Enhanced Brain Tumor Classification from MRI Images Using Deep Learning Model

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Introduction

DICOM Image

- De-facto standard for medical imaging. e.g. CT scan, Radiography, Ultrasonography, MRI, etc
- Water molecules of a patient's body release energy that is captured by the machine
- A 3D imagery is generated from where a slice of the clear abnormalities is taken
- DICOM is not just a file format. Rather it is a complete package of data transfer, storage, and display protocol that provides all functionalities.

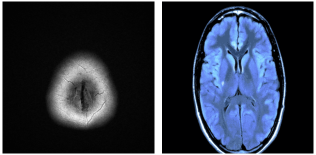


Figure: Brain MRI

Introduction (Cont.)

Issues of DICOM Image

- Uses 16-bit signed data to represent pixel intensities that ranges from -32,768 to 32, 767
- Irregular pixel intensities

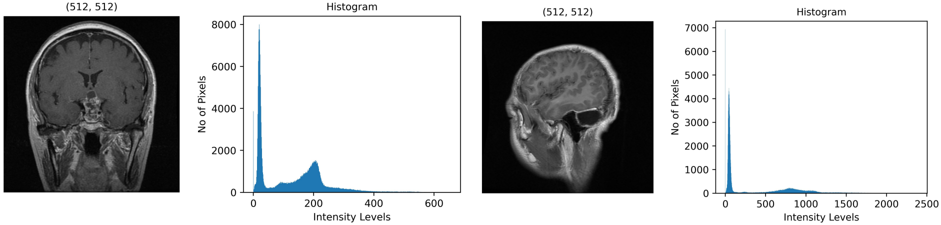


Figure: Inspection of MRI Image [1]

Ref. 1: J. Cheng, ”brain tumor dataset”, `https://figshare.com/articles/dataset/brain_tumor_dataset/1512427`, 4 2017.

Related Work-I

Brain tumor classification using convolutional neural network [2]

Contribution:

- Proposed pre-processing techniques such as Gaussian Filtering and Histogram Equalization
- Less complex CNN model with good performance

Limitation:

- Did not consider to map/scale pixel intensities
- Not efficient compared to other state of the art methods

Ref. 2: S. Das, O. F. M. R. R. Aranya, and N. N. Labiba, "Brain tumor classification using convolutional neural network," in 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), pp. 1–5, 2019.

Related Work-II

An efficient method to classify brain tumor using cnn and svm [3]

Contribution:

- Combined CNN and SVM to create a Hybrid model
- Compared the CNN and the Hybrid model

Limitation:

- Did not apply any kinds of pre-processing
- Complex model

Ref. 3: Z. A. Sejuti and M. S. Islam, "An efficient method to classify brain tumor using cnn and svm," in 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), pp. 644–648, 2021.

Related Work-III

Brain tumor classification for mr images using transfer learning and fine-tuning [4]

Contribution:

- Normalized pixel intensities using Min-Max Normalization
- Block-wise fine tuning and Transfer Learning
- Good Performance

Limitation:

- Used VGG19, that is too complex and resource hungry
- Overfitting issues

Ref. 4: Z. N. K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali, S. Ahmed, and J. Lu, “Brain tumor classification for mr images using transfer learning and fine-tuning,” Computerized Medical Imaging and Graphics, vol. 75, pp. 34–46, 2019.

Related Work-IV

Brain tumor detection using convolutional neural network [5]

Contribution:

- Proposed methodology on Binary classification BRATS Dataset
- Performed classification using traditional algorithms from statistical features and CNN

Limitation:

- Did not apply pre-processing for CNN
- Too simple CNN model, not reliable

Ref. 5: T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim, and F. Muhammad Shah, “Brain tumor detection using convolutional neural network,” in 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), pp. 1–6, 2019.

Research Questions

- How to deal with DICOM image?
- Does our deep learning model perform better compared to other state of the art methods?
- Is the proposed method good?

Research Objectives

- Biomedical Image Processing
- Building an efficient Convolutional Neural Network Model
- Improved Classification Accuracy
- Lower Computational Cost and Higher Performance

Flow Diagram

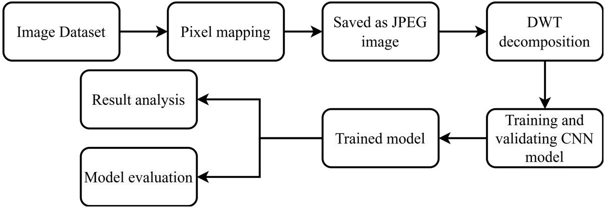


Figure: Proposed methodology for classification using CNN

Reading Dataset

- 3,064 T1-weighted CE-MRI images [1] from 233 patients
- 3 kinds of brain tumor: Meningioma (708 slices), Glioma (1426 slices), and Pituitary tumor (930 slices)
- Stored in Matlab file format(.mat) where image pixel data denotes the DICOM image

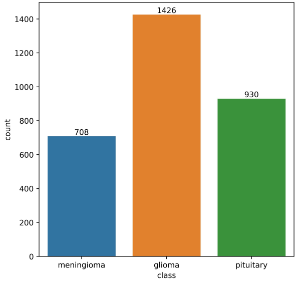


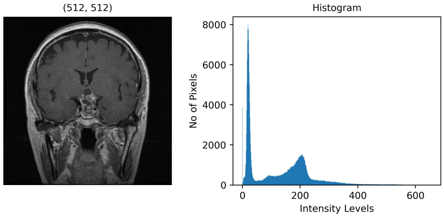
Figure: No. of Samples and Types

Ref. 1: J. Cheng, ”brain tumor dataset”, https://figshare.com/articles/dataset/brain_tumor_dataset/1512427, 4 2017.

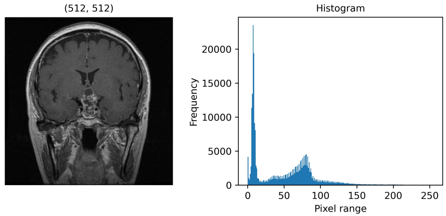
Pre-processing-I

Pixel Scaling

$$scaled\_img = \frac{img - \min(img)}{\max(img) - \min(img)} \times 255$$



(a) Before Scaling (512 × 512)



(b) After Scaling (512 × 512)

Figure: Pixel Scaling

Pre-processing-II

2-level Discrete Wavelet Transformation

- Configuration: haar wavelet, periodization mode
- Input Image $\rightarrow$ cA_1 (approximation coefficient 1), cH_1 (horizontal detailed coefficient 1), cV_1 (vertical detailed coefficient 1), and cD_1 (diagonal detailed coefficient 1)
- $cA_1 \rightarrow cA_2$, cH_2, cV_2, cD_2

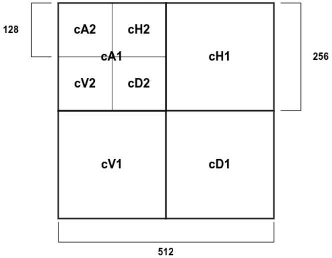


Figure: Image Decomposition using DWT

Model Architecture

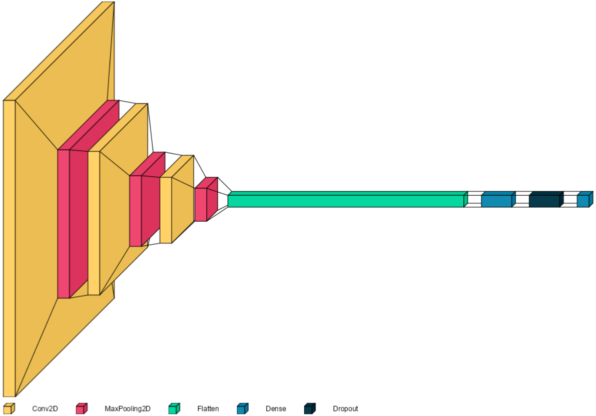


Figure: CNN Model

Model Architecture (Cont.)

Table: Model Summary

Layers	Output	Parameters
Conv1	(None, 126, 126, 32)	320
Max_Pool_1	(None, 63, 63, 32)	0
Conv2	(None, 61, 61, 32)	9248
Max_Pool_2	(None, 30, 30, 32)	0
Conv3	(None, 28, 28, 64)	18496
Max_Pool_3	(None, 14, 14, 64)	0
flatten	(None, 12544)	0
fc1	(None, 512)	6423040
dropout	(None, 512)	0
fc2	(None, 3)	1539
Total trainable parameters: 6,452,643, Non-trainable parameters: 0		

Hyperparameters

Table: Parameters used in the proposed method

Image Augmentation Parameters	i. Rescale	1./255
	ii. Fill mode	nearest
	iii. Shear range	0.2
	iv. Zoom range	0.2
	v. Horizontal flip	True
Model Parameters	i. Epoch	100
	ii. ReduceLROnPlateau	Factor 0.8
		Patience 5
		Cooldown 1
		Min lr 1.00E-04
		Monitor val_loss

System Algorithm

Algorithm Overall Proposed Methodology

Start
Import Image Dataset
Pre-process the input data:
  i. Pixel mapping and storing in the local drive.
  ii. Achieve ideal dimension of 128x128 using 2D DWT
Pass the pre-processed data to the CNN
Extract features using CNN
Perform classification using Neural Network
End

Experiments

Table: Experiment 1

Method	Metrics Accuracy(%)		
	OA	**AA**	**Kappa**
Pixel saturation → Gaussian filtering→Histogram Equalization + CNN [2]	91.85	90.6	85.68
Exp1: Pixel mapping → Gaussian filtering →Histogram Equalization + CNN	**94**	**93.32**	**90.66**

Ref. 2: S. Das, O. F. M. R. R. Aranya, and N. N. Labiba, “Brain tumor classification using convolutional neural network,” in 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), pp. 1–5, 2019.

Experiments (Cont.)

Table: Experiment 2

Method	**Metrics**		
	Accuracy(%)		
	OA	**AA**	**Kappa**
Exp2: Pixel mapping + Proposed CNN	96.13	96.08	93.92
Proposed: Pixel mapping→2D DWT + CNN	**96.9**	**96.55**	**95.16**

Performance Comparison

Table: Performance Comparison with Existing Methods

Method	Metrics				Class		
	Accuracy(%)			Others	Meningioma	Glioma	Pituitary
	OA	AA	Kappa				
Pixel saturation → Gaussian filtering→ Histogram Equalization + CNN [2]	91.85	90.6	85.68	Sensitivity	0.94	0.84	0.98
				Precision	0.79	0.96	0.95
				Specificity	0.97	0.88	0.99
CNN-1 [3]	90.23	88.83	84.53	Sensitivity	0.76	0.91	0.99
				Precision	0.8	0.9	0.97
				Specificity	0.934	0.917	0.995
CNN + SVM [3]	92.83	90.92	88.59	Sensitivity	0.78	0.96	0.99
				Precision	0.88	0.93	0.96
				Specificity	0.939	0.96	0.995
VGG19 + Fine Tuning [4]	94.29	93.84	91.09	Sensitivity	0.9	0.96	0.95
				Precision	0.88	0.95	1
				Specificity	0.967	0.962	0.981
CNN-2 [5]	90.38	88.33	84.76	Sensitivity	0.7	0.96	0.99
				Precision	0.9	0.87	0.96
				Specificity	0.905	0.966	0.995
Experiment 1: Pixel Mapping → Gaussian filtering → Histogram Equalization + CNN	94	93.32	90.66	Sensitivity	0.86	0.96	0.98
				Precision	0.91	0.92	0.99
				Specificity	0.955	0.962	0.991
Experiment 2: Pixel Mapping + Proposed CNN	96.13	96.08	93.92	Sensitivity	0.95	0.96	0.97
				Precision	0.9	0.97	1
				Specificity	0.984	0.964	0.988
Proposed: Pixel Mapping → 2D DWT + CNN	**96.9**	**96.55**	**95.16**	Sensitivity	0.93	0.98	0.99
				Precision	0.95	0.96	1
				Specificity	0.976	0.981	0.995

Graphs

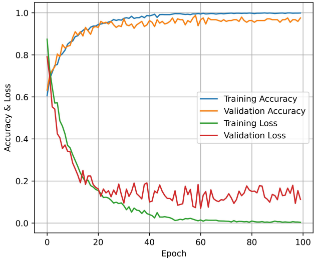


Figure: Training-Validation Accuracy and Loss Curve

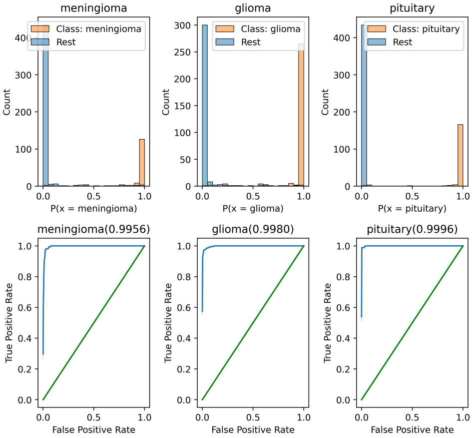


Figure: ROC-AUC OVR

Conclusion

- Practical and Efficient
- Optimized approach to extract features
- Better performance compared to other state of the art methods

Future Work

- To make the model more simple
- More experiments on other datasets
- More analysis on different methods

References

[1] J. Cheng, "brain tumor dataset." `https://figshare.com/articles/dataset/brain_tumor_dataset/1512427`, 4 2017.

[2] S. Das, O. F. M. R. R. Aranya, and N. N. Labiba, "Brain tumor classification using convolutional neural network," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, pp. 1–5, 2019.

[3] Z. A. Sejuti and M. S. Islam, "An efficient method to classify brain tumor using cnn and svm," in *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, pp. 644–648, 2021.

[4] Z. N. K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali, S. Ahmed, and J. Lu, "Brain tumor classification for mr images using transfer learning and fine-tuning," *Computerized Medical Imaging and Graphics*, vol. 75, pp. 34–46, 2019.

[5] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim, and F. Muhammad Shah, "Brain tumor detection using convolutional neural network," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, pp. 1–6, 2019.

QnA

Thank You!