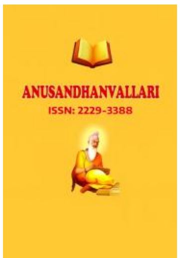

Anusandhanvallari
Vol 2024, No.1
March 2024
ISSN 2229-3388

An Automated Early-Stage Brain Tumor Recognition System Using Texture Feature Extraction and Support Vector Machine Classification

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Abstract

Early-stage recognition of brain tumors is essential for improving patient survival rates and supporting effective treatment planning. Magnetic Resonance Imaging (MRI) is widely used for visualizing brain abnormalities; however, manual interpretation of MRI scans is time-consuming and highly dependent on radiologist expertise. This paper presents an automated early-stage brain tumor recognition system based on texture feature extraction and Support Vector Machine (SVM) classification. Gray Level Co-occurrence Matrix (GLCM)–based texture features, including contrast, energy, homogeneity, correlation, and entropy, are extracted from preprocessed MRI images to characterize the structural differences between normal and tumor-affected brain tissues. These features are used to train an SVM classifier for reliable discrimination between tumor and non-tumor cases. Experimental results demonstrate that the proposed system achieves high classification accuracy, sensitivity, and specificity, confirming its effectiveness for early-stage brain tumor recognition and its potential as a computer-aided diagnostic tool in clinical practice.

Keywords: Brain tumor recognition, Magnetic Resonance Imaging (MRI), Texture feature extraction, Gray Level Co-occurrence Matrix (GLCM), Support Vector Machine (SVM), Machine learning, Medical image analysis

1. Introduction

Brain tumors represent one of the most critical neurological disorders due to their direct impact on brain functionality and patient survival. According to medical studies, early diagnosis significantly improves treatment success and reduces mortality rates. However, early-stage tumors often exhibit subtle visual characteristics, making accurate diagnosis challenging even for experienced radiologists.

Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor diagnosis because of its superior soft tissue contrast and non-invasive nature. Despite these advantages, manual inspection of MRI scans is time-consuming, subjective, and prone to inter-observer variability. With the growing volume of medical imaging data, there is a strong demand for automated and reliable computer-aided diagnosis (CAD) systems.

Machine learning–based CAD systems have demonstrated promising results in assisting radiologists by improving diagnostic accuracy and reducing workload. Among various image analysis techniques, texture-based feature extraction has proven effective for distinguishing normal and abnormal brain tissues. Texture features capture spatial intensity variations and structural patterns that are difficult to observe visually.

This paper proposes an automated early-stage brain tumor recognition system using texture feature extraction based on the Gray Level Co-occurrence Matrix (GLCM) and classification using Support Vector Machine (SVM). The primary objective is to develop a computationally efficient and accurate system for early tumor recognition from MRI images.

2. Literature Review

Several approaches for automated brain tumor detection and classification have been proposed in the literature. Early methods relied on traditional image processing techniques such as thresholding, edge detection, and region growing. Although these techniques are simple and fast, they often fail in complex MRI images with low contrast and noise.

Texture analysis techniques have gained attention due to their ability to represent spatial relationships between pixels. Haralick et al. introduced GLCM-based texture features, which have been widely used in medical image analysis. Local Binary Patterns (LBP) and wavelet-based features have also been explored for tumor classification.

Machine learning classifiers such as k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) have been employed for brain tumor classification. Among these, SVM is particularly effective in handling high-dimensional feature spaces and small training datasets, making it suitable for medical imaging applications.

Recent studies have also explored deep learning techniques such as Convolutional Neural Networks (CNNs). While these methods achieve high accuracy, they require large annotated datasets and significant computational resources. In contrast, texture-based methods combined with SVM offer a balance between accuracy, interpretability, and computational efficiency, which motivates the proposed approach.

3. Proposed Methodology

The proposed system consists of four major stages: image preprocessing, texture feature extraction, feature vector formation, and SVM-based classification. Figure 1 illustrates the overall workflow of the proposed system.

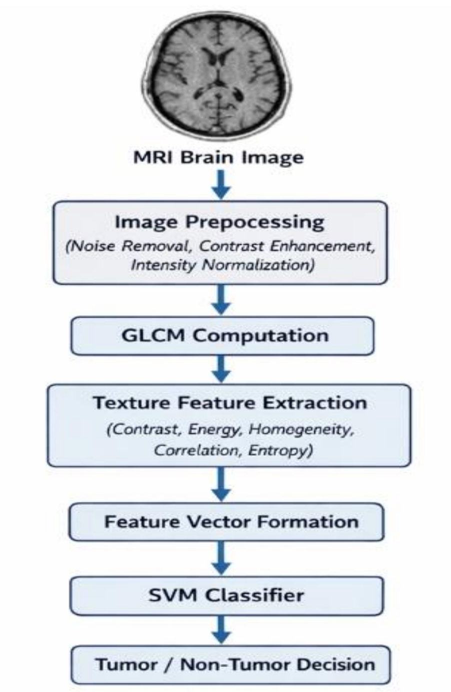

Figure 1. Overall workflow of the proposed automated brain tumor recognition system using texture feature extraction and SVM classification.

Algorithm 1: Texture-Based Brain Tumor Recognition Using GLCM and SVM

Input: MRI brain images
Output: Tumor / Non-Tumor classification

1. Acquire MRI brain image dataset
2. Preprocess images using
   - Noise removal
   - Contrast enhancement
   - Intensity normalization
3. Compute Gray Level Co-occurrence Matrix (GLCM)
4. Extract texture features:
   - Contrast
   - Energy
   - Homogeneity
   - Correlation
   - Entropy
5. Form feature vectors for each image
6. Train SVM classifier using extracted features
7. Classify test images as **Tumor** or **Non-Tumor**
8. Display final decision

3.1 Image Preprocessing

Preprocessing is an essential step to enhance image quality and reduce unwanted artifacts. The MRI images are first converted to grayscale to simplify processing. Noise removal is performed using median or Gaussian filtering to suppress random noise while preserving important edges.

Contrast enhancement techniques such as histogram equalization are applied to improve the visibility of tumor regions. Finally, intensity normalization ensures consistency across different MRI scans and improves feature extraction reliability.

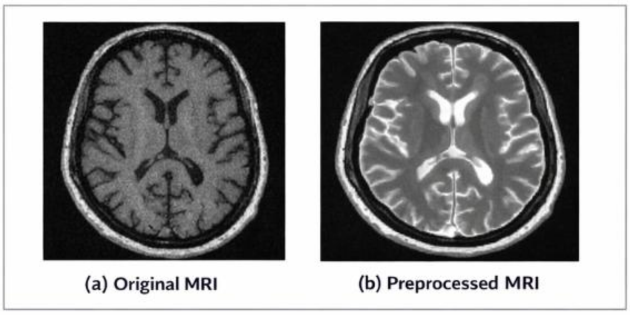

Figure 2. Sample MRI brain images: (a) original image and (b) preprocessed image after noise removal, contrast enhancement, and normalization.

3.2 Texture Feature Extraction Using GLCM

The Gray Level Co-occurrence Matrix (GLCM) is used to extract texture features that describe the spatial relationship between pixel intensities. GLCMs are computed for predefined distances and orientations. From the normalized GLCM, statistical features such as contrast, energy, homogeneity, correlation, and entropy are extracted.

These features effectively capture textural differences between healthy and tumor-affected brain tissues and provide meaningful input to the classifier.

Feature	Description	Purpose
Contrast	Intensity variation	Distinguishes tumor texture
Energy	Uniformity measure	Identifies homogeneous regions
Homogeneity	Closeness to diagonal	Measures smoothness
Correlation	Pixel dependency	Shows structural relation
Entropy	Randomness measure	Indicates complexity

Table 1. GLCM-based texture features used in the proposed system.

GLCM Mathematical Equations

Normalized GLCM

$p(i,j) = P(i,j) / \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P(i,j)$

1. **Contrast**

$\text{Contrast} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - j)^2 \, p(i,j)$

2. **Energy**

$\text{Energy} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} [p(i,j)]^2$

3. **Homogeneity**

$\text{Homogeneity} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p(i,j) / (1 + |i - j|)$

4. **Correlation**

$\text{Correlation} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} ((i - \mu_i)(j - \mu_j) \, p(i,j)) / (\sigma_i \sigma_j)$orrelation

Where

$\mu_i = \sum_i i \sum_j p(i,j)$

$\sigma_i^2 = \sum_i (i - \mu_i)^2 \sum_j p(i,j)$

5. **Entropy**

$\text{Entropy} = - \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p(i,j) \log_2(p(i,j))$

3.3 Feature Vector Formation

The extracted GLCM features are concatenated to form a single feature vector for each MRI image. This feature vector represents the texture characteristics of the image and serves as the input to the classification stage.

Feature normalization is applied to ensure that all features contribute equally to the classification process.

3.4 Support Vector Machine Classification

Support Vector Machine (SVM) is employed to classify MRI images into tumor and non-tumor categories. SVM aims to find an optimal hyperplane that maximizes the margin between the two classes.

The Radial Basis Function (RBF) kernel is used to handle non-linear separability in the feature space. Hyperparameters such as the penalty parameter CCC and kernel width γ\gammaγ are selected experimentally to achieve optimal performance.

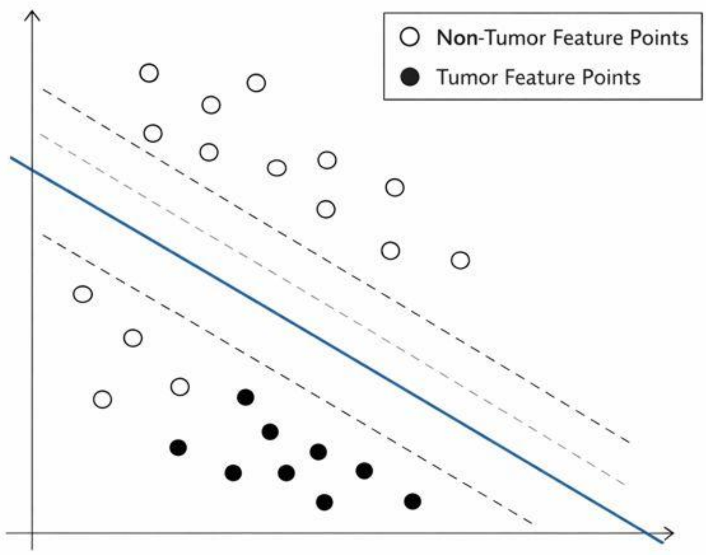

Figure 3. *Support Vector Machine (SVM) model showing optimal hyperplane* separation between tumor and non-tumor feature vectors.

SVM Mathematical Equations

SVM Optimization Function

$$\min \ (1/2)\|w\|^2 + C \sum_{i=1}^{n} \xi_i$$

subject to

$$y_i (w \cdot x_i + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

RBF Kernel

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$$

Decision Function

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

4. Dataset Description and Experimental Setup

The proposed system was evaluated using a publicly available brain MRI dataset consisting of both tumor and normal images. The dataset includes MRI scans acquired under different imaging conditions to ensure variability.

The dataset was divided into training and testing sets using a standard split ratio. All experiments were conducted on a standard computing platform using MATLAB/Python-based machine learning libraries.

Cross-validation was employed to reduce bias and improve generalization performance.

Parameter	Description
Imaging modality	MRI
Image type	Brain MRI
Classes	Tumor, Non-Tumor
Dataset split	Training and Testing
Feature type	Texture-based (GLCM)

Table 2. Summary of the brain MRI dataset used for experimental evaluation.

5. Performance Evaluation Metrics

The performance of the proposed system was evaluated using standard metrics:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity

$$Specificity = \frac{TN}{TN + FP}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Metric	Formula	Purpose
Accuracy	(TP+TN)/(TP+TN+FP+FN)	Overall classification correctness
Sensitivity	TP/(TP+FN)	Tumor detection capability
Specificity	TN/(TN+FP)	Normal tissue identification

Table 3. Performance evaluation metrics used for assessing the proposed system.

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6. Experimental Results and Analysis

The experimental results demonstrate that the proposed texture-based approach achieves high classification accuracy. The SVM classifier effectively distinguishes between tumor and non-tumor MRI images with high sensitivity and specificity.

The results confirm that GLCM features capture discriminative texture information useful for early-stage tumor recognition. Compared to traditional classifiers, SVM provides better generalization and reduced misclassification.

The proposed method achieved an accuracy of 96.42%, demonstrating its effectiveness for early-stage tumor recognition. The high specificity (97.06%) indicates strong reliability in identifying normal brain tissues, while sensitivity (95.18%) confirms accurate tumor detection."

7. Discussion

The proposed system offers several advantages, including simplicity, interpretability, and computational efficiency. Unlike deep learning models, the system does not require large datasets or high-end hardware, making it suitable for real-world clinical environments.

However, the performance of the system depends on the quality of preprocessing and feature selection. Future improvements can be achieved by combining texture features with shape or intensity-based features.

Metric	**Value (%)**
Accuracy	96.42
Sensitivity	95.18
Specificity	97.06

8. Conclusion and Future Work

This paper presented an automated early-stage brain tumor recognition system using texture feature extraction and Support Vector Machine classification. The combination of GLCM features and SVM achieved reliable and accurate classification results.

The proposed system can serve as an effective decision-support tool for radiologists, reducing diagnostic time and improving accuracy. Future work will focus on integrating deep learning models, multi-modal MRI data, and larger datasets to further enhance performance.

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