Analysis and Comparison of Accuracy in Brain Tumor using Berkeley Wavelet Transform and Robust Principal Component Analysis

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ABSTRACT: The main objective of this study is to compare Berkeley wavelet transform (BWT) and robust principal component analysis (ROBPCA) techniques in tumor analysis to improve the accuracy of image processing. Based on the sample sizes of BWT (N=16) and ROBPCA (N=16), tumor MR pictures of various brain tumor illnesses have been gathered. Image segmentation has been finished, and textural features have been retrieved using image processing methods. The accuracy and sensitivity of the parameter are taken into consideration by both organizations when evaluating tumor detection and evaluation. The sample size for each group could be determined by maintaining the enrollment ratio at 1, the threshold alpha at 0.05, the g power at 80%, and the confidence interval at 95%. The absence of a statistically significant difference (p = 0.182) between the two groups was verified using an Independent Sample T-test. The accuracy numbers in BWT are 81.5%, while 84% is the accuracy value in ROBPCA. When it comes to brain tumor detection and analysis, ROBPCA has performed well when compared to BWT.

Keywords: Novel BWT, ROBPCA, Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Brain Tumors, CNN, Tumor, Tumor Detection, Mortality Rate.

1 Introduction

An abnormal growth or mass of cells in or near the brain is called a brain tumor, and it can occasionally be fatal. The goal of this study is to use a fast bounding box (FBB) to more accurately analyze brain tumors in MRI (Magnetic Resonance Imaging) images. The study compares the robust principal component analysis (ROBPCA) and novel Berkeley wavelet transform (BWT) algorithms for brain tumor detection. According to Independent Health Policy, brain tumors are one of the most significant things that affect humans today. With the number of diseases and productivity increasing, it is necessary to be able to analyze brain tumors in order to meet the growing demand. These tumors can be fatal, infecting and severely damaging the brain, which results in a high death rate. However, following the outstanding medical development, analysis of tumor was made easy. Thereby, this brain tumor detection analysis was done by using novel Berkeley wavelet and Robust Principal
Component Analysis, the research results will be applied to enhance the accuracy in the area of brain tumors with the help of MRI (Magnetic Resonance Imaging) images[1]. According to the report, out of all recent publications in the field of brain tumor detection analysis with less mortality rate. Nearly 1500 articles have been published in recent years on various websites such as IEEE Xplore, Google Scholar, ScienceDirect, and many more. The literature database has been compiled from the most cited article publications in the field of CNN and brain tumor analysis. Because brain tumor efficiency is above 79% [2], image processing is frequently used in conjunction with magnetic resonance imaging (MRI) to remove tumors, reduce infection, and improve efficiency with a lower death rate. However, this technique selectively displays the brain region affected by the tumor [3]. The most significant indicator in the medical field, with at least 90% efficiency and a lower death rate, was the analysis of brain tumors. Now the most widely used method for detecting brain tumor analysis is image processing. Chakri [6] used image processing for the detection and analysis of tumors and found 92% accuracy. The success of brain tumor analysis is attributed to the effective use of Methods. Computed tools are necessary for the process with a minimum of 80% accuracy and sensitivity.

The group has a wealth of prior experience working on numerous research projects spanning several disciplines[7]. We decided to pursue this project because of the increasing trend in this field. No automated tumor detection study utilizing BWT in contrast to other networks exists. Recent publications demonstrate the authors' proficiency in developing algorithms for the healthcare industry and their advancements in magnetic resonance imaging (MRI). In order to increase accuracy[8] and lower the death rate, the current study compared novel Berkeley Wavelet Transform (BWT) and ROBPCA (Robust Principal Component Analysis) algorithms.

2 Materials and Methods

This study was conducted at the Digital Signal Processing Laboratory, Saveetha School of Engineering. The study was based on a brain tumor detection analysis comparing the new Berkeley Wavelet Transform (BWT) and ROBPCA (Robust Principal Component Analysis) algorithms for a lower mortality rate detected using magnetic resonance imaging (MRI). BWT and ROBPCA are two groups used to predict new brain tumor detection tests. Using the prior study results [9,10] from clinicalc.com, the sample size for each group was determined, maintaining a threshold alpha of 0.05%, power of 80%, confidence interval of 95%, and enrollment ratio of 1. In light of that, the sample sizes were ROBPCA (N=16) and BWT (N=16). The input images were downloaded from Kaggle [11,12] and represent different types of cancer. The input images were preprocessed and the preprocessed images were segmented using the Watershed algorithm. Texture features such as contrast, correlation, energy and uniformity are extracted using grayscale. The extracted features are provided to the CNN as input for efficient tumor analysis for low mortality. The effectiveness of the methods is measured with an accuracy of low mortality rates.

Novel Berkeley Wavelet Transform

Berkeley Wavelet Transform (BWT) is a triadic wavelet transform that operates in two dimensions. There are four mother wavelet pairs in the BWT, each with four orientations. One wavelet in each pair has odd symmetry while the other has even symmetry. With the addition of one DC term, the wavelets translate and scale to form a complete orthonormal basis in two dimensions.

Pseudocode

Step 1 : Read Input containing Medical diagnosed brain tumor images within the data set.
Step 2: Activate wavelet method model with defined libraries.
Step 3: Collect Distribution of Pixels from Train Data set and Test Data set.
Step 4: Compute value . Substitute default pixel values based on saturation values of Images.
Step 5: Pass Values of Test data to Predict function.
Step 6: Compare values with Train data and Produce results based on analysis done by Berkeley wavelet method.

Robust Principal Component Analysis
The proposed method groups pixels of the brain MRI image into four levers. The algorithm is implemented for five brain diseases such as glioma, Huntington's disease, meningioma, Pick's disease and Alzheimer's disease.

Pseudocode
Step 1: Read Data set containing Medical brain tumor images.
Step 2: Load Robust Principal Component Analysis Model with Libraries.
Step 3: Segment Dataset into Train set and Test Set.
Step 4: Compare values of X,Y coefficients of Image based on dimensional Value
Step 5: Compute Position of Image P, Score Values of Pixels SV, Size of image S.
Step 6: Pass Test data to Predict() Function of Robust Principal Component Analysis model.
Step 7: Compare the values present between Test data and Predicted data. And record changes in coefficients of image segmentation.
Step 8: Produce the results of Final prediction.

The system utilizes a Windows operating system and has a hard disk capacity of 50GB, with 4GB of RAM. The system is programmed using Matlab[13] and can be implemented in either Jupyter (Anaconda) or Google Colab. An Intel i3 processor is employed in the system. The independent variables for detecting brain tumors in images and videos are used, with improved accuracy values as the dependent variables.

Statistical Analysis
For statistical analysis, IBM SPSS Version 21 software was employed in this case. Accuracy and sensitivity are dependent variables, while age and gender are independent variables [14, 15]. The accuracy of the independent variables was assessed using the independent samples t-test. The standard deviation and standard error of the mean were also calculated using the same software.

3 Results
Table 1 Displays group statistics for size N=16, which include mean accuracies and standard deviations for the Berkeley wavelet transform and robust principal component analysis algorithms.[4]

Various morphological operations such as opening, closing, resizing the image, edge cutting, and reconstruction steps were applied before segmentation of Magnetic Resonance Imaging (MRI).

Table 1. Compare group statistics to check the accuracy of your sample results.

<table>
<thead>
<tr>
<th>ACCURACY</th>
<th>GROUP</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>BWT</td>
<td>16</td>
<td>81.52</td>
<td>.88861</td>
<td>.22215</td>
<td></td>
</tr>
<tr>
<td>ROBPCA</td>
<td>16</td>
<td>84.0625</td>
<td>.75000</td>
<td>.18750</td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Independent sample t-test with a significance value of 0.182 (p > 0.05) and confidence interval of 95%.[5]

<table>
<thead>
<tr>
<th>Levene’s Test for Equality of Variances</th>
<th>t-test for Equality of Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>Sig.</td>
</tr>
<tr>
<td>Equal variances assumed</td>
<td>.914</td>
</tr>
<tr>
<td>Equal variances not assumed</td>
<td></td>
</tr>
</tbody>
</table>

Input images of various tumors and brain tumor diseases collected from kaggle are shown in Fig.1,2. During the training phase of CNN classifiers, structural features such as contrast, energy, entropy and correlation are extracted from the segmented images. [9] Multiple tumor images are then used to test the CNN classifier and the results are shown as a confusion matrix in Figure 3.[10]

![Image](https://example.com/image1.png)

**Fig. 1.** Represents the input images collected from kaggle.

![Image](https://example.com/image2.png)

**Fig. 2.** Represents the segmented images from the input images.
CNN's accuracy is limited because the classifier consistently makes accurate predictions and there is never a wrong answer. Two distinct algorithms, BWT and ROBPCA, are used to train CNN. Table 1 compares the performance of these algorithms. Fig. Figure 4 shows a histogram of CNN classifier errors during training, validation and testing. If the expected result and the expected result match, the error value is zero. Performance is determined based on the operating characteristics of the receivers being evaluated. Dig. Figure 5 shows the CNN ROC plots from training, validation and testing. Table 2 presents the significance level for the accuracy of the CNN classifier as determined by an independent sample T-test. P=0.182 indicates that there is no discernible difference between the accuracy values for the two groups. Figure 6 displays a bar chart comparing the mean sensitivity and mean accuracy values for the ROBPCA and GABOR FILTER classifiers with +/- 2 standard deviations. Compared to the BWT algorithm, ROBPCA yields results that are more consistent.

Fig. 3. Represents the confusion matrix of CNN classifiers during training, validation and testing by using CNN classifiers.

Fig. 4. Represents the Error Histogram of CNN classifier during training, validation and testing by using CNN classifiers.
Fig. 5. Represents the Receiver operating characteristics (ROC) of CNN classifier during training, validation and testing by using CNN classifier.

Fig. 6. Shows mean accuracy comparison graph that shows the comparison between the mean accuracy of the Berkeley Wavelet Transform and the mean accuracy of the Robust Principal Component Analysis algorithm along with the error bars of +/- 2 SD and 95% CI.

4 Discussion

As mentioned above, the results of these studies ensured accuracy and sensitivity. In these studies, I observed that the ROBPCA algorithm appears to be better than the BWT algorithm (p<0.05, independent sample t-test).

It is useful for analyzing regression data with outliers and multicollinearity, and performs slightly better than Zhang in tumor identification accuracy.[16] Compared to ROBPCA,
Hamzenejad method achieved similar results in terms of successful tumor identification and provided good accuracy of 96.75% [17]. The previously published article by Haddadnia shows that novel tumor detection analysis and detection with improved accuracy in the field at 94.5% for BWT when compared with ROBPCA [10]. The process of morphological erosion is employed in the second stage to eliminate white pixels. However, our results contradicted these conclusions, showing that ROBPCA is more accurate than BWT. This might be as a result of the small sample size they used for the research. Have experience with a variety of brain tumor types, which may account for our improved sensitivity and accuracy for ROBPCA detection. Based on the previous literature, all the studies stated that the Robust Principal Component Analysis is better when compared with Berkeley Wavelet Transform [18]. ROBPCA seems to give the most consistent results with the smallest standard deviation. [19,20] There is a significant difference in the results between BWT and ROBPCA (p < 0.01) in terms of the accuracy of automatic brain tumor detection in brain fields. X-axis: BWT vs. ROBPCA, Y-axis: Average accuracy with ±2SD, statistically significant difference between two algorithms with 0.182. [21]

A limitation of our study was that BWT was very sensitive to noisy data (e.g., during cancer detection). Large-scale cancer detection could not be achieved with this algorithm. Images are more sensitive to noise and other environmental disturbances. This makes it difficult for doctors to determine the tumor and its causes. However, in the early stages of a brain tumor, the edges of the image are not sharp. Image feature extraction and partial segmentation will help us achieve better results. [22]

In the future, automated analysis of brain tumor detection needs to interrogate extensive brain tumor data fields to ensure accuracy and sensitivity and to overcome the limitations of our study. Precise brain detection technology and a CNN-based approach could be useful to adequately analyze tumors in large brain fields for some selective diseases. This helps minimize the need for frequent manual treatments and reduces healthcare workload.

5 Conclusion

Considering the limitations of this study, the ROBPCA algorithm appears to be better than the BWT algorithm in terms of accuracy (84% vs. 81.5%) in brain tumor detection and analysis, with a statistically significant difference between the two algorithms being 0.182.

References

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