Classificatin of Brain Tumors by Machine Learning Algorithms

Gökalp Çınarer
Department Of Conputer Technologies
Bozok Univercity
Yozgat, Turkey
gokalp.cinarer@bozok.edu.tr

Bülent Gürsel Emiroğlu
Department Of Conputer Engineering
Kırıkkale Univercity
Kırıkkale, Turkey
bulentgursel@gmail.com

***Abstract*— Brain tumors are one of the most important causes of death among cancer types. Early and accurate diagnosis of brain tumor plays a key role in the successful implementation of the treatment. Nowadays, new technologies that increase the success rate of neurosurgery and prevent complications continue to develop. Magnetic resonance (MRI) technique is one of the most popular methods used to examine brain tumor images. There are many possible techniques and algorithms for the classification of images. The main purpose of machine learning and classification algorithms is to learn automatically from training and finally make a wise decision with high accuracy. In this study, the performances of tumor classification methods for the classification of MR brain image features as n/a, multifocal, multicentric and gliomatosis were analyzed. In the classification process, the statistical properties of the input images were analyzed and the data were systematically divided into various categories. These data were tested with KNN (k nearest neighbor), RF(random forest), SVM(support vector machines) and LDA(linear discriminant analysis) machine learning algorithms. SVM (support vector machines) algorithm with 90% accuracy rate was found to be better compared to other algorithms.**

Keywords—brain tumor, machine learning, classification

I. Introduction

Cancer is among the most researched disease groups in the world. Brain tumors are also common types of cancer. Brain tumors grow anywhere in the skull, pressure the brain and appear with different symptoms [1].

Brain tumors have two general types, primary and metastatic brain tumor. Primary brain tumors occur in the brain and tend to stay here. Primary brain tumors are examined in two ways as malignant and benign. Metastatic brain tumors start as cancer in a different part of the body and expand into the brain. Uncertainties about the structure, properties and spread patterns of malignant gliomas it reveals once again the importance of image processing techniques and classification algorithms.

In the diagnosis of brain tumors, many imaging techniques such as neurological test, X-ray MRI, CT scan, MRS, 3D imaging and biopsy are evaluated and the results are obtained.

Magnetic Resonance Imaging (MRI) is a method based on the measurement of the strong magnetic fields in the nucleus of hydrogen atoms in the body and the magnetic field vectors obtained after a suitable excitation of radio frequency pulses [2].

MRI does not use ionized radiation unlike CT and X-ray imaging. Uncontrolled techniques similar to fuzzy c tools are used to classify human brain MRI images in combination with classifiers such as artificial neural networks, support vector machines. Supervised classification methods such as K-NN closest neighbors group the similarities of the pixels of each trait extracted. [3].Among the learning techniques, the unsupervised neural network learning method was proposed by Suchita and Lalit in the classification of brain MRI images [2].

Daljit Singh et al. classify brain MR images with their proposed hybrid technique and examine the extracted features in two ways, normal or abnormal, with the support vector machine (SVM), a machine learning algorithm. [4].

Gadpayleand and Mahajani proposed a model for the detection and classification of brain tumors using the BPNN and KNN classifiers. Brain MRI images were classified as normal or abnormal. KNN 70% and BPNN 72.5% accuracy results were obtained[1].

Ramteke and Monali examined brain MR images in two groups as normal or abnormal in their proposed automatic classification model. They classified the images with the CNN classifier and achieved a rate of 80% [17]. In the study of Lukas, A et., For the estimation of the stages of brain tumor diagnosed patients, LS, RBF nuclei by Linear Separation Analysis, Support Vector Machines technique using [5].

Shafaghi performed brain tumor detection with support vector machines (SVM) in the proposed hybrid approach. The accuracy of about 83.22% [6]. Seda Kazdal et. Achieved 82.49% classification success on medical images. [3]. Ryu et al. Classify low and high grade gliomas with 80% accuracy by tissue analysis of glioma heterogeneity [4].

Kanas used a multivariate estimation model based on the imaging features contained in the VASARI dictionary to classify the promoter methylation status from gliomas obtained from Cancer Genoma Atlas. The result was 74% accuracy. [6]. Ahmadvand et. In 2016, the Random Forest classifier was used for the classification of tumor-free and tumor-free MR images and the classification performance was found to be 90% on average [7]. Amine et. In 2017, tumor-free and tumor-free MR images were classified with the Support Vector Machine (DVM). 97.10% accuracy, 91.90% sensitivity and 98% specificity were achieved in system performance [8].

In the literature, results are evaluated using a single classification algorithm. In this study, four different classification algorithms were used.

The aim of this study is to classify MR images of brain tumors as n/a, multifocal, multicentric and gliomatosis. The

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accuracy values of machine learning algorithms were examined comparatively.

II. MATERIAL AND METHODS

A. Dataset

The Rembrandt data set was used to evaluate the classification algorithms. Rembrandt is a data set published by the National Cancer Institute in the Cancer Imaging Archive (TCIA) database [9]. All patients in this retrospective study were previously identified by Cancer Genome Atlas (TCGA), a public data set that did not include a link to patient identifiers and was in compliance with the Health Insurance Portability and Accountability therefore an institutional review board. All patients with untreated GBM were analyzed with imaging data uploaded to the TCGA GBM collection of the Cancer Imaging Archive. TCIA is an open access platform extensive archive of medical images [10].

All images in the REMBRANDT dataset consist of axial, sagittal and coronal image planes of a total of 33 patients, with an average of 20 images per patient. 30 different features were extracted from each tumor brain MR images. Rembrandt images (VASARI) were analyzed by feature evaluation performed by 3 of TJU's radiologists while reviewing the TJU images. In this way, a data set consisting of a total of 99 patients and 30 different features was obtained.

B. Classification

The Machine learning algorithms are used for classification of MR brain image either as n/a, multifocal, multicentric and gliomatosis. We investigate and compare the performance of four machine learning algorithms namely KNN (k nearest neighbor), RF (random forest), SVM (support vector machines) and LDA (linear discriminant analysis) machine learning algorithms.

K-NN (K-nearest neighbor) algorithm, lack of training, easy to perform, analytically traceability, adaptable to local information, suitable for parallel operation, noisy resistant to educational data classification applications with many advantages particularly preferred [11].

The K-nearest neighbor algorithm (KNN) is one of the basic, functional and popular classification algorithms. K-NN algorithm, the training set examples with n-dimensional numerical attributes identified. In this method, the similarity of the data to be classified to the normal data sets in the learning set is calculated; classification is made according to the threshold value obtained by averaging the k data considered to be the closest [12].

The biggest disadvantage is that each of the nearest k is equally important in the KNN algorithm. The closer the neighbor is, the more likely it is that f vector is in this neighbor's class. Therefore, it is more accurate to assign neighbors with different voting weights by looking at their distance from the f vector [13].

LDA (Linear Discriminate Analysis) is a very common technique for machine learning and classification applications. LDA is a method used to reduce the size of groups belonging to different classes in the data to a single dimension used for reducing and separating LDA data from higher to lower dimensions [14].

In LDA, the characteristics of each class are considered independently and the variance of each group is taken to a minimum and group averages are kept at maximum level apart.

SVM (Support Vector Machine) is an algorithm that can be used easily in difficult and complex data thanks to its high accuracy. SVM is generally known as non-parametric models, but this is considered because the parameters available in Svm are not previously defined and their numbers depend on the training data used.

Svm faces optimization problems but this is solved by a binary formulation that makes it dependent on the number of support vectors. This eliminates the algorithmic complexity that can be used in a linearly separable state. With these advantages, Svm is one of the most widely used classification methods in mathematical optimization [15].

RF (Random Forest) algorithm is called a collection of tree-type classifiers. In this method, not a single decision tree is produced, a large number of trees are trained in different training clusters and the decisions are combined and the result is reached. Instead of using the best branch among all variables, RF separates the nodes into branches using the best of the randomly selected variables in each node.

Each dataset is generated displaced from the original dataset and the trees are continuously improved by selecting a random attribute. Estimates are made by the majority of trees (classification) or by means of their means (regression) [16].

III. RESULTS

In this section, we will examine the results of various classification techniques. Classification results of Knn, Svm, Lda and Rf algorithms are included. The results of the classifiers were evaluated according to the results of radiologists, accuracy, sensitivity, f1 score and sensitivity results.

Train score and test score values were also examined. Parameter configurations were tested for each classifier to determine the most successful performance values.

In the performance metrics, the confusion matrix "Table 1" used for binary classification was calculated.

TABLE I. CONFUSION MATRIX

		Estimation Class	
		Positive	**Negative**
Actual Class	**Positive**	***tp (true positive)***	***fn (false negative)***
	Negative	***fp (false positive)***	***tn (true negative)***

A. Accuracy

The most commonly used classification accuracy to determine classification performances is used to measure the overall effectiveness of the classifier.

$$\text{Accuracy} = \frac{tn+tp}{tp+fp+fn+tn}$$

"Table 2" and "Figure 1" are examined, the accuracy of the SVM classifier is 90%. KNN, LDA and RF have an accuracy of 87%, 83% and 83% respectively. The SVM classifier has a higher accuracy compared to all other classifiers.

TABLE II. COMPARISON OF ACCURACY RESULTS

Machine Learning Algorithms	Accuracy
KNN	***0,87***
SVM	***0,90***
LDA	***0,83***
RF	***0,83***

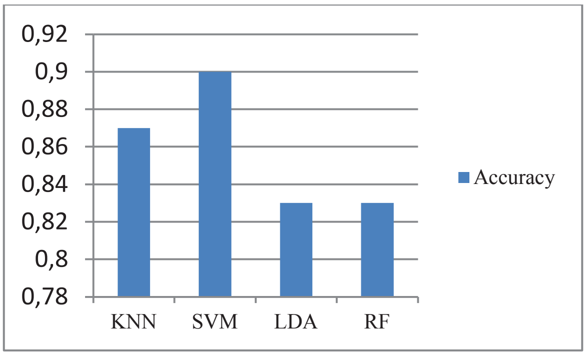

Fig 1. Comparison Of Accuracy Results Of Machine Learning Algorithms

B. *Precision*

The term precision refers to the deviation of the result set from the arithmetic mean of the cluster. It indicates success in a positively predicted situation.

$$\text{Precision}=\frac{\text{tp}}{\text{tp+fp}}$$

The precision for SVM is 90% whereas KNN, LDA and RF have precision of 86,7%, 83,3% and 83,3%. SVM has a higher precision when compared with all other classifiers

C. *Sensitivity*

Sensitivity determines, under many assumptions, how much the different values of an independent variable affect a particular dependent variable. The test is the ability to distinguish the real patients from the patients.

$$\text{Sensitivity}=\frac{\text{tp}}{\text{tp + fn}}$$

The sensitivity for SVM is 90% whereas KNN, LDA and RF have precision of 86%, 83% and 83%. SVM has a higher sensitivity when compared with all other classifiers

D. *F1 Score*

In order to make a sound decision about classifier performance, results other than classification accuracy should also be evaluated. The F1 score calculated for this purpose measures the relationship between the positive information of the data and those given by the classifier.

$$\text{f1 score}=\frac{\text{2tp}}{\text{2tp+fp+fn}}$$

The F1 score for SVM is 90% whereas KNN, LDA and RF have precision of 86%, 83% and 83%. SVM has a higher precision when compared with all other classifiers

E. *Train And Test Score*

The train set is used for training the classifier, and the test set is used for the evaluation of the classifier. The classifier with high accuracy for the train set is overfit if the test set has low accuracy. An algorithm must undergo training-test steps in order to make predictions and to make predictions in numerical or classification. In this study, the data set was formed as 70% training and 30% test group. The test and train results of all classification algorithms are shown in "Table 3" and "Figure 2".

TABLE III. TRAIN-TEST SCORE ANALYSIS

Machine Learning Algorithms	Score Analysis	
	Train Score	***Test Score***
KNN	***0,83***	***0,90***
SVM	***0,83***	***0,90***
LDA	***0,90***	***0,83***
RF	***0,83***	***0,90***

The LDA's train score rate was the highest with 90%. However, the same success was not achieved in the test group and this rate decreased to 83%. In this case, the LDA classification was overfit.

On the other hand, train score value of SVM algorithm is 83% and test score value is 90%.

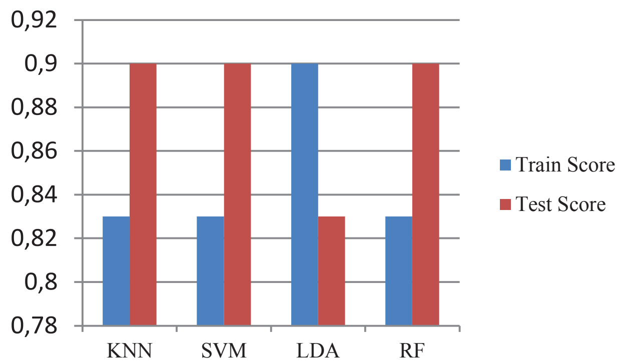

Fig 2. Score Analysis Of Machine Learning Algorithms

IV. *DISCUSSION AND CONCLUSION*

This article examines the performance of machine learning algorithms in brain tumor classification. The data set created by using tissue-based properties of Mr images was applied to classification algorithms. The properties of the image discussed in this proposed study were evaluated according to accuracy, precision, sensitivity, f1 score results.

For classification purposes, SVM, Knn, RF and LDA machine learning algorithm was used and maximum 90% accuracy was obtained in SVM algorithm.

SVM has a high sensitivity and accuracy and is much more efficient compared to all other classifying techniques as discussed in this paper. Due to the different appearances and complexity of tumors, the accuracy obtained is satisfactory. This accuracy can probably be improved by considering a large data set and subtracting density-based properties in addition to texture-based properties.

Generalizing this study for different types of lesions and tumors other than brain MR images will allow the scope of the study to be expanded. Another factor that will extend the scope of the study is the number of samples in the data set used and the variety of texture properties.

If these deficiencies are eliminated, it will contribute to the solution of the segmentation and classification problems of the tumor types and the classification performance of the algorithms will be improved.

These applications, which can be utilized by radiologists for radiological examinations, will enable the diagnosis and treatment planning stages to be performed in a shorter time, in a healthier and more effective manner.

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