ITDAT304 EMERGING TRENDS IN DATA TECHNOLOGY

FINAL CASE STUDY REPORT

Report on MRI Tumor Classification and Segmentation Using Image Processing Techniques

Ashitosh Dhungana

Introduction:

MRI also known as Magnetic Resonance Imaging is a widely used imaging technique the provides high-contrast images of soft tissued in the brain making it particularly effective in detecting brain tumors. In comparison to other imaging methods like CT, MRI is highly effective when it comes to visualizing soft tissues due to its sensitivity to water content and its capability to produce high-resolution images.

It can take a lot of time and skill to manually analyze MRI scans. This procedure is streamlined by automatic classification and segmentation models, which enable quicker, more reliable, and maybe more accurate tumor identification. Automatic systems can help radiologists and doctors by identifying problem areas and provide quantitative insights by utilizing machine learning and deep learning models.

Objective:

The main goal of this project is to enhance and observe the techniques of medical image processing and build a system that can classify and segment brain tumors in MRI images.

In summary, this study blends sophisticated segmentation methods with the strength of CNN-based classification. It seeks to develop a tool that can both detect the existence and kind of a tumor and display a comprehensive visual map of the tumor's area. Such a technology could help physicians make well-informed judgements by increasing the speed and accuracy of diagnostics. In addition to that, it also focuses on several image processing methods like windowing, histogram analysis, storing metadata in dataframe, voxel size and volume, segmentation using clustering techniques.

Fundamentals of Image Processing:

Preprocessing is considered a crucial step in image processing that prepares the data for further analysis and ensures consistency in the input images that will be later fed in the model.

In this project resizing and normalization have been applied as a step for preprocessing. Every MRI image is scaled to 128x128 pixels for this project. This particular size was selected to minimize computing expenses while balancing the requirement for enough resolution to identify tumor features. Because the downsized photos match the CNN's predicted input shape, the model can analyze each image consistently.

Consistent input dimensions enhance the overall performance of the classification and segmentation tasks by facilitating batch processing and increasing the effectiveness of model training.

Also, normalization was done during segmentation to adjust pixel values in images to a common range typically between 0 and 1. Pixel intensities in MRI pictures change because to variations in lighting, machine settings, and imaging techniques. In order to assist the model train more efficiently and prevent the issue of one image's high intensity overpowering another, normalizing the pixel values guarantees the input photos to have consistency in intensity levels.

Windowing: Windowing is a common image processing method in medical image processing which modifies an image's contrast to highlight particular tissue types.

A broad range of intensity levels can be seen in the images produced by MRI or CT imaging. Applying a certain window, we can emphasize particular structures (such as tumors or brain tissue) by concentrating on particular intensity ranges.

Windowing MRI images helps by enhancing tissue contrasts, allowing both the classification model and segmentation algorithms (e.g., K-means clustering) to better differentiate between tumor and non-tumor regions.

A close-up of a brain scan

Description automatically generated

Fig: Windowing activated

Conversion of Metadata into a Dataframe:

Metadata is arranged in a tabular fashion when it is converted to a DataFrame structure (using libraries like pandas), making it simpler to analyze, filter, and integrate with other patient data.

A DataFrame can store details about each MRI scan as individual rows, with columns for attributes like tumor type, acquisition parameters, and voxel size. This format facilitates the exploration of metadata for insights or quality control.

The model's performance may be impacted by variations in scan quality or resolution that are disclosed by the metadata.  
It is also easy to find any discrepancies in voxel sizes or acquisition settings that could require standardization by looking at the information in a DataFrame.

A screenshot of a computer

Description automatically generated

Fig: Conversion of metadata to dataframe

Voxel Size and Histogram Analysis:

The foundation for comprehending picture resolution consistency which is necessary to preserve model accuracy across various scans is provided by voxel size analysis.

A screenshot of a computer screen

Description automatically generated

Fig: Histogram analysis of the pixel distribution

According to both figures, the majority of intensities are grouped around comparable low values, indicating that the intensity distributions across many photos are generally consistent. Because the images have same intensity characteristics, this consistency can help with model training.

By normalizing and windowing, the data becomes more uniform and relevant to the regions of interest (e.g., tumor areas), which should help the model focus on meaningful structures, improving classification and segmentation accuracy.

Methodology:

The dataset that was analyzed was obtained from a reliable source(Kaggle) that consisted of training and testing set of images were organized on the basis of tumor types. Each MRI image was labeled with its respective tumor type.

To improve the model's generalization and diversify the training material, data augmentation was used. Typical augmentation methods consist of:  
Rotation: Images are slightly rotated to mimic MRI scan variances.  
Flipping: To enhance orientation diversity, perform both horizontal and vertical flips.  
Scaling: To simulate varying scan resolutions, zoom in and out.  
Brightness Adjustments: Modifying the brightness of an image to mimic changes in illumination. This helped the data to reduce overfitting enabling the model to learn invariant features and improve performance.

A computer screen shot of a computer program

Description automatically generated

Fig: Data Augmentation

Model Architecture and Training:

To classify the MRI images into their respective tumor types, a Convolutional Neural Network (CNN) was employed. CNNs are highly effective in image classification tasks due to their ability to capture spatial hierarchies in data.

The architecture consists of multiple convolutional layers with ReLU activation function that extracts features from the images by learning filters that work on specific patterns.

Followed by pooling layers that reduce dimension of the image to retain essential feature of the MRI image.

Furthermore, those features are flattened and passed by the fully connected layers and finally activated via SoftMax activation function to output the probabilities of the four classes (glioma, meningioma, nontumor and pituitary) specifying a multi-class classification output.

When it comes to the loss function, categorical cross entropy guides the model to adjust the weight to improve classification accuracy.

A diagram of a diagram of a computer

Description automatically generated with medium confidenceFig: Model Architecture

The training of the model is done through training dataset, with validation dataset(being split form the training dataset itself)is used to tune the hyperparameters and prevent overfitting. Furthermore, the training process is iterated over 20 epochs and all the results produced post training are noted.

Segmentation:

For the purpose of segmentation, K-means clustering was applied to segment the MRI images by distinguishing tumor and non-tumor regions based on pixel intensity. In MRI scans, tumors and non-tumor regions often have distinct pixel intensities. Tumor regions may appear brighter or darker than surrounding tissue, depending on the imaging modality and scan settings. K-means was configured for this project to produce two clusters (K=2), one of which represented the tumor region and the other the non-tumor/background regions. The program can split the image according to intensity ranges with the help of these clusters.

After clustering, morphological techniques (such erosion and dilatation) were used to overcome the constraints of K-means. These procedures aid in the removal of tiny, isolated areas and improve the segmented tumor area's interconnected structure.

Thus, post all the morphological processing and K-means clustering, the segmentation map that is produced provides a basis for more intricate analysis or model training, particularly in projects where obtaining pixel-level annotations is difficult.

Evaluation and Results:

The classification model was trained to categorize MRI images into four classes: glioma, meningioma, pituitary, and no tumor. The following metrics were used to evaluate the model's performance on the test set:

Accuracy: The model achieved an accuracy of approximately 90% on the test set, demonstrating its effectiveness in distinguishing between tumor types and normal cases.

Loss: The final test loss was around 0.23, indicating that the model had a low error rate in its predictions.

A screenshot of a computer screen

Description automatically generated

Fig: Classification Results

A screenshot of a computer

Description automatically generated

Fig: Classification Results

Glioma: The model's F1 score is 0.91 due to its high precision (0.95) and recall (0.88). This suggests that although the model has some false negatives (lower recall), it is quite good at accurately identifying glioma cases.  
Meningioma: With an F1 score of 0.82 and precision and recall of 0.88 and 0.78, respectively, the model performs somewhat worse for this class. This reduced recall implies that meningioma patients may be missed by the model on occasion.  
Pituitary: With a high F1 score of 0.95 and a recall of 1.00, which means it detected all pituitary cases, the model performs exceptionally well for pituitary tumors. This implies that the model has few misclassifications and is especially good at detecting pituitary tumors.

No Tumor: This class has strong metrics, with precision of 0.93 and recall of 0.99, resulting in an F1 score of 0.96. The model correctly identifies nearly all cases of no tumor.

It has been noted that the significant lower recall (0.78) for the meningioma class indicates that some meningioma instances may be missed by the model. Techniques like data augmentation, more training samples, or adjusting model hyperparameters could enhance this.

Segmentation Results:

The tumor regions in the MRI scans were well delineated by the segmentation results. Glioma, meningioma, and pituitary tumor locations were precisely identified on the segmentation map superimposed on the original MRI scans.

A close-up of a scan of a brain

Description automatically generated

Fig: Glioma - The segmentation mask accurately outlining the glioma region.

In some cases, the tumor boundary was faint or blended into surrounding tissues, making it difficult for the segmentation to accurately delineate the edges. This led to partial or incomplete segmentation.

The size, form, and intensity of tumors vary widely. Because some tumor shapes were irregular and deviated from standard patterns, these changes made continuous segmentation difficult.

Lessons Learned and Future Works:

A significant amount of image processing insights were gathered along with use of deep learning and image processing methods for medical imaging, particularly in the segmentation and classification of brain tumors, throughout this study. Among the most important lessons learned were the value of clustering-based segmentation techniques in identifying tumor locations and the significance of pre-processing processes like normalization and resizing in improving model performance and consistency. The difficulties in identifying low-contrast tumor boundaries and controlling class imbalances were also acknowledged by us, underscoring the necessity for larger, more varied datasets and more reliable augmentation methods.

In order to enhance tumor border identification in subsequent research, a plan to improve the segmentation process by including cutting-edge techniques like U-Net will be examined. Furthermore, the diagnostic capabilities of the model might be improved by adding 3D volumetric data and metadata analysis, such as voxel sizes and patient demographics. Other possible directions for project expansion include investigating real-time deployment in clinical settings and adding more uncommon tumor forms to the dataset. By taking these actions, the system's applicability and dependability in supporting medical professionals would be significantly improved.

Conclusion:

This project effectively illustrated the use of deep learning and image processing methods for the segmentation and classification of brain tumors from MRI scans. Furthermore, it was also able to classify tumor types into glioma, meningioma, pituitary tumours, and no tumour categories with excellent accuracy by using a CNN-based classification algorithm. By using techniques like K-means clustering, the segmentation method successfully separated tumor areas and produced a visual representation to aid in diagnosis. These techniques demonstrate how automated technologies can speed up diagnostic procedures, increase accuracy, and support physicians' decision-making. With all the fundamental image processing techniques like windowing, histogram analysis, and augmentation, the project also proved that thorough pre-processing, sophisticated segmentation techniques, and a variety of datasets are the key things in improving model performance. In order to get closer to real-world use in clinical settings, this study lays the groundwork for future research that will integrate more sophisticated segmentation systems, use 3D imaging data, and investigate real-time applications.

References:

Methil, A.S., 2021, March. Brain tumor detection using deep learning and image processing. In *2021 international conference on artificial intelligence and smart systems (ICAIS)* (pp. 100-108). IEEE.

Jia, Z. and Chen, D., 2020. Brain tumor identification and classification of MRI images using deep learning techniques. *IEEE Access*.