Weekly Project Report – 2

Ahmedabad University

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Automated Multi-Parametric MRI Segmentation of Post-Treatment Glioma Sub-Regions Using Classical Machine Learning and Contour-Based Methods

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***Abstract*—In this report, we present the progress of our project in Week 2 on automated brain tumor segmentation using classical machine learning techniques. This week, we have read two important research articles related to the subjects of Random Forest-based segmentation and atlas-enhanced ensemble learning. With the help of their advantages, we developed a simplified hybrid structure based on feature engineering, abnormality modeling, Multi-scale Random Forest classification, and Markov Random Field (MRF) refinement. The dominant interest of the project is implementation of Tumor vs Non-Tumor by using multi-modal MRI images. This report describes the problem, literature research, methodology with MRF refinement and implementation plan of Week 3.**

I. Introduction

Brain tumor segmentation is one of the activities that can be accomplished in the process of analyzing medical imagery. It helps physicians to learn the dimensions, shape and location of the tumors. The aim of such a project will be to create a classical machine learning system which will be capable of automatically detecting the existence of tumors in multi-modal MRI images.

We possess the BraTS data set [1]giving us MRI images and manually localized tumors.

The first objective will be to use binary segmentation:

- Class 0: Non-Tumor
- Class 1: Tumor

This model will also be extended to recognize tumor sub-regions during later stages.

II. Problem Statement

The problem of voxel classification is referred to as segmentation. Voxels (pixels) of the MRI image are supposed to be identified as tumor or non-tumor.

The main challenges are:

- The severity of MRI images of different patients is different.
- The areas of tumors are much smaller in comparison to the normal brain tissue (class imbalance).
- Intensity overlap can be found in tumor and normal tissue.
- Tumor morphology and demarcation is disrupted.
- The noisy output of at pixel level classification may be segmentation.

To overcome these barriers we use extraction of features, scoring of abnormalities, multi-scale Learning of Random Forests and spatial refinement with the assistance of MRF.

III. Literature Review

A. Paper 1: Random Forest with Active Contour

The classical model of learning proposed in the first article [2] has multi-step stages that include:

- Multi-scale local and contextual image patch feature extraction.
- Random Forest probability predictors of tumor in voxels.
- Active Contour refinement to smooth out boundary of segmentation.

This particular method is a combination of machine learning classification and geometry refinement of boundaries.

B. Paper 2: Ensemble Learning with Atlas-Based Enhancement

The second paper [3] has presented a classical ensemble learning procedure that:

- Normalization of intensity histogram.
- Gradient and texture measures are measures that are graphically drawn.
- Atlas based modeling of abnormalities to identify deviation of normal brain tissue.
- Ensemble classifiers based on segmentation tree.

This method helps to improve the identification of the tumors; method implies statistical comparison with the normal brain areas.

C. Summary of Literature Study

In accordance with the studies of the two papers we have observed:

- Paper 1 deals with learning in a large scale and boundary refinement.
- Paper 2 is concentrated on the preprocessing and the identification of the abnormalities.

Based on these observations, we came up with a hybrid classical model that combines the multi-scale learning of the Random Forest on the multi-scale level and abnormality modeling and spatial refining of Markov Random Fields.

IV. Proposed Hybrid Methodology

Our proposed approach will be a preprocessing with approach, feature extraction with approach, abnormality scoring with approach, multi-scale Random forest classification with approach and MRF-based refinement with approach.

A. Step 1: Preprocessing

- Normalization of the values in the MRI intensity by histogram.
- Create multi modes MRI (T1, T1c, T2, FLAIR).

This is to ensure that the same level of intensity is given to the patients.

B. Step 2: Feature Extraction

For each voxel, we extract:

- The strength values of option MRI modalities.
- Mean and quality of the neighborhoods.
- Strength of gradient to identify edges.

These properties assist the model in the recording of texture and structural data.

C. Step 3: Abnormality Score

A voxel intensity is contrasted with the statistical properties of normal brain tissue of the training data in order to obtain the abnormality score.

In areas where the tumor is likely to be a part of the voxel, the voxel is likely to be very dissimilar to one another in the sense of patterns of normal tissues.

D. Step 4: Multi-Scale Random Forest Classification

Two training of the Random Forests is performed using:

- Minor places in neighborhood (as to details).
- Greater neighborhood characteristics (in order to possess greater structural background).

Both of them are then implemented to give out the probability of the output which is utilized in the creation of a voxel based tumor probability map.

E. Step 5: Tumor vs Non-Tumor Prediction

Each voxel is classified as:

- Non-Tumor (0)
- Tumor (1)

Training is done using a balanced sampling to deal with the problem of class imbalance.

F. Step 6: Markov Random Field (MRF) Refinement

Once the voxels are classified, then it becomes possible to see the discrepancies in space. We use Markov Random Field (MRF) refinement step to enhance the quality of segmentation.

MRF uses a spatial smoothness in which neighboring voxels are promotional of similar labels. It integrates:

- A value of information (the proposed random forest probabilities).
- A smoothness score (penalization of non-similarity in the adjacent voxels).

The refinement process is also performed to correct the problem of single noisy proposals and generate less bumpy boundaries of the tumor.

G. Step 7: Final Cleaning

In order to create the final tumor mask, there are some elementary morphologic operations to perform, 1 removal of thin details and the sealing of holes.

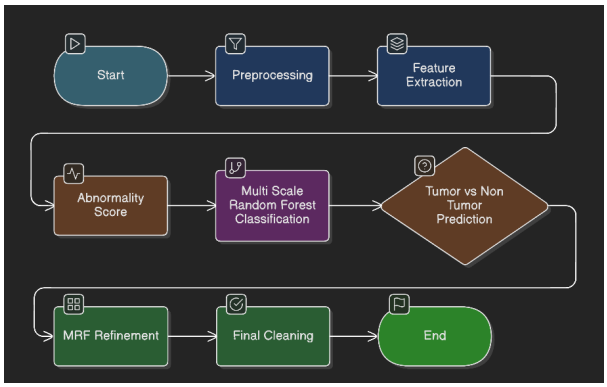

Fig. 1: Flowchart of the methodology

V. Week 2 Progress

During Week 2, we:

- There were two typical papers on ML segmentation that were analyzed.
- Their weak points and strong points were established.
- This led to the development of a hybrid system that integrated random forest, abnormalities modeling and optimization of MRF.
- The preprocessing strategies, feature extraction strategies and training strategies.

VI. Plan for Week 3

For Week 3, we intend to:

- Implement intensity normalization.
- Scoring of abnormalities and feature.
- Random forest binary classifier training.
- MRF matrix spatial smoothing.
- Test modalities combinations.
- New Tumor VS Non-Tumor segmentation mask preparation.
- Dice Similarity Score basing on performance.

The actual functional basis of simple binary tumour segmentation is with MRF refined which is the main objective of week 3.

References

[1] B. H. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging, 2015.

[2] C. Ma, G. Luo, and K. Wang, "Concatenated and Connected Random Forests with Multiscale Patch Driven Active Contour Model for Automated Brain Tumor Segmentation."

[3] Á. Győrfi, L. Szilágyi, and L. Kovács, "A Fully Automatic Procedure for Brain Tumor Segmentation from Multi-Spectral MRI Records Using Ensemble Learning and Atlas-Based Data Enhancement," Applied Sciences, 2021.