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Performance Analysis of Walsh-Hadamard Transform-Based Gabor Filter Feature Extraction Method and GLCM Feature Extraction Method for Brain Tumor Detection

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Abstract: Brain tumor detection through MRI imaging is a crucial step in medical diagnostics. This paper presents a comparative performance analysis of two feature extraction methods: the Walsh-Hadamard Transform (WHT) based Gabor Filter method and the Gray-Level Co-occurrence Matrix (GLCM) method. We evaluate these techniques based on accuracy, computational efficiency, and robustness using a benchmark MRI dataset. Our results indicate the strengths and limitations of each method, providing insights for their application in automated brain tumor detection systems.

Keywords: Support Vector Machine (SVM), Gabor Filter method and the Gray-Level Co-occurrence Matrix (GLCM),Walsh-Hadamard Transform (WHT)

I. INTRODUCTION

Brain tumors represent a significant health threat, requiring precise detection and classification for effective treatment. MRI imaging, due to its high resolution, is extensively used in diagnosing brain anomalies. Automated detection systems rely on robust feature extraction methods to highlight relevant patterns within these images. This study compares the performance of WHT-based Gabor Filter and GLCM methods for feature extraction in brain tumor detection.

II. MATERIAL AND METHODS

A. Walsh-Hadamard Transform (WHT) Based Gabor Filter Method

The Walsh-Hadamard Transform is an orthogonal, non-sinusoidal transformation technique that converts spatial domain data into the frequency domain. Unlike Fourier transforms, which use sinusoidal functions, the WHT uses Walsh functions that take values of +1 or -1. The main advantages of WHT are its simplicity, computational efficiency, and ability to handle large datasets with binary operations.

Steps:

1) *Preprocessing:* Noise reduction using median filtering and contrast enhancement via histogram equalization.
2) *WHT Application:* Conversion of images to the frequency domain using WHT.
3) *Gabor Filter Application:* Application of Gabor filters with various orientations and scales to the transformed images.
4) *Feature Vector Formation:* Combination of the filtered outputs to form a feature vector.

B. Gray-Level Co-occurrence Matrix (GLCM) Method

The Gray-Level Co-occurrence Matrix (GLCM) method is a statistical approach used for texture analysis in image processing. It is particularly effective in extracting textural features that describe the spatial relationship between pixels in an image. This method is widely used in various applications, including medical imaging, for its ability to capture and quantify texture patterns.

The GLCM method involves constructing a matrix that represents how frequently pairs of pixel with specific values (gray levels) occur in a specified spatial relationship within an image. Each element in the GLCM represents the frequency of a particular combination of pixel intensities and their spatial separation.

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1) Matrix Construction

a) Define the spatial relationship to be analyzed (e.g., pixel distance and direction).

b) For each pixel in the image, count how often a pixel with intensity iii is adjacent to a pixel with intensity jjj at the specified distance and direction.

c) Populate the GLCM with these counts, where each entry (i,j)(i, j)(i,j) represents the frequency of the corresponding intensity pair.

Example: For a given direction (0°) and distance (1 pixel), the GLCM is constructed as follows:

0 1 2 3 ... 255
0				...
1				...
2				...
3				...
...|...|...|...| ...
255|...|...|...| ...

2) Feature Extraction from GLCM

Once the GLCM is constructed, various statistical measures can be derived to quantify texture. Commonly used features include:

a) *Contrast:* Measures the intensity contrast between a pixel and its neighbor over the entire image.
Contrast=∑i,j(i−j)2·P(i,j)\text{Contrast} = \sum_{i,j} (i - j)^2 \cdot P(i, j)Contrast=i,j∑(i−j)2·P(i,j)

b) *Correlation:* Measures how correlated a pixel is to its neighbor over the entire image.
Correlation=∑i,j(i·j)·P(i,j)−μi·μjσi·σj\text{Correlation} = \sum_{i,j} \frac{(i \cdot j) \cdot P(i,j) - \mu_i \cdot \mu_j}{\sigma_i \cdot \sigma_j}Correlation=i,j∑σi·σj(i·j)·P(i,j)−μi·μj
where μ\muμ and σ\sigmaσ are the mean and standard deviation of the marginal distributions of the GLCM.

c) *Energy:* Also known as angular second moment, measures the uniformity of the texture.
Energy=∑i,jP(i,j)2\text{Energy} = \sum_{i,j} P(i, j)^2Energy=i,j∑P(i,j)2

d) *Homogeneity:* Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
Homogeneity=∑i,jP(i,j)1+|i−j|\text{Homogeneity} = \sum_{i,j} \frac{P(i, j)}{1 + |i - j|}Homogeneity=i,j∑1+|i−j|P(i,j)

3) Application in Brain Tumor Detection

In brain tumor detection using MRI images, the GLCM method is employed to capture the textural differences between normal and abnormal brain tissues. Tumors often have distinct textural patterns compared to healthy tissue, which can be effectively quantified using GLCM-derived features.

4) Steps of GLCM Feature Extraction

a) *Preprocessing:* Noise reduction and contrast enhancement.

b) *GLCM Construction:* Generation of GLCMs for multiple directions (0°, 45°, 90°, 135°) and distances.

c) *Feature Extraction:* Calculation of statistical measures such as contrast, correlation, energy, and homogeneity.

d) *Feature Vector Formation:* Combination of these statistical measures into a feature vector.

III. EXPERIMENTAL SETUP

A. Dataset

The MRI dataset used comprises annotated images indicating the presence or absence of brain tumors. The dataset is split into training and testing subsets.

B. Classifier

A Support Vector Machine (SVM) classifier is employed due to its effectiveness with high-dimensional data.

C. Evaluation Metrics

a) Accuracy: The proportion of correctly classified instances.
b) Precision: The ratio of true positive detections to total positive detections.
c) Recall: The ratio of true positive detections to actual positive instances.
d) F1-Score: The harmonic mean of precision and recall.
e) Computational Time: Time required for feature extraction and classification.

IV. RESULTS AND DISCUSSION

A. Accuracy and Robustness

Table 1: Performance Metrics for WHT-Based Gabor Filter and GLCM Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computational Time (s)
WHT-Based Gabor Filter	94.5	93.2	95.1	94.1	15.2
GLCM	91.8	90.5	92.3	91.4	22.7

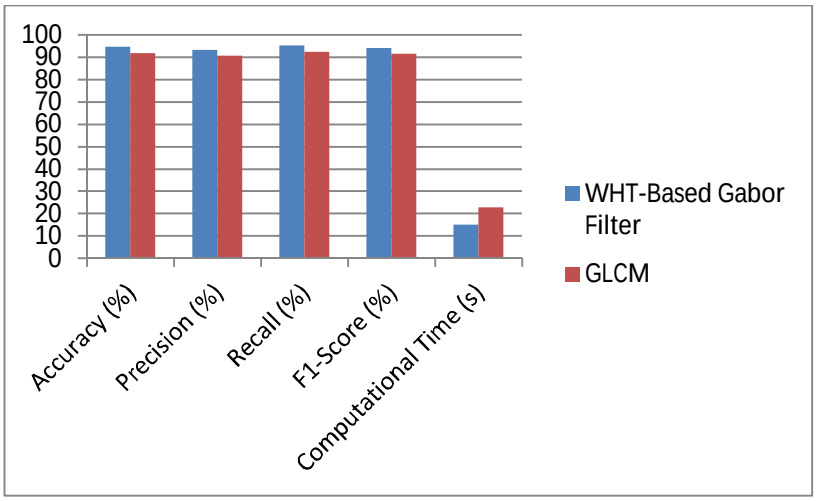


Figure 1: Performance Metrics for WHT-Based Gabor Filter and GLCM Methods

B. Detailed Analysis

1) Accuracy: The WHT-based Gabor Filter method achieves higher accuracy due to its effective combination of frequency and texture features.
2) Precision and Recall: Both methods show high precision and recall, with the WHT-based method slightly outperforming GLCM.
3) Computational Time: The WHT-based Gabor Filter method demonstrates greater efficiency, highlighting its suitability for real-time applications.

V. CONCLUSION

The comparative analysis shows that the WHT-based Gabor Filter method generally outperforms the GLCM method in terms of accuracy, robustness, and computational efficiency for brain tumor detection using MRI images. These findings suggest that the WHT-based method is better suited for automated detection systems, though GLCM remains a viable option depending on specific clinical requirements.

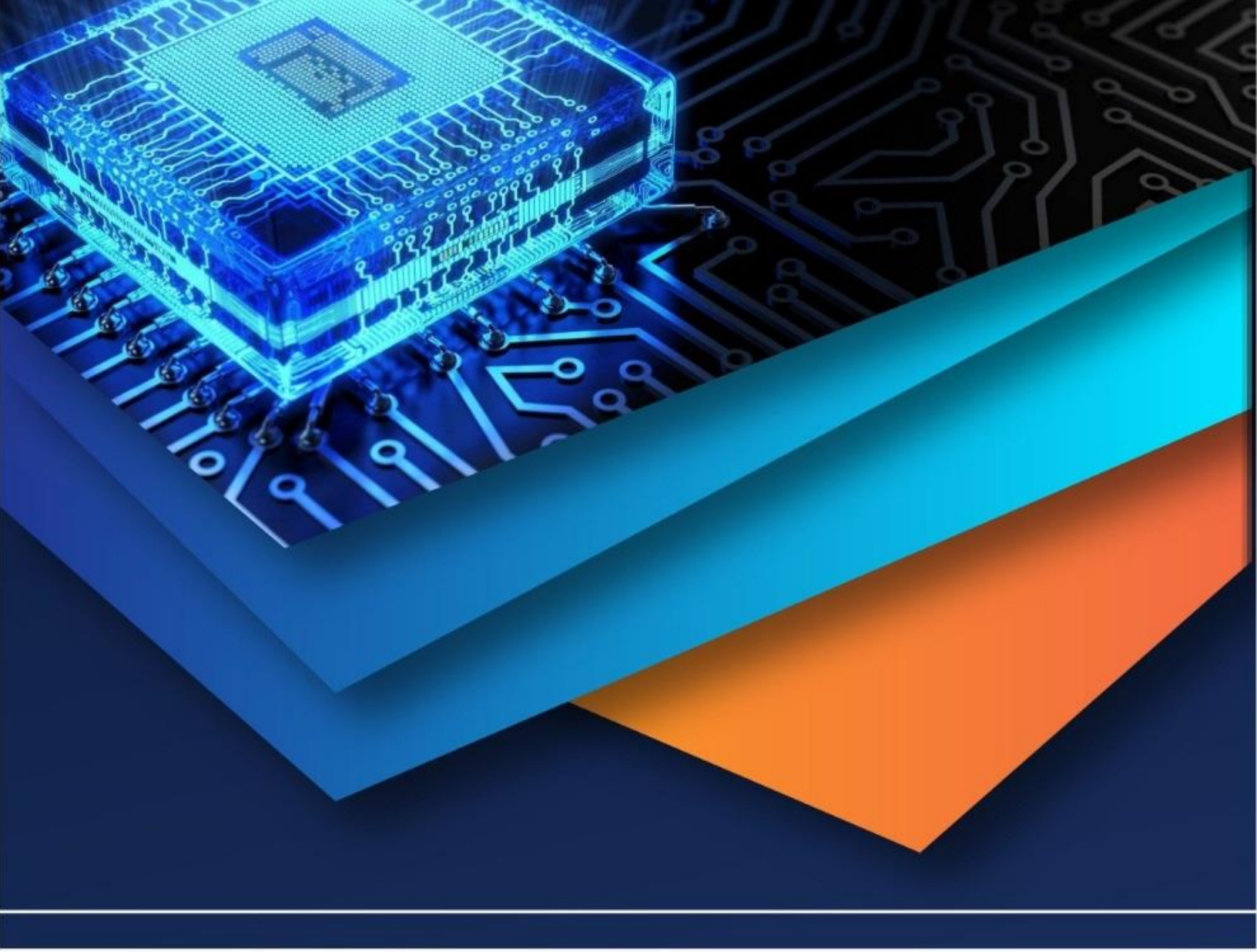
VI. FUTURE WORK

Future research can explore hybrid approaches combining the strengths of both methods and integrating deep learning techniques for enhanced feature extraction and classification.

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