



## Classification of Hydrocephalus using TAN

<sup>1</sup>Eman M. Ali, <sup>2</sup>Ahmed F. Seddik, <sup>3</sup>Mohamed H. Haggag

<sup>1</sup>Department of Computer Science, Helwan University, Cairo, Egypt

<sup>2</sup>Dean of Faculty of Computer Science, Nahda University, Professor at the Biomedical Engineering Department, Helwan University, Cairo, Egypt

<sup>3</sup>Vice Dean for Student Affairs at Faculty of Computers and Information, Professor at Computer Science Department Faculty of Computers and Information, Helwan University, Cairo, Egypt

**Abstract**— *Hydrocephalus is considered to be one of the diseases that may cause damage in children brain especially infants. MRI (Magnetic resonance Imaging) is one source of hydrocephalus detection tools, but using MRI in children brain diseases classification is considered to be difficult process according to the variance and complexity of brain diseases. This paper presents a solution of detecting one of the children brain diseases which is hydrocephalus. The proposed system consists of four stages, namely, MRI Preprocessing stage, Segmentation stage, Feature extraction, and Classification stage. In the first stage, the main task is to eliminate the medical resonance images (MRI) noise found in images due to light reflections or operator performance which may cause inaccuracies in the classification process. The second stage, which is the stage where ROI is extracted (tumor region). In the third stage, the features related with MRI images using Haar wavelet transform (HWT) will be obtained. The features of magnetic resonance images (MRI) have been decreased using (HWT) to essential features only. And finally the fourth stages, where new classifier will be presented and finally the result will compare the proposed classifier with six other classifiers have been used.*

*Image classification is an important task in the medical field and computer vision. Image classification refers to the process of labeling images into one of a number of predefined categories. This survey will use the Tree augmented Naïve Bayes classification technique to detect and classify one of the children brain diseases, and classify the hydrocephalus type depending on MRI. And it's expected to achieve a high accuracy in hydrocephalus detection to help the radiologist in the disease detection process.*

**Keywords**— *Hydrocephalus, MRI, Image Classification, Tree augmented Naïve Bayes, children brain diseases .*

### I. INTRODUCTION

Early detection and classification of brain diseases are very important in clinical practice. Several kinds of research have been proposed different techniques for the classification of brain tumors using different sources of information [1], but there is still a lake in hydrocephalus detection algorithms. In this paper, a process for hydrocephalus classification, depending on the analysis of Magnetic Resonance (MR) images and Magnetic Resonance Spectroscopy (MRS) data collected for patients with obstructive, Non-obstructive, and Normal Pressure Hydrocephalus is presented.

The hydrocephalus word stands for "hydro", which means water and "cephalus", meaning head, so hydrocephalus means water in the brain. Hydrocephalus is considered to be a complex disease, which commonly affecting newborns. The aim is to achieve a high accuracy in discriminating the three types of hydrocephalus through a combination of several techniques for image denoising, image segmentation, feature extraction and classification. The proposed technique has the potential of assisting medical diagnosis.



Fig.1. Hydrocephalus compresses and displaces normal brain tissue, Increasing size, pressure and swelling cause symptoms like seizures or headaches.

Hydrocephalus can be classified according to two criteria which are pathology and etiology. According to pathology criteria, hydrocephalus is classified into obstructive (non-communicating) or non-obstructive (communicating). And normal pressure hydrocephalus (NPH) according to etiology criteria, which mainly affect older children, see Fig. 1[2].

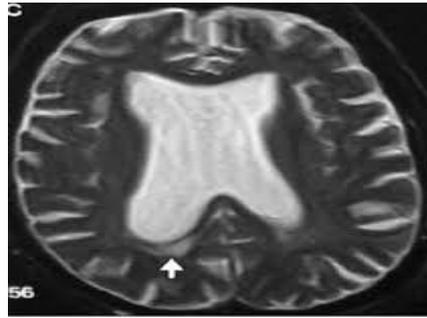


Fig.2. Hydrocephalus MRI with obstructive hydrocephalus region [2].

Infants can suffer from hydrocephalus at birth and can be caused by Dandy-Walker malformations, porencephaly, spina bifida, Chiari I and II malformations, arachnoid cysts, and most commonly aqueductal stenosis.

Both types are potentially disabling and life-threatening. Because space inside the skull is limited, their growth increases intracranial pressure, and may cause edema, reduced blood flow, and displacement, with consequent degeneration, of healthy tissue that controls vital functions [3]. Brain tumors are, in fact, the second leading cause of cancer-related deaths in children and young adults. According to the Central Brain Tumors Registry of the United States (CBTRUS), there will be 64,530 new cases of primary brain and central nervous system tumors diagnosed by the end of 2014 among children. Overall more than 600,000 people currently live with the disease. [3]

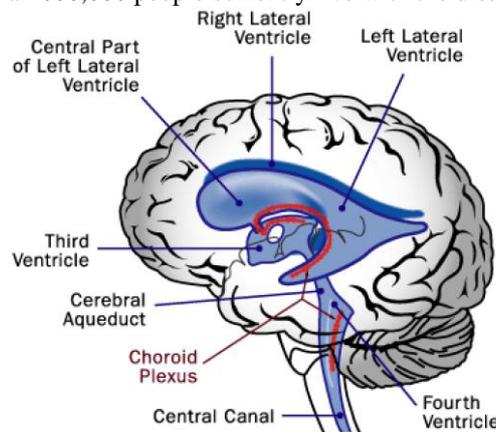


Fig.3. Brain with obstructive hydrocephalus region [2].

Hydrocephalus goes mainly untreated in developing countries because neurosurgical care is simply not available. This year alone, CURE conservatively estimates that nearly 400,000 newborns (3/1,000 births) will suffer from infant hydrocephalus around the globe and over 310,000 (79%) of these children will be born in the developing world with limited or no access to critical life-saving care see Fig. 3 [4].

Many kinds of research depending nowadays on using computer technology in medical diagnoses such as cancer-related research in brain, breast, and liver. MRI is one of the technologies used to take a photo of the body organs through the usage of the magnetic field. It has much higher features than other radiation tools such as x-ray and computed tomography (CT) [4]. The researcher had proposed various features for classifying tumor in MRI. The statistical, Intensity, Symmetry, Texture features etc., which utilize a gray value of tumors are used here for classifying the tumor. However, the gray values of MRI tend to change due to over-enhancement or in the presence of noise [5].

Though, the main objective of all proposed classification algorithms, whether it relies on characterizing texture to its statistics or modeling the medical image, aim to learn from how interestingly discern medical images to eventually develop “knowledgeable” computer systems. Thus, the objective of this paper presents an appraisal of the existing and conventional methods for the classification of medical images and based on these observations; propose a framework for medical image classification. The rest of the paper is structured as Section 2 to Section 5.

Section 2 presents a survey of previous brain hydrocephalus identification and classification techniques. Section 3 illustrates the proposed framework followed by a comparative analysis of the presented classification techniques in Section 4. And finally the conclusion in Section 5.

## II. SURVEY ON PREVIOUS TECHNIQUES

Most of the researchers presented in medical field focus only on tumors, in brain or breast. But there are very few studies used to detect hydrocephalus disease. Here in this paper image processing techniques to detect and classify the children brain hydrocephalus are used.

### 2.1 Javeed Hydrocephalus detection method [4]

In this method, they make use of the Fuzzy c-means algorithm for the detection of hydrocephalus in infants based on MRI images.

## 2.2 Ivkovic Hydrocephalus Detection Method [5]

In this method Ivkovic depending on using image histogram analysis to detect the hydrocephalus region. Ivkovic present a technique consist of only two phases, image acquisition and preprocessing phase, and histogram analysis phase. In this technique, they only detect they detect the hydrocephalus region but they didn't classify the extracted region to which kind of hydrocephalus.

## 2.3 Sweetman Hydrocephalus Detection Method [6]

Sweetman et al. [6] considered the problem of computational prediction of cerebrospinal fluid flow in the human brain. By the use of image reconstruction software Mimics 12.11, the authors developed the 3D model from MRI brain images, which reproduces pulsatile CSF motion and predicts intracranial pressures and flowrates. The model of a healthy brain helps to predict CSF flow correctly, however, accurate prediction of pathological brain dynamics (such as hydrocephalus) require model refinement.

## III. PROPOSED TECHNIQUE

The proposed system has mainly four modules namely Pre-processing, segmentation using Contribution-Based Clustering Algorithm, Feature extraction, and hydrocephalus classification. According to the need of the next level, the pre-processing step converts the image. It performs filtering of noise and other artifacts in the image and sharpening the edges in the image. RGB to gray conversion and reshaping also takes place here. It includes a median filter for noise removal. The feature extraction is extracting the cluster, which shows the predicted hydrocephalus at the Haar wavelet transform output. The extracted cluster is given to the threshold process. It applies a binary mask over the entire image.

In hydrocephalus detection and classification step, the hydrocephalus area is calculated using the binarization method making the dark pixel darker and white brighter. In threshold coding, each transform coefficient is compared with a threshold and if it's less than the threshold value, it is considered as zero or else one. In the approximate reasoning step, the hydrocephalus area is calculated using the binarization method. That is the image having only two values either black or white (0 or 1). Here 200x200 JPEG image is a maximum image size. The binary image can be represented as a summation of a total number of white and black pixels. Pre-processing is done by filtering.

Segmentation is carried out by Content-based Image Retrieval (CBIR) algorithm. The feature extraction is done by considering the threshold and finally, approximating the classification method to recognize the hydrocephalus shape and position in MRI image using edge detection method [15] see Fig. 4.

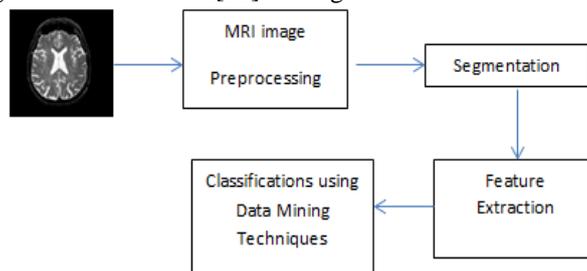


Fig.4. Block diagram of the proposed brain diseases classification system.

## 3.1 Image Preprocessing

In the preprocessing stage, first transform the brain MRI image from RGB mode to Grayscale level and from eight bit to double precision pattern to get a high-resolution image of the brain while at the same time being noninvasive. The aim of this paper is to detect, segment and classify the hydrocephalus cells, but for the complete stage it needs the process of noise removal.

To get the best MR image quality, a median filter was used to remove any noise from the original image see fig. 5.

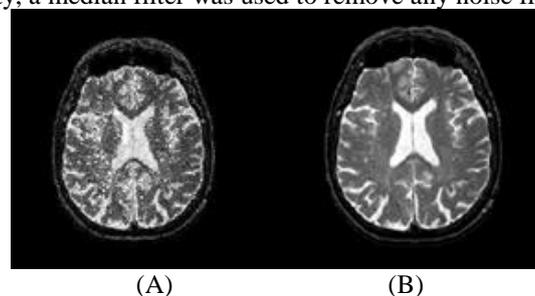


Fig.5. (A): The Original MRI image with noise. (B): The same image after applying the median filter.

After applying the median filter to the noisy image now, the brain MR images are ready to go to the segmentation phase and isolate the hydrocephalus region fig. 5 state the block diagram of the proposed system.

## 3.2 Segmentation

In this paper, use one of the unsupervised classifications clustering forms, which are used to group the image pixels based on the similarity between this pixels. This partitioned clustering algorithm is based on the notion of 'contribution

of a data point'. The content-based image retrieval algorithm will be applied and compare its performance with that of the k-means clustering algorithm. In comparison with the k-means algorithm, CBIR achieves a better result in measuring the similarity of both intra-cluster and inter-cluster [6].

The algorithm aims at partitioning a group of data points into disjoint clusters optimizing a specific criterion [2]. When the number of data points is large, a brute-force enumeration of all possible combinations would be computationally expensive. Instead, there are many algorithms are applied to find the optimal partitioning. The most popular criterion function used for partition clustering is the sum of squared error function given by:

$$E = \sum_{i=1}^k \sum_{x \in C_i} (x - m_i)^2 \quad (1)$$

Where k is the number of clusters,  $C_i$  is the  $i$ th cluster,  $x$  is a data point and  $m_i$  is the centroid of the  $i$ th cluster. A widely used squared-error based algorithm is the k-means clustering algorithm [2]. Here, a clustering algorithm similar to the k-means algorithm will be used. The contribution of a data point belonging to a cluster is defined as the impact that it has on the quality of the cluster. This metric is then used to obtain an optimal number of clusters from the given set of data points.

While this work uses the concept of contribution to finding the optimal number of clusters, CBIR is used for optimal partitioning of the data points into a fixed number of clusters.

The proposed outline presents contribution-based clustering algorithm. It optimizes on two measures, namely the intra-cluster dispersion given by:

$$\alpha = \frac{1}{n} \sum_{x \in C_i} (x - m_i)^2 \quad (2)$$

And the inter-cluster dispersion given by:

$$\beta = \frac{1}{k} \sum_{i=1}^k (m_i - \bar{m})^2 \quad (3)$$

Where k is the number of clusters and  $\bar{m}$  is the mean of all centroids. The algorithm tries to minimize  $\alpha$  and maximize  $\beta$ .

After founding the tumor pattern region, a resize of the tumor region will take place to be  $200 \times 200$  to have a suitable region to have enough features, to get a high performance in the next phase.

### 3.3 Feature Extractions

Once the local tumor pattern is found, which is a  $200 \times 200$  image, now the local tumor features are found but, this tumor feature vector is too large to use it in the classification phase so, to generate a  $50 \times 50$  feature vector for this pattern the Haar wavelet transform is used. Haar wavelet can be used to decompose the data in the tumor region into sub-components that appear in different resolution. It divides the tumor image into four sub-images [7]. These resulted images consist of two high-resolution images one image that has been high pass in horizontal and vertical directions and one that has been low pass filtered in both directions.

In comparison with other methods by using the Haar wavelet transform, it successfully reduces the feature vector which affects the overall performance of the system and decrease the classification process overall time.

### 3.4 Classification

Image classification refers to the labeling of images into one of a number of predefined categories [8-21]. Classification system consists of a database that contains predefined patterns that compare with a detected object to classify into the proper category. Image classification is an important and challenging task in various application domains.

According to the classification process, there are three main types of hydrocephalus that the Tree augmented Naïve Bayes is used to classify the extracted image region to one of them, which are:

1. Obstructive (Non-communicating) hydrocephalus.
2. Non-obstructive (communicating).
3. Normal Pressure Hydrocephalus.

In many kinds of research, there are a lot of classification techniques applied and most of them based on detecting a sequence similarity between features extracted from the image and the pattern stored in the database.

Most of these classifiers use binary classifiers for classification of the image as a normal image or abnormal image only without detecting which kind of hydrocephalus the child suffering from such as Neural Networks, Support Vector Machines (SVMs), etc.

This paper presents a framework using the Tree-Augmented Bayesian Networks (TAN) which performs multi-classification based on the theory of learning Bayesian Networks. In order to enhance TAN's performance, pre-processing of data is done by feature discretization and post-processing is done by using Mean Probability Voting (MPV) scheme. The advantage of using Bayesian approach over other learning methods is that the network structure is intuitive.

The main process of the TAN is to assign the extracted region to one of the classes of the predefined images in the dataset.

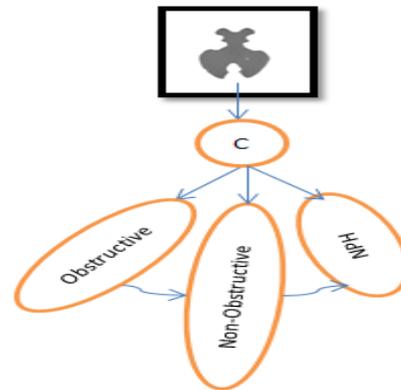


Fig.5. Classification process using TAN.

The system focuses on calculating the probability that the extracted image  $q$  belong to one of the three classes of hydrocephalus as shown in Fig. 5.

#### IV. EXPERIMENTAL RESULTS

In this section, the results obtained using a database of images is presented. Start by presenting the database with which conducted in tests, and then, present the results according to the used structure.

##### 4.1 Database

The famous medical imaging is MRI. A magnetic resonance imaging (MRI) scanner uses powerful magnets to polarize and excite hydrogen nuclei (single proton) in human tissue, which produces a signal that can be detected and it is encoded spatially, resulting in images of the body.

The MRI dataset consists of 33 Children MRI in jpg format images, with 15 images containing obstructive hydrocephalus, 13 images containing non- obstructive hydrocephalus and 5 normal pressure hydrocephalus images. These images are divided into three categories, 70% for training, 15% for testing and 15% for validation.

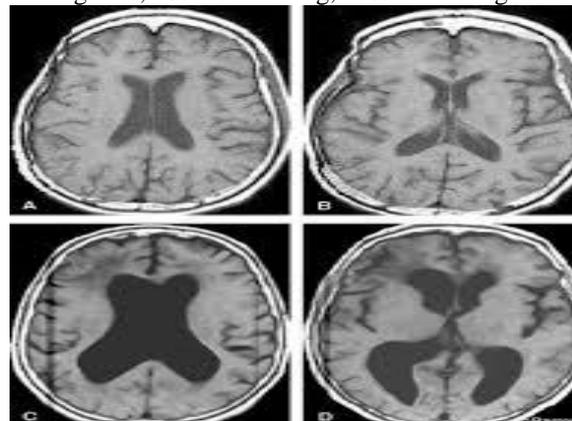


Fig.6. Samples of children brain dataset containing hydrocephalus.

##### 4.2 Comparative analysis

Next figures show the images as an output gray scale image and extracted hydrocephalus from MRI image. For this purpose, real-time patient data is taken for analysis. As hydrocephalus in MRI image have an intensity more than that of its background so it become very easy locate it and extract it from MRI image.

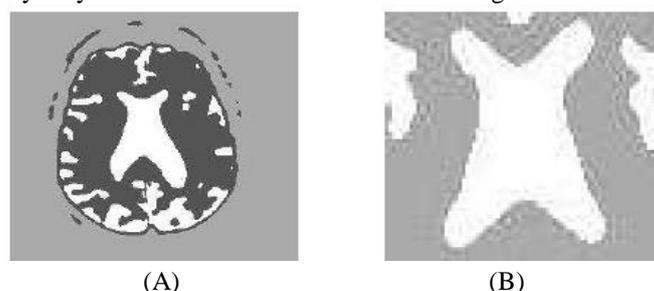


Fig.7. (A): MRI image of hydrocephalus affected brain grayscale image. (B): the extracted hydrocephalus region.

After using two kinds of segmentation techniques on these images, contribution based information retrieval achieving better performance compared with K-Means algorithm see Fig. 8 and Fig. 9.

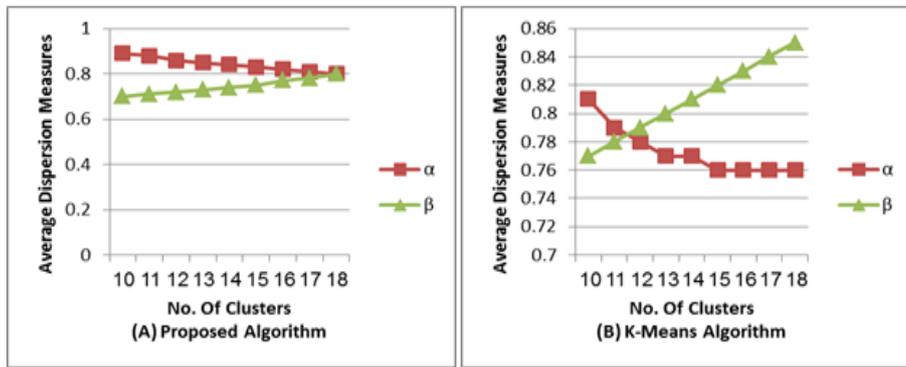


Fig.8. Average value of  $\alpha$  and  $\beta$  against the number of clusters.

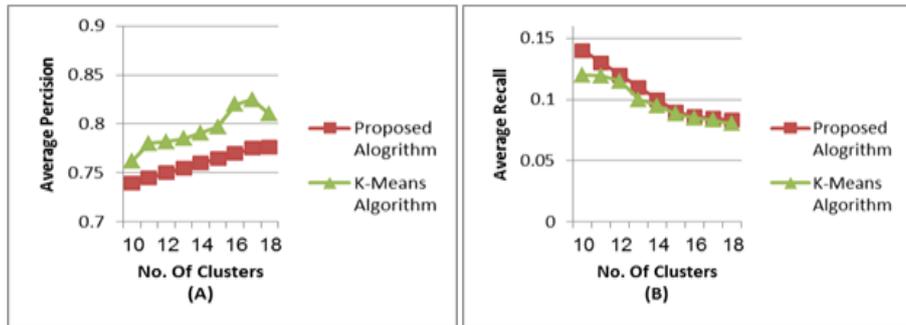


Fig.9. Average Precision and Recall against the number of clusters.

The next table shows the classification accuracy using CBIR and k-Means segmentation techniques.

TABLE 1 THE ACCURACY OF THE CLASSIFICATION TECHNIQUES USING K-MEANS AND CBIR SEGMENTATION ALGORITHMS

Segmentation	DA	NN	NB	SVM	DT	KNN	TAN
Brain MRI using (K-Means)	75.93	91.44	76.08	92.59	87.04	82.3	99.4
Brain MRI using (CBIR)	90.12	96.10	93.52	92.59	96.19	93.7	99.8

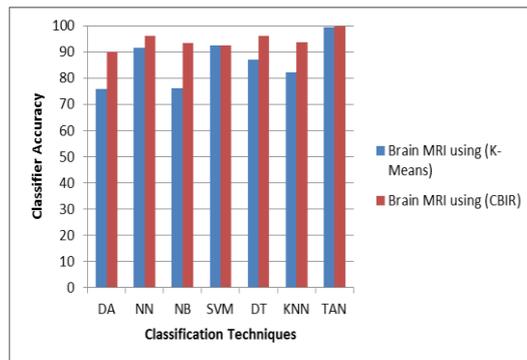


Fig.10. The accuracy of classification techniques using CBIR and K-mean Segmentation techniques.

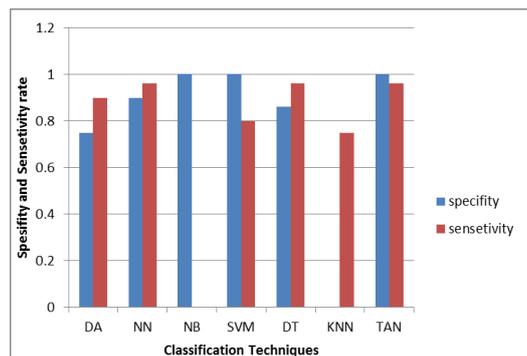


Fig.11. Classification results in terms of specificity and sensitivity.

The next table states a comparison between the classification techniques according to the classification time see table 2.

TABLE 2 THE CLASSIFICATION TECHNIQUES CLASSIFICATION TIME.

Classification Technique	Classification Time (seconds)
DA	760.8
NN	754.3
NB	11.6
SVM	735.7
DT	10.06
KNN	0.03
TAN	1.6

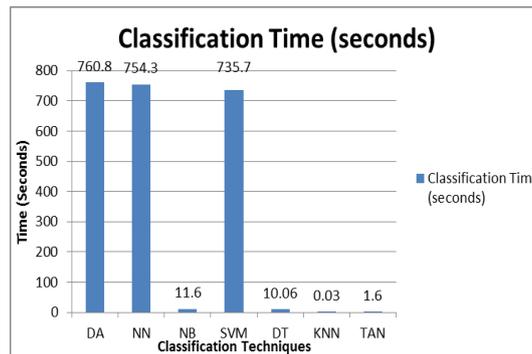


Fig.12. A comparison between classification techniques according to classification time.

From the results of experiments, the tree augmented naïve Bayes algorithm gave the best detection rate. It, achieving a classification rate of 99.8 %. But when considering computational performance, however, K-Nearest Neighbor algorithm proved to have a faster build time (Time it takes to build a model on network training data) at 0.03 seconds while having a detection rate of 93.7% as shown in table 1. Tree augmented Naïve Bayes had the second best build time at 1.6 seconds and a detection rate of 99.8%. Computational performance is particularly important when considering the real-time classification of potentially thousands of simultaneous networks traffic. From experiments, Tree augmented Naïve Bayes appears to be the best suited for real-time classification tasks due to its relatively fast classification speed and high detection rate.

## V. CONCLUSION

This paper presents a survey on various image mining techniques that was proposed earlier by researchers for the better development in the field of content-based image retrieval. The purpose of the mining is to produce all considerable patterns without prior knowledge of the patterns. Important information can be hidden in images, conversely, few research talks about data mining on them. Image segmentation is the primary phase in image mining. In other words, image mining is simply an expansion of data mining in the field of image processing. Image mining handles with the hidden knowledge extraction, image data association and additional patterns which are not clearly accumulated in the images. Also, this paper provides a marginal overview for future research and improvements. Certain possible future investigations that are discussed may be done in the area of image mining which included the experimentation's on other image elements such as textures, shape, etc.

In future, this program can be done more advanced so that hydrocephalus growth can be analyzed by plotting the graph which can be obtained by studying sequential images of hydrocephalus affected patient.

The future research work may include the implementation of the Bayesian networks for relevance feedback and more extensive tests with other examples of image forensic work. It is also envisaged that subjective testing will be performed with input from forensic experts.

Some possible future studies that may be conducted in the area of image mining include the experimentation's on other image elements such as textures, shape, and so forth. It will also be interesting to investigate hidden relationships among images. For example, intensive and extensive exploratory pattern analysis involved in the existing systems in the database can be very useful.

## ACKNOWLEDGMENT

I am very grateful and would like to thank my guides Prof. Mohammed Haggag and Prof. Ahmed Farag for their advice and continued support. Without them, it would not have been possible for me to complete this paper. I would like to thank my husband for the thoughtful and mind stimulating discussion we had, which prompted us to think beyond the obvious.

## REFERENCES

- [1] K. Kharat, P.Kulkarni, M.B.Nagori, " Brain Tumor Classification Using Neural Network Based Methods ", International Journal of Computer Science and Informatics ISSN (PRINT): 2231 –5292, Vol-1, Iss-4, 2012.
- [2] Brain MRI dataset, www.CEwebservice.com, 2014.
- [3] V. Gladis, P. Rathi, S. Palani, " BRAIN TUMOR MRI IMAGE CLASSIFICATION WITH FEATURE SELECTION AND EXTRACTION USING LINEAR DISCRIMINANT ANALYSIS ", Sudharsan Engineering College Sathiyamangalam, Pudukkottai , India,2014.
- [4] J. Hussain, P. V. Sree, "Detection of Hydrocephalus Lateral Ventricles Quantitatively in Brain MRI images of Infants", International Journal of Computer Applications, Vol. 83, No. 9, PP. 12, December 2013.
- [5] M. Ivkovic, M. Zimmermann, "MRI assessment of the actazolamide and External lumbar drainage in idiopathic Normal Pressure", University of Miami School of Medicine , USA,2015.
- [6] Sweetman B., Xenos M., Zitella L., Linninger A.A.: Three-dimensional computational prediction of cerebrospinal fluid flow in the human brain, Computers in Biology and Medicine, Vol. 41, pp. 67-75, 2011.
- [7] A. Gale, S. Salankar, " A Review On Advance Methods Of Feature Extraction In Iris Recognition System " , International Conference on Advances in Engineering & Technology – 2014 (ICAET-2014), PP 65-70,2014.
- [8] M. Nagori, S. Mutkule , "Detection of Brain Tumor by Mining fMRI Images", International Journal of Advanced Research in Computer and Communication Engineering , Vol. 2, Issue 4, January 2013.
- [9] A. Jose, S.Ravi, M.Sambath , "Brain Tumor Segmentation Using K-Means Clustering And Fuzzy C-Means Algorithms And Its Area Calculation" , International Journal of Innovative Research in Computer and Communication Engineering, Vol. 2, Issue 3, March 2014.
- [10] S. Anwar , R. Ibrahim, "A Framework for Medical Images Classification Using Soft Set", The 4th International Conference on Electrical Engineering and Informatics (ICEEI 2013), Malaysia.,2013.
- [11] P. Kamavisdar, S. Saluja, S. Agrawal, "A Survey on Image Classification Approaches and Techniques", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 1, January 2013.
- [12] H. Aslam, T. Ramashri, M. Ahsan, "A New Approach to Image Segmentation for Brain Tumor detection using Pillar K-means Algorithm" , International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 3, March 2013.
- [13] K.Kothavari, R.Keerthana, M.Mariselvam,S.Kaveya, L.Mekala, "A Hybrid approach for PNN-Based MRI Brain Tumor Classification and Patient Detail Authentication Using Separable Reversible Hiding" , International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, Issue 4, April 2013.
- [14] V. Rekha, S. Anantharajan, "C.A.D.S., for Classification of MRI Brain Tumor Using Decision Tree", International Journal of Innovative Research in Science, Engineering and Technology, Vol. 3, Issue 3, March 2014.
- [15] M. Suganya, M. Menaka, "Various Segmentation Techniques in Image Processing: A Survey", International Journal of Innovative Research in Computer and Communication Engineering, Vol.2, Special Issue 1, March 2014.
- [16] C. P. Loizou, M. Pantziaris, C. S. Pattichis, I. Seimenis, "Brain MR image normalization in texture analysis of multiple sclerosis", Journal of Biomedical Graphics and Computing, Vol. 3, No. 1, 2013.
- [17] P. Loizou, C. Kyriacou, "Brain white matter lesion classification in multiple sclerosis subjects for the prognosis of future disability", Intelligent Decision Technologies, Pp. 3–10, 2013.
- [18] Dr S. McKay, Dr R. Hadfield, "Current Knowledge in Brain Cancer Research", Developed for Cure Brain Cancer Foundation, Pp. 1-33, May 2014.
- [19] A. Morgado, L. Caldeira, N. Silva, "Dynamic analysis of MR-PET data on brain tumors", 3rd Conference in PET/MR and SPECT/MR , Kos Island, Greece. 19-21 May 2014.
- [20] B. Wei, Z. Yu, G. Yang, "A New Multistage Medical Segmentation Method Based on Super pixel and Fuzzy Clustering" , Hindawi Publishing Corporation Computational and Mathematical Methods in Medicine, Volume 2014, Article ID 747549, 13 pages, 2014 .
- [21] Ms. P. Jayashri, Mrs. D.Gandhimathi, "COMPARATIVE STUDY ON DIFFERENT BRAIN TUMOR SEGMENTATION IN MRI IMAGES", International Journal of Advanced Technology in Engineering and Science, Volume No.02, Issue No. 09, September 2014.