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Improving Prediction Model Accuracy by Wavelet Transform Based on MRI Images of Brain Tumour Patients

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Abstract— Medical imaging provides proper diagnosis of brain tumour. Various techniques are implemented to detect the brain tumour from MRI images. One among them is the Denoising wavelet transform (DWT) method which is used to improve the accuracy of a prediction model by making use of MRI images in order to predict the overall survival time of brain tumour patients. Wavelet transform method detects the location and size of the tumour. The proposed methodology consists of image acquisition, Calculation of tissue density maps, statistical analysis. MRI provides generous information about the human soft tissue, which helps in the recognition of brain tumour. Image Segmentation categorises pixels into sections and hence defines the object regions. This paper proposes the image and feature fusion techniques to improve the accuracy of the prediction model.

Keywords— *Machine learning, Denoising wavelet transform, MRI images, Histogram, Glioma brain tumour, Linear Regression*

I. INTRODUCTION

Identification of early brain tumor plays an essential role in diagnosis and treatment of brain diseases. For analysis and localization of brain tumors, radiologists and physicians use medical imaging techniques. Magnetic Resonance Imaging is widely used for medical imaging. To distinguish between normal and tumorous tissues, a contrast resolution may be induced. The contrast in MRI images is the solution to segregate healthy from tumors tissues. The widely used weighted sequences in MRI images are: T1-weighted, T2-weighted and Proton-Density Weighted. T1 relaxation time or spin-lattice relaxation time, caused by the interaction between the spin and its environment. T2 is the transverse relaxation time or spin-spin relaxation time, caused by the interaction between the spin and other nearby spins, and proton density represents the number of protons per unit volume. The presence of a tumor inside normal brain tissues makes the temperature to increase and these changes in thermal behaviour is caused by the relatively higher metabolic heat generation, their angiogenesis, and their vascular dilation in comparison with healthy tissues. Several MRI frameworks such as, T1 and T2 [2] relaxation times, proton density, diffusion coefficient changes depending on the temperature. These characteristics has been used for non-invasive temperature measurement for thermotherapy monitoring for the clinical treatment of tumors.

As mentioned earlier tumors alter the temperature distribution around tumorous cells and therefore these generated temperatures have an effect on MR parameters. In the present work we have used T1 relaxation time to measure tumour temperature effect on MRI signal by simulating T1 weighed images using spin echo (SE) pulse sequence. This parameter has been shown its dependence on temperature. The effect of temperature changes is easily identifiable using T1-weighted sequences, since the increase in temperature is seen by a loss of signal.

II. RELATED WORK

[1] BH Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", where fusing several good algorithms using a hierarchical majority vote yielded segmentations that consistently ranked above all individual algorithms. The BRATS image data and manual annotations continue to be publicly available through an online evaluation system as an ongoing benchmarking resource.The main advantage here is online evaluation system are available for benchmarking resources. Disadvantage is methodological improvements are required.

[2] S. Bakas et al., "Advancing the Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features", where Gliomas belong to a group of central nervous system tumors, and consist of various sub-regions.The glioma sub-region labels were produced by an automated state-of-the-art method and manually revised by an expert board-certified neuroradiologist.The advantage is, it is highly used in clinical prognosis. Disadvantage is it fails in case of varying density clusters.

[3] H. Ohgaki and P. Kleihues, "Population-based studies on incidence, survival rates, and genetic alterations inastrocytic

and oligodendroglia gliomas," where the data on prognostic and predictive factors in patients with gliomas are largely based on clinical trials and hospital-based studies. This review summarizes data on incidence rates, survival, and genetic alterations from population-based studies of astrocytic and oligodendrogliomas that were carried out. The advantage is improving clinical outcomes in glioblastoma. Disadvantage is the utility of perfusion MRI becomes increasingly recognized.

[4] L. Chato and S. Latifi, "Machine Learning and Deep Learning Techniques to Predict Overall Survival of Brain Tumor Patients using MRI Images", where This paper presents a method to automatically predict the survival rateof patients with a glioma brain tumor by classifying the patients MRI image using machine learning (ML) methods.The best prediction accuracy based on classification is achieved by using deep learning features extracted by a pre-trained convolutional neural network (CNN) and was trained by a linear discriminant. The advantage is the best prediction accuracy based on classification is achieved. Disadvantage is it does not work well in case of high dimensional data.

III. METHODOLOGY

This paper consists of 6 modules, which are,

1.Image acquisition: Picture obtaining in picture preparing can be comprehensively characterized as the activity of recovering a picture from some source, so it tends to be gone through whatever forms need to happen a short time later. The picture has been acquired; different techniques for preparing can be connected to the picture to play out a wide range of vision undertakings.

In this paper wavelet transformation is used to convert image into binary vector format i.e. machine-readable format. To find correlation between the prediction classes. The Discrete Wavelet Transform is based on sub band coding. In this transform, wavelets are sampled discretely and there is convolution followed by decimation. The most important information in the signal appears in high amplitudes and the least important information in the signal appears in very low amplitudes. The basic idea is simple. Appropriate high pass and low pass filters are applied to the data at each level and also there is down sampling done at each level. The image is divided in to four sub bands (LL, LH, HL, HH) by using DWT. The sub bands will have half of the size of the original image. The LL sub bands can be regarded as the approximation component of the image, while the LH,HL,HH sub bands can be regarded as the detailed components of the image. The advantages of Discrete Wavelet transform are as follows: It provides fast computation. It can be implemented easily and also reduces the computation time and resources required. The Discrete wavelet transform provides sufficient information for the analysis and synthesis of the signal. The Discrete Wavelet Transform also suffers from the following drawbacks: Poor directionality, Translational invariant and Lack of phase information. In order to overcome the translational invariant of the Discrete Wavelet transform, Stationary Wavelet Transform is designed. In this transform, there is no down sampling occurs between levels. They provide better time-frequency localization and the design is simple. The basic idea is simple. Appropriate high pass and low pass filters are applied to the data at each level and it produces two sequences at the next level. There is no decimation step in SWT as in DWT therefore the new sequences have the same length as the original sequence and it provides redundant information.

Histogram Equalization: The intensity level equalization method is an image with increased dynamic range, which will tend to have high contrast. The increased in contrast is due to the significant spread of the histogram over the entire intensity scale. In overall the increase intensity is due to the fact that the average intensity level in the histogram of the equalized image is better than the original. Its function is increase the dynamic range of intensity levels in an image.

2. Pre-processing: Every one of the pictures are first pre-processed in three stages: I) commotion decrease force non consistency redress) direct power standardization into range (0-100) utilizing a power histogram coordinating strategy. The T1w and FLAIR [2] pictures are straight co-enlisted utilizing a 6-parameter inflexible enrolment. The T1w pictures are first directly and after that nonlinearly enrolled to a normal layout made dependent on information from the ADNI1 [2] think about , empowering the utilization of anatomical priors in the division procedure. A cerebrum cover is made by twisting the layout veil back to the person's local space.

3. Features:

The process of collecting high level information of an image such as shape, texture, colour and contrast. In fact, texture analysis is an important parameter of human visual perception and, machine learning system. It is used effectively to improve the accuracy diagnosis system by selecting prominent features.

The accompanying area and power highlights are made utilizing data from the preparation information just as the person's T1w and FLAIR (Fluid Attenuated Inversion Recovery) [4] pictures. FLAIR is an MRI sequence with an inversion recovery set to null fluids. These highlights have been recently approved and checked to be useful in distinguishing WMHs.

To lessen the element space measurement and subsequently the computational weight, each picture voxel was treated as a different information point.

A highlight set was characterized dependent on an assortment of force and likelihood parameters.
All the highlights (with the exception of the MRI forces) were determined dependent on preparing information.

4. Calculation of tissue density maps: Intensity-based Segmentation Methods Classify Individual Pixels/Voxels dependent on their power.

The power probabilities of WMH and typical solid tissues (PH and $PWMH$) were acquired by ascertaining histograms of force runs inside the physically fragmented WMH veils and non-WMH cerebrum areas, separately.

The preparing dataset was created from countless named voxels; for example, all voxels inside the mind veil for the subjects that were chosen for preparing were utilized to make the preparation set - this incorporates all positive (WMH) and negative (non-WMH) model voxels.

The divisions are performed in local FLAIR space to keep away from the obscuring brought about by Resampling. To accomplish this, all pictures are non-sprightly changed to the ADNI format space, and every one of the priors and midpoints are determined and after that enlisted back in the local space utilizing the backwards nonlinear changes. Thusly, the FLAIR picture isn't resampled and just a 6-parameter inflexible change is connected to the T1w picture.

5. Classification: Irregular choice timberlands perform characterization by developing a progression of autonomous choice trees and casting a ballot between their expectations to get the grouping yield. Here, execution of arbitrary woodlands classifier is utilized with 100 estimators. Ten times cross approval crosswise over subjects was utilized to approve the execution of the classifiers. The spatial WMH likelihood maps, normal forces, and PWMH and PH were additionally determined through the cross-approval to abstain from over fitting.

Linear regression
A linear regression classifier with thresholding because of its low change, high exactness and lower calculation time contrasted and different classifiers.
Intensity-based strategies (counting thresholding, area developing, grouping, and bunching).

6. **Statistical analysis**: The power likelihood highlights mirror the probability of the anomaly of the force of the current voxel, for example how likely it is for a voxel with such force to be either WMH or typical tissue.

The estimation of the edge can decide the affectability and explicitness of the divisions; for example picking lower limit esteems can expand the affectability of the divisions with the cost of diminishing the explicitness, and the other way around.

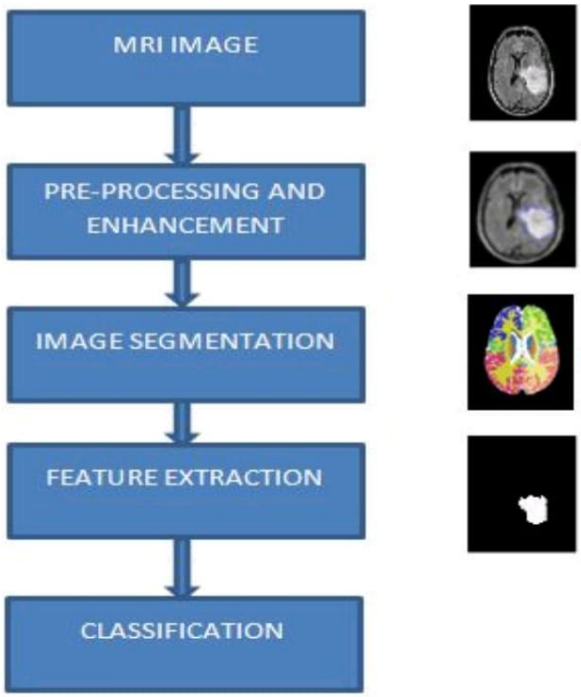


FIG1: MRI Image Processing

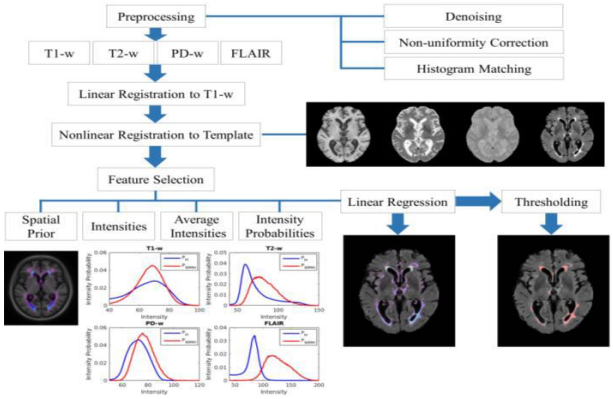


FIG2: System architecture

Design: Design consists of three levels
In first level MRI images acquiesced which will be converted to binary representation using wavelet transformation noise reduction and intensity resolution has been made and then tumour features are extracted. Extracted image and trained dataset are sent to the modules which will read the features and data from features and trained data respectively. Machine learning algorithm applied to the extracted features. In this paper Linear Regression algorithm has been applied to predict the tumour level. There are two types of tumours benign tumour and malignant tumour. Benign tumours are not harmful. A malignant tumour leads to the death of the person. If the tumour is greater than 0.75 it

is considered as high level tumour, if it greater than 0.5 it is considered as intermediate level tumour if it is less than 0.5 it is considered as low level tumour.

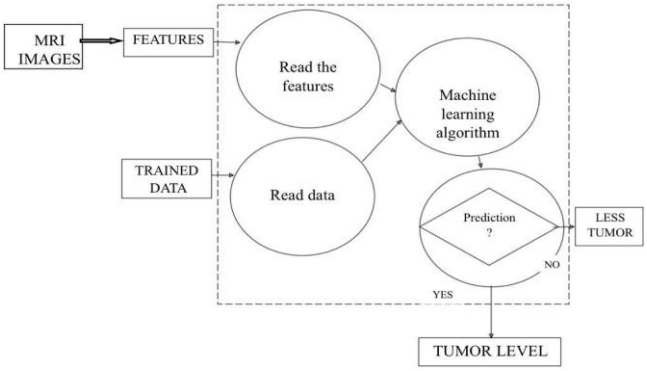


FIG 2: Dataflow Diagram

Based on the tumour level we can predict the survival time of the patient.

Algorithm used is Linear Regression Classifier

A linear regression classifier with thresholding due to its low variance, high accuracy and lower computation time compared with other classifiers. A linear regression classifier with thresholding due to its low variance, high accuracy and lower computation time compared with other classifiers. The value of the threshold can determine the sensitivity and specificity of the segmentations; i.e. choosing lower threshold values can increase the sensitivity of the segmentations with the price of decreasing the specificity, and vice versa. A linear regression line has an equation of the form $Y = a + bX$, where X is the explanatory variable and Y is the dependent variable. The slope of the line is b, and a is the intercept (the value of y when x = 0).

Input: Data points (x, y)
Output: y = ax+b

Compute **a** and **b** by

$a = (n\sum xy - \sum x\sum y) / (n\sum x^2 - (\sum x)^2)$

$b = (1/n)(\sum y - a\sum x)$

To predict y value,

y = ax+b

where,

x & y are given data points

a is slope of x

b is intercept with respect to y.

However, the proposed LRC approach, for the first time, simply uses the down sampled images in combination with the linear regression classification to achieve superior results compared to the benchmark techniques. The problem of severe contiguous occlusion, a modular representation of images is expected to solve the problem. Based on this concept, we propose an efficient Modular LRC Approach. The proposed approach segments a given occluded image and reaches individual decisions for each block. These intermediate decisions are combined using a novel Distance-based Evidence Fusion (DEF) algorithm to reach the final decision. The proposed DEF algorithm uses the distance metrics of the intermediate decisions to decide about the "goodness" of a partition. The proposed LRC and Modular LRC algorithms are described. This is followed by extensive experiments using standard databases under a variety of evaluation protocols.

IV. Results and Discussion

The result shows tumour level, and the life span of the patient i,e. 0.733 which is high level tumour the patient can survive for 2 years and on other hand other shows intermediate level tumour I,e 0.693.The lifespan of the patient is 3 years.

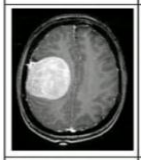
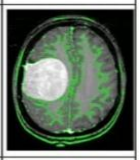
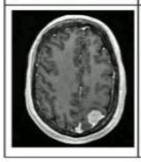
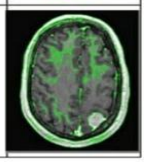
ORIGINAL IMAGE	TUMOR LEVEL	LIFESPAN	ACCURACY	RESULT IMAGE
	0.773 HIGH LEVEL TUMOR.	2 YEARS.	93.0	
	0.698 INTERMEDIATE TUMOR.	3 YEARS.	93.0	

FIG 3: Classification of tumour levels.

V. Conclusion and Future Scope

Image segmentation is extensively used in numerous biomedical-imaging applications .The focus is directed toward improvement of information from images obtained through the slice orientation and perfecting the process of segmentation to get an accurate picture of the brain tumour. Hence, an elaborated methodology that highlights new vistas for developing more robust image segmentation technique is much sought. Wavelet Transform improves the quality of the MRI images as well as the performance of a prediction model for the overall survival time of the brain tumor patients based on MRI images. The image and feature fusion techniques are used to improve the accuracy of the prediction model**.**

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