Volume: 5, Issue: 6
Page: 12-20
2021

International Journal of
Science and Business
Journal homepage: ijsab.com/ijsb

IJSAB International

A comparison study: Classification brain tumor based on Support Vector Machine and K-Nearest Neighbors

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Abstract:
Brain tumor is one of the commonest tumors. For the diagnosis of this disease, automated detection and classification are crucial. Magnetic resonance imaging (MRI) is a unique sort of imaging which is utilized for detecting these tumors and categorizing them as benign or malignant using special algorithms such as of K-Nearest Neighbors (K-NN) and Support Vector Machine (SVM). The classification of brain tumors through imaging can be divided into four phases: pre-processing, extraction, segmentation and classification. This paper reviews some recent studies that highlight the efficacy of K-NN and SVM accuracies in classifying brain MRI images as normal or abnormal, benign or malignant.

IJSB
Literature review
Accepted 5 March 2021
Published 9 March 2021
DOI: 10.5281/zenodo.4590054

Keywords: *brain tumor, Magnetic resonance imaging (MRI), classification, SVM, K-NN.*

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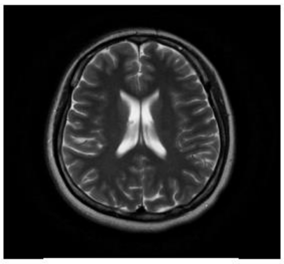
1. Introduction

The brain is the core part of the human body, which controls the nervous system. This system, in turn, controls the functions of various other organs including the heart (Naz & Hameed, 2017). The brain is a complex organ consisting of a huge network of nerve cells (neurons), as shown in figure 1.Once these cells grow in an uncoordinated pattern, brain tumor develops (Du et al., 2017; Sangeetha, 2014). The tumors are usually of two types: benign or malignant. The latter, shown in figure 2, can either be primary or secondary. The primary ones arise from the brain tissues, while the secondaries consist of cells that are originally reached the brain from other body parts such as the lungs and breasts (Kumari & Saxena, 2018; Louis et al., 2007).



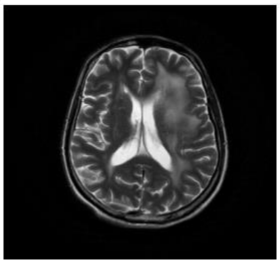


Fig.1 normal brain Fig.2 abnormal brain (Othman et al., 2011).

The MRI has been shown to be the most responsive and efficient imaging device used to clarify brain pathologies (Shobana & Balakrishnan, 2015; Georgiadis et al., 2008; Suneetha & JhansiRani, 2017; Abdulazeez et al., 2020). It is also used for the diagnosis of brain tumors (Zhou et al., 2006). Different modalities of MRI are generated by altering the time of excitation while gaining the images. These MRI sequences produce various sorts of tissue contrast images and provide beneficial structural details (Işın et al., 2016; D. A. Zebari et al., 2020). A huge collection of data is defined in the brain MRI. The MRI data track the size of the brain tumor and its response to treatment (Banday & Mir, 2016). The tumor is displayed in a white-color MRI image.

The imaging procedure used to identify brain tumors involves: pre-processing, segmentation, feature Extraction, and classification. To enhance the quality of the image, pre-processing is used. Then, the image is separated into multiple regions. The extraction function is the process of knowledge reduction, i.e., the process of data reduction. During the feature extraction phase elimination of the problem of the fitting is performed. Finally, the classification of the tumor is to decide whether a tumor is normal or abnormal. The best classifiers for brain tumors, suggested by several researchers, are SVM and K-NN (Zhang et al., 2011; Bhatia, 2010; Vidyarthi & Mittal, 2017; D. A. Zebari et al., 2019). In this review, we demonstrated a comparison between SVM and K-NN algorithms for classifying brain MRI images as normal or abnormal. The rest of this paper is structured as follows: section 2 contains theoretical background, section 3 includes related work of the subject, section 4 contains the comparison and discussion of the findings, and in section 5 the review is concluded.

2. Methodology

The first step in image processing is pre-processing. After which the segmentation of the image is done, this is followed by feature extraction and, finally, image classification using various types of ML algorithms.

2.1. Image pre-processing

Image pre-processing methods are used to enhance the image's consistency before being processed into an application (Zebari et al., 2020). This uses a small region of the pixel in the input image to get a new brightness value in the output image. These pre-processing techniques are often referred to as filtering and resolution enhancers. Medical image quality parameters are primarily noise and resolution. So the noise is pre-processed using a denoising technique. The image resolution is often a medical image processing problem, which means loss of quality at the edges of the image. Resolution enhancement is used to retain edge and contour detail. The primary use of these methods is the identification of tumor cells in the human body (Constantin et al., 2010; Koley & Majumder, 2011; Zeebaree et al., 2020).

2.2. Segmentation

Segmentation of brain tissue is one of the most utilized phases of imaging in the field of medical image processing. It provides comprehensive quantitative brain examination for correct diagnosis, identification and classification of abnormalities of the disorder. It plays a key role in the discrimination of healthy tissues from unhealthy ones. Therefore, effective disease diagnosis and treatment plans depend solely on the success of the segmentation method used (Dora et al., 2017; Kharat et al., 2012; Zeebaree et al., 2019).

2.3. Feature extraction

A large amount of data, which takes a large amount of memory and time, is needed to represent an image. The features are extracted from an image in order to decrease the amount of data, memory and time. The extracted characteristics contain the image's relevant details (Jolliffe, 2003; Zeebaree et al., n.d.; Zeebaree et al., 2019). It can be used for image classification and segmentation as an input to the classifier (Yogalakshmi & Rani, 2020; Nawzat Sadiq Ahmed & Sadiq, 2018). The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another (Martin & Tosunoglu, 2000; Yamazaki et al., 2013; N. A. Zebari et al., 2021; R. Zebari et al., 2020).

2.4. Classification

Brain MRI classification means that the form and the grade of the tumor can be predicted (Constantin et al., 2010), whether the image is regular or abnormal (Koley and Majumder, 2011; Nawzat S. Ahmed, 2013; Abdulkareem & Abdulazeez, 2021). The goal of classification is to gather objects into groups that have similar characteristic values. By making a classification judgment based on the importance of the linear combination of features, classification accomplishes this. The primary objective of image classification is to organize images by using the features and predict the input image categories (El-Dahshan et al., 2010; Bargarai et al., 2020; Nawzat S. Ahmed & Yasin, 2012). There are different classifiers, such as ANN (Artificial Neural Neural Network), SVM (Vector Machine Support), Random Forest, K-NN, Decision, Adaptive boost (Ada boosted) (Zeebaree et al., 2020). But the review focused on K-NN and SVM algorithms to classify brain tumor.

2.4.1 K-Nearest Neighbors

A simple supervised machine learning algorithm is the K-NN algorithm. In this approach, no underlying assumption on the dataset is needed and it can be used for both classification and regression. How similar items are closer to each other is dependent on the approach (Keller et al., 1985; Zeebaree et al., 2017; A. Jahwar & Ahmed, 2021). For brain MRI classification, K-NN is used (El-Dahshan et al., 2010; Fletcher-Heath et al., 2001). The K-NN estimate is based on focusing for the K samples closest to the test sample of the same form within a collection of training samples. The K-NN classifier calculates the distances between x test samples and all training samples, and then K samples, it out n samples for training, In order to choose the class, those nearest to x are subject to a majority vote (CoverP, 1967; Salim & Abdulazeez, 2021). The Euclidean distance is the distance measurement between a test sample and a training set of samples. The Euclidean distance between any two samples p and q is given by Euclidean space for N-dimensional space (1).

$$D = \sqrt{\sum_{i=1}^{N} (p_i - q_i)^2} \qquad (1)$$

When qi and pi are the coordinates of p and q in dimension i. Distances between x and entire training set, y1 to yn, are considered and then, the number characteristics with minimum distances are exposed to a majority vote, which leads to a final decision.

2.4.2 Support Vector Machine (SVM)

SVM is a supervised method of machine learning used for problems with classification and regression (Huang et al., 2003). SVM is typically used for binary classification. By drawing a hyperplane, SVM classifies the dataset into two groups. A hyperplane is a line separating the plane into two parts. Also called decision boundary. Kernel techniques regularly use circular hyperplane drawing for a more complicated dataset where a straight line cannot be drawn (Sachdeva et al., 2011) . There are various types of SVM kernels, such as the Gaussian or radial base, Function kernel, linear kernel, polynomial kernel, etc, and better than other kernels is the Gaussian kernel (Chaplot et al., 2006). The most critical problem is to cope the spatial characteristics of SVMs' learning and lucidity throughout the vector space, this results in a double representation, i.e., the projection of each , and each class in the dataset and compute the hyperplane from each separate points in vector space that the greatest edge for the detachable case (Jain, 1989; Wang & Japkowicz, 2010; A. F. Jahwar & Abdulazeez, 2020).

3. Related work

Many researchers have used techniques to classify brain tumors.

Chato & Latifi (2017) using 163 samples from BraTS 2017, different features were extracted and trained by different ML techniques. Then, employed ML techniques contain SVM, K-NN, tree, ensemble, logistic regression and linear discriminant. By using convolutional neural network (CNN) to extract the feature, the linear discriminant get the highest accuracy than other algorithms. The accuracy of Linear Discriminant is 91% with 5 folds, and 86.4% for the linear SVM technique. Even so, using a different test dataset, the accuracy of these predictions did not exceed 55 %. Therefore, when using the Linear Discriminant method, the best overall precision from the training dataset and the test dataset was 73 %. Shil et al. (2017) presented the model to identify the normal and abnormal brain MRI. At first, the system prepared the MRI, then performed pre-processing, processing, post-processing and classification. Applied gray conversion to image in pre-processing. Usage of K-means and segmentation used in the processing stage. Discrete Wavelet transform (DWT) used for feature extraction post processing, and principle component analysis (PCA) applied for feature reduction. Finally, SVM classify tumor type. The research showed a classification accuracy of 99.33%, sensitivity 99.17% and specificity 100 percent. Hebli & Gupta (2017) suggested a classification that was evaluated using three separate Linear, Polynomial, and RBF SVM kernels, by using clinical database from Gokul Scan center, Mumbai and non-clinical data bases and images from google website. The test showed that kernels of RBF and polynomials have100 percent accuracy of training and research on the integrated database and in the RBF clinical and non-clinical database offers 100 percent training and testing outcomes.

Bangare et al. (2017) proposed a method that convert MRI image to gray scale, and then to binary image converted for noise reduction. To increase image intensity, the system applied histogram equalization after that process. After that, canny edge detection applied which worked as filter to the passed image and then applied morphological operations on image. Then, for feature selection genetic algorithm was used. Later, SVM technique used for tumor detection. The mixed technique approach displays the possibility of improved brain tumor classification. The main advantage of this system is precise diagnosis of tumor classification. Khan et al. (2020) used MRI images from Image Archive public access, then images are utilized in classification by using SVM. Features are calculated and displayed on the Graphic User Interface (UCI) as the four kernels. The main benefit of GUI is that it can change the parameters without having to rewrite the entire program so according our requirements. The process of detection is quick and effective. In conclusion the acquisitions demonstrate greater precision and less time consumption. Qasem et al. (2019) presented a methodology that contained three stages: pre-processing, morphological processing and segmentation. The segmentation was done by watershed method then K-NN classifier is used to detect brain tumor. The proposed methodology tested on big dataset of images and get the precise results. By using K-NN that achieved best accuracy at 86%.

Reddy et al. (2019) presented an effective decision making in diagnostic system. Dataset from Harvard Medical school and MRI images Archives were used. First, by using median filtering in preprocessing image, fuzzy C- used for segmented image, and Gray Level Co-occurrence Matrix (GLCM) for selecting features. Finally, in classification K-NN was used and it performed better than previous classifier such as (Naïve Bayes, SVM, and Probability Neural Network). The researchers suggested classification model will be evaluated other types of high-level medical images by reducing modalities. Jayade et al. (2019) presented hybrid approach of classifier, it is the combination of K-NN and SVM. Numerous strategies of image processing were used to get the best results for cancer classification, such as image enhancement, morphological operations, segmentation and extraction of characteristics. For feature extraction GLCM method for dimensionality reduction was used. The SVM and K-NN classifiers were applied and provided 91.21 percent and 79.23 percent accuracy, respectively. In terms of accuracy, the proposed hybrid classifier SVM and K-NN is efficient; its precision is 94.13 percent, which is better compared to other methods. Islam et al. (2020) proposed a model to detect brain tumors that contained K-means and an improved SVM (ISVM). First of all, the MR image is retrieved from the database that the median filter reprocesses. Second, using the K-means algorithm, the image is segmented; ultimately, irregular cells, such as tumors, are identified using the ISVM algorithm. From the result observed the proposed algorithm achieved better accuracy when compared to other algorithms. additionally, ISVM decreased the execution time, in short time it can detect tumor.

Garg & Garg (2021) suggested proposing a hybrid ensemble technique that uses (RF, K-NN, Decision Tree (DT) (RF-K-NN-DT) majority voting. Segmentation is done by Otusu's Threshold method. Stationary Wavelet Transform (SWT), GLCM, and PCA utilized for feature extraction which gives 13 features for classification. The classification done by (KNN-RFDT). Old classifiers have a benefit over deep learning models because they require small training datasets and have small computational time complexity, low usage costs, and less educated people can easily implement them. Overall, the proposed approach is evaluated on a dataset of 2556 images, and gave a high accuracy (97.3%). The following Table 1 show the result of K-NN and SVM algorithms for classification of brain tumors.

Table 1 comparison between SVM and K-NN for classification brain tumors

References	Year	Dataset	Techniques	Result and accuracy
(Chato et al., 2017)	2017	Sample from BraTS 2017	• SVM • K-NN • Linear discriminant • Tree • ensemble logistic regression	Linear discriminant have the best result, with accuracy 91%.
(Shil et al., 2017)	2017	280 images from Brats17	• SVM	SVM have the high accuracy at 99.33%
(Hebli et al., 2017)	2017	Images from clinical, website, combination between medical image and website image	• SVM kernels • Linear • Polynomial • RBF	RBF and polynomial kernels get accuracy at100%
(Bangare et al., 2017)	2017	MRI images	• SVM	The result showed higher accuracy achieved by mixed method.
(Qasem et al., 2019)	2019	1532 images	• K-NN	Get the accuracy at 86%
(Reddy et al., 2019)	2019	Tested on MRI, evaluated on MRI and CT images	• K-NN	The result have a high accuracy 97.3% by using MRI, for CT at 94.6%
(Jayade et al., 2019)	2019	120 MRI	• SVM • K-NN	The outcome of the SVM-K-NN hybrid classifier is performance efficient; its precision is 94.13%
(Khan et al., 2020)	2020	110 MRI images	• SVM	The result get high accuracy and less time consumption.
(Islam et al., 2020)	2020	20 MRI	• ISVM	ISVM Have the good result, accuracy 95%, sensitivity 94% and specificity 94.74.
(Garg et al., 2021)	2021	2556 images	• hybrid ensemble classifier (KNN-RF-DT)	Ensemble classifier reached 97.305 %. accuracy, 97.73 % precision, 97.60 % specificity.

4. Comparison and discussion

For classification purposes, both SVM and K-NN algorithms were used to detect brain tumors in this review. The SVM is highly accurate and much more efficient than K-NN, as seen from table1. In terms of accuracy, SVM is more accurate than K-NN. But for tumor detection, it takes more time than K-NN. ISVM is a way to enhance SVM efficiency and reduce execution time so that a tumor can be diagnosed in a shorter time. However, the K-NN and SVM hybrid algorithms are better linked to big data, and the time needed for their computation was less.

5. Conclusion

The contribution of this review is to show the basic steps of brain image processing, the result and accuracy of SVM and K-NN algorithms in classifying brain tumors. Both SVM and K-NN deal with different MRIs and utilize various techniques to extract features from the images. In terms of classification accuracy, it can be safely assumed that SVM is much better and much more reliable than K-NN but needs more time. A hybrid base classification that combines both classifiers attained 94% classification accuracy, this technique improves the overall performance of the classifiers. However, larger scale studies are needed to prove this concept.

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Cite this article:

Shler Farhad Khorshid & Nawzat Sadiq Ahmed (2021). A comparison study: Classification brain tumor based on Support Vector Machine and K-Nearest Neighbors. *International Journal of Science and Business, 5*(6), 12-20. doi: https://doi.org/10.5281/zenodo.4590054

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