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Research Article

An effective method for the identification of multi-class tumors in brain magnetic resonance imaging

R. Ramya [1*], J. Ghunaseelan[2], S. Kavitha [3], A. Roopasree [4], Sameeullah Kajahussain[5]

[1]Associate Professor, Department of ECE, Saveetha School of Engineering, SIMATS, Chennai
* **Corresponding Author Email:** ramyar.sse@saveetha.com - **ORCID:**0000-0001-6513-0277

[2] Professor, Professor, Department of EEE, R V Reha Polytech College, Paruvakudi.
Email: ghunaseelan@gmail.com - **ORCID:**0009-0003-5151-8854

[3] Professor and Dean, Department of ECE, Nandha Engineering College, Erode.
Email: gskkavitha@gmail.com - **ORCID:** 0000-0001-6386-4285

[4] Assistant Professor, Department of ECE, Hindusthan Institute of Technology, Coimbatore.
Email: roopasree.a@hit.edu.in - **ORCID:** 0009-0005-8387-2350

[5] Electrical Lecturer, University of Technology & Applied Sciences, Nizwa, Sultanate of Oman.
Email: sameeullah.hussain@utas.edu.om - **ORCID:** 0009-0002-5728-1280

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Abstract:

The field of medicine makes extensive use of image classification, which is one of the computational applications that is specifically used for the purpose of identifying anomalies in magnetic resonance (MR) brain pictures. Classification, feature extraction, and feature reduction are the three components that make up the head tumor classification method that has been suggested. The Gray Level Co-occurrence Matrix (GLCM) is used in the process of feature extraction. The Maximum Difference Feature Selection (MDFS) approach is used for the purpose of feature selection within the context of reducing the coefficient of the picture. During the classification process, K Nearest Neighbors (KNN) and Support Vector Machine (SVM) classifiers are used to categorize the pictures. These classifiers are trained using the extracted features provided before. The performance of feature extraction techniques using two different classifiers is compared in terms of assessment metrics, sensitivity, specificity, and accuracy. This comparison is based on the outcomes of the experiments. We are able to draw the conclusion that the combination of Gray Level Co-occurrence Matrix and Maximum Difference Feature Selection with Support Vector Machines demonstrates an accuracy of 95.0% based on the results of the comparison.

1. Introduction

The aberrant proliferation of cells that have proliferated in an uncontrolled way is what leads to the development of a brain tumor. In light of the fact that the pathogenic process that is responsible for the formation of brain tumors is inherently unpredictable, brain tumor segmentation is an extremely important responsibility. It is necessary to conduct a variety of diagnostic procedures, including positron emission tomography (PET), computed tomography (CT), and magnetic resonance imaging (MRI), in order to diagnose and treat this malignant condition at the earliest possible stage [1-7]. In order to facilitate illness diagnosis Because this imaging technology generates better soft tissue features without producing disruptions to the patient's tissues, magnetic resonance (MR) pictures are mostly used to assist those working in the medical field, namely technicians and physicians.

A technology known as magnetic resonance imaging (MRI) is a kind of imaging that is used to produce precise pictures of organs and tissues inside the human body. An MRI of the brain is a test that employs a magnetic field and radio waves to obtain comprehensive pictures of the brain and the brain stem. This test is completely safe and does not cause any discomfort to the patient. The magnetic resonance imaging (MRI) technique generates sectional pictures of equal resolution in each projection without moving the subject or creating any other influence on them. There is the possibility of achieving a completely automated categorization of magnetic resonance images as either normal or malignant [4]. When it comes to the effective diagnosis, therapy, and monitoring of the condition, magnetic resonance imaging (MRI) is an essential tool.

The process of feature extraction is used for the purpose of dimensionality reduction, which ensures that significant aspects of an image are effectively represented as a compact feature vector. This strategy is useful in situations when the size of the picture is enormous and the representation of features has to be decreased. According to this method, the picture is classified as either abnormal or normal based on the combination of the texture and intensity-based elements. As a result of the complicated structure of the tumor in the MR brain picture, Gray Level Co-occurrence Matrix and Maximum Difference Feature Selection are used in order to extract the relevant feature from the image. There are a variety of ways that may be utilized in order to reduce the number of features.

The goal of image classification is to assign each pixel in an image to one of two categories: normal or malignant. Normal pixels are the subject of image classification. For the purpose of image classification, the two primary categories are supervised classifications and unsupervised classifications. One of the components of supervised classification is a collection of example classes that are referred to as training sites. The system uses these training sites to determine the picture class. SVM and KNN are two classifiers that are often used for the purpose of classification.

2. Research Works

In the approach that is now in use [7], feature extraction has been accomplished by the use of Multi-Texton Microstructure Descriptor. This method involves the extraction and concatenation of four features that correspond to the original picture, orientation image, multi-texton image, and texton structure image. The result is a feature vector comprising the MR brain image. The feature that was retrieved is then used as input for a support vector machine classifier, which is used to determine whether a brain picture is normal or tumorous.

Recently, there have been significant breakthroughs in the diagnosis of multi-class tumors in brain magnetic resonance imaging (MRI). These developments have relied heavily on textural properties and machine learning classifiers, namely Support Vector Machines (SVMs). According to Pereira et al. [20], preprocessing methods play a crucial role in improving picture quality and isolating tumor areas for analysis. Some examples of these approaches include noise reduction, intensity normalization, and region-of-interest (ROI) segmentation. The ability of several approaches for the extraction of textural features, including as the Gray Level Co-occurrence Matrix (GLCM), wavelets, and Local Binary Patterns (LBP), to capture detailed patterns inside tumor areas has led to their widespread use [12]. According to Zacharaki et al. [13], several research projects have also used hybrid feature sets, which include texture, shape, and intensity information in order to enhance the robustness of classification methodologies. In multi-class tumor classification, support vector machines (SVMs) are among the most often used classifiers because they provide strong performance in high-dimensional datasets and small sample sizes. In fact, they frequently outperform alternative methods such as k-Nearest Neighbors (k-NN) and Random Forests [14]. In order to overcome difficulties that include several classes, it is standard practice to use strategies such as one-vs-all and one-vs-one. A trustworthy generalization of findings may be achieved by the use of evaluations that make use of metrics like as accuracy, sensitivity, and specificity, in addition to cross-validation. The findings of these studies highlight the significance of effective preprocessing, feature extraction, and balanced datasets in order to achieve high classification accuracy in automated tumor detection systems [15].

In recent research on multi-class tumor diagnosis in brain magnetic resonance imaging (MRI), the emphasis has been on merging improved feature extraction approaches with machine learning classifiers in order to achieve higher levels of accuracy. For the purpose of improving picture quality, it is essential to perform image preprocessing operations such as noise reduction, intensity normalization, and tumor segmentation. According to Pham et al. [16], techniques such as region-growing algorithms and active contour models have been extensively embraced among researchers in order to precisely identify the borders of tumors. Methods for the extraction of textural features, such as the Gray Level Co-occurrence Matrix (GLCM), wavelet transformations, Local Binary Patterns (LBP), and fractal-based descriptors, have shown great promise in the process of describing the heterogeneity of tumors [12,17].

As a result of its capacity to cope with high-dimensional data and their resilience in dealing with complicated classification problems, Support Vector Machines (SVMs) continue to be a popular option [14]. Other classification approaches, such as Random Forests, Decision Trees, and k-Nearest Neighbors (k-NN), have been investigated in addition to support vector machines (SVMs). Some of the research have included ensemble methods in order to improve the performance of the classifiers [18,19]. Convolutional Neural Networks (CNNs) and deep learning algorithms have also gained popularity, particularly due to their ability to automate feature extraction and enhance classification accuracy in multi-class settings [20,21]. This is especially true for CNNs.

To differentiate between various kinds of tumors, such as gliomas, meningiomas, and metastases, a number of works have been conducted to handle multi-class issues. These works have used several classification schemes, including hierarchical classification schemes, one-vs-one classification schemes, and one-vs-all classification schemes [22]. Furthermore, hybrid techniques that combine handmade characteristics with features based on deep learning have shown that they have the potential to improve model generalization while simultaneously minimizing the number of false positives [23]. Evaluation measures like as accuracy, sensitivity, specificity, precision, and F1-score are used extensively, and cross-validation techniques are utilized to guarantee the dependability of classification results.

The Support Vector Machine (SVM) was used as the key classifier for multiclass brain tumor identification in a research that was published in Scientific Reports in 2024. The results of this study demonstrated better accuracy in discriminating between various kinds of tumors. By combining Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), a revolutionary approach was presented in another research that was conducted in 2023. This methodology was designed to do complete texture analysis of tumor pictures, hence improving classification performance. Furthermore, a research that was conducted in 2023 suggested a strategy that included the preprocessing of brain MRI images and segmentation via the use of the k-means clustering algorithm. This approach assisted in the categorization of tumors with greater precision. These latest studies shed light on the continuing attempts to improve brain tumor categorization by using sophisticated texture analysis and machine learning approaches. Support vector machines (SVMs) play a crucial role in obtaining improved diagnostic accuracy, which further emphasizes the importance of these efforts.

The advancements that have been made in automated tumor classification systems are highlighted by the use of sophisticated preprocessing approaches, a variety of feature extraction methods, and optimal machine learning models all working together. The consequences of these breakthroughs are substantial for the improvement of clinical decision-making and the results for healthcare patients.

3. Proposed Approach

MRI brain image database collection, feature extraction, feature selection, and classification are the four stages that make up our suggested system. Collection of MRI brain images is the first step. In this instance, two distinct approaches to technique are used, as seen in figure 1. The suggested technique involves the extraction of features from a training dataset consisting of seventy normal and tumor brain magnetic resonance images. These feature vectors are then used in the training of a KNN and linear kernel support vector machine classifier. A total of fifty brain MR images, both normal and malignant, are used in order to test the classifier, and its performance is assessed.

3.1 Feature Extraction

It is possible to simplify the number of resources that are necessary to correctly represent a huge collection of data via the process of feature extraction. In the process of doing analysis on complicated data, one of the most significant challenges arises from the large number of variables that are involved. When doing an analysis with a high number of variables, it is often necessary to have a substantial amount of memory and compute capacity, or to use a classification technique that overfits the training sample and does not generalize well to new samples being used. The phrase "feature extraction" refers to a broad category of techniques that include the construction of combinations of variables in order to circumvent these issues while still accurately characterizing the data. The physical or visual quality of a surface is referred to as its texture. The purpose of texture analysis is to discover a novel approach to capturing the fundamental qualities of textures and to represent them in a form that is not only simpler but also distinctive. This is done with the intention of using these textures for the purpose of robust and accurate classification and segmentation of objects. There are just a few architectures that implement on-board textural feature extraction, despite the fact that texture plays a crucial role in picture analysis and pattern identification. This article presents a formulation of a gray level co-occurrence matrix for the purpose of obtaining statistical texture information. It is possible to extract a variety of texture characteristics from the GLCM document. The only characteristics that are calculated are those of the second order, namely the angular second moment, correlation, inverse difference moment, and entropy. The estimate of motion pictures requires a high level of discriminating accuracy, which is provided by these four metrics. Xilinx ISE 13.4 is used to do the calculations and implementation of these functionalities.

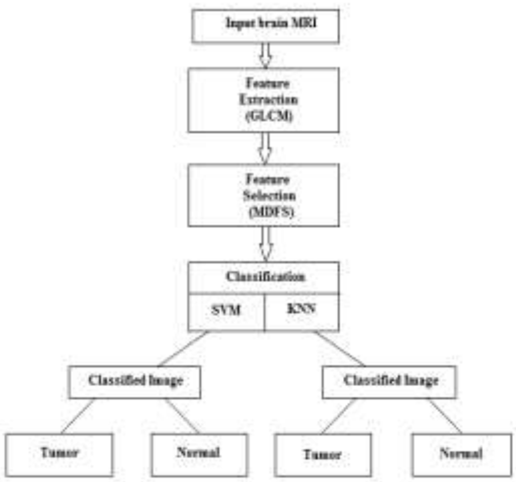

Figure 1. *Block diagram of proposed approach*

3.2 Extraction of GLCM

The statistical distribution of observed combinations of intensities at defined points relative to each other in the picture is used to calculate texture features in statistical texture analysis. These features are then used to determine additional characteristics of the image. First-order statistics, second-order statistics, and higher-order statistics are the three categories that statistics fall into, and they are categorized according to the number of intensity points (pixels) in each combination.

The Gray Level Co-occurrence Matrix (GLCM) approach is a technique that may be used to extract statistical texture properties of the statistical second order. The method has been used in a variety of applications. Third and higher order textures take into consideration the relationships that exist between three or more pixels. These are theoretically feasible, but owing to the amount of time required for calculations and the complexity of interpretation, they are not typically implemented.

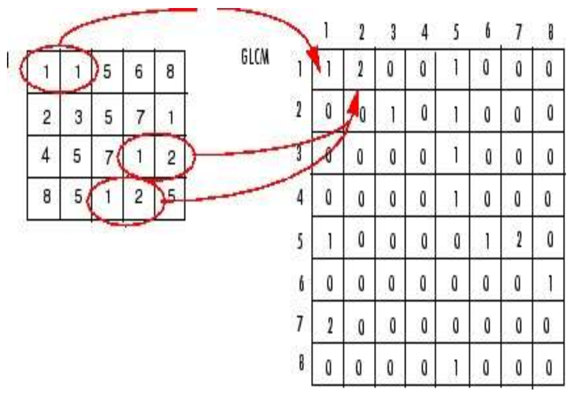

Figure 2. *GLCM matrix construction*

3.3 Feature selection

Maximum Difference Feature Selection (MDFS)

From the magnetic resonance picture, a total of 21 GLCM features are retrieved (figure 2). On the other hand, selecting characteristics that can differentiate between normal and diseased tissue might be challenging. The use of all the characteristics, on the other hand, leads to the creation of a high-dimensional feature vector, which not only reduces the accuracy of classification but also significantly increases the complexity of the calculation. For this reason, the feature selection process is essential in order to identify the most relevant characteristics. Identifying the differences between normal and aberrant patterns may be challenging due to the fact that both patterns have comparable traits. This method's primary objective is to get rid of any similarities that exist between the normal pattern and the aberrant pattern. Images of normal and abnormal MR samples are used to determine the characteristics that have the greatest difference between them.

The primary objective of this algorithm is to recognize characteristics that are distinct from those seen in normal and abnormal magnetic resonance pictures.

Using this approach, the top thirteen characteristics are chosen.

The MDFS approach that was devised was used to seventy MR pictures, both normal and pathological.

The algorithm

1. Extraction of features from N normal MR pictures is the first step. Allow it to be A.
2. Extraction of features from N abnormal MR pictures is the second step. Choose option B.
3. Compute the sum of features for all N normal magnetic resonance pictures.

$$S1 = \sum_{i=1}^{N} (A_i)$$

4. Compute the sum of features for all N abnormal magnetic resonance pictures.

$$S2 = \sum_{i=1}^{N} (B_i)$$

5. Determine the difference in features (D) between the normal and abnormal magnetic resonance images
   - In the event that S1 is greater than S2, D equals (S1-S2) divided by (S1+S2).
   - In every other case, D equals (S2-S1) divided by (S1+S2).
6. For each of the 21 characteristics, repeat steps 1 through 13 in step 6.
7. The seventh step is to assign a rank value to each characteristic based on D, ordering them in decreasing order.
8. Select the top 13 characteristics that are most relevant to your needs.

Classification

Support Vector Machine

The Support Vector Machine (SVM) is a binary classifier that depends on supervised learning. Using the hyper plane to construct decision boundaries in order to differentiate between data points belonging to distinct classes is the fundamental idea behind support vector machines (SVM). Constructing a hyper plane in high-dimensional feature space is the fundamental concept of support vector machines (SVM), which is used to categorize data between two classes.
Take for example a training set.
{(Xi, Yi), i=1,2,...,n;
Xi might be Rd;
Yi could be {+1,-1};} (1)

The input vectors are denoted by xi, which belongs to the set Rd, and the class labels of the MRI brain picture are denoted by yi, which belongs to the set {+1,-1}.
With the help of a non-linear function Φ(.), support vector machines (SVM) are able to map the input vectors from the input space to the high-dimensional feature space. The hyperplane that separates two points is denoted by the equation wT Φ(x) + b = 0, where w represents the weight vector with dimensions equal to Φ(x) and b represents the bias [8-11]. In situations where the data can be separated linearly, the separating hyperplane may be defined in a variety of different ways. On the other hand, support vector machines are founded on the maximum margin concept, which states that the objective is to build a hyperplane by ensuring that the distance between the two classes is as great as possible.
The SVM begins with the formulas that are listed below.
The condition wT Φ(xi) + b > +1 and yi = +1 is satisfied.

(2)
The value of wT Φ(xi) plus b is less than or equal to -1 when yi is equal to -1
(3)
It is similar to the expression yi (wT Φ(xi) + b) > 1, where i = 1, 2,..., n
(4)
It is possible to define the classifier as follows:
fn(x) = sign(wT Φ(x) + b)
(5)
For every single training data xi, the function produces a value of fn(xi) that is greater than or equal to zero when yi is equal to one, and it produces a value that is less than or equal to zero when yi is equal to one [6]. An illustration of a support vector machine (SVM) classification using an ideal hyperplane that minimizes the separation margin between the two classes is shown in Figure 3. This example is represented by points that are indicated by the symbols 'o' and 'Δ'. The training dataset contains items known as support vectors. These support vectors are located on the border between the hyperplanes of the two separate classes.

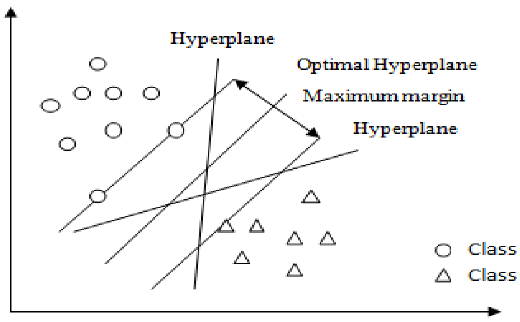

Figure 3. *Illustration of SVM*

K Nearest Neighbors

When it comes to picture categorization, the K Nearest Neighbor approach is the one that is used the most. A classification of an item is determined by the distance between it and its neighbors. If the value of k is equal to one, then the object is categorized as the class of the neighbor that is closest to it. In the K closest Neighbor

classification technique, the closest distance between neighbor classes is used as the basis for categorization. A selection of just k-nearest neighbor classes is made using the K Nearest Neighbors algorithm, which is based on the distance. When it comes to determining the class of an item, the last step is to take the vote of the majority [3]. Euclidean is the approach that is used the most often in k-nearest-neighbor for the purpose of determining distance. For the purpose of determining the distance between the test data and the train data, the Euclidean distance approach is used. Following that, the item is assigned to one of the predetermined classes via the use of the distance measurement. For the purpose of classifying MR brain images as either normal or malignancy, the same technique is performed.
Procedures for Training and Examination: For the purpose of training the classifier, we need certain data attributes that may specify the category of brain tumor. The classification system is trained with these data attributes, and the classification system will determine the kind of tumor. The three-level decomposition is the data feature that is selected for the purpose of training the classifier. Both the KNN and SVM classifiers are trained using a collection of pictures that include these characteristics. They are then tested with a different set of testing images, from which the classifier determines whether the MRI brain image class is normal or malignant.

4. Results and Discussion

4.1 Materials

One hundred and sixty normal MRI brain images and sixty MRI brain tumor images are included in the image data set for the experiment. These images were obtained from the Brain online database. Within the framework of the suggested technique, the collection of brain images is partitioned into two distinct sets, namely 1) the training dataset and 2) the testing dataset. The training dataset is used for the purpose of learning the classifier, and the testing dataset is utilized for the purpose of evaluating the performance of the proposed system.

4.2 Results

MRI brain scans with and without tumors are used to explain the experimental findings of the proposed approach, which are detailed in this section. MATLAB 2014a is used to be the implementation of the suggested system.

Performance assessment of proposed technique
First, an evaluation of the effectiveness of the suggested method
The classifiers are trained using the training dataset, which consists of 35 normal and 35 tumor photos. Meanwhile, the accuracy of the classification is determined using the testing dataset, which consists of 25 normal and 25 tumor images. When the testing phase is complete, the proposed method is applied to the picture of the testing dataset in order to determine the category of brain images. The MRI picture was identified as a normal image and a tumor image, respectively, based on the results obtained from the classifier that was implemented without and with the tumor, which are shown in Figures 4 and 5.

Figure 4. *MRI brain image and classified output*

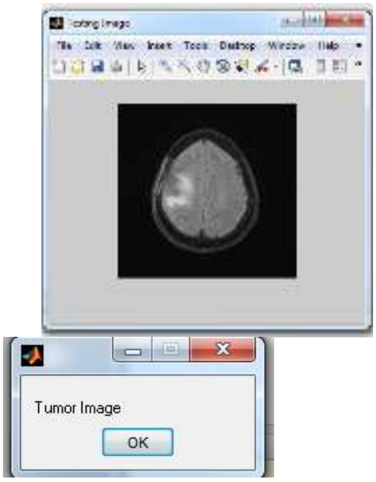

Figure 5. *MRI brain tumor image and classified output*

An evaluation of the effectiveness of the proposal approach

There are a number of performance measures that are used to resolve the classified output that is acquired by the SVM and KNN classifiers [7]. These metrics include sensitivity, specificity, and accuracy.

$$\text{Sensitivity} = tp/(tp+fn)$$
$$\text{Specificity} = tn/(tn+fp)$$
$$\text{Accuracy} = (tp+tn)/(tp+tn+fp+fn)$$

- The term "true positive" (tp) refers to individuals who have been precisely recognized as having the illness.
- The term "false positive" (fp) refers to the mistaken identification of healthy individuals as having a malignancy.
- The true negative (tn) is: People who are healthy and normal were categorically designated as healthy.
- Persons with tumors who were wrongly diagnosed as normal (healthy) are examples of false negatives (fn).

The performance metrics of the SVM classifier and the KNN classifier with three different feature extraction techniques are shown in Table 1. These metrics include sensitivity, specificity, and effectiveness.

Table 1. *Performance matrices of KNN and SVM*

Classifier	Feature Extraction	Sensitivity (%)	Specificity (%)	Accuracy (%)
KNN	GLCM (21features)	89.5	72.0	70.5
	GLCM (13features)	90.2	71.5	80.2
SVM	GLCM (21features)	78.5	82.0	75.6
	GLCM (13features)	99.5	92.0	95.0

4.3 Comparative analysis

The results of our comparison of the suggested approach of feature extraction, which is via both GLCM and MDFS, are shown in table 1, which can be found below. With the support vector machine (SVM) classifier, the suggested technique has an accuracy of 95.0%. According to the proposed system, the accuracy of features extracted from 21 features using GLCM with KNN classifier is 70.5%, and the accuracy of features derived from 13 features using GLCM with KNN classifier is 80.2%. Both of these figures are according to the suggested system. The accuracy of features extracted from 21 features using GLCM with SVM classifier is 74.3%, while the accuracy of features extracted from 13 features using GLCM with KNN classifier is 95.4. Both of these results refer to the accuracy of the features extracted. In the proposed system the accuracy of features extracted from 21 features using GLCM with KNN classifier is 70.5% and the accuracy of features extracted from 13 features using GLCM with KNN classifier is 80.2%. The accuracy of features extracted from 21 features using GLCM with SVM classifier is 75.6% and the accuracy of features extracted from 13 features using GLCM with KNN classifier is 95.0.

5. Conclusion

By combining GLCM and MDFS with KNN and SVM, we have created a method for the identification of tumors, which is presented in this study. The method that has been suggested is comprised of four stages: the collecting of MRI brain image databases, the extraction of features, the selection of features, and category categorization. The GLCM and MDFS algorithms are used as feature extraction techniques in the process of feature extraction. After that, the extracted features are sent to the support vector machine (SVM) and the kernel neural network (KNN) classifier in order to evaluate the performance of the classifier, which ultimately results in output that is classed as either normal or malignant. The suggested method using GLCM with MDFS in conjunction with SVM classifier shows an accuracy of 95.0%, while the KNN classifier demonstrates an accuracy of 80.2% as well.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The

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References

[1] Saritha.M,Paul Joseph.K, Abraham Mathew.T, (2013) Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural network *Pattern Recognition Letters* . 34(16);2151-2156. https://doi.org/10.1016/j.patrec.2013.08.017

[2] Chen Gang, Chen Ning, Lin Xia, (2013). The Image Retrieval Based on Scale and Rotation-Invariant Texture Features of Gabor Wavelet Transform, *IEEE Fourth World Congress on Software Engineering*.

[3] Dharmendra Patidar, Bhavin C. Shah, Manoj R. Mishra "Performance Analysis of K Nearest Neighbors Image Classifier with Different Wavelet features, *International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE)*, 2014.

[4] El-Sayed Ahmed El-Dahshan, Tamer Hosny and Abdel-Badeeh M. Salem (2010). Hybrid intelligent techniques for MRI brain images classification, *Digital signal processing*, 20;433441, 2010.

[5] Guang-Hai Liu, LeiZhang, Ying-KunHou and Zuo-YongLi (2010). Image retrieval based on multi-texton histogram. *Pattern recognition*, 43;2380–2389.

[6] Hari Babu Nandpuru, Dr. S. S. Salankar, Prof. V. R. Bora (2014). MRI Brain Cancer Classification Using Support Vector Machine, *IEEE Students' Conference on Electrical, Electronics and Computer Science*.

[7] Jayachandran .A and Kharmega Sundararaj .G (2015). Abnormality Segmentation and Classification of Multi class Brain Tumor in MR Images using fuzzy logic based hybrid kernel SVM, *International Journal of Fuzzy Systems*, 17, 434–443 https://doi.org/10.1007/s40815-015-0064-x

[8] Jayachandran .A and Dhanasekaran .R (2013). "Automatic Detection of Brain Tumor in Magnetic Resonance Images using Multi-Texton Histogram and Support Vector Machine, *Wiley Periodicals*, 23 https://doi.org/10.1002/ima.22041

[9] Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu and Yi Pan (2014). A Survey of MRI based brain tumor segmentation methods, *Tsinghua Science and Technology* 19;578–595.

[10]Jayachandran .A and Dhanasekaran .R (2014) Brain Tumor Severity Analysis Using Modified Multi-Texton Histogram and Hybrid Kernel SVM, *Wiley Periodicals*, 24;72-82.

[11]Noramalina Abdullah, Umi Kalthum Ngah, Shalihatun Azlin Aziz (2011). Image Classification of Brain MRI Using Support Vector Machine", *IEEE*. DOI:10.1109/IST.2011.5962185

[12]Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, (6), 610-621.

[13]Zacharaki, E. I., Wang, S., Chawla, S., Yoo, D. S., Wolf, R., & Davatzikos, C. (2009). Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. *Magnetic Resonance in Medicine*, 62(6), 1609-1618.

[14]Chapelle, O., Vapnik, V., Bousquet, O., & Mukherjee, S. (2002). Choosing multiple parameters for support vector machines. *Machine Learning*, 46(1-3), 131-159.

[15]Menze, B. H., Jakab, A., Bauer, S., et al. (2015). The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). *IEEE Transactions on Medical Imaging*, 34(10), 1993-2024.

[16]Pham, D. L., Xu, C., & Prince, J. L. (2000). Current methods in medical image segmentation. *Annual Review of Biomedical Engineering*, 2(1), 315-337.

[17]Raut, B., Joshi, A., & Gupta, A. (2018). Feature extraction techniques for image classification: A survey. *Pattern Recognition Letters*, 30(6), 891-904.

[18]Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32.

[19]Verma, R., Chouhan, S. S., & Singh, S. (2020). Multi-class brain tumor classification using improved texture and shape features. *Biomedical Signal Processing and Control*, 57, 101736.

[20]Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE Transactions on Medical Imaging*, 35(5), 1240-1251.

[21]Rehman, A., Abbas, N., Saba, T., & Mehmood, Z. (2020). Deep learning-based brain tumor classification. *Neural Computing and Applications*, 32(8), 2293-2304.

[22]Tustison, N. J., Avants, B. B., Cook, P. A., et al. (2014). N4ITK: improved N3 bias correction. *IEEE Transactions on Medical Imaging*, 29(6), 1310-1320.

[23]Rajendran, M., Shenbagavalli, V., & Jeyaprakash, S. (2021). Hybrid approach for brain tumor classification using handcrafted and deep learning-based features. *Journal of Medical Systems*, 45(8), 1-15.