Brain Tumors Classification From MR images Using a Neural Network and the Central Moments

Salim Ouchtati
Electronic Research Laboratory of Skikda (LRES)
20 August 1955 University - Skikda
Skikda, Algeria
ouchtatisalim@yahoo.fr

Jean Sequeira
Laboratory of Information Sciences and Systems (LSIS)
(UMR CNRS 7296), Aix Marseille University
Marseille, France
Jean.Sequeira@univ-amu.fr

Belmeguenai Aissa
Electronic Research Laboratory of Skikda (LRES)
20 August 1955 University - Skikda
Skikda, Algeria
belmeguenaiaissa@yahoo.fr

Rafik Djemili
Electronic Research Laboratory of Skikda (LRES)
20 August 1955 University - Skikda
Skikda, Algeria
djemili_rafik@yahoo.fr

Mohamed Lashab
Electronics Department
Larbi Ben Mehidi University
Oum El-bouaghi, Algeria
lashabmoh@yahoo.fr

***Abstract*— In the context of medical images classification, we proposed a novel method for the classification of Magnetic Resonance (MR) images of the brain. The proposed system is based on the use of a new method for the features extraction. The principal objective is to calculate the histogram of each zone selected by sliding a window of size 16×16 Pixels on the MR image of the brain, this allow us to obtain sixty four (64) histogram, and each obtained histogram will be considered as a sequence for which we calculate the central moments of order 1, 2 and 3. The classification is achieved by a multilayer perceptron.**

***Keywords*— magnetic resonance image; medical images processing; brain tumor; central moments; neural networks.**

I. Introduction

Brain tumor can be defined as a group of abnormal cells that grows inside or around the brain, in other words, a brain tumor is an uncontrolled growth of solid mass formed by undesired cells either located in one or more brain parts such as glial cells, neurons, lymphatic tissue, blood vessels, pituitary and pineal gland, skull, or spread from cancers mainly located in other organs. The type of tumor, its localization, its size and its evolution are among the most important factors occurring in the choice of the appropriate method for the treatment of a brain tumor. Brain tumors can be benign or malignant, benign tumors are non cancerous, they do not invade nearby tissue or spread to other parts of the body, sometimes they do not require treatment, unless symptoms indicate a serious problem. Surgery is a common type of treatment for benign tumors; the goal is to remove the tumor without damaging surrounding tissues. Other types of treatment may include medication or radiation. In most cases, and after they were removed, they do not come back. Malignant tumors are cancerous, they spread rapidly invading other tissues of brain, sometimes cells move away from the original (primary) cancer site and spread to other organs or bones where they can continue to grow and form another tumor at that site. This is known as metastasis or secondary cancer. They are often resistant to treatment, and they sometimes recur after they were removed.

Computer-Aided diagnostic technology has become a very important technological tool in the medical field, many medical problems have found a solution through the use of this technology, and the medical images processing has progressed immensely in recent years ([1]-[4]), it is one of the most encouraging areas of research, since it offers facilities for the diagnosis and treatment decisions of a large number of diseases such as cancer and in particular brain tumors. Today, the study of this type of brain abnormalities using the medical images processing is becoming a very challenging task, several techniques and several methods have been proposed for the detection of their existence, their exact location , their size and their nature [5] most of these methods are based on the processing of the MRI (Magnetic Resonance Image) brain images ([6]-[8]), this imaging modality is widely used by radiologists to visualize the internal structure of the human body, the level of information inside the image is surprising compared with any other imaging modality, today, it is becoming the most modality used to evaluate the patients who present signs indicating the existence of a cerebral anomaly especially brain tumors.

In this study, a new neuronal approach is proposed for the classification of brain tumors from MR images. The used database is composed of a set of MR images of brain tainted by several types of brain tumors and belonging to different persons. the three processing steps that compose the proposed system have been described, namely, the preprocessing step where we have showed that the size of the MR brain images must be normalized, features extraction step, where we have used the central moments of order 1, 2 and 3 of histograms of zones obtained after sliding a window of size 16×16 pixel on the image of the brain, and the classification step achieved using a multilayer perceptron.

II. PROPOSED SYSTEM

A. *Description of the used database*

In this study, the used database is composed by a set of MR images of the brain extracted from "Whole Braine Atlas" site [9], these are grayscale images, for which, each pixel is encoded on 8 bits (this means that the gray levels vary from 0 to 255). Firstly, this set of brain images is divided in two main parts: the first part is composed by the MR images that do not have any abnormalities, while the second part is composed by those affected by one or more tumors. Secondly, and according to the type and the location of the tumor in the brain, the second part of this set is also divided into several parts. Finally, the number of brain image classes obtained and considered for this study is equal to six (6), with ten (10) different samples for each class, these classes are defined as follows:

- The first class (Class 01): The MR images of brain belonging to this class are characterized by the absence of any type of anomalies (healthy person). The figure 1.a shows some samples of this class.
- The second class (Class 02): The MR images of brain belonging to this class are affected by a tumor in the lower right part of the brain (Figure 1.b).
- The Third class (Class 03): All the MR brain images of this class are affected by a tumor in the left lower part of the brain (see the Figure 1.c)
- The Fourth class (Class 04): The MR brain images belonging to this class are affected by a tumor in the center lower part of the brain. Some samples of this class are shown on the Figure 1.d.
- The Fifth class (Class 05): Existence of a tumor in the left higher part of the brain in the MRI brain images belonging to this class (see the Figure 1.e).
- The Sixth class (Class 06): The MRI brain images belonging to this class are affected by many tumors in different place of the brain (see the Figure 1.f).

B. *The Different parts of the proposed system*

The proposed system is composed of three steps:

1) *Preprocessing step*

The preprocessing operations are classical operations in image processing, they are used to "clean" and "prepare" the MR image of the brain for the subsequent processing steps. For our case, the only preprocessing operation that we have considered necessary is the resizing of the image size, this operation is imposed for two reasons, firstly, the nature of MR images of the brain used in this study which are of variable size, and secondly, the nature of the method chosen in the next step for features extraction which is applied only on normalized images. Note that all MR images of the used database were resized to a size equal to 128×128 pixels, this size was chosen to facilitate the application of features extraction method. Fig. 2 shows some MR brain images and their normalization.

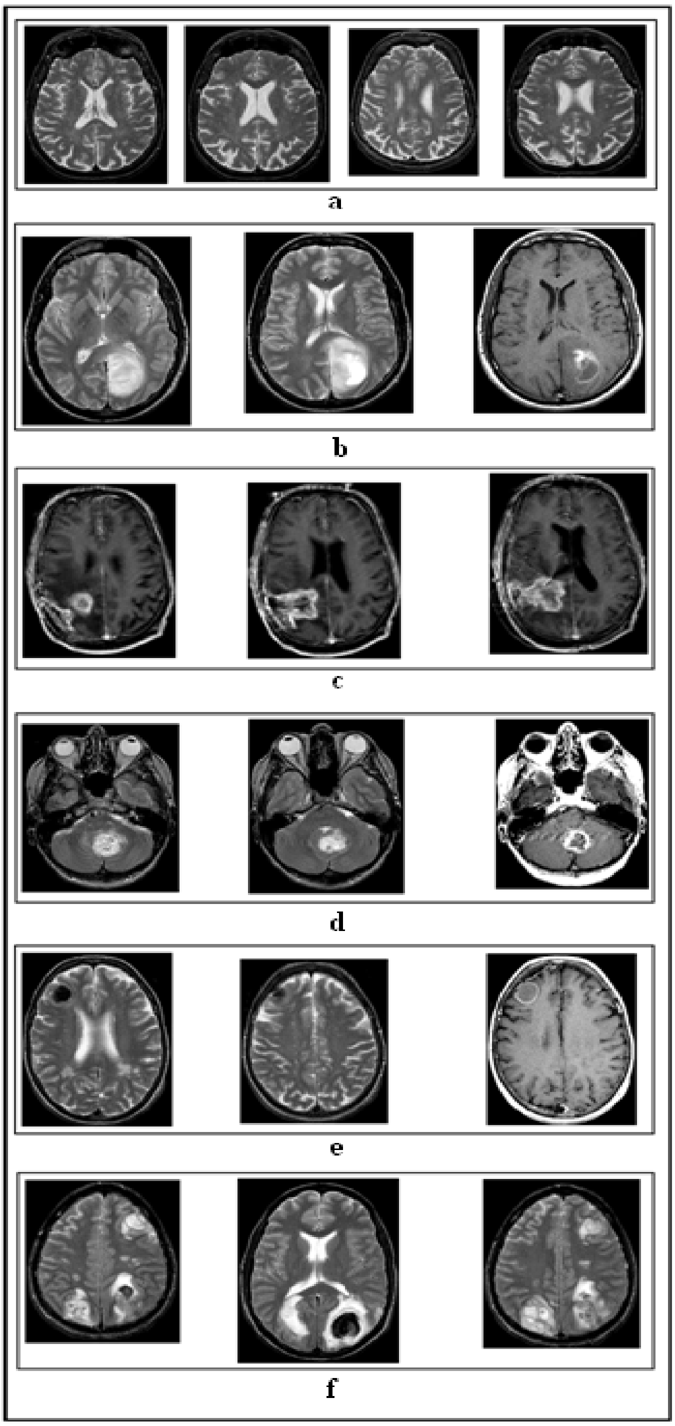

Fig. 1. Some samples of each class of the used database: a) Samples of the first class, b) Samples of the second class, c) Samples of the third class, d) Samples of the fourth class, e) Samples of the fifth class, f) Samples of the sixth class.

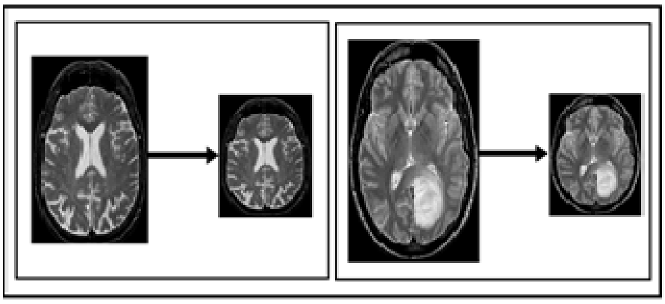

Fig. 2. Example of resizing some MR images of the brain.

2) Features Extraction step

This step is considered as the most important step in the classification and recognition systems, it has been a very active research topic especially in the field of the classification of medical images, therefore, many methods and techniques of features extraction have been developed ([10]-[11]). The principle objective of the features extraction step is to facilitate the task of the classifier, it consists to replace the image presented at the system input by a set of features extracted from the image. In this paper, the method that we have used to extract the features is based on the calculating of the central moments of order k, this method was used in several studies of pattern recognition. For a given sequence of size M, the central moments of order k are calculated from the following formulas:

$$\mu_k = \sum_{i=1}^{M} \left(x_i - \overline{x} \right)^k p(x_i) \quad (1)$$

$$\overline{x} = \sum_{i=1}^{M} x_i p(x_i) \quad (2)$$

Where:

- $\overline{x}$: is the mean value of the sequence.
- $p(x_i)$: is the probability of l 'element x_i in the sequence.
- M: is the size of the sequence.
- k: the order of the moment.

The principle consists firstly to calculate the histogram of each zone selected by sliding a window of size 16 ×16 Pixels along the MR image of the brain (see Fig. 3 and Fig. 4), this allow us to obtain sixty four (64) histogram, and each obtained histogram will be considered as a sequence for which we calculate the central moments of order 1, 2 and 3 using the formulas (1) and (2), this means that the number of features obtained by this method is equal to hundred and ninety-two (192) features. Fig. 5 shows the values of central moments of some MR images of the used database.

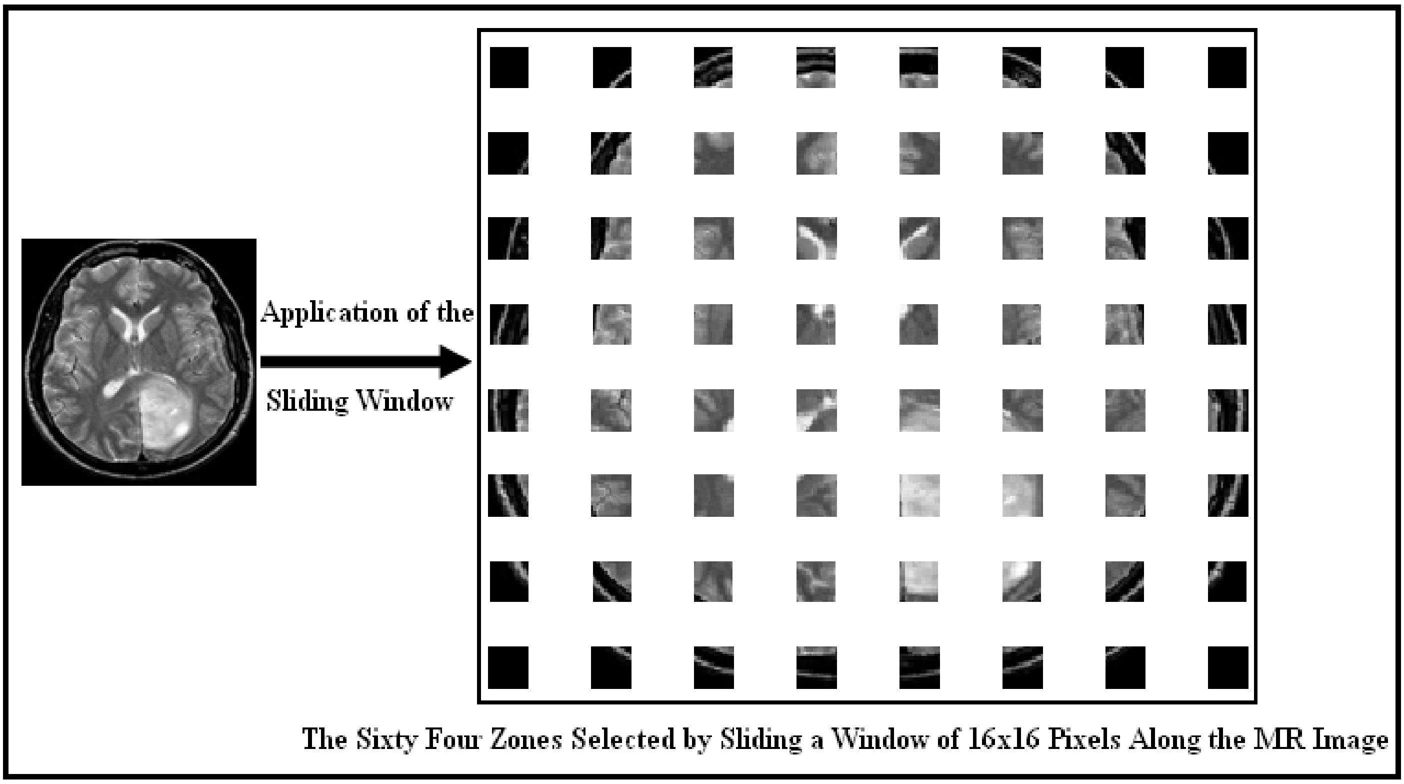

Fig. 3. Application of the sliding window of 16x16 pixels on sample 01 of the second class.

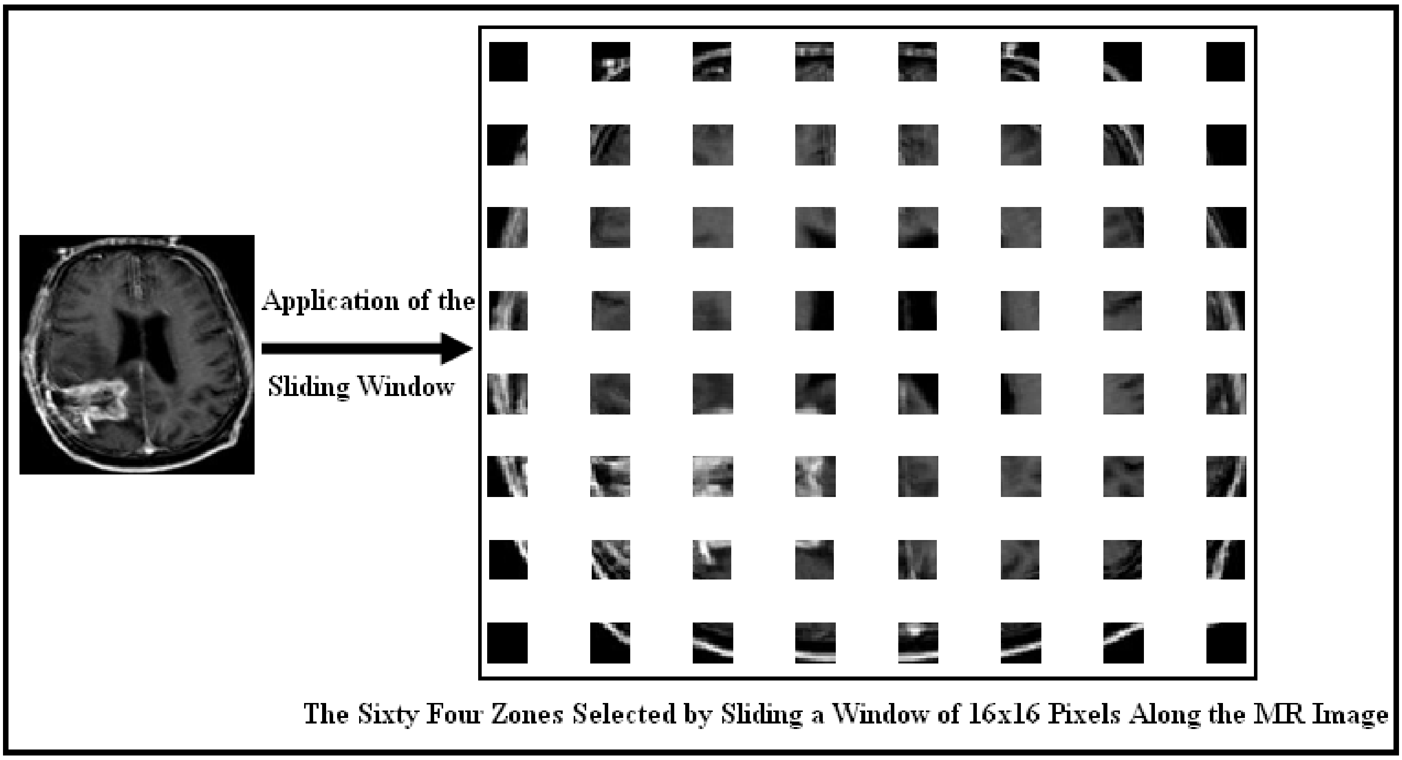

Fig. 4. Application of the sliding window of 16x16 pixels on sample 02of the third class.

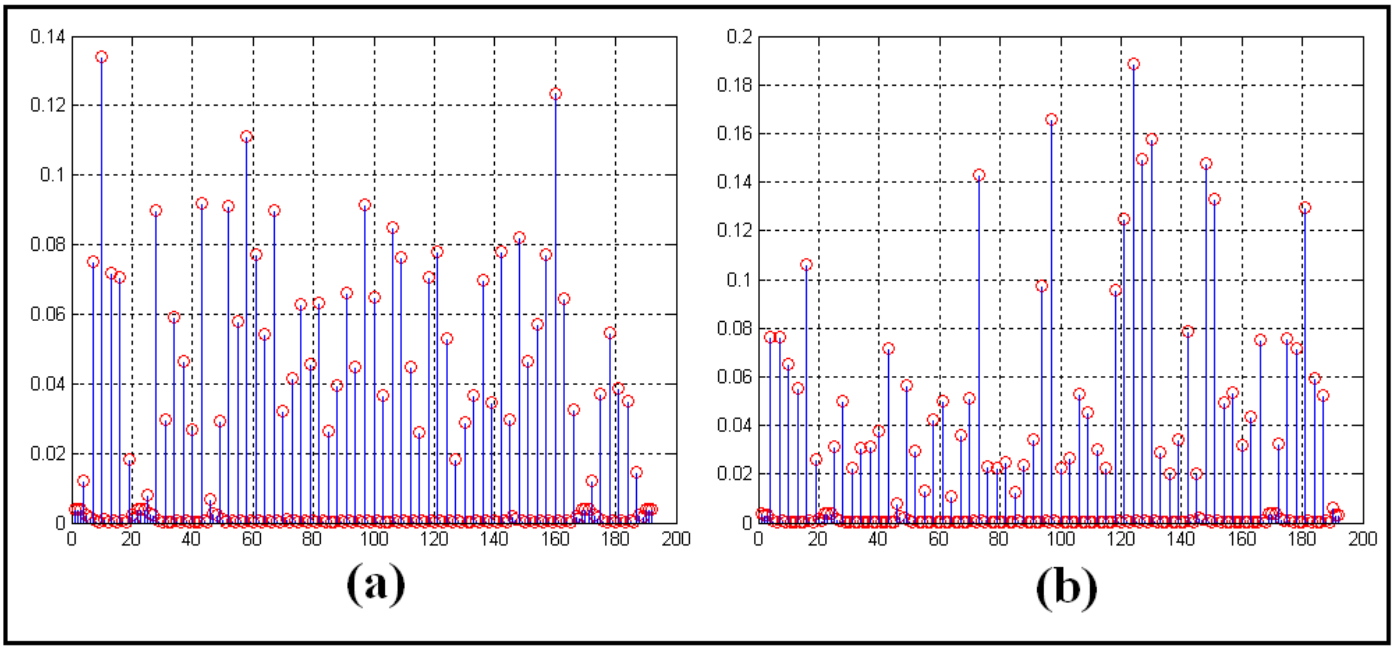

Fig. 5. Example of the values of central moments of some MR images: (a) Central moments of the sample 01 of the second class, (b) Central moments of the sample 02 of the third class.

3) Brain tumors classification

This step consists to affect the brain image fed into the input of the proposed system to an appropriate class. Several classification methods have been proposed for the recognition and classification of medical images ([12]-[14]). For our study, the classification is achieved by the use of a Multi-Layer Perceptron (MLP), the good results obtained using this type of neural networks in several problems of classification and pattern Recognition have motivated us to opt for this choice. The used neural network is composed of three layers, the input layer neurons number is equal to the number of central moments used as a features to characterize the MRI brain image (N_IL=192), the output layer neurons number is equal to the number of the classes brain tumor to be recognized (N_OL=6), while the number of hidden layers and the number of neurons per hidden layer are determined by groping, for our case, we used one hidden layer, and the neurons number of this layer is equal to forty five (45) (N_HL=45). The initial connection weights are in the range [-1, 1]. For the transfer function, we have opted for the familiar sigmoid function. The brain tumors classification proceeds in two steps: the learning step and the test step

a) The learning process

For learning the neural network, we have opted for the use of the Back propagation algorithm; this choice is justified by the simplicity of this algorithm and by the encouraging results obtained during its multiple uses in several problems of pattern recognition. The algorithm uses two parameters, namely: the learning rate η and the momentum μ which are experimentally chosen. For having a good and easily convergence, the experimenter must appropriately choose these two parameters. In this study, the values that we have chosen of the learning rate and momentum are respectively: $\eta = 0.8$ and $\mu = 0.3$. The training process for the network is stopped only when the sum of squared error falls below 0.001. (See Fig. 4). Let's note that during this phase, only forty two (42) sample (seven samples of each class) from the database are used (this is equivalent to 70% of the used database), this will allow us to test the neural network by some samples which are not part of the learning base.

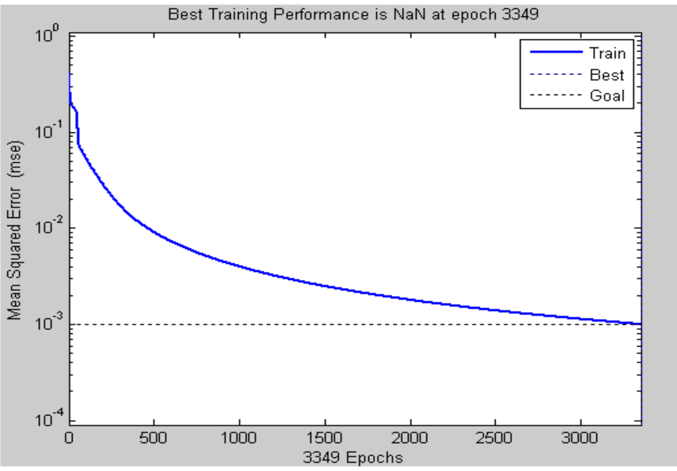

Fig. 6. Example of resizing some MR images of the brain.

b) The test process

During this phase, all samples of the database are presented at the system entry as a successive manner, and for each sample the system takes a decision of its affectation to one of the possible classes. The response of the system can be:

- Recognized brain image: the system arrives to properly affect the MR brain image presented at its entry to one and only one class.
- Ambiguous brain image: the system associates the MRI brain image presented at its entry to more than one class.
- Rejected brain image: the system is unable to assign the MR brain image presented at its entry to any class.
- Wrong brain tumor: this case is encountered when the system assigns of an incorrect manner the MR brain image presented at its entry to one of the possible classes.

III. OBTAINED RESULTS

Based on the four types of possible responses of the proposed system, we have defined four rates: Recognition Rate (R_R), Ambiguity Rate (A_R), Rejection Rate (RJ_R) and Error Rate (E_R), these are the rates used to evaluate the performances of the realized system, the main objective is to obtain a high recognition rate as much as possible. It should be noted that the test of the realized system has been performed using all samples of the database (the ten (10) samples of each class), the obtained results are very encouraging and very promising, the system arrives to recognize 88.333% of the used database, this means that on the sixty (60) samples of the database, the system arrives to associate correctly and properly fifty three (53) sample to their classes, while for the rest of the samples, the system fails to correctly affect them to appropriate classes, and its response may take several forms. It may be "Brain Tumor Rejected", this is the case for three (03) samples of the database (equivalent to 5%), for which the system does not takes any decision of classification. It may be also "Ambiguous Tumor Brain", where the system proposes an assignment to more than one class of the MR image fed into its input, this is the case of two (02) samples of the database (equivalent to 3.333%) which was affected to two classes. Finally, the system response may be "Wrong brain tumor", in this case, the system takes a decision for MR brain image presented at its input, but it is not the good decision, this is the case of two (02) other samples of the database, which is equivalent to 3.333%. Table I shows the obtained rates.

TABLE I. DIFFERENT OBTAINED RATES.

Rate Type	R_R(%)	A_R(%)	RJ_R(%)	E_R(%)
Rate value (in %)	88.333	05.000	03.333	03.333

Where:

- R-R: Recognition Rate.
- A-R: Ambiguity Rate
- RJ-R: Rejection Rate.
- E-R: Error Rate.

IV. CONCLUSION

This study falls within the framework of automating the process of detection and classification of brain tumors from MR images of the brain. The importance of this type of studies resides in the solutions that they propose to overcome the multiple difficulties which prevent until today the realization of a universal system for the automatic classification of brain tumors, these difficulties are mainly due to the variable nature of the size and location of the tumor in the brain. The study is based on the proposal of a novel method for the classification of brain tumors from MR brain images; the used feature vector is composed of parameters obtained by applying the central moments method. The obtained results are very encouraging and very promising, the system arrives to properly affect 88.333% of the images of the databases, this is a very interesting recognition rate and very motivating, the results can be further improved, this can be achieved by analyzing the images for which the system has encountered difficulties for affecting them to their proper classes. This analysis allows to identifying the reasons for the misclassification and therefore to propose the necessary solutions.

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