarct and meningitis	100%	100%	100%
	Infarct and normal	100%	100%	100%
	Meningitis and sinusitis	100%	100%	100%
	Meningitis and normal	100%	100%	100%
	Sinusitis and normal	91.18%	94.42%	91.18%
	Atrophy, infarct and meningitis	72.22%	83.33%	85.19%
	Atrophy, infarct, meningitis and normal	81.25%	65.62%	85.94%
	Atrophy ,infarct, meningitis and sinusitis	73.08%	52.56%	85.9%
	Atrophy , infarct, meningitis, sinusitis and normal	90.91%	45.45%	84.09%
	Average	92.03%	88.09%	92.37%

MaZda software works as a machine learning effectively classifies different diseases into distinctive clusters; discriminate them from each other and from the normal individual. From the above mentioned comparison table 2, PCA yields the best classification results while NDA have higher misclassification rates. By LDA accuracy is 92.03%, by NDA accuracy is 88.09% and by PCA accuracy is 92.37%. ANN classified 92.37% accurate results.

4. DISCUSSION

In this presented work ANN-1 class is used which uses a basic neural network with accuracy of 92.37% to separate data into different groups, and work well for linearly separable problems leading to faster training and easier implementation. In related work presented in the research by Chawla M. et al. [13] researchers achieved 96% classification accuracy for brain tissues in CT scans using SVM with wavelet-based features. While, Singh M.et al. [14] work on ischemic brain stroke using CT images achieved 93.3% classification accuracy by applying KNN and statistical classifiers to differentiate between normal and affected tissues. Out of 90 images, 84 were correctly classified. On the other hand, Padma, A. et al. [15] study the brain CT image classification using SVM achieved high accuracy rates 98.55% for distinguishing benign and malignant tumors, 97.11% with wavelet-based texture features, and 96.29% using wavelet co-occurrence features.

Highest misclassification rate in case of NDA, PCA and LDA was observed in comparison between Atrophy, infarct, meningitis, sinusitis and normal, Atrophy and Infarct, and Atrophy, Infarct and Meningitis respectively. The projection matrix for Most Discriminating Features (MDF) indicates significant linear separability, suggesting that the selected features can distinguish between different categories at moderate extent. The linear dimensionality of the data is 8 on average, which means that the first 8 principal component collectively capture the significant variance in the data. The remaining components contribute only marginally to the overall variance. The specific sample misclassified suggest that while the models performed better, there remain edge cases where the model struggles possibly due to intrinsic similarities in feature sets of disease.

There are many reasons leads to misclassification such as error in marking the region of interest, similarity between the texture patterns of different diseases, age variation, mistake in locating the area of disease by specialist and difference in tissue textures. Overlapping of clusters resulting from

LDA, NDA and PCA could be attributing to several factors such as age variation and texture pattern similarities among different diseases.

Limitations

This research provides valuable results of brain diseases classification through texture analysis, while there are some limitations. Some data set may limit the generalizability of findings because there are number of other brain diseases so, analysis can be done with more number of patients than selected in this research. There may not be enough high quality, annotated CT images of testing data. There are many other imaging techniques, such as MRI, SRECT, PET and Ultrasound can be utilized for imaging disorders, while in this research only computer tomography is used. In this research, only ANN method is applied while other methods like SVM and KNN can be used. If the model is tested on specific types of data, it might not perform well for other types or populations.

5. CONCLUSION

MaZda software serves as a machine learning, which successfully classifies different diseases into distinct clusters; differentiate them from each other as well as from the normal individual brain. In this work 138 patient's images and 20 normal brain images were selected for database. Two region of interest (ROI) are selected from each image and computed first order and second order texture parameters. POE+ACC technique is used to select most descriptive features. Three sets of graphs were produce from each class using PCA, LDA, and NDA. After analysis, it concluded that PCA yields the best classification results while NDA have higher misclassification rates. By LDA accuracy is 92.03%, by NDA accuracy is 88.09% and by PCA accuracy is 92.37%. ANN classified 92.37% accurate results.

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