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OPTIMIZED SIMILARITY BASED HIERARCHICAL CLUSTERING APPROACH FOR BRAIN MRI IMAGE SEGMENTATION

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Abstract

Brain Magnetic Resonance Imaging (MRI) techniques are the kind of diagnostic techniques that are used to analyse and understand the structure of human brain which serves as a starting point in identifying and understanding brain activity and diagnosis and treatment of several neurological disorders. The proposed Optimized Similarity based Hierarchical Clustering (OSBHC) is useful for the segmentation of images of the brain MRI. Hierarchical clustering is useful for data analysis. It catches the full image of the brain in all sides. It is a well proved method. OSBHC has improved segmentation performance and can precisely segment brain tissue, according to the segmentation results of a large number of brain MRI images. The OSBHC technique outperforms other related clustering algorithms in terms of performance and flexibility.

Keywords: Clustering approach, image segmentation, neurological disorders, MRI images.

1. INTRODUCTION

The most significant component of the central nervous system is the brain.An MRI scans of the brain a simple skill that delivers crystal-clear images of the internal head components, primarily the brain. Brain MRIs are used by medical professionals to assess, identify, and keep track of a variety of medical disorders that affect your brain or other head structures. A semi-imaging technique called magnetic resonance imaging (MRI) creates three-dimensional, intricate anatomical images. For disease detection, diagnosis, and therapy monitoring, it is frequently employed. Based on cutting-edge technology, it stimulates and detects changes in the rotational axis of protons in the water that makes up living tissues.

Using MRI camera system, doctors and researchers must study the semi shape and function of the human brain. Cells of numerous sorts build up the corpse. Every single cell has a distinct purpose. When cells are unable to manage its natural development, they divide frequently and randomly. A tumour is a mass comprising consisting of cells of extra cells. When a doctor is diagnosing and treatment a person, an MRI assists in the diagnosis. Pictures of fatty tissue are generated using this imaging method.

The obtained medical photos depict the inside structure, but the doctors are interested in more information than just equal photographs, such as how to highlight unusual tissue and identify its own thickness, shape, and other characteristics. If these duties are carried out by the doctors themselves, it may be inefficient, time-consuming, and burdensome for them. In order to accurately detect brain tumours from Neuroimaging, a machine system can be created.Brain tumours can be roughly categorised as primary brain tumours, where the tumour originates in the brain, and secondary brain tumours, where the tumour has moved to the brain through metastasis from another part of the body. Secondary brain tumours have always been dangerous, but primary brain tumours do not migrate to other body parts and might be either noncancerous. Compared to benign tumours, malignant tumours are riskier and more dangerous. Benign tumours are harder to detect than malignant tumours. A 3-D brain model and three dimensional analyserprograms are necessary for the precise detection of a cancerous growth.

A recursive division of a dataset into progressively smaller clusters is known as a hierarchical clustering. A weighted graph with edge weights that represent pair wise similarities or differences between data points serves as the input. A rooted branch is used to portray a hierarchical clustering, with each leaf representing a data point and each internal node representing a cluster that includes its descendant leaves. A common method for analysing, categorising, and pre-processing huge sets is computing a hierarchical clustering, which is a fundamental issue in data analysis.

To separate an MRI brain image into distinct areas with various granularities, to identify communities, or to ascertain the origin of life, hierarchical clustering can be applied. In various academic fields, including machine learning, large data analysis, and bioinformatics, developing efficient and consistent algorithms for computing hierarchical clustering is crucial. From a theory perspective, hierarchical clustering has received much less attention than flat partition-based clustering, which divides the dataset into k pieces.

When discussing partition-based clustering, a well-defined target, such as k-means, k-medians, etc., is often minimised. Regarding the techniques utilised in practise, hierarchical clustering has instead been examined at a more procedural level. Such algorithms can be broadly divided into two categories: agglomerative heuristics that construct the candidate cluster tree top-down, such as bisection k-means and recursive sparsest-cut, and divisive heuristics that construct the tree bottom-up, such as average-linkage, single-linkage, and complete-linkage.

2. LITERATURE SURVEY

Tianbao Ren et al [1]proposes a method based on fuzzy clustering where emphasizes the role of pre-processing based on histogram equalization to improve the performance of fuzzy clustering to extract relevant features from MRI images. Histogram equalization is a method thatworks by enhancing image contrast by disseminating grey values in an image uniformly and improving image contrast to focus on relevant details in an image.Khairul et al[2] proposes a method for brain tumour detection from MRI images using k-meansalgorithm, principal component analysis and super pixels.The feature extraction method SLIC and PCA based approaches are used where this method groups pixels nearby and based on similarity considering intensity and compactness.Principal component-based feature extraction which generates eigen vectors and covariance matrix by identifying similarities from large data and the features extracted are given to k-means for obtaining better results.

The identification of tumours and the challenging task and this identification can be improved by better pre-processing and feature extraction approaches which can make clustering and classification tasks even easier. Li Liu et al[3] proposes a multimodal approach for brain tumour segmentation by combining multiple modals of brain MRI data using sparse clustering algorithm by grouping images based on similarity with same characteristics such as texture, brightness and contrast and generating super pixels.Li Liu et al[3] also discuss about the problems in image segmentations such as nonstandard intensity ranges, shape of tumour, Riciannoise and large lesions that may affect the overall structure of the brain

Muhammad Arif et al[4] proposes a method which extracts features GLCM that generates covariance matrix as statistical texture features by considering relationship among pixels such as energy, homogeneity ,corelation and contrast and also feature extraction is done using genetic algorithm and classified using naïve Bayesian classifier and SVM classifier. ROI based region extraction [5]is proposed where dependent salient regions are extracted from MRI images using visual saliency. By combining saliency and FCM clustering for segmentation better results are obtained and ROI based image extraction performance is improved without pre-processing in MRI images.

There are various distance measures such as Euclidean distance, city block distance, cosine and Chebyshev that can play an important role in clustering algorithm [6]. These measures which are found by the location and proximity of pixels. When it comes to hierarchical clustering out of these distance measures city block and corelation is better for k-means.Mirzaei et al discusses about proximity criterion functions in clustering such as single, complete,average, centroid linkage and sum of squared distance.

Medical images such as MRI images have intricate structures and precise results in segmentation is very important for medical diagnostics. The identification of tumours in these images plays an integral part in treatment of psychiatric disorders, neurogenerative diseases and surgical planning [6]. Segmentation methods can be classified as region-based, pixel-based classification, threshold-based, and model-based. A combined clustering approach of PSO algorithm and fuzzy entropy clustering [7] is proposed which uses entropy measures to identify clusters from given data set.

3. METHODOLOGY

Clustering algorithms are frequently utilised in Data Mining and are widely used to solve real-world problems in domains such as Medicine, Psychology, Botany, and so on. Clustering algorithms group similar data elements in to clusters from a given dataset. Among different types of clustering algorithms hierarchical algorithms are frequently used.

Hierarchical clustering algorithms simultaneously detecting various clustering’s that could reveal previously unidentified underlying patterns in the data set.When these algorithms are applied to a data collection, a hierarchy is always produced even if the data set is entirely random and devoid of any sort of cluster structure. It is known that different hierarchical clustering algorithms, each with its own attributes and requirements, can produce distinct cluster structures when applied to a data set with a cluster structure.

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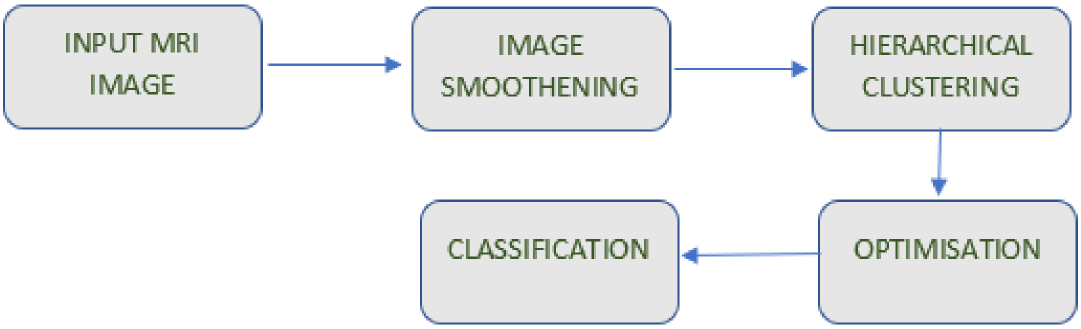

Fig 3.1 Proposed methodology

Image Pre-processing

The main purpose of pre-processing is to raise the image's quality so that we can analyses on it more effectively. Pre-processing allows us to eliminate unwanted distortions and improve specific qualities that are essential for the application we are working on. Those characteristics could change depending on the application.To eliminate high spatial frequency noise from a digital picture, low pass filtering (also known as smoothing) is used. Low-pass filters typically use a moving window operator, which affects one pixel at a time, altering its value by some function of a local region (window) of pixels. The operator goes over the picture, affecting all of the pixels.

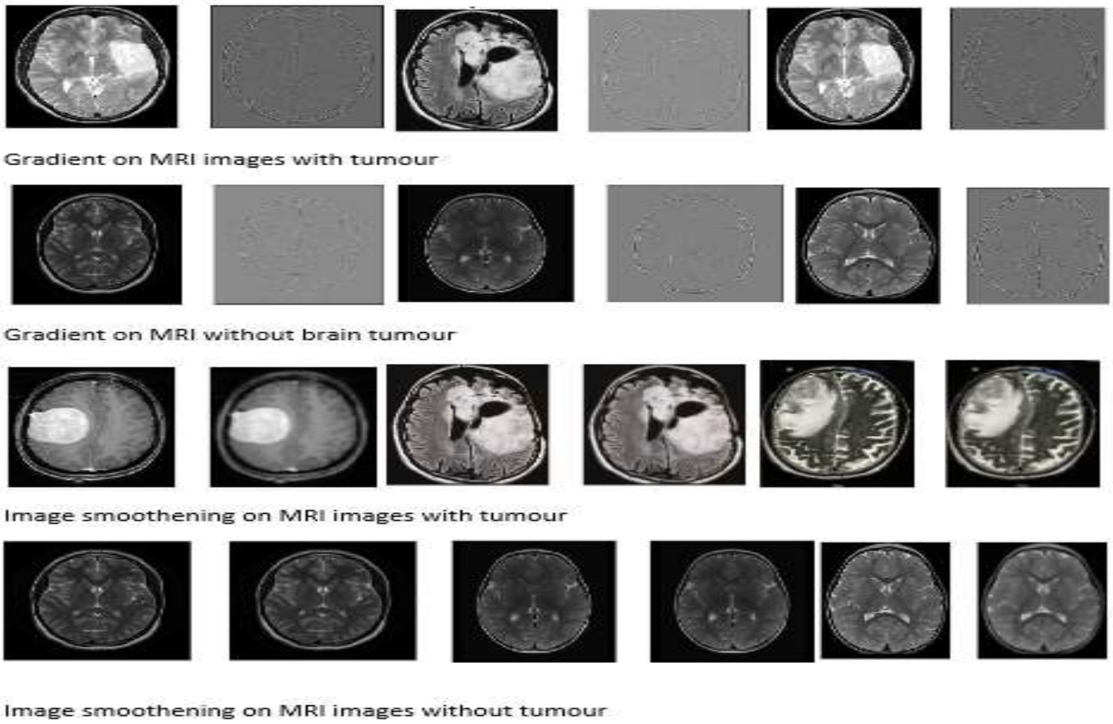

Fig 3.2 Image smoothening on MRI images

Agglomerative clustering

A type of hierarchical clustering algorithm is agglomerative clustering. It is an unsupervised machine learning technique that divides the population into several clusters, with similar data points in the same cluster and dissimilar data points in different clusters. Points in the same cluster are more closely spaced. The points in the various clusters are far apart.We need methods for measuring object similarity in order to decide which objects/clusters should be combined or divided.The Manhattan distance captures the distance between two pixel locations by averaging the pairwise absolute difference between each variable, whereas the Euclidean distance does it by averaging the squared difference in each variable.

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CLUSTERED IMAGES WITH BRAIN TUMOUR

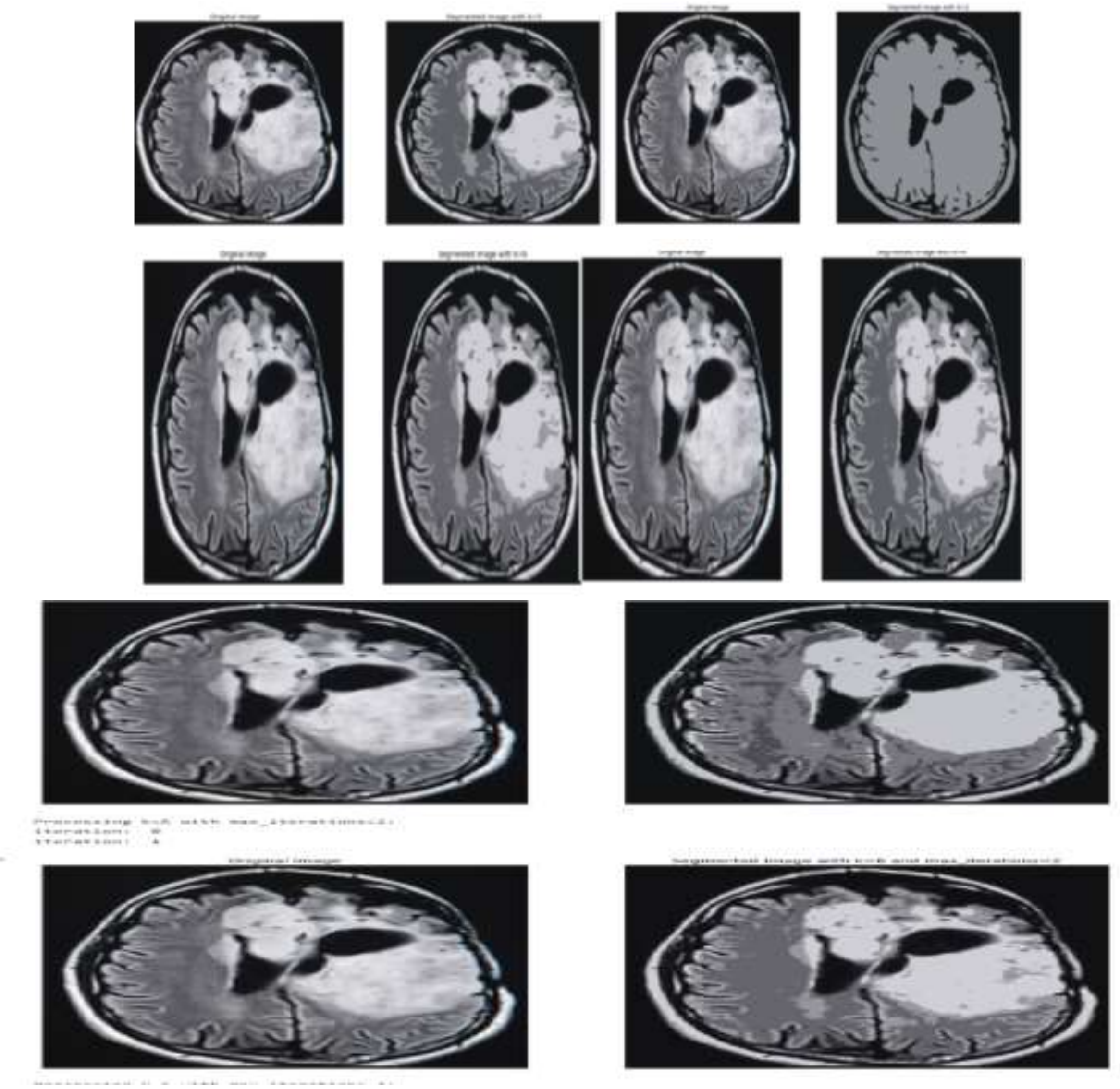

Fig 3.3 Agglomerative clustering on MRI images

Optimization

The Firefly Algorithm is a population-based metaheuristic inspired by nature that is computationally effective. It derives its solution technique from the properties of fireflies. A meta-heuristic approach based on population that draws inspiration from the natural world's firefly flashing behaviour.

STEPS IN FIREFLY OPTIMIZATION

1. INITIAISE POPULATION
2. CALCULATE FITNESS
3. MOVE FIREFLY I TOWARDS J
4. CALCULATE ATTRACTIVENESS
5. REPEAT UNTIL MAXIMUM ITERATION

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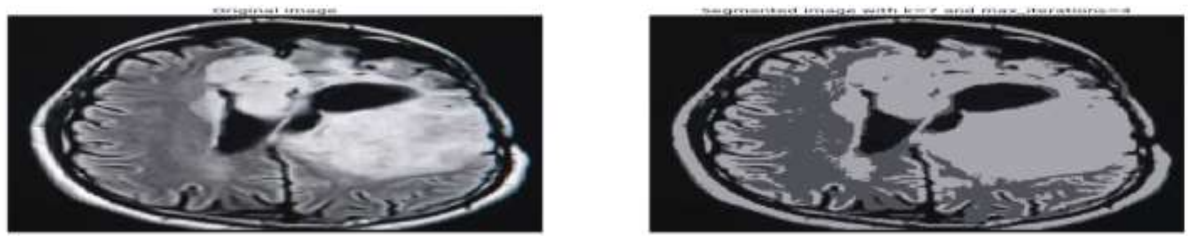

Fig 3.4 Optimized clustering on MRI images

4. CONCLUSION AND FUTUREWORK

An extremely successful combination of the hierarchical clustering and firefly optimization with the exploratory bio inspired nature of genetic algorithms offers remedies for comparable computational resources but greater quality. Future research would examine performance of other optimisation algorithm and other image pre-processing techniques.

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