Brain Tumor Detection in Fmri Images

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***Abstract*: This paper proposes an algorithm that detects brain tumors on fMRI images. Brain tumor detection in early stages is very important for patients because the earlier a brain tumor is detected the higher the chances of survival of the patient are. FMRI is a method that is used to obtain detailed body images, for example also of the brain. These images are used by radiologist to diagnose the patient with a brain tumor if there is one in the images. This approach uses machine learning to detect brain tumors automatically and support doctors in their diagnosis**

***Index Terms*: fMRI, brain tumor, machine learning, pattern recognition**

I. INTRODUCTION

Brain tumors belong to the most dangerous and deadly diseases. Not many diseases are as life changing as brain tumors are, as they affect the brain which is without doubt the most important organ in the human body. It is what we are, if you apply minor changes to a person brain the person will change. Now if something like a brain tumor grows in the brain, exerts pressure on other brain areas and possibly also spreads out to other areas of body and brain, this affects a person's brain and therefore everything the person is. Alas, it often ends fatally. This year's estimations predict that around 17,000 people will die from brain or spinal cord tumors and around 24,000 people will be diagnosed with such a tumor in the USA this year [1].

The term" brain tumor" describes the abnormal growth of cells in the brain. Brain tumors can be divided into two main categories: benign and malignant tumors [2]. The main difference between these two types is that malignant tumors are cancerous while benign tumors are not. Malignant tumors being cancerous means that they will usually spread to adjacent areas of the brain and maybe also of the body. Furthermore, they have a much higher growing rate and are therefore considered as HGG (high-grade gliomi). They are much more aggressive and life threatening then benign tumors. Benign tumors grow much slower, do not spread out and usually have a very clear boundary which makes them easier to treat. These kind of brain tumors are usually treated by surgery or radiation therapy. Sometimes it is not even necessary to treat them. If it is, treatment is very likely to be successful, the reoccurrence probability for benign tumors is very low unlike the one of malignant tumors. As benign tumors are not as dangerous as malignant tumors the 5-year

survival rate for benign tumors varies between 80% and 100% which is very high. The 5-year survival rate for malignant brain tumors lies between 30% and 40%.

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Of course, these 5-year survival rate percentages depend highly on factors like age, gender and location of the brain tumor. Usually the most important factor is the stage of the brain tumor, patients whose brain tumor is detected in an early stage have much better chances of survival than patients whose brain tumor is detected in a non-early stage. With increasing stage of the brain tumor, the 5-year survival rate of the patient decreases drastically. This is what makes early detection of brain tumors so important, it can be the decisive factor that decides between death and life of the patient. However, detecting brain tumors in early stages is very difficult for the human eye. Therefore, research in this field of machine learning and brain tumor detection is very important.

Functional magnetic resonance imaging (fMRI) is used detect and classify tumors by experts. fMRI is a method of body imaging which has a very high spatial resolution. This method is therefore well fitted for the purpose of brain tumor detection. Its high resolutions allows precise analysis of the texture of the brain and possible infected regions. The features that are considered during brain tumor detection are: intensity, shape and texture of the infected region. Numerous approaches towards brain tumor detection in fMRI images have been made which also use these three features. The approach of S. Ouchtati et Al. sounds promising and in the following paper the proposed method will be validated on a larger dataset and if possible, also improved.

II. RELATED WORK

Before focusing on the approach that will be tested and improved later one should get an idea about related work. Many different approaches have been proposed and it is likely that it is possible to extract ideas from some approaches, combine them with other ideas from other approaches and thereby increase the performance of the algorithm. In this section some of these approaches will be briefly summarized and presented. A survey of the achieved results can be seen in Table 1.

Many researchers used support vector machines to classify extracted features. Nilesh et Al. [3] for example classified features that were extracted from the grey level co-occurrence matrix of the infected region and thereby reached an accuracy of 96.51%.

K. B. Vanishanvee et Al. [4] also classified features extracted from the gray level co-occurence matrix using principal component analysis. They used a standard support vector machine and a proximal support vector machine. The standard approach reached an accuracy of 82% while the proximal support vector machine performed better and reached an accuracy of 92%.

F. P. Polly et Al. [5] used discrete wavelet transform to

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extract features which were then classified by a support vector machine into high-grade glioma and low-grade glioma. An accuracy of 99% was reached. T. Chithambaram et Al.

[6] classified texture and intensity features that were extracted using genetic algorithms. The support vector machine reached an accuracy of 91.7% while an artificial neural network that classified the same features reached an accuracy of 94%. Nitish et Al. also used artificial neural networks to classify brain tumors, this time in four different classes. They used the Levenberg Marquart nonlinear optimization algorithm to optimize the artificial neural network and reached an accuracy of 97.5%.

Another way of using an artificial neural network to detect brain tumors was shown by S. Ouchtati et Al. [7], they used the central moments of subparts of the image as input of an artificial neural network which then gave an indication about amount and location of brain tumors. An accuracy of 88.333% was reached.

Algorithm	Accuracy
SVM and GLCM features	96.51%
SVM and GLCM PCA features	82%
PSVM and GLCM PCA features	92%
SVM and discrete wavelet transform	99%
SVM and GA for feature extraction	91.7%
ANN and GA for features extraction	94%
ANN and Levenberg Marquart algorithm	97.5%
ANN and central moments of subpart of the images	88.333%

TABLE I: Results of related work

III. PROPOSED METHODOLOGY

In this paper we will focus on the approach proposed by S. Ouchtati et Al. [7], which can be seen in Fig. 1 and will be explained in the following subsections. We will change parameters such as window size or extracted features in order to improve the performance. Also, we will train the algorithmon a larger database (around 2000 images) because S. Ouchtati et Al. [7] used a database which was rather small and we think that using more samples for training and validation can improve the performance and is more trustworthy than using a small dataset. Another change we are going to make is that our algorithm no longer classifies the image into six classes but only in to two (tumorous or non-tumorous).

What S. Ouchtati et Al. [7] did is the following. They used a neural network and the central moments of subparts of the image to classify the image into six classes:

Class 1: There is no brain tumor
Class 2: There is a brain tumor in the lower right part of the brain
Class 3: There is a brain tumor in the lower left part of the brain
Class 4: There is a brain tumor in the lower center part of the brain
Class 5: There is a brain tumor in the higher right part of the brain
Class 6: There is more than one brain tumor in different places of the brain

The algorithm that was used to classify the images can be divided into three steps:

A. Preprocessing

In the preprocessing step the fMRI image is reshaped to 128x128 pixels. After that one divides the image into 64 smaller images which are of the size 16x16 as seen in Fig. 2 That is why the reshaping step is important, the amount of pixels in the image has to be the same as the amount of windows times the amount of pixel in one sub-window.

The following parameters can be changed in this step to maybe improve the algorithm:

- reshaping size
- amount of windows window size

B. Feature Extraction

Now by calculating and storing the central moments of each window we obtain our features. The central moments are:

- Mean:

$$\mu = \frac{\sum_{i=1}^{N} I(p(i))}{N}$$

- Variance

$$\sigma^2 = \frac{\sum_{i=1}^{N}(I(p(i)) - \mu)^2}{N}$$

- Standard deviation: $\sigma = \sqrt{\{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(xi - \mu)^2\}}$

In order to increase the performance or runtime one could here try to only use two values for example use mean andvariance and drop standard deviation or maybe also add feature such as for example a gray level co-occurrence matrix feature,

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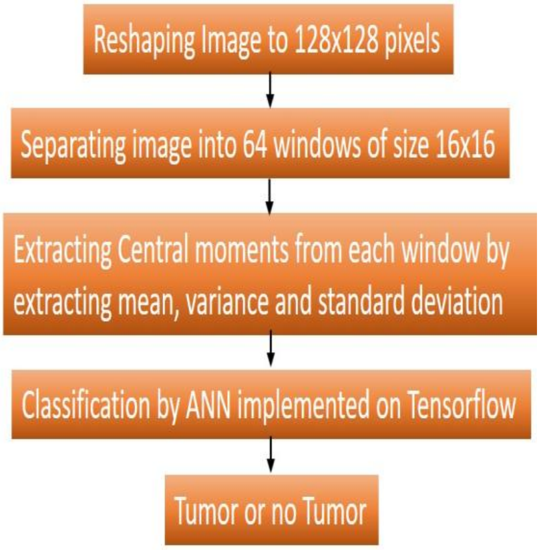


Figure 1: Flowchart of the algorithm

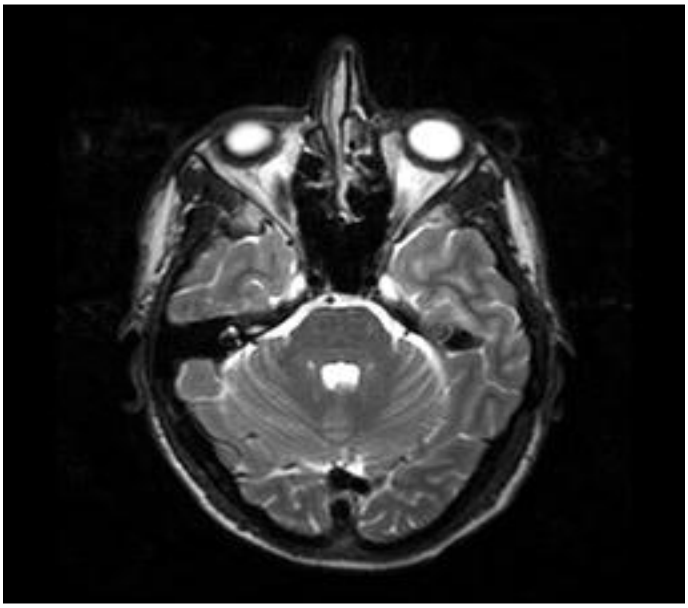
C. Feature Classification

The extracted features are now fed into an artificial neural network. In the training phase this artificial neural network is trained via backpropagation. After training this approach reached an accuracy of 88.333%. However, the database which was used for the training and validation contained only 60 images, which is usually not a sufficient size for the training of a neural network. We do not know anything about the structure of the network which was used by S. Ouchtati et Al. [7]. Therefore, it is up to us to find a suitable number of layers and neurons, a suitable learning rate and maybe some extra methods in order to further increase performance.

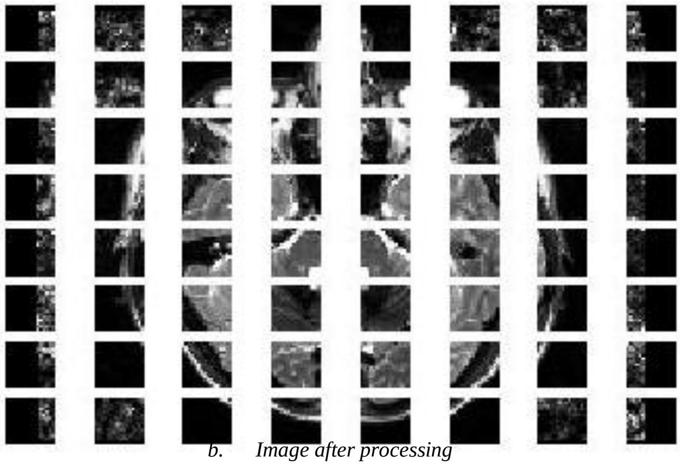
D. Improvements and Changes

In this section our changes to the algorithm will be explained and whether the changes improved the performance or not. The first thing we did differently is the following: S. Ouchtati et Al. [7] classified the images into six classes, we will only have two classes, tumorous and non-tumorous. Therefore, our algorithm will be a simple brain tumor detection algorithm.

The second larger difference is the database that we used. S. Ouchtati et Al. [7] used a database which had the size of 60 images, ours contains 1947 images, 995 of them tumorous images and the rest non-tumorous. All images are top view fMRI images, T1 as well as T2. Two samples of our databasecan be seen in Fig. 3, Fig. 3 (a) shows an image of a brain with a tumor which is marked by a red rectangle. Thislarger database allows a better training for the artificial neural network, as more data means that it is easier and first of all possible for the artificial neural network to generalize and learn the underlying principle of the features. The danger ofThe danger oftraining a neural network using less data is that the neuralnetwork overfits, this means that it would only learn thetraining examples by heart and fail to classify new, unseendata.



a. Image before processing



b. Image after processing

Figure 2: Dataset samples(a.) brain MRI image, (b.) segmentation of image

We used minibatch training to train our network. Inminibatch training small subsets of the whole dataset are usedsequentially. We used a batch size of 100. Another thing thatwe did in order to prevent overfitting is a method calleddropout. This method is applied on a layer of the neuralnetwork where it randomly drops neurons such that the other training a neural network using less data is that the neural network overfits, this means that it would only learn the training examples by heart and fail to classify new, unseen data. We used minibatch training to train our network. In minibatch training small subsets of the whole dataset are used sequentially. We used a batch size of 100. Another thing that we did in order to prevent overfitting is a method called dropout. This method is applied on a layer of the neural network where it randomly drops neurons such that the other

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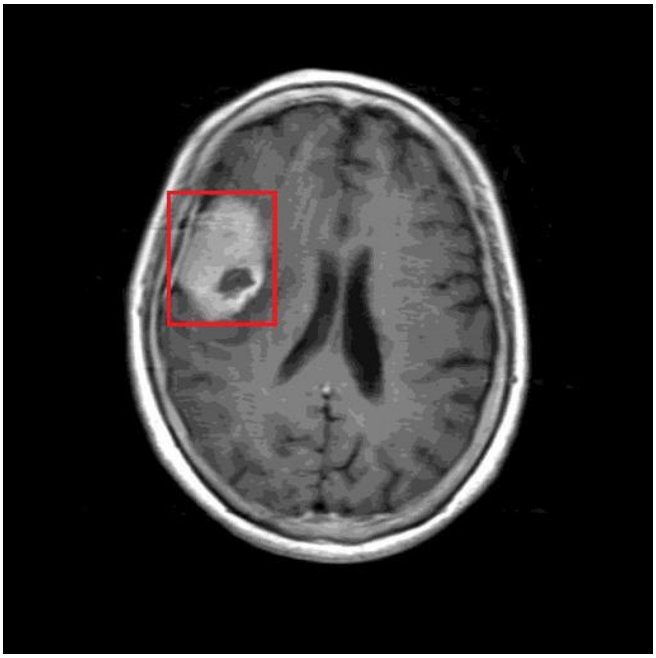
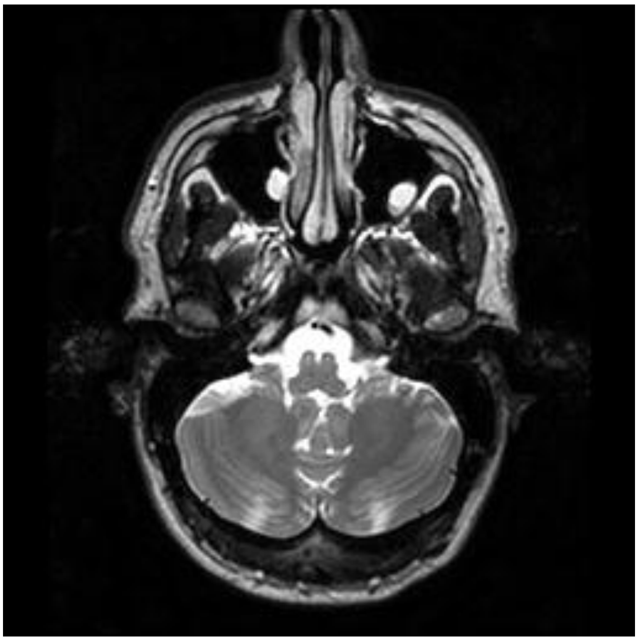


a. Tumoruos T1 image



b. Healthy T2 images

Fig. 3: Dataset samples

neurons learn not to depend too much on the input of other neurons. We only use that method during training such that all neurons are functioning during validation, this makes training a lot easier.

Also, we decided to not use all three central moments but only mean and variance. The performance of the algorithm was about the same, however the runtime decreased drastically which is very important for live application.

IV. IMPLEMENTATION ON RASPBERRY PI

After training our algorithm with the dataset we implemented the algorithm on the Raspberry Pi 3. The Raspberry Pi is a small computer that does not work as fast as a laptop but is nevertheless fully functioning and can be used for various application. We implemented our algorithm on the Pi so that the algorithm can be used in real time application by connecting the Pi to a fMRI machine. Our algorithm on the Pi would then immediately classify the images and say if a brain tumor is present. That is the reason why a low runtime is important. After the training of our algorithm on the whole dataset we saved all the crucial variables and stored them one the Pi. Now if we want to classify something with the Pi it will simply restore the trained model and then run the algorithm.

We implemented our algorithm on the Raspberry Pi 3. The Raspberry Pi 3 uses a 64-bit quad core processor.

V. RESULTS

In this section we are going to discuss the results of the algorithm and the results of the that changes we have made. We tested each algorithm on 500 images which were not used in the training and are therefore unknown to the algorithm. Our benchmark value is the accuracy of the algorithm that was proposed by S. Ouchtati et Al. [7] after it is trained on our dataset. It reaches an accuracy of 92.17%. Processing one image takes 6.97 ms. If we only extract mean and variance from the sub images and feed them into the classifier, we reach an accuracy of 89.06%. In this case however the time for one iteration is only 4.24 ms. Now if we further add dropout to both versions, we obtain an accuracy 89.25% for the version that uses mean, variance and standard deviation and an accuracy of 91.91% for the pruned version. The former needs 6.77 ms to process one image and the later needs 3.87 ms and is therefore the fastest. Note that in a live application the image would also have to be send to the Pi first, then loadedand then processed.

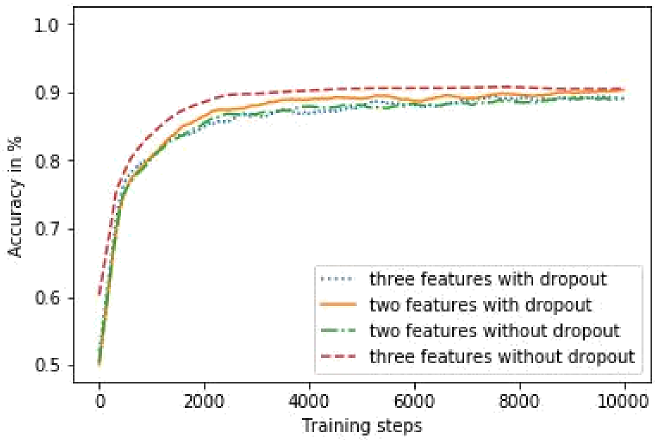


Fig. 4: Results in comparison

As we can see in Fig. 4 all version performs almost equally well. The version that uses three features and no dropout learns fastest; it already reaches accuracies very close to its best value after 3000 training steps. The one that uses two features and dropout learns a bit slower, however after 9000 to 10000 training steps it almost caches up with the version discussed previously. The standard approach still performs better by 0.26%. However, as you can see in Table 2. our modified version that uses two features and dropout performs much faster. It only takes 3.87 ms for this version

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to process and classify one image while it takes 6.97 ms for the standard approach. Therefore, our approach is better suited for live applications.

Algorithm	Accuracy	Runtime
Three features no dropout	92.17%	6.97ms
Two features no dropout	89.06%	4.24ms
Three features with dropout	89.25%	6.77ms
Two features with dropout	91.91%	3.87ms

TABLE II: Results of different configurations of the algorithm

VI. CONCLUSION

In this study we have tested and improved the methodology proposed by Ouchtati et Al. for automatic brain tumor detection in fMRI images. Ouchtati et Al. already reached a promising accuracy of 88.333%, we managed to obtain an even better accuracy of 92.17% by training their algorithm on our dataset and restricting the classification to the presence of a brain tumor instead of one that also indicates the location of the brain tumor. We also managed to speed up the algorithm such that it can be used parallel to the fMRI scan, the cost of this is that the accuracy of the live algorithm decreases by under 0.26% which is a comparable small loss considering that an expert will double check the result of the algorithm in either way. After all it can be concluded that 92.17% is a result which is very encouraging for future research. More computing power, more provided brain tumor data and combination of already proposed methods could increase the accuracy further, such that it might actually be used during the fMRI scan to give a first indication about the presence or absence of a brain tumor.

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Mrs. Roshan Jahan is assistant professor in Department of Computer Science, Integral University, Lucknow. She is gold medalist in B.Tech and overall topper in masters (M.Tech), she has more than 8 years of Teaching. Mrs Jahan has Won Best Paper Award for paper presentation in International Conference ACEIT-2016, and ACEIT-2018. Her research area is image processing, machine learning and expert systems. Three of her projects got selected for DAAD-RISE fellowship program run by Germany. Currently involved in aproject related to implementing sensor networks in forests to save wildlife, and also medical imaging to detect tumors and Alzheimer diseases. She has published more than eighteen papers in international journals and conferences andvarious seminars organized by professional bodies and industry associations worldwide. Mrs. Roshan, holds professional associations with IEEE Technical Committee, and ISTE.

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