

# Classification of Brain Tumors by Image Processing and Ensemble Learning

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**Abstract**—When diagnosed at a late stage, brain cancers and tumors provide very short life expectancy and a high mortality rate because of their aggressive nature. In order to diagnose and detect the tumor on the brain at the earliest stage possible, various medical imaging techniques such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) are used. Unfortunately, the diagnosis and treatment of the tumor depends highly on the physician’s medical knowledge. Hence, many different systems have been proposed in the past decade to automatically detect brain tumors by using machine learning. One major problem with these approaches is the fact that they usually need lots of training data (MRI Scans).

In this project, we detect brain tumors from MRI images with a limited amount of training data, around 120 images. Specifically, we use an ensemble learning approach that is based on Support Vector Machines (SVM). After applying image processing techniques such as low-pass filtering to all the images, the most common prediction from different SVM classifiers is chosen for a testing image. Validation accuracies are used to select the best image processing techniques and their optimal parameters. Our experimental results suggest that the Ensemble Classifier achieves an accuracy of 87% with low time complexity.

**Index Terms**—Brain Tumor, Image Classification, Ensemble Learning, Medical Imaging, SVM

## I. INTRODUCTION

### A. Motivation

Brain cancers and tumors affect the life of humans negatively, as abnormal growth of brain cells damage the functioning of the brain and might even lead to death. With increased usage of cell phones, the incidence rate of brain tumors is predicted to rise rapidly [1]. Furthermore, the mortality rate of brain cancers have also been increasing constantly in the past decade [2]. In order to reduce the mortality rate and treat brain tumors, diagnosis should be done in the earliest stage possible.

Medical imaging is used to diagnose and visualize different types of tumors in the human body. Various medical imaging techniques such as CT Scan, MRI, or X-Ray is used in hospitals for diagnosis. Magnetic Resonance Imaging (MRI) is generally used for brain tumor diagnosis as it shows the inside of the brain with contrast [7]. With the use of MRI, brain tumors are identified as soon as possible by many physicians. However, some MRI scans are hard to read and there is a

chance that physicians can make a mistake during diagnosis. When a physician decides that a tumor in the brain does not exist but in reality there is a tumor, a false negative diagnosis occurs and such diagnosis can be catastrophic for the patient. Hence, many different systems have been proposed in the past decade that automatically identifies brain tumors in an MRI scan. Even though most of these approaches have good accuracy and results, they usually need a huge number of training data and computation resources. Therefore, new approaches for brain tumor classification must be considered.

In this work, we propose to detect brain tumors from MRI images with a limited amount of training data. Specifically, we use image processing and ensemble learning through Support Vector Machines (SVM) to classify whether an MRI scan has a tumor or not. Our main goal in this study is to maximize the classification accuracy and minimize the number of false negatives. We use different image processing techniques, including Low-Pass Filter (LPF), High-Pass Filter (HPF), Median Filter (MF), and Low-Pass - High-Pass Filter (LPF+HPF). Then, we apply different machine learning algorithms such as k-NN, SVM, and Neural Networks (NN). To summarize, we make three main contributions in this paper:

- We apply different image filters to MRI scans and analyze the best processing technique for tumor detection.
- We experiment with three different machine learning algorithms and state their accuracy for different image processing techniques.
- We propose an ensemble learning approach that successfully identifies a tumor in the brain with a minimum number of false negatives.

Our experimental results suggest that LPF+HPF is the best filter to use for tumor detection, with an average classification accuracy of 84%. Additionally, we observed that Support Vector Machines (SVM) gives the optimal results in terms of classification. Finally, our ensemble learning approach that is based on different filters and Support Vector Machines outputs a classification accuracy of 87% and a 2% false negative rate.

### B. Related Work

The development of brain tumor recognition has been increasing in the past decade. Many approaches have been

proposed that build different models for MRI scan classification. Some approaches use image processing techniques, whereas some approaches are solely focused on deep learning to identify tumors. Some of the related work to our project is presented below.

Firstly, Praveen [3] introduced the use of image processing and segmentation for the problem of tumor detection. Different imaging filters such as median filter, wiener filter are used to process images and different edge detection and feature extraction techniques are used for classification. Then, Gaikwad et. al [4] experimented with dimensionality reduction of MRI images using Principal Component Analysis (PCA) and developed a Probabilistic Neural Network for tumor classification.

Apart from image processing or segmentation, Ari et. al [5] used deep learning to classify brain tumors by focusing on extreme learning machine local receptive fields (ELM-LRF) based tumor classification. Their work showed very promising accuracy results. Similarly, Seetha et. al [6] used convolutional neural networks with deep architecture and small kernels to classify brain tumors. By setting the weights of neurons to small values, their results were also very promising. The only problem with deep learning approaches is the fact that they usually need lots of training data.

As compared to these works, we experiment with a wide range of image processing techniques and we analyze the best imaging filter to use for tumor detection. Even though our accuracy value is not very high compared to works that used deep learning, we propose a classifier that can work well with limited amount of training data. To the best of our knowledge, this project is the first to apply ensemble learning for tumor identification. Finally, this work is also the only one that tries to minimize false negatives as well as accuracy, and discuss the results. Hence, we believe our contribution to brain tumor classification is significant.

## II. METHODOLOGY

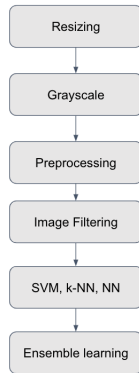


Fig. 1. Flowchart of the project that summarizes our process for our experiments.

For this project, we used an MRI Scan dataset that has a total of 255 images. The dataset is balanced, where there are

156 positive images and 99 negative images. From the 255 images, 70% is used for training and 30% is used for testing. After that, all the images are resized to a certain size and each image is converted to grayscale. This was because the MRI scans usually consist of black and white pixels and RGB colors does not contribute to identification of tumors. Note that the methodology behind this project is shown in Figure 1.

### A. Image Preprocessing

To be fed into the classifier, the images had to be resized to a common size. In our case, we resized them all to  $350 \times 300px$  around which most images were distributed (Figure 2). The method used is either downsampling for downscaling or up-sampling the images using bicubic interpolation for upscaling.

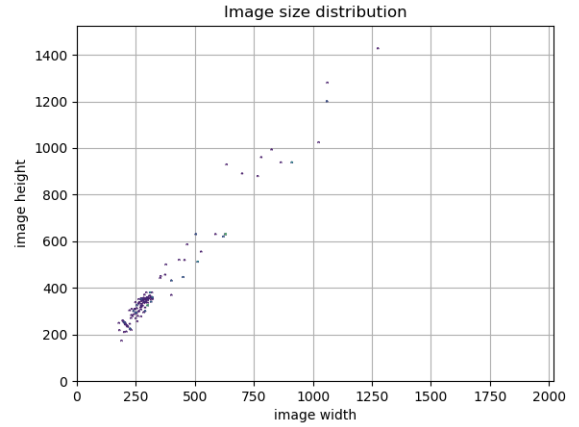


Fig. 2. Original image size distribution in pixels.

From this homogeneous dataset, two sub-datasets were created : the first one adds contrast to the images, the second one equalizes the histograms.

*Contrast addition:* In the following example (Figure 3), the tumor stands out by the luminance difference with healthy brain tissue. Thus our hypothesis is that adding contrast can help emphasizing the even more the tumor. The method used is a sigmoid transformation : for every pixel  $x \in [0; 255]$ ,

$$x \leftarrow x \times \frac{1}{1 + e^{-0.02(x-127)}}$$

*Equalization:* In the following example (Figure 4), there is no clear tumor (and in fact there is no tumor, but we don't know it beforehand), and most pixels are concentrated around a certain gray value, making it difficult to distinguish details. Thus our hypothesis is that histogram equalization can help distinguishing details, for example distinguishing a tumor when its luminance is close to healthy brain tissue.

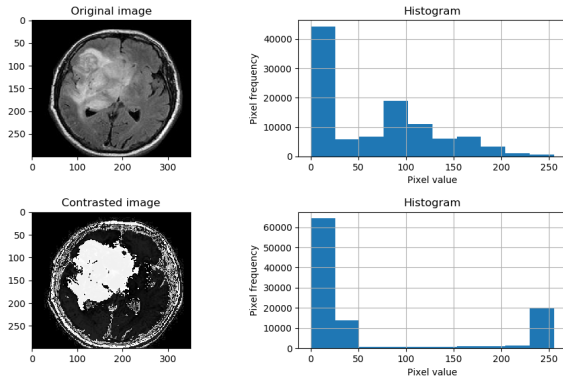


Fig. 3. Sample image of a brain having tumor and associated histogram before and after adding contrast.

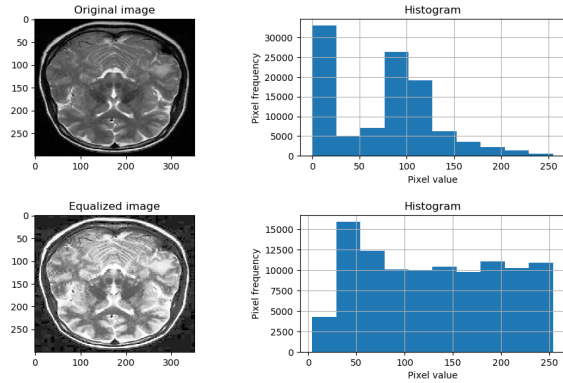


Fig. 4. Sample image of a brain without tumor and associated histogram before and after equalizing histograms.

### B. Image Filtering

For image filtering, a low pass filter (LPF) is used to smooth the images and remove the high frequency components and noise in the images. LPF is applied with various sigma values to the contrast and equalized images. Additionally, a high pass filter (HPF) is used with various sigma values on the contrast and equalized images. HPF helped us to concentrate on the high frequency regions in MRI scans and we assumed that the tumors in the images had high frequency. Figure 5 shows example MRI scans after LPF and HPF filtering, whereas Figure 7 presents the general structure and visualization of both filters.

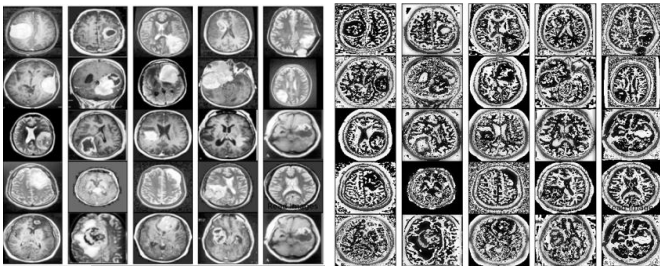


Fig. 5. LPF and HPF image examples respectively.

We also combined the above two filters to filter the images in our dataset. Specifically, we first applied the low-pass filter and then the high-pass filter (LPF+HPF) as it helped us to remove the noise in the images and then perform the classification on the relatively high frequency content in the image. Finally, we used the Median Filter to filter the images as it outputs good quality images for the classification part of our project. The filter takes the median of the neighborhood of each of the pixels in the image and replaces the specified pixel by that value. Example images after applying LPF+HPF and Median Filter is shown in Figure 6.

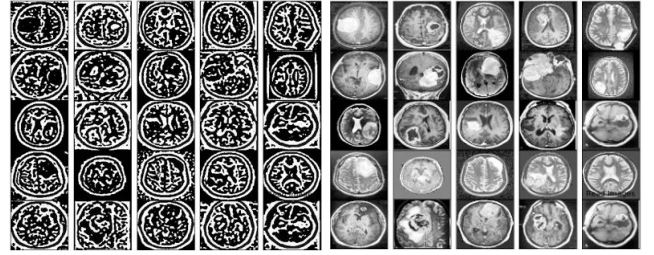


Fig. 6. LPF+HPF and Median image examples respectively.

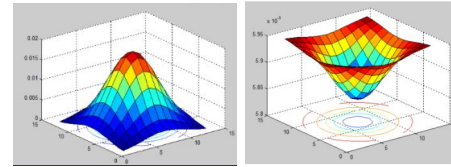


Fig. 7. Visualization of Gaussian LPF and HPF respectively.

### C. Machine Learning

After creating the contrasted, equalized versions of the dataset and applying different image filters, classification experiments are conducted by applying three different machine learning algorithms. As stated before, k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Artificial Neural Networks (NN) are applied on our data. k-NN is chosen because of its simplicity and the fact that our images are not that complex in nature. SVM, on the other hand, is selected as a machine learning algorithm because it can work very well with low amount of training data and it handles outliers very well. Finally, because image classification is usually done with Neural Networks, we chose NN as the last algorithm.

After choosing the algorithms, the dataset is split into training, validation, and testing. As stated before, 70% of data is used for training and 30% of training set is used for validation. Then, all the specified machine learning algorithms are applied to the training set and cross-validation approach is used to tune the parameters of each algorithm. After the optimization of the classifiers, accuracy results are collected for different classifiers, different image filters, and their different sigma values. Such results are presented in section 3.

Finally, best 8 classifier/filter/sigma combinations that had the maximum but different accuracies are selected for ensem-

ble learning. Ensemble learning is applied because some of the classifiers had overfitting and there was a need to generalize the data better. At the end, the most common prediction from the 8 classifiers is taken as the final result. In the case of a tie, the classifier predicts a positive instance to lower the number of false negatives. Figure 8 shows our final classifier with best classifier and sigma selections.

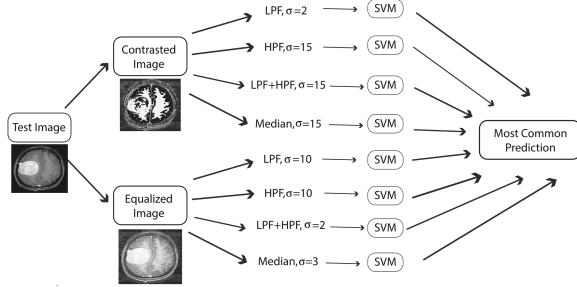


Fig. 8. Final classifier diagram for brain tumor identification that is based on ensemble learning.

### III. EXPERIMENTAL RESULTS

Tables 1 through 3 present and summarize our experimental results for this project. As stated, we experimented with a wide range of imaging filters with different sigma values. For each sigma value, accuracy result from imaging filters are collected from both contrasted and equalized versions of MRI images. The first row of accuracy values in each table provides contrast image values, whereas the second rows show the accuracy values of equalized images.

Experimental results suggest that applying a low-pass filter and a high-pass filter (LPF+HPF) outputted the best accuracy values among all classifiers on average. Specifically, SVM classifier had an average of 0.8247 from LPF+HPF technique among all sigma values and both contrasted and equalized images. The worst filter in terms of accuracy among all classifiers was the median filter, with an average of 0.7353.

Other than that, the results from different classifiers suggest that SVM is the best classifier for all different image processing techniques and sigma values, with an average of xxx. The worst classifier, in terms of accuracy, is Neural Network (NN) classifier, with an average of xxx.

Finally, the results suggest that, low sigma values benefit the accuracy score for LPF, whereas high sigma values benefit the accuracy score for HPF processing technique. For LPF+HPF and Median Filter, all the sigma values show similar results across all classifiers. An evaluation of our results and a thorough analysis is presented in the next section.

### IV. ANALYSIS OF RESULTS

### V. CONCLUSION AND FUTURE WORK

### REFERENCES

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SVM	LPF	LPF+HPF	HPF	Median
Sigma = 2	0.8289	0.8157	0.75	0.7916
	0.8157	0.8421	0.77	0.8151
Sigma = 5	0.8289	0.8354	0.71	0.8026
	0.8289	0.8289	0.7894	0.8026
Sigma = 10	0.8157	0.8157	0.8157	0.8026
	0.8421	0.7891	0.8373	0.8026
Sigma = 15	0.8157	0.8421	0.8555	0.8157
	0.8157	0.8289	0.8157	0.7894

TABLE I  
SVM RESULTS

KNN	LPF	LPF+HPF	HPF	Median
Sigma = 2	0.6184	0.8026	0.8151	0.6050
	0.7894	0.8026	0.7243	0.7894
Sigma = 5	0.6728	0.8151	0.789	0.6050
	0.7368	0.8151	0.8289	0.8026
Sigma = 10	0.7105	0.8151	0.7140	0.5526
	0.7368	0.8289	0.7519	0.7763
Sigma = 15	0.7763	0.8233	0.6766	0.6050
	0.7336	0.8684	0.7243	0.7763

TABLE II  
KNN RESULTS

NN	LPF	LPF+HPF	HPF	Median
Sigma = 2	0.8026	0.7894	0.6315	0.7763
	0.7763	0.8026	0.7243	0.7894
Sigma = 5	0.7763	0.7894	0.6315	0.7376
	0.7519	0.8026	0.7376	0.7376
Sigma = 10	0.6315	0.8032	0.6982	0.7376
	0.7368	0.7894	0.7376	0.7376
Sigma = 15	0.6050	0.7763	0.7336	0.6315
	0.7763	0.7763	0.7336	0.6315

TABLE III  
NN RESULTS

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