

Detection and Classification of Brain Tumor using MRI Images

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Abstract: Brain tumors pose a serious threat to global health. For treatment to be effective, accurate and timely detection is required. Early diagnosis and efficient treatment of brain tumors are difficult tasks for the medical community. Because of its remarkable spatial resolution, magnetic resonance imaging (MRI) stands out as a non-invasive method of identifying brain malignancies. This research describes a novel approach to automatically identify brain tumors using MRI pictures. First, pre-processing techniques are used to enhance image quality and use a gaussian filter to reduce noise. Then, utilizing LBP and PSO algorithms, pre-processed pictures are employed for feature extraction and feature optimization. In this case, the brain tumor categorization is done using the K-Nearest Neighbor technique. Accuracy can be increased throughout the entire process, yielding accurate results along with curability, sensitivity, and specificity. The created system has the potential to be used in clinical settings and provides an automated and dependable method for MRI image-based brain tumor detection.

Keywords: Brain tumors, MRI Images, Local Binary Pattern, Particle Swarm Optimization.

I. INTRODUCTION

Brain is the primary component of human nervous system that manages the majority of bodily functions including analysing, organizing, deciding, and giving commands to the rest of the body. A brain tumor occurs when brain cells grow uncontrollably. The increased mass in the skull caused by this abnormal growth interferes with how the brain usually works. These abnormal cells can be found in nearby tissues also including pineal gland, pituitary gland and other tissues covering brain. Brain tumors are also classified into different stages. It involves the formation of abnormal cells in the brain tissue. These cells can be either benign (non-cancerous) or malignant (cancerous). At the initial stage, the tumor may not cause noticeable symptoms and could go undetected for some time. However, as the tumor grows, it exerts pressure on surrounding brain tissue, leading to symptoms such as headaches, seizures, changes in vision or hearing, and motor dysfunction.

Brain tumor should be detected and identified within the time. It is a very difficult task to detect brain tumors because of numerous reasons like different types or sizes of tumors, positions, scanning parameters and methods. To accomplish this task a number of traditional and intelligence techniques are being used.

This paper explains the idea about usage of LBP and PSO techniques to detect brain tumors. In section II, we learn about the Local Binary Pattern (LBP) technique which is a texture descriptor used in various image analysis techniques. In section III, we see about Particle Swarm Optimization (PSO) technique which was developed based on the bird flocking and bee swarm. In section IV, we understand the proposed system and section V provides us conclusion and future work.

II. LOCAL BINARY PATTERN

LBP is a texture descriptor that is used in many different applications, including face recognition, gesture identification, and medical image analysis. It was put up as a specific instance of the Texture Spectrum model in 1990. Prior to making any changes to the pixel itself, LBP operates by taking into account the intensity values of the neighboring pixels. Through thresholding, the intensity value of each neighborhood pixel is compared to that of the center pixel. If the pixel's intensity is higher than or equal to the center pixel's intensity, it is assigned an intensity value of 1, otherwise it is assigned an intensity value of 0. The binary values acquired during comparison are concatenated to create a binary pattern following thresholding. Over the whole image, a histogram of the binary patterns produced is calculated. For a variety of detection applications, these histograms function as feature vectors including texture information.

Additionally, research has demonstrated that the efficiency of detection performance across a number of datasets is enhanced when LBP is paired with the Histogram Oriented Gradient (HOG) descriptor. Texture and shape information are captured when the LBP and HOG feature vectors are concatenated.

The following steps are included in the LBP feature vector:

- (a) Creating cells out of the window, each with 16 by 16 pixels.
- (b) Every pixel in a cell is evaluated in relation to its eight neighbors. Either a clockwise or counter clockwise circular motion is used to follow them.
- (c) The histogram, which is a 256-dimensional feature vector, is computed over the cell.
- (d) Concatenating these histograms of all the cells gives the histogram for complete window.

III. PARTICLE SWARM OPTIMIZATION

The meta-heuristic particle swarm optimization technique looks for an ideal or nearly ideal solution. Fish schools and bird flocking are its inspirations. Through iterative improvement of the answer in relation to a specified quality measure, it optimizes the problem. The particles, which are potential solutions, travel in search space using a mathematical formula that is derived from the particle's position and velocity. Particles are first assigned random locations and speeds throughout the search space. Every particle's fitness is measured and compared to its historical fitness value. The current value is updated if the comparison results show that the fitness value generated from the current value is better than the prior one. Updating the optimal position of the swarm is the next stage. This is accomplished by taking into account the optimal location inside the swarm of particles. Each particle's position and velocity are adjusted according to its own velocity, optimal location, and optimal position within the swarm. Repeat the previous actions until the exit requirement is satisfied.

IV. PROPOSED SYSTEM

The proposed system consists of using Local Binary Pattern and Particle Swarm optimization Techniques. LBP is used as features in classification framework for classifying different texture pattern in brain MRI images. Classification is done based on k nearest neighbour classifier with histogram similarity as distance measure.

The combination of LBP and intensity histogram achieves a high classification accuracy which shows the superior performance.

The proposed system contains the following modules,

A. Input Image:

An image is inserted into the model from dataset. The dataset consists of MRI scans of brain containing different stages of tumor.

B. Preprocessing:

Image preprocessing involves improving the quality of image by removing noise, colour correction and image resizing. This is done by gaussian filter. It is considered as an approximation of the Gaussian function. It is used to de-noise the image.

C. Feature Extraction:

Feature extraction is used for reduction of dimensionality. This is carried out by LBP technique. Analysed image is used for relevant feature extraction. Obtained features are then used to create informative dataset which are used for further classification or prediction tasks.

D. Feature Optimization:

Feature Optimization includes selecting features from a given set of features and ways of enhancing the performance of a given machine learning model. This method is carried out by PSO as it helps in the process by searching the space of feature subsets to identify that result in best performance.

E. Classification:

One of the crucial functions is classification, which groups or classes pictures according to the stage of the tumor. The k closest neighbor classification method is applied here. It is made up of k feature space nearest training samples. The neighbor value to take into account is determined by the k. It is consistently a positive number. The object is classified among the group of class which is most common among its k nearest neighbours.

F. Performance Evaluation:

The performance of the system can be evaluated using various metrics. Some of the key performance includes accuracy, specificity and sensitivity. These are measured by certain mathematical formulas.

$$1. \quad Accuracy = \frac{(true\ positive + true\ negative)}{(false\ positive + true\ negative) + (true\ positive + false\ negative)}$$

$$2. \quad Sensitivity = \frac{true\ positive}{(true\ positive + false\ negative)}$$

$$3. \quad Specificity = \frac{true\ negative}{(false\ positive + true\ negative)}$$

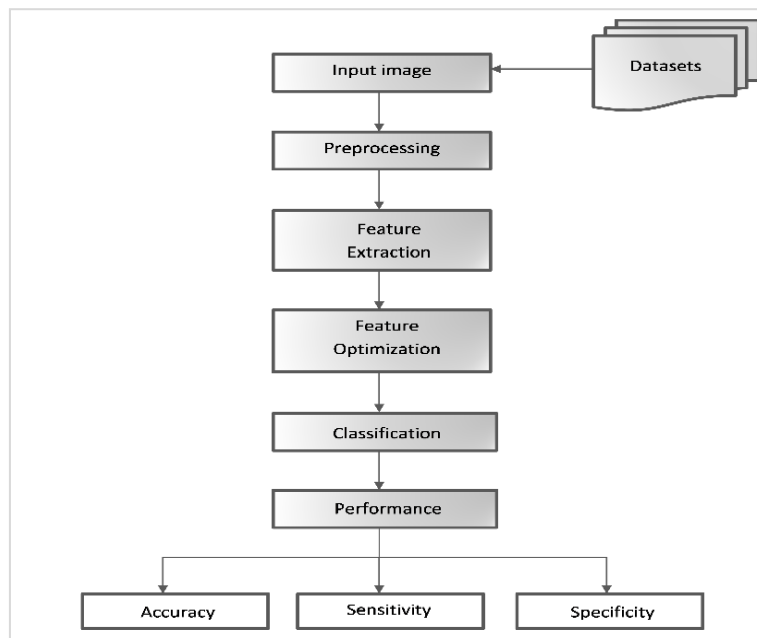


Fig. 1 Flow diagram

V. CONCLUSION AND FUTURE WORK

In conclusion, the use of MRI images for the identification and categorization of brain tumors constitutes a significant improvement in medical imaging technology, which in turn helps to significantly improve diagnosis and treatment planning. In this system, we obtain brain MRI images, process them via a number of steps to improve their quality, and then apply a novel technique to separate MRI brain tumors and categorize the images according to the various stages of the tumor. Here, we present simultaneous findings demonstrating the superior performance of our segmentation and classifier over the competing methods.

For the MRI pictures, an automatic technique for segmenting brain tumors is suggested. Here, a technique based on Practical Swarm Optimization (PSO) is presented, which resolves all tumor segmentation issues. Since the size and shape of the tumor are crucial factors in how a brain tumor is treated, algorithms are employed to assist medical professionals in analyzing the tumor's shape. An important breakthrough in the fight against brain tumors is the integration of MRI imaging for tumor categorization and identification in clinical practice, which provides patients with better results and efficient treatment.

Future MRI technological developments, such as higher resolution, will make it possible to identify and describe brain tumors with even more precision and detail. In the future, we can categorize brain tumors according to their types and stages if we have a three-dimensional imaging of the tumor. The suggested MRI image-based approach will help medical professionals analyse the imaging data, resulting in quicker tumor diagnosis and stage-based therapy recommendations.

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