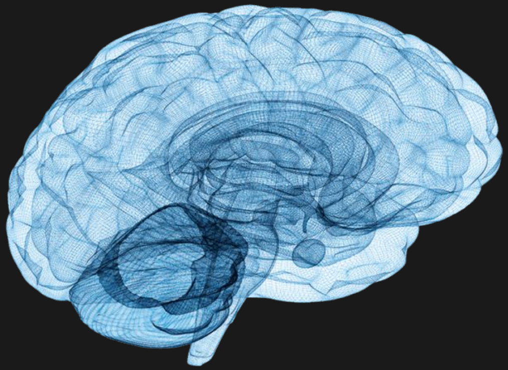
Group-6

A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network

Group Members: 1. Unnat Maaheshwari (B21072)
2. Aman Kumar Mohanty (B21036)
3. Shashank Dwivedi (B21023)
4. Srijan Sood (B21227)

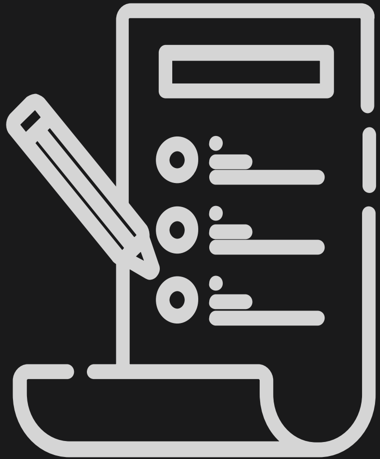


https://www.mdpi.com/2227-9032/9/2/153

Outline

This research paper introduces an innovative deep learning framework for the automatic segmentation and classification of brain tumors by:

- Using a multiscale convolutional neural network (CNN) to process MRI images at three spatial scales.
- Mirroring hierarchical visual processing for enhanced accuracy.
- Identifying meningioma, glioma, and pituitary tumors across sagittal, coronal, and axial views.
- Eliminating the need for preprocessing steps to remove structures like the skull or vertebral column.



Background

- Brain tumors require accurate segmentation and classification for effective diagnosis and treatment.
- Manual analysis of MRI images is time-consuming and prone to errors.
- Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved medical image analysis.
- Multiscale processing, inspired by the human visual system, enhances feature extraction and model performance.
- This research leverages a multiscale CNN to automatically segment and classify brain tumors from MRI data, aiming to improve accuracy and efficiency.

Objectives

- Develop and evaluate a fully automatic brain tumor segmentation and classification model using a multiscale CNN.
- Identify and distinguish between meningioma, glioma, and pituitary tumors from T1-weighted contrast-enhanced MRI images.
- Enhance model accuracy and robustness by leveraging multiscale processing.

Information about Dataset

- 3064 T1 weighted Contrast Enhanced Images
- 233 patients with 3 kinds of Brain Tumors:

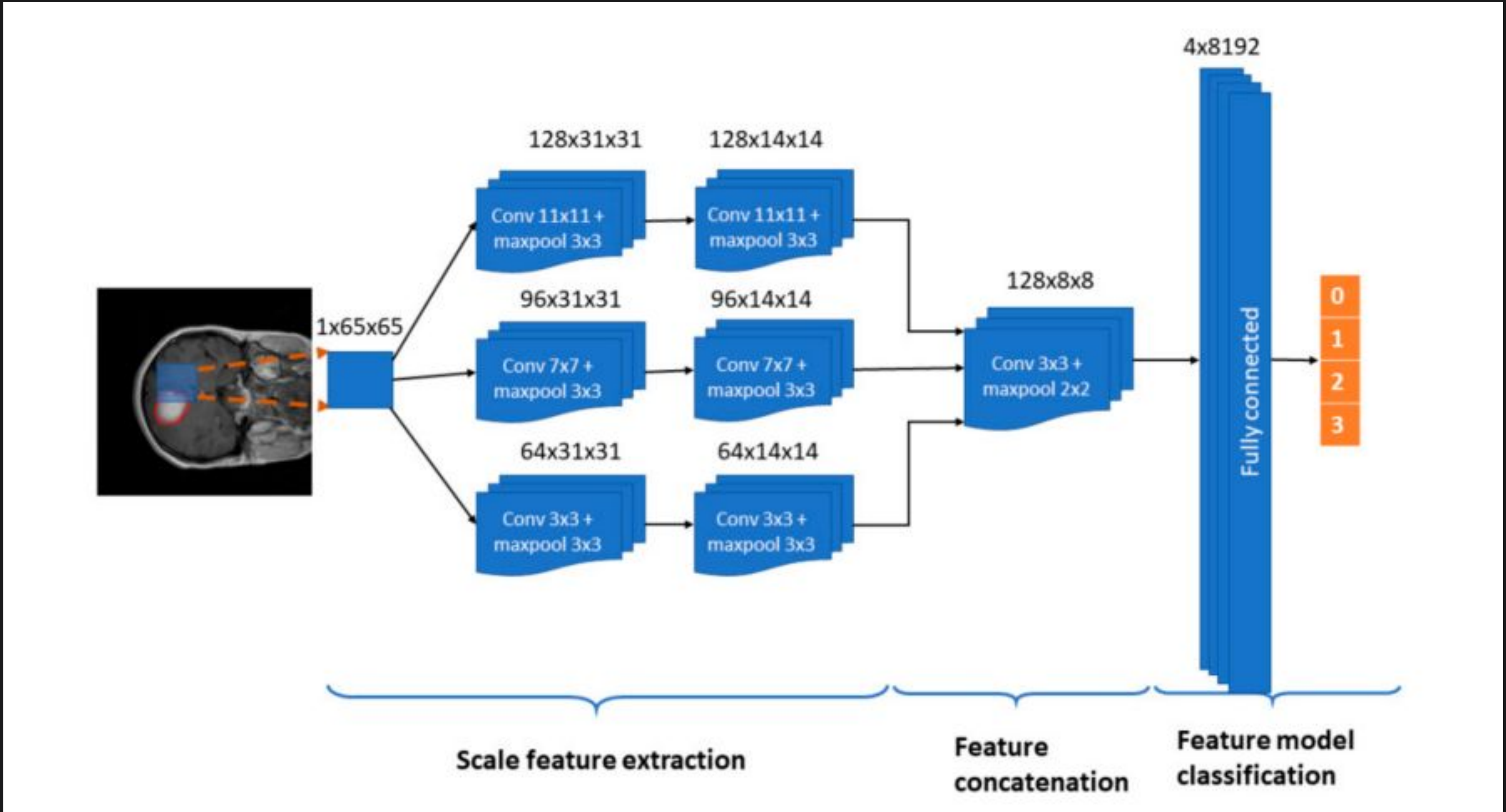
1. Meningioma - 708 Slices (Label: 1)
2. Glioma - 1426 Slices (Label: 2)
3. Pituitary Tumor - 930 Slices (Label: 3)

State-of-the-art (SOTA)

- Utilizes a novel multiscale CNN that mimics the hierarchical processing of the human visual system.
- Excels in segmentation tasks, validated by superior performance in metrics like Dice Coefficient and Sensitivity.

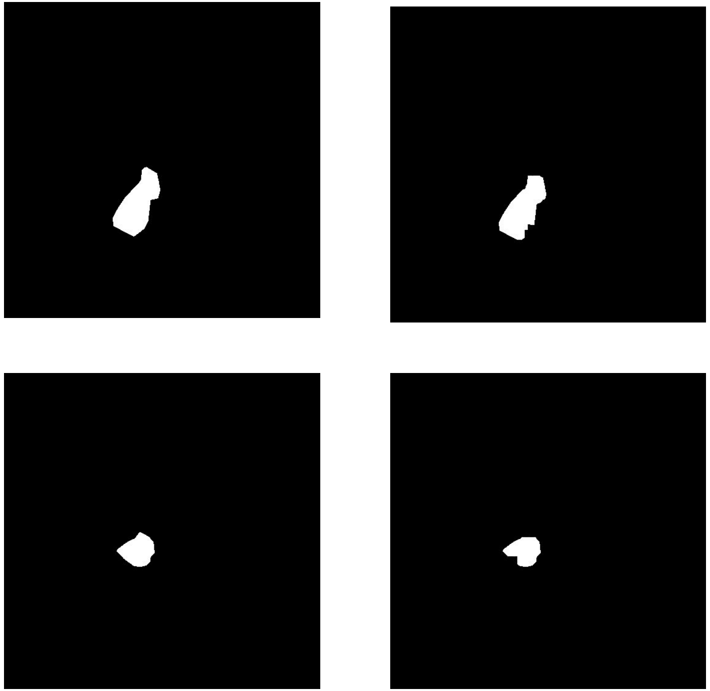
Methodology

1. **Multi-Pathway CNN Architecture:**
   - Classifies each pixel within MRI slices using a sliding window technique.
2. **Data Augmentation:**
   - Utilizes elastic transformation to enhance model robustness.
   - Prevents overfitting for more reliable results using drop-out layers.
3. **Testing:**
   - Tested on a publicly available dataset of 3064 MRI slices from 233 patients.

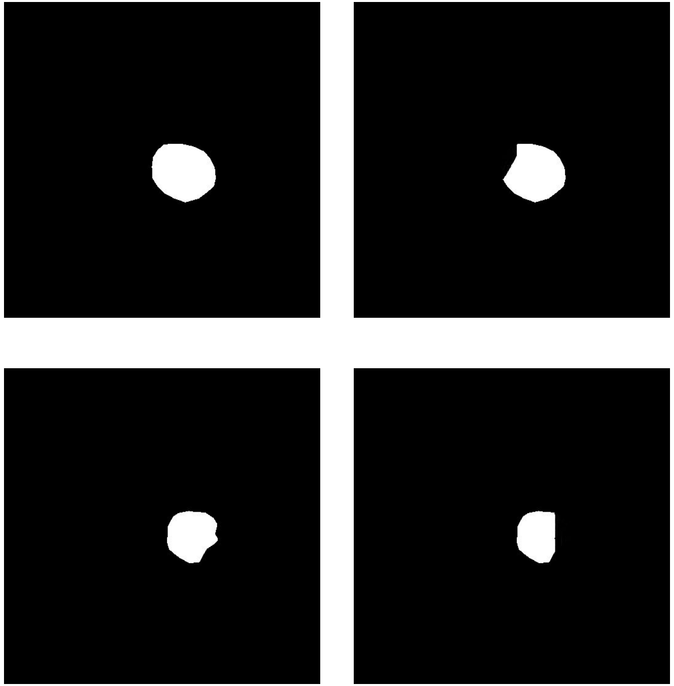


4x8192
128x31x31
128x14x14
Conv 11x11 + maxpool 3x3
Conv 11x11 + maxpool 3x3
128x8x8
96x31x31
96x14x14
1x65x65
Conv 7x7 + maxpool 3x3
Conv 7x7 + maxpool 3x3
Conv 3x3 + maxpool 2x2
Fully connected
0
1
2
3
64x31x31
64x14x14
Conv 3x3 + maxpool 3x3
Conv 3x3 + maxpool 3x3
Scale feature extraction
Feature concatenation
Feature model classification

Implementation - Results



ACTUAL
VS
PROJECTED



Implementation - Analysis

Original Model:

1. Accuracy: 0.973
2. Dice Index: 0.828 (average)
3. Sensitivity: 0.940 (average)

Our Implementation:

1. Accuracy: 0.831
2. Dice Index: 0.717 (average)
3. Sensitivity: 0.78 (average)

Objectives Achieved

- Fully automatic segmentation and classification using multiscale CNN.
- No need for preprocessing steps like skull stripping.
- Achieved 0.831 accuracy.
- Dice Index: 0.717
- Sensitivity: 0.78
- Segmentation and classification of meningiomas, gliomas, and pituitary tumors.
- Developed an FCN architecture and apply the method to other imaging fields.

Future Scope and Conclusion

- Assists medical professionals in diagnosing brain tumors more efficiently and accurately.
- Promises improved patient outcomes.
- Future work will explore the adaptability of this multiscale CNN approach to other medical imaging challenges.
- Emphasizes the model’s potential for broad applicability in healthcare diagnostics.

Thank You

Any Questions?