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Classification of Stroke Using Brain CT Digital Images

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Abstract:

A special enhancement process was needed before implementing these methods to get better results and removing the noise. The supervised classification process (K-NN) was used to classify stroke area and its approximate stroke time. This method needed to color the image with hot and jet colors for hemorrhagic and ischemic types respectively to classify the normal and abnormal parts depending on color feature. The (K-NN) process submits useful information that may help to specify the stroke age and its transformation time that could assist to determine the best treatment or doing surgery to remove the stroke effects.

Key words: Hemorrhage stroke; Ischemic stroke; CT scan image; K-NN classification.

1. Introduction:

There are two types of stroke, ischemic and hemorrhagic, obstructive be disclosed by checking CT scan where hemorrhagic stroke appear in white color and ischemic appear in black [1]. This paper is concerned with brain strokes and investigates proposed image processing techniques to improve the classification of strokes. The adopted procedure is illustrated in the flow chart shown in figure (1).

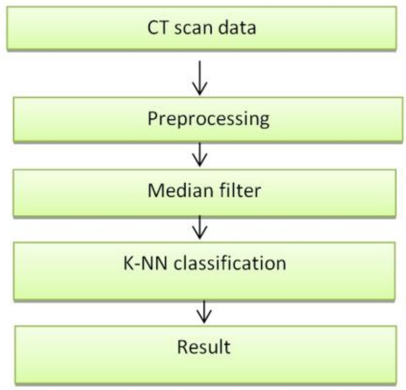


Figure (1) the diagram for the assumed system for the classification of strokes from CT brain images.

2. Preprocessing

CT images need preprocessing operations because of unorganized nature of the brain tissue that is why we applying method for the diagnosis of the infraction.

2.1 Gray image

The images received from CT scansare usually colored by RGB (red, green and blue) components. However, they are converted into gray-scale image by eliminating brightness information, thus converting the image format 512✕512✕3 color RGB to 512✕512 gray-image [2] as shown in figure (2-a). This image was obtained from CT scanning of the head of a patient suffering from brain stroke.

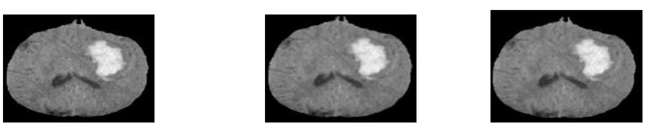
2.2 Skull removal (Brain Insulation)

The removal of the bony skull surrounding the brain tissue is considered as a challenge to the brain isolation as shown in figure (2-b, c).

2.3 Filtering

The resulting image need a filtering operation so a median filter the best-known order statistic filter[3] of window [3 X 3] was applied on the image for three successive time to remove the noise in the CT image. Smother images were obtained as can be clearly seen in figure (2-d, e, and f).

Original image | a) Gray image | b) Isolated skull | c) Image after remove skull



d) Median filter first time | e) Median filter second time | f) Median filter third time

Figure (2) images obtained from the Preprocessing

3. K- Nearest Neighbors Algorithm

The K-nearest neighbors or, in short K-NN, is a supervised classification algorithm which assigns an object or a test patterns to a class based on majority of its K-nearest neighbors in the feature space.In this search the modified K-NN is used which dependent on the color and the distance between the classes. Each part of the image has a specific color which gives indication about its texture. So the color and the distance are parameters for classification [4].

3.1 Classification

K-NN is a classification method that categorizes objects based on nearest training examples in the feature space. So that it was implemented to differentiate the normal brain tissue from the affected area depending on the color features. For this reason, the image was colored after the process of skull removing by hot color (for hemorrhage stroke) and jet color (for ischemic stroke). The function hot generates a color map containing shades of reds, oranges, and yellows. Typically, a given image matrix has a specific color map associated with it, this hot color map ranges varies smoothly from black through shades of red and yellow to white. Moreover, the function jet ranges from blue to red, and passes through the colors cyan, yellow, and orange.

The images were classified into 6 classes where each class represents a color layer as shown in figures (3, 4, 5, and 6).

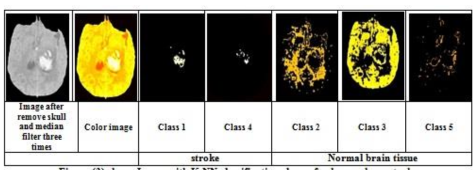


Figure (3) shows Image with K-NN classification classes for hemorrhage stroke

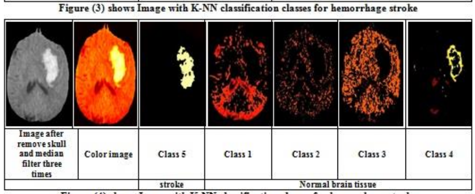


Figure (4) shows Imagewith K-NN classification classes for hemorrhage stroke

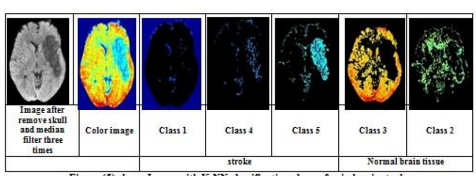


Figure (5) shows Image with K-NN classification classes for ischemic stroke

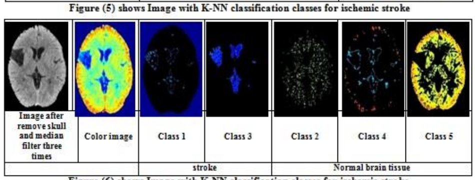


Figure (6) shows Image with K-NN classification classes for ischemic stroke

4. Feature Extraction Phase

In this stage, seven of statistical texture features were extracted for further analysis. These characteristics are mean, energy, entropy, standard deviation, variance, skewness and kurtosis. They were calculated for both stroke areas as can be seen in Tables (1, 2, 3, and 4).For two type of strokes.

4.1 First-Order Histogram features

The random variable *i* represents the gray levels of the image region. The first-order histogram p (*i*) is defined as: [5]

$$\mathrm{p}(i) = \frac{\text{number of pixels with gray level } i}{\text{total number of pixel in the region}} \quad \text{.......................... (1)}$$

P (*i*) = H (*i*)/NM

P (*i*) = is the probability of occurrence of the *i*.

Where *i*=0, 1, 2.........G-1

G= gray level tone of an image (255), N= number of cells in the horizontal domain.

M= number of cell vertical domain [6].

Mean: $\mu = \sum_{i=1}^{G-1} ip(i)$ .... (2)

Standard deviation: $\sigma = \sqrt{\sum_{i=0}^{G-1}(i-\mu)^2\, p(i)}$ ....(3)

Energy: $E = \sum_{i-1}^{G-1}(p(i))^2$ .... (4)

Entropy: $\mathrm{H} = -\sum_{i=1}^{G-1} p(i)log2\,[p(i)]$ .... (5)

Variance: $\sigma^2 = \sum_{i=1}^{G-1}(i-\mu)^2 p(i)$ .... (6)

Skewness: $skew = \sigma^{-3}\sum_{i=1}^{G-1}(i-\mu)^3\, p(i)$ ....(7)

Kurtosis: $kurt = \sigma^{-}4\,\sum_{i-1}^{G-1}(i-\mu)^4\, p(i)$ .... (8)

Table (1) texture features for stroke tissues from figureNo. 3

Tissue Type	Mean	Energy	Entropy	Variance	Standard Deviation	Skewness	Kurtosis
Stroke	4.1898	0.9615	0.015	513.1982	22.65387	6.18E-04	1.20E-06

Table (2) texture features for stroke tissues from figureNo. 4

Tissue Type	Mean	Energy	Entropy	Variance	Standard Deviation	Skewness	Kurtosis
Stroke	8.186	0.9285	0.0641	1.38E+03	37.1039	1.03E-04	7.52E-08

Table (3) texture features for stroke tissues from figureNo.5

Tissue Type	Mean	Energy	Entropy	Variance	Standard Deviation	Skewness	Kurtosis
Stroke	5.1449	0.8709	0.3444	218.4973	14.78165	0.0012	5.40E-06

Table (4) texture features for stroke tissues fromfigureNo.6

Tissue Type	Mean	Energy	Entropy	Variance	Standard Deviation	Skewness	Kurtosis
Stroke	2.2872	0.9472	0.1504	59.3963	7.70689	0.0135	2.27E-04

Conclusion

1. From the color gradient of the both types of stroke, the time past (in hours or days) and the beginning of the attack can be concluded approximately. The brain stroke usually damages the brain tissue and this damage will cause certain malfunctions in the body depending on the area that was affected.
2. During the gradual diminution of the hemorrhagic stroke effects, the mass starts to be smaller in size and area (Pease remain called fibrous tissue) or even the stroke mass diminished entirely. While in ischemic stroke, the tissue becomes similar to the CSF (cerebrospinal fluid) and stroke area is filed by it that is why the area in the image appears darker.

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