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LOCATING TUMOR IN MRI BRAIN IMAGE BASED ON CLASSIFICATION AND 3D RECONSTRUCTION

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ABSTRACT

Brain tumour is the most dangerous disease to cure which occurs when abnormal cells grows in the brain. In this paper, we proposed a methodology to analyse the brain images and 3D reconstruction of MRI images. Initially, the redundant tissues and noises are purged from the input image by means of the skull stripping approach. Then, segmentation using FCM is applied on the skull stripped image. After that the firstorder statistical attributes and the co-occurrence matrix are calculated from the segmented image. These extorted attributes are then inputted to the K-NN classifier to categorize the normal and the anomalous MRI brain images. Ultimately, the images categorized as anomalous then undergoes 3D reconstruction process by means of the depth map estimation so as to position the tumour precisely.

***Keywords*: Skull Stripping, K-NN Classifier, 3D Reconstruction, MRI, Feature Extraction, Depth-Map Estimation.**

I. INTRODUCTION

The medical imaging is an ingredient of natal imaging which ascertains an anatomy and physiology database that recognizes the aberrations in humans [1]. In accordance with the images of brain it affords signals of brain anatomy and is valuable in the analysis of several brain aberrations like malevolent glioma tumor and skull have appeared intensity that builds

Mechanical tumor detection tricky. In order to conquer this confront, skull-stripping technique is preferred as a pre-processing phase for identifying the brain tumor [2].The extortion of three dimensional objects and its visualization is the vital step in the psychiatry of the preprocessed medical image data, which facilitates to carry out recognition, treatment planning and treatment deliverance [3][4].

A budding three dimensional method exhibits several applications such as cinema, gaming, photography and edification etc. The two dimension to three dimension conversion is categorized into two approaches namely the i) semi-automatic approach and ii) full-automatic approach. Although the semi-automatic conversion approach [5] is broadly utilized till now, it needs significant period and human reserves. Full mechanical two dimensional to three dimensional conversions is yet again classified into two approaches: The first approach depends on the depth map and the second approach depends upon the sparse three dimension statistics of attribute spots on the image. The technique employing depth map is termed as depth image based rendering i.e., DIBR approach [6][7]. Depth extortion is the fundamental method in conversion procedure. The huge dissimilarity amid the two dimensional and the three dimensional image is the depth statistics [8]. The depth cues based approach allocates depth values by means of image categorization, machine learning, depth from focus or defocus, depth from view of geometry, depth from the texture gradient, depth from comparative height and depth from multi scale attributes of local and global image [9].

Classification includes two approaches. The first one is supervised learning technique where the ANN, SVM and KNN are employed and the other one is the unsupervised learning technique for clustering of data similar to Self Organizing Map and K-means Clustering. In our work we employs the supervised learning technique which means the KNN is utilized as it yields enhanced classification precision and performance [10]. KNN holds the characteristic of unfussiness, usefulness, intuitiveness and proficient categorization performance in various domains. It is strong to noisy training data and is effectual if the training statistics is huge [11].

II. RELATED WORK

Janusz Konrad*et.al* [12] have intended a novel class of approaches depending upon the drastically dissimilar method of studying the two dimension to three dimension conversion from instances. They build up two forms of techniques. The first technique was depends upon the erudition of a point mapping from the local image or video characteristics to scene-depth at the pixel by utilizing a regression form proposal. The next approach depends on approximating the complete depth map of a query image openly from a depository of three dimensional images by means of a nearest neighbor regression form proposal.

Swati Arora*et.al* [13] have exhibited a quantitative psychiatry of the error in rebuilding a three dimensional sight which was detained with Synthetic Aperture Integral Imaging scheme. The three dimensional data was attained from the two dimensional images when the camera strictures were unidentified. The replica employed for attuning the Integral Imaging camera arrangement depends upon the fuzzy schemes. This scheme offers the chance for molding of circumstances which were essentially inaccurately described. They reveals that the error in the three dimensional renovation not only based upon the no of cameras, however to the comparative locations. The replica was employed to an array of images detained experimentally from a genuine object. An exact color real scale three dimensional rebuilding was attained effectively.

Youngmo Han *et.al* [14] have projected a two dimensional to three dimensional graphic human movement converter which rebuilds three dimensional visual movement from the two dimensional visual human movement in an image series. The article introduces a systematic elucidation form of three dimensional reconstruction processes in place of the nonlinear iterative forms. In order to obtain a systematic resolution, that article projects a proposal which frames a human body linkage as a two dimensional worldwide joint replica as a substitute of several frequent three dimensional spherical joint replicas.

Shuhan*et.al* [15] have projected a depth-map integration depending upon the manifold View Stereo technique for large-scale sights where the accurateness and effectiveness was taken into consideration. In that intended technique, a proficient patch based upon the stereo matching procedure was utilized to create depth-map at every image with tolerable faults, subsequent to a depth-map refinement procedure to implement reliability above adjacent visions. In addition, the intended approach is simply parallelized at image echelon.

III. PROPOSED WORK

Aproficient brain tumor detection approach is introduced in our paper by means of K-NN classifier and 3Dreconstruction. Originally, the key in of MRI brain image is taken from the database which holds the normal and the anomalous MRI brain images. The obtained input image then undergoes skull stripping procedure so as to eliminate the skull for attainingproficientrate of accuracy in categorization. Then, segmentation using FCM is applied on the skull stripped image.Subsequently, the statistical and the co-occurrence matrix attributes are extorted from the segmented image. Next the extorted attributes are inputted to the k-NN classifier in order to categorize the normal and anomalous images. Ultimately, after performing classification the tumor image then undergoes 3D reconstruction. Ourprojectedapproach includes five phases which are mentioned below:

(i) Pre-processing
(ii) Segmentation
(iii) Feature Extraction
(iv) Classification
(v) 3D Reconstruction

Consider the database (D) which holds the MRI brain images and let $x_{i,j}$ be aparticular MRI brain images of size $(m \times n)$ obtained from the database as an input where $i \in 1,2,..m$ and $j \in 1,2,..n$.The segmentation will be healthier if the image does not hold any noise. Hence, Gaussian filtering is employed on the anomalous MRI images so as to eliminate the noise and perk up the image quality.

3.1 Pre-processing

The Brain MRIs are sulliedthroughout the imaging procedure owing to image transmission and image digitization by noise and thesubsistence of extra-cranial tissues in the MRI like Skull, bone, skin, air, muscles, and fat. The skull stripping procedure is employed to confiscate skull from the Brain MRI images. It amputates brain from the scalp, skull and the other adjacent regions of brain. Originally the MRI brain image ($x_{i,j}$) obtained from the database is inputted for skull stripping. Then the preprocessed image($px_{i,j}$) is subjected for feature extraction process.

3.1.2 Tumor Segmentation

Segmentation of medical images is an exigent and difficultchore for the precisedetection of brain tumor.For the brain MRI images, the most appropriate segmentation approach is the clustering technique. However, in the other approaches, the cancer cells close to the MRI image surfacewhich are plump; therefore it seems dark and is puzzling for the segregation of the edge or theborder of the tumor and the non-tumor portion. Hence, the Fuzzy C-means clustering approach is employed in [16] is used in our paper, whereeach tip holds a quantity of belongingness to cluster for a particular dataset.

3.2 Feature Extraction

The outcome of the segmentation process is denoted as $px'_{i,j}$ which then undergoes feature extraction. For that the first order statistical attributes fs_k like mean (m_k), variance (v_k), skewness (s_k), kurtosis (k_k), energy (e_k), entropy (et_k) and the second order statistical attributes ss_k i.e., the co-occurrence matrix like correlation (c_k), inertia (ine_k), inverse difference (ind_k), entropy (en_k), maximum probability (p_k) and absolute value (a_k) are extorted which are employed for classification [17]. Here (k) indicates $px'_{i,j}$.

3.3 Classification

The extorted attributes of fs_k and ss_k are inputted to the classifier. Then, the tumor (t_x) and the non tumor images (nt_x) classification takes place with the help of k-NN classifier.

K-NN classifier is a technique which hoards all the brain images which undergoes training and categorizes fresh input brain images depending upon the distance function resemblance. An image is categorized in accordance with the greatest choice of its neighbours. In the proposed K-NN classifier, cosine similarity is computed instead of Euclidean distance which is detailed below:

3.3.1 Cosine Similarity Computation

To obtain the distance, cosine similarity is employed in our intended approach. It is an evaluation of the correlation of two vectors of an internal product space also it computes the cosine of the angle amid them. It is a verdict of direction and is exercised in high dimensional optimistic space and the outcome ranges from 0 to 1.

$$\cos\theta = \begin{cases} 1, & \theta = 0 \\ <1, & \theta \neq 0 \end{cases} \quad (1)$$

When the two vectors hold similar orientation in that case the cosine similarity is 1. When the two vectors are 90° in that case the cosine similarity is 0. When the two vectors are entirely dissimilar in that case the cosine similarity is -1.

Assume the vectors of the testing image and training image attributes as (T_x) and (Tt_x) correspondingly. The cosine similarity (cs_x) is ascertained by means of the Euclidean dot product equation,

$$\cos\theta = \frac{T_x . Tt_x}{\|T_x\| \|Tt_x\|} \quad (2)$$

Where,

$$T_x . Tt_x = \sum_{i=1}^{I} T_{xi} \times Tt_{xi} \quad (3)$$

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$$\|T_x\|\|Tt_x\| = \sqrt{\sum_{i=1}^{I} T_{xi}^{\ 2}} \times \sqrt{\sum_{i=1}^{I} Tt_{xi}^{\ 2}} \quad (4)$$

With the values of (3), (4) and (2), (cs_x) is deliberated. The product of (2) constantly ranges from -1 to 1. As previously illustrated in table 1, -1 denotes that both are dissimilar, 1 denotes that both are similar and 0 denotes that both are self reliance and the values excluding that denotes the dissimilarity or in the midst of similarity.

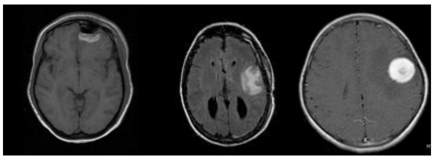
In accordance with the measure of similarity, the specified test image is categorized as anomalous brain image or the normal brain image. The brain images showing tumor then subjected to 3D reconstruction phase for alteration.

3.4 3D Reconstruction

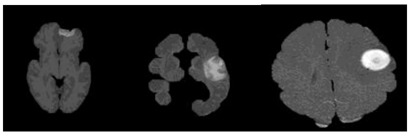
The tumor images attained in the classification phase then subjected to reconstruction. The 3D reconstruction is employed to positon tumors in MR images of dissimilar shapes of brain. Here, the pseudo depth map estimation technique [18] is utilized for reconstruction.

IV. EXPERIMENTAL ANALYSIS

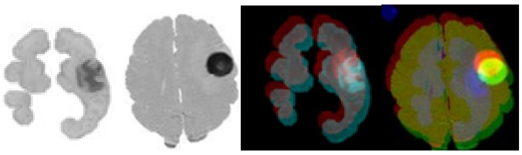
Our intended technique of brain tumor classification and 3D reconstruction via the K-NN classifier and the depth map approximation is executed in the MATLAB working platform. The functioning of the intended approach is examined by means of MRI brain image database holding 250 normal and the anomalous brain images. Figure.1 illustrates the tasters of input images, skull stripped images, depth map estimated images and the reconstructed images.



(a)



(b)



(c)(d)

Fig 1: (a) normal and abnormal brain images (b) skull stripped Normal and abnormal images(c) Depth map of the classified tumor images(d)3D reconstruction of tumor images

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The performance of our intended approaches examined by altering the distance in the KNN classifier. The frequently employed performance metrics like accuracy, sensitivity, specificity and F-Measure of our intended approach are related with that of the conventional approaches which are exhibited in table (1). Our intended technique here mentioned in table 1 is the cosine distance.

Table1: Performance Measures

Distance	Accuracy	Sensitivity	specificity	F-Measure
Euclidean	96	1	88	97
Cityblock	96	1	88	97
Cosine	98	1	93	98.5
Correlation	95	1	89	89

The performance metrics are computed by altering the resemblance metrics like Euclidean Distance, City block, Correlation and cosine employed in the KNN classifier. These performance metrics are computed out of one. Euclidean distance is one resemblance metrics employed in KNN classifier to analyse the performance. By employing the Euclidean distance and city block in categorization, the ensuing accuracy is 96%. Our intended cosine similarity measure yields the accuracy of 98%. As when related with the intended approach the Euclidean distance achieves less accuracy at the rate of 2%. The similarity measurement is a correlation employed for categorization. By means of the correlation metrics in categorization, the classification accuracy attained is 95% which means 1% less than that of the proposed approach. The F-measure of the intended approach is more than that of the other approaches. F-measure is a gauge mainly employed to check the accuracy of an approach it is a combination of precision and recall. The F-measure attains its excellent score as 1 and worst score as 0. F-measure of our intended approach is 98.5% which is 8.5% rates more than correlation; 1.5% rates more than the Euclidean distance and the city block. By considering all the above metrics, our intended approach which employs the cosine distance attains superior performance than the other conventional techniques and it is employed in real time cases.

V. CONCLUSION

A brain tumor recognition and reconstruction approach via the K-NN classifier and the depth map assessment is introduced in this paper. The intended approach is executed in MATLAB and the performance is assessed by employing several MRI brain images. The quantitative analysis of the intended approach is performed by means of the statistical measures and the result is related with that of the conventional techniques.

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