International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

# Classification of Brain MRI Tumor Images

Dr. Umar Alqasemi, Mohammed Bamaleibd, Abdullah Al Baiti
King Abdulaziz University

***Abstract*:- Medical image processing is a challenging and plays many important roles in several applications. Computer-Aided Detection (CAD) provides a great distribution in detecting and diagnosing several diseases precisely, such brain tumor which is our field of study in this paper. By using machine learning algorithms, we can demonstrate automated tumor detection, as implemented in this paper. With this method, diagnosing may perform with high quality, and less effort and time.**

**The purpose of this paper is designing a system that will automatically classify the brain images in terms of normality and abnormality. This system incorporates with several stages such as preprocessing, feature extraction, feature selection, classification and performance assessment. MATLAB program was used for designing and implementation. In the end, the designed system successfully classified the two classes (normal and abnormal) with accuracy of 100%**

***Keywords: Brain tumor, MRI images, normal, abnormal, machine learning based techniques.***

## INTRODUCTION:

Growth of cancerous cells in the tissues of the brain is a brain tumor [1]. It can be benign (noncancerous) or malignant (cancerous). the benign tumor may not spread to far areas or grow into nearby tissues, but they can destroy, press, grow on normal tissues, which may cause harmful or even life-threatening damage. Malignant tumors can spread throughout the body and damage other structures [2]. So benign or malignant, all brain tumors are serious because they will eventually harm and damage other structures within the brain [3].

According to the WHO Classification of Tumors, brain tumors are classified into class I, II, III, or IV based on disorders of the cells they contain [4]. Lower class tumor such as class I and II tend to develop slower and less likely to grow into adjacent tissues. Higher class tumor such as class III and IV tend to develop quicker and grow into nearby tissues. [2].

Brain tumors are categorized into primary tumors, start in brain tissue, and secondary tumors, from another area of the body, reaching the brain [3]. About 30% of brain tumors. Meningioma and Glioma are most known types of main brain tumor. Almost 30% of brain tumors are Meningioma, it can grow and press against the brain. Most of Meningioma tumor are benign and most can be removed with surgery or treated by radiation [5]. Glioma is a group of tumors start in the brain's glial tissue. Glioma group contains Astrocytomas, Brain stem gliomas, Ependymomas, Oligodendrogliomas, and Optic gliomas [2].

Sophisticated imaging techniques can pinpoint brain lesion. Magnetic resonance imaging (MRI) and computed tomography (CT or CAT scan) are diagnostic tools. Magnetic resonance spectroscopy (MRS) is used for examining the nature of the tumor observed on the MRI and to analyze the tumor's chemical profile. To recognize recurring brain lesion, positron emission tomography (PET) is used. Sometimes, the neurosurgeon uses the biopsy to create a certain diagnosis of a brain tumor, and the pathologist decides the final determination whether any benign or malignant tumor is appearing and grade it accordingly. [6].

In 2020, around 23,890 malignant tumors (10,300 females and 13,590 males) will be analyzed. If benign (non-cancer) tumors were counted, these numbers would be much higher. Caused by brain and spinal cord tumors, around 18,020 individuals (7,830 females and 10,190 males) will die. Generally, less than 1% is the possibility that an individual will have a malignant tumor of the spinal cord or brain during a lifetime. The hazard of developing any sort of spinal cord or brain tumor is a bit higher in females than males, but it's slightly higher for men than women when it comes to malignant tumor. This is explained by that some sorts of tumor are more present in one gender than the other. [7].

To recognize forms and features indicatives of tumors and other disorders, computerized algorithms are used. In concept, there is a similarity between biomedical image processing and signal processing. They are similar in terms of enhancement, analysis and displaying images taken by nuclear medicine, ultrasound, x-ray, MRI, and optical imaging technologies. To automatically analyze and distinguish what may not be observed by human eye, image processing software is used and the basic eyeballing an x-ray is abolished. Aspects as volume, diameter, and vasculature of a lesion or organ, are being determined via image analysis and processing associated with the suitable image technique and diagnosis. [8].

## LITERATURE REVIEW:

R. Anitha1 and D. Siva [9] proposed a random forest classifier system-based brain tumor detection and segmentation method. For eliminating and detecting noises in brain image, adaptive medial filter is used. Via texture features, features are extracted from the de-noised brain image, such inverse difference moment (IDM), variance inertia, angular second moment (ASM), energy, dissimilarity, and homogeneity that are acquired from grey level co-occurrence matrix (GLCM). Classifier such


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

random forest (RF) is used to segment the original brain image into normal or abnormal. For severity diagnosis, RF classifier used weighted voting method to segment the brain images. Figure (1), shows the final result of the isolated tumor as pixel segmented image (A), and the spot of the detected tumor of the input image (B)

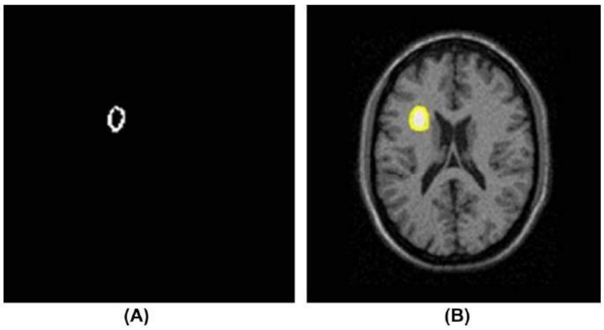


Figure 1: A, Extracted tumor pixels image. B, Tumor-detected brain MR image.

Pushpa B R, F. Louies [10] suggested a methodology where a framework is built to classify and detect the tumor. The proposed method passed through stages, preprocessing, segmentation, masking, feature extraction, and classification. Preprocessing images done through median filter and Gaussian high pass filter. Morphological operation was used to separate the tumor and the normal region. Feature that are extracted are symmetrical, texture and grayscale using multiple extraction methods like DWT (discrete wavelet transform) techniques. Support vector machine (SVM) classified the tumor as benign, malignant or normal with accuracy of 99%.

Johnpeter, J. and Ponnuchamy, in 2019 [11], developed an image fusion and co-active adaptive neuro fuzzy inference system (CANFIS) as a classification method for brain tumor detection and segmentation by combining with the principal components analysis (PCA) and discrete wavelet transform (DWT). Their work contains 4 steps. Step 1, brain MRIs database acquisition used a dataset of 66 brain MRIs into 4 classes e.g. normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors. All the brain MRIs was in axial plane, T2-weighted and 256x256 pixel. Step 2, image segmentation using Fuzzy C-means (FCM) to separate the different normal brain tissues. In step 3, feature extraction using discrete wavelet transform (DWT) and using Principle component analysis (PCA) method to estimate the original extracted features with degraded dimensional feature vectors. Last step is classification using Deep Neural Network (DNN) classifier.

Suhag, S. and Saini, L. [12] improved a system that automatically detect and classify brain tumor using MATLAB GUI tool into normal or abnormal then classify the abnormal into Gliomas, Metastasis and Astrocytoma. The proposed system started with pre-processing the image to de- noise and smoothing the edges using median filtering. Then applied fuzzy c-means (FCM) for segmentation method. A gray level co-occurrence matrix (GLCM) technique used to extract feature and the useful feature was selected by sequential forward selection (SFS). SVM classifier has been used to classify the images to tumor or non-tumor and Multi-SVM is used to determine the type of tumor whether it is Gliomas, Metastasis or Astrocytoma.

A. Jayachandran and R. Dhanasekaran [13] suggested a hybrid algorithm for recognizing brain tumor in MR images. The proposed algorithm consists of pre-processing, segmentation, feature extraction, feature reduction and classification. In preprocessing stage, the background noise, low frequency removed. The segmentation of brain tissues is done by skull stripping and features extracted using the gray level co-occurrence matrix (GLCM). the Fuzzy based Support Vector Machine classifier (FSVM) classified the brain images into tumor or non-tumor with 94% score in accuracy.

Minz et al, in 2017[14], proposed a scheme for classification of brain tumor types from MR images. Threshold-based image segmentation was performed along with processing like RGB to gray color space conversion and filtering for noise removal. Then GLCM based textural features were extracted from the segmented images. An adaptive boosting technique called AdaBoost outperformed neural network with 89.90% accuracy.

Kinani et al, in 2020 [15], optimized a computer-aided detection (CADe) system to develop accuracy of tumor detection and to reduce radiologists' workload by giving more quantitative (objective) decisions added to the qualitative (subjective) evaluation of radiologists. Databases were prepared by 3 different ROIs sizes. Their CADe calculated parametric features extracted from ROIs using statistics, histogram, GLCM and wavelet techniques. To study the significance of features, sequential Forward Selection (SFS) technique is used. Many types of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers were trained to distinguish between normal and abnormal ROIs.

Kumar et al, in 2019 [16], discussed how to observe the abnormal structures of human brain image. Their proposed mechanism consists of various phases, pre-processing, segmentation, feature extraction, and classification. They used filtering algorithm for pre-processing, clustering algorithm for segmentation, and Gray Level Co-Occurrence Matrix (GLCM) for feature


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

extraction. By using ensemble classification, automatic brain tumor step is performed. This stage distinguishes brain images into tumor and non-tumors.

Ghotekar et al, in 2016 [17], proposed a brain MRI image classification system. In proposing work image preprocessing is done with median filtering and skull stripping method to remove noise and tissues from medical images. It shows better performance. The features were extracted using GLCM techniques and a linear SVM is used as a classifier. Results of Sensitivity 91.52%, Specificity of 67.74% and Accuracy of 83.33%, was given by SVM approach.

Megha et al, in 2019 [18], presented machine learning based approach. In preprocessing step, they performed skull stripping to remove all extra tissues in the skull images. For feature extraction, Gray Level Concurrence Matrix (GLCM) was used and then selecting the prominent features. For segmentation of brain images and recognition of tumor using Support Vector Machine (SVM) classification method. Reason of SVM is to separate the non-linear transformation into a linear transformation using kernel functions of SVM. They used Gaussian kernel that has made the classification very smooth and convenient. They argued that tumor detection was faster and more accurate comparing with manual segmentation carried out by radiologists. Results are 83.3% accuracy recognizing if the tissue is normal or abnormal. Figure (2), illustrates the original image (A), and the final output image after performing skull stripping and threshold segmentation.

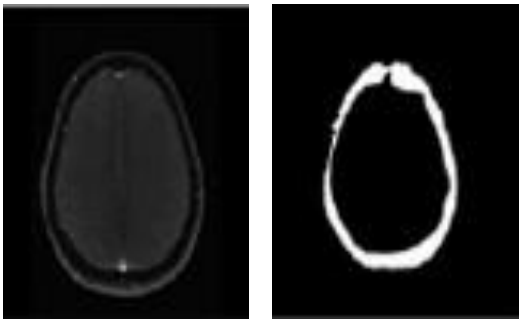



Figure 2: (A) Original image, (B) Final segmented image

## METHODOLOGY

In machine learning, there are some sequential steps must be followed in order for the CAD system to perform properly. Figure (3), shows the processing blocks contained in our CAD system.

1. *Database Source:*

To conduct this study a data samples were accumulated from Kaggle website [19]. These samples contain 144 MRI images of both malignant and benign cases. The samples were of different resolutions. These datasets were categorized into 72 normal, 72 abnormal in which 98 ROIs were used for learning and 46 ROIs for testing.

2. *Preprocessing*:

We manually cropped a Region of Interest (RIO) with size of 32x32 pixels to concentrate our work mainly on the damaged area for further processing. This size was a result of many experiments where original image sizes where implemented but algorithm performance was best observed with lower size samples. ROIs were imposed for two different transformation techniques which are Radon Transform (RT) and Discrete Cosine Transform (DCT).


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

### 3. *Features Extraction:*

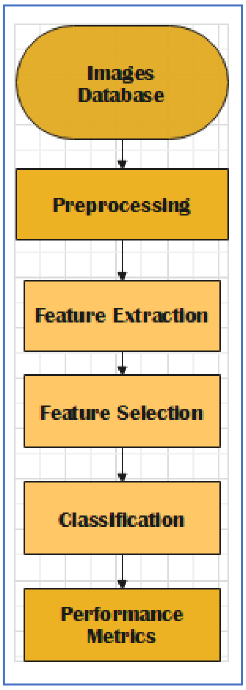



Figure 3: CAD processing blocks

We have conducted many features extraction functions which act as a mathematical description of samples characteristics to help classifiers to distinguish normal from abnormal cases. After, applying Cosine transformation to RIOs, we have investigated 23 features and only 17 passed the T-test with P value less than 0.05:

- Statistical features on ROIs:
  Those features are: (Mean, STD, Square of STD, Mode, Median, Percintile Quantile, Third Moment, Skewness, kurtosis, MAX, MIN)
- GLCM features:
  Level of 32 and shift or distance (d =1) in all direction (angles = 0º, 45º, 90º, 135º, 180º, 225º, and 270º). Those features are: (Contrast, Energy, Correlation, Homogeneity).

We excluded features that didn't pass the T-test for the P-value (must be <0.05). For evaluating the classification, all classifiers were assessed based on performance metrics such accuracy, sensitivity and specificity.

### 4. *Classification:*

After implementing features extractions and selecting the best performed ones, we began the classification which contains two phases. In the learning phase, the data clearly represents the nature of ROIs and teach the classifier whether it's normal or abnormal. During the test phase, the classifier works based on the previous taught instruction. We have used two types of classifiers as shown in table below.

| Classifier | Abbreviation | Parameters |
|---|---|---|
| Support Vector Machine | SVM | Linear, Polynomial, Gaussian and Radial Basis Function |
| K-Nearest Neighbor | KNN | 1, 2, 3, 4, and 5 |

*Table 1: Classifiers used in the system.*

In this step, the data is classified into two classes of brain images; normal and abnormal images. In this paper, nine classifiers were used and compared. The best accurate classifier will be selected for any further processes on this approach. The classifiers are SVM classifiers that has discriminant function of the type "RBF", "POLYNOMIAL", "GAUSSIAN" ,and "LINEAR". The other classifiers that are used are KNN classifiers that have k values of 1,2, 3,4 and 5.

RESULTS & DISSCUSSION


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

Results were obtained after implementing three trials with two different transformed ROIs. Features were first extracted from original ROI (ORIO), then from Radon transformed ROIs (RT), and finally from Discrete Cosine transformed ROIs (DCT). The testing ratio for the database was almost 32% out of 144 ROIs with 23 normal and 23 abnormal. MATLAB software was used in this approach. Each trial was assessed with five performance assessment metrics (Sensitivity, Specificity, Positive Predicted Value (PPV), Negative Predicted Value (NPV), and Accuracy). The following graph, Figure (4), indicates that the SVM did not perform well with neither original untransformed ROIs nor the with the Radon transformed ROIs.

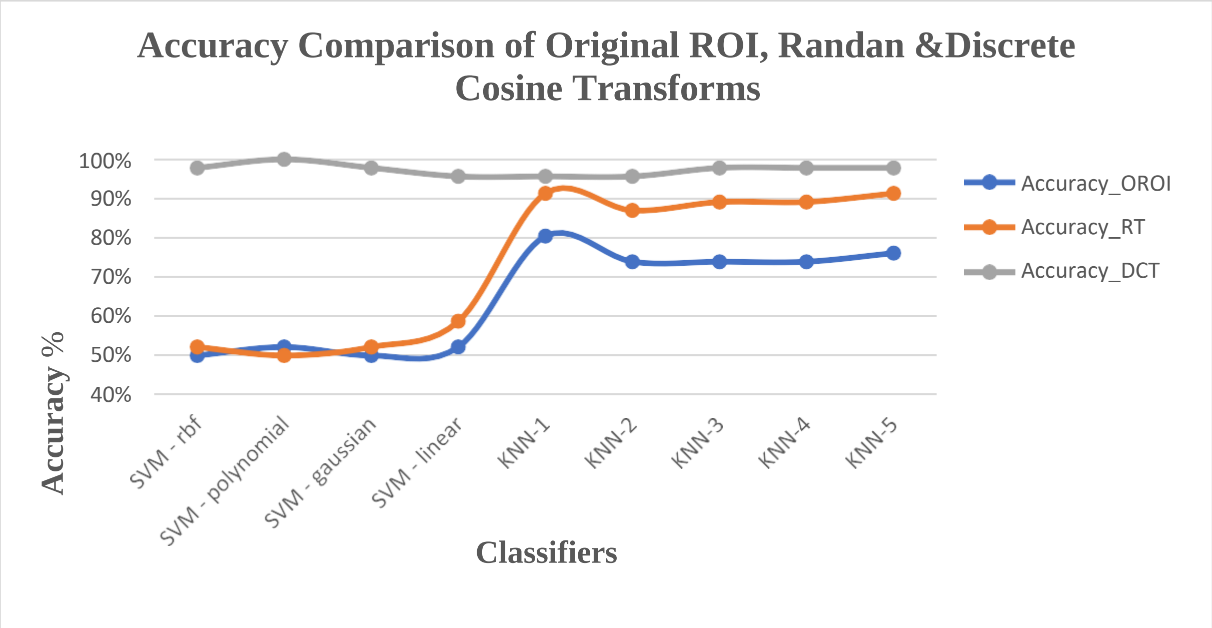



Figure 4: Accuracy comparison of classifiers


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

DISCRETE COSINE TRANSFORM

Discrete Cosine Transform gives the best results for detecting brain tumor in four types of Support Vector Machine classifier (SVM-RBF, SVM-polynomial, SVM-gaussian, and SVM-linear), and five types of k- Nearest Neighbors classifier (KNN-1, KNN-2, KNN- 3, KNN-4, KNN-5). Appling T-Test obtained 17 useful features (P-Value < 0.05) , showing in figure (5).

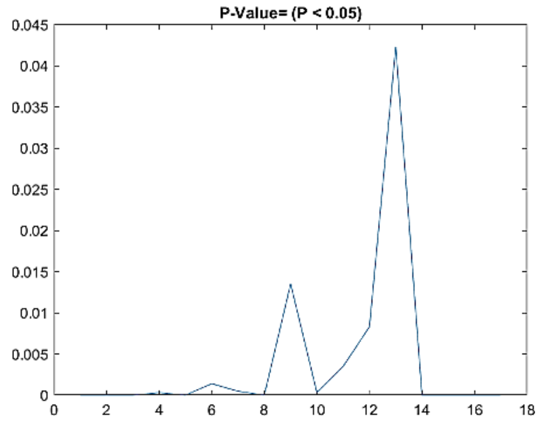
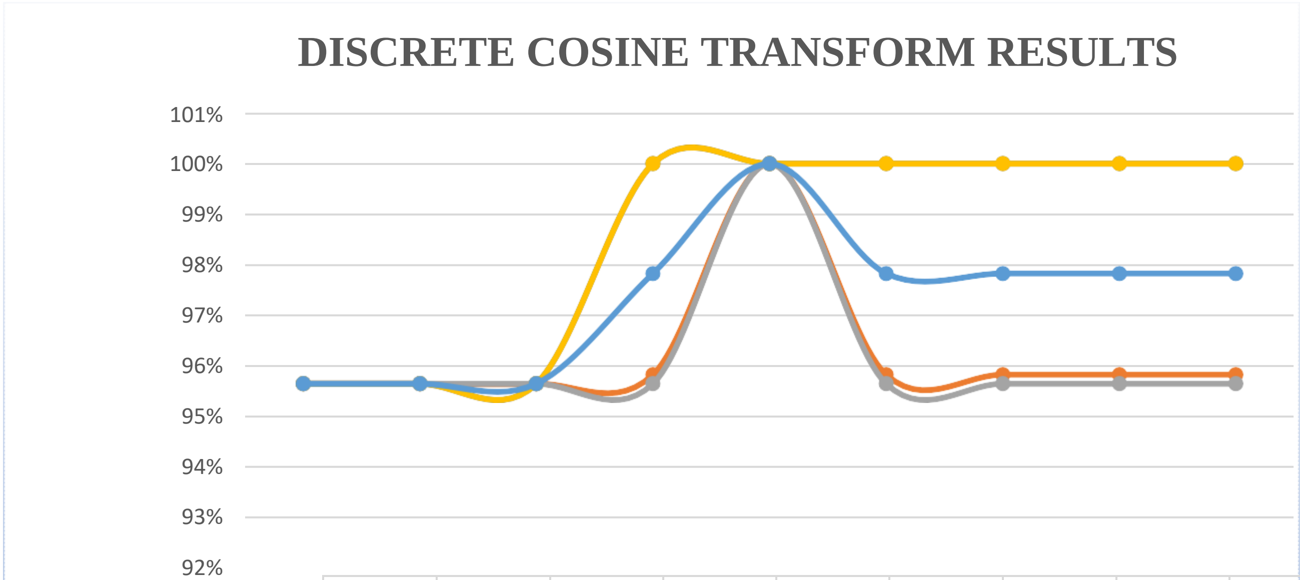



Figure 5: P-Value




| | SVM - linear | KNN-1 | KNN-2 | SVM - rbf | SVM - polynomi al | SVM - gaussian | KNN-3 | KNN-4 | KNN-5 |
|---|---|---|---|---|---|---|---|---|---|
| Sensitivity | 96% | 96% | 96% | 100% | 100% | 100% | 100% | 100% | 100% |
| Specificity | 96% | 96% | 96% | 96% | 100% | 96% | 96% | 96% | 96% |
| PPV | 96% | 96% | 96% | 96% | 100% | 96% | 96% | 96% | 96% |
| NPV | 96% | 96% | 96% | 100% | 100% | 100% | 100% | 100% | 100% |
| Accuracy | 96% | 96% | 96% | 98% | 100% | 98% | 98% | 98% | 98% |

Figure 6: Discrete cosine transform results of all classifiers

Figure (6), shows that the best classifier was SVM-Polynomial with sensitivity, specificity, PPV, NPV, and accuracy = 100%. Followed by SVM-RBF, SVM-Gaussian, KNN-3, KNN-4, and KNN- 5 with accuracy=98%. This result was obtained using 17 features distributed as first-order statistical, second-order statistical, and higher order statistical. These results indicated that the DCT is useful with multi-order feature extraction.


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

| Author and date | Features Used/ Method | Features Elimination Technique | Classifiers | Accuracy Sensitivity Specificity |
|---|---|---|---|---|
| R. Anitha1 and D. Siva. 2017 [9] | GLCM | N/A | Random forest (RF) | - 95 98 |
| Pushpa B R, F. Louies 2019 [10] | GLCM/DWT | N/A | SVM | 99 - - |
| Johnpeter, J. and Ponnuchamy.2019 [11] | Image fusion, Complex wavelet transform | N/A | CANFIS | 98.8 96 97.7 |
| Suhag, S. and Saini, L. 2015 [12] | GLCM | SFS | SVM | 91 - - |
| A. Jayachandran and R. Dhanasekaran 2013 [13] | GLCM | PCA | FSVM | 94 90 95 |
| Minz et al, 2017[14] | GLCM | NA | Adaboost | 89.9 88 62.5 |
| Kinani et al, 2020 [15] | GLCM and wavelet techniques | Sequential Forward Selection (SFS) | SVM and KNN | 97 95 100 |
| Kumar et al, 2019 [16] | GLCM | NA | Ensemble | 91.1 95.4 - |
| Ghotekar et al, 2016 [17] | GLCM | Forward selection & backward elimination | SVM | 83 91 67 |
| Megha et al, 2019 [18] | GLCM, Mean, Standard deviation, Entropy, Skewness, Kurtosis, Energy | NA | SVM | 83.3 - - |
| **Proposed Method** | Statistical features & GLCM | T-test | SVM-Polynomial | 100 100 100 |

*Table 2: PREVIOUS STUDIES SUMMARIZATION*

Table (2), illustrates the previous studies related to tumor segemtation techniques and gives a brief comparision bwtween them. Our proposed method shows outstanding results in terms of accuracy, sensitivity, and spesivitity.

## CONCLUSION

This study develops a CAD system to get better detection for brain tumors. 144 MRI images database (72 normal and 72 abnormal) were resized into 32x32 ROI. Three experiments with two different transformed ROIs were applied for results comparision. 17 features were extracted from each experiment and then were used for classification. Features were of first-order statistical, second-order statistical, and higher-order statistical features. Two main classifiers were used for classification. Support Vector Machine classifier (SVM-RBF, SVM-polynomial, SVM-gaussian, and SVM-linear), and k-Nearest Neighbors classifier (KNN-1, KNN-2, KNN-3, KNN-4, KNN-5) are the ones applied in our paper. Each classifier was assesed with 5 assesment parameters (Sensitivity, Specificity, PPV, NPV, and Accuracy). Best results were observed from the Discrete Cosine Transfomed (DCT) ROIs associated with the SVM-Polynomial classifier of 100% score in sensitivity, specificity, PPV, NPV, and accuracy.

## REFERENCES:

[1] Medlineplus.gov. 2020. *Brain Tumor*. [online] Available at: <https://medlineplus.gov/braintumors.html> [Accessed 8 October 2020].

[2] Cancer.org. n.d. *Types Of Brain Tumors And Spinal Cord Tumors In Adults*. [online] Available at: <https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/about/types-of-brain- tumors.html> [Accessed 13 December 2020].

[3] Harvard Health. 2019. *Brain Tumor Overview - Harvard Health*. [online] Available at: <https://www.health.harvard.edu/a_to_z/brain-tumor-overview-a-to-z>

[4] Abta.org. n.d. *Brain Tumor Education – American Brain Tumor Association*. [online] Available at: <https://www.abta.org/about-brain-tumors-4/brain-tumor-education/>

[5] Ciattei, J., n.d. *Meningioma | Department Of Neurology And Neurosurgery*. [online] Hopkinsmedicine.org. Available at: https://www.hopkinsmedicine.org/neurology_neurosurgery/centers_clinics/brain_tumor/center/m eningioma/index.html>

[6] Aans.org. n.d. *Brain Tumors - Classifications, Symptoms, Diagnosis And Treatments*. [online] Available at:


(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 03, March-2021

<https://www.aans.org/en/Patients/Neurosurgical-Conditions-and- Treatments/Brain-Tumors>

[7] Cancer.org. n.d. *Key Statistics For Brain And Spinal Cord Tumors*. [online] Available at: <https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/about/key-statistics.html>

[8] Embs.org. n.d. *Biomedical Imaging & Image Processing – EMBS*. [online] Available at: <https://www.embs.org/about-biomedical-engineering/our-areas-of-research/biomedical- imaging-image-processing/>

[9] Anitha, R. and Siva Sundhara Raja, D., 2017. Development of computer-aided approach for brain tumor detection using random forest classifier. *International Journal of Imaging Systems and Technology*, 28(1), pp.48-53.

[10] Pushpa B R and Flemin Louies, 2019. Detection and classification of brain tumor using machine learning approaches. *International Journal of Research in Pharmaceutical Sciences*, 10(3), pp.2153-2162

[11] Johnpeter, J. and Ponnuchamy, T., 2019. Computer aided automated detection and classification of brain tumors using CANFIS classification method. *International Journal of Imaging Systems and Technology*, 29(4), pp.431-438.

[12] Suhag, s. and Saini, l., 2015. automatic brain tumor detection and classification using svm classifier. *International Journal of Advances in Science Engineering and Technology*, [online] Available at: <http://www.iraj.in/journal/journal_file/journal_pdf/6-190-1444460329119- 123.pdf>.

[13] Jayachandran, A. and Dhanasekaran, R., 2013. Brain Tumor Detection and Classification of MR Images Using Texture Features and Fuzzy SVM Classifier. *Research Journal of Applied Sciences, Engineering and Technology*, 6(12), pp.2264-2269

[14] Minz, A., & Mahobiya, C. 2017. MR Image Classification Using Adaboost for Brain Tumor Type. 2017 IEEE 7th International Advance Computing Conference (IACC). doi:10.1109/iacc.2017.0146

[15] Kinani, L. and Alqasemi, U., 2020. Computer-Aided Diagnosis of Mammography Cancer. International Journal of Engineering and Advanced Technology, 9(5), pp.725-731.

[16] Kumar,, P. and VijayKumar, B., 2019. Brain Tumor MRI Segmentation and Classification Using Ensemble Classifi. International Journal of Recent Technology and Engineering (IJRTE, (2277-3878,).

[17] Ghotekar, B. and Mahajan, K., 2016. Brain Tumor Detection and Classification using SVM. National Conference on Innovative Trends in Science and Engineering (NC-ITSE'16), 4(7).

[18] Megha, C. and Sushma, J., 2019. Detection of Brain Tumor Using Machine Learning Approach. *Communications in Computer and Information Science*, pp.188-196.

[19] Kaggle.com. 2020. *Brain MRI Images For Brain Tumor Detection*. [online] Available at: <https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection> [Accessed 26December 2020].

AUTHORS

Dr. Umar S. Alqasemi, Associate Professor of Biomedical Engineering at the Dept. of Electrical and Computer Engineering, King, Abdulaziz University, Jeddah 21589, Saudi Arabia. PhD and MSc degree in Biomedical Engineering from UConn, Storrs, USA. Research work in ultrasound, optical, and photoacoustic imaging, medical imaging recognition, bioelectronics, and digital and analog signal and image processing.

**Mohammed A. Bamaleibd**, Received bachelor degree in Biomedical Engineering from King Abdul-Aziz University, KSA. Currently MSc. Electrical and Biomedical Engineering in King Abul-Aziz University, KSA.

**Abdullah A. Al Baiti,** Received bachelor degree in Biomedical Engineering from King Abdul-Aziz University, KSA. Currently MSc. Electrical and Biomedical Engineering in King Abul-Aziz University, KSA.


(This work is licensed under a Creative Commons Attribution 4.0 International License.)