BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

AUTHORS:

1. Sunanda Das
2. O. F. M. Riaz Rahman Aranya
3. Nishat Nayla Labiba

Dept. of Computer Science and Engineering,
Khulna University of Engineering & Technology

PAPER ID: 455

OUTLINE

1. INTRODUCTION
2. OBJECTIVES
3. DATASET COLLECTION & DESCRIPTION
4. PRE-PROCESSING
5. CLASSIFICATION USING CNN
6. PERFORMANCE EVALUATION
7. CONLUSION
8. REFERENCES

INTRODUCTION

- BRAIN TUMOR IS ONE OF THE MOST FEARED DISEASES IN MEDICAL SCIENCE.
- IT IS THE ABNORMAL GROWTH OF CELLS IN THE BRAIN.
- THERE ARE MANY KINDS OF BRAIN TUMOR.
- SOME ARE CANCEROUS AND SOME ARE NOT.
- SURVIVAL RATES OF BRAIN TUMOR VARY ACCORDING TO THE TYPE OF THE BRAIN TUMOR & AGE OF THE PATIENT.

OBJECTIVES

- CLASSIFY THREE TYPES OF BRAIN TUMOR ACCURATELY.
- TO ENSURE PROPER TREATMENT IN TIME.
- CONVOLUTIONAL NEURAL NETWORK IS USED.

DATASET COLLECTION & DESCRIPTION

TOTAL 3064 IMAGES COLLECTED FROM 233 PATIENTS

ARRANGED IN MATLAB FORMAT

INFORMATION ABOUT LABEL, PID, IMAGE DATA, TUMOR BORDER, TUMOR MASK

DATASET IS DIVIDED INTO THREE SETS

HISTOGRAM EQUALIZATION

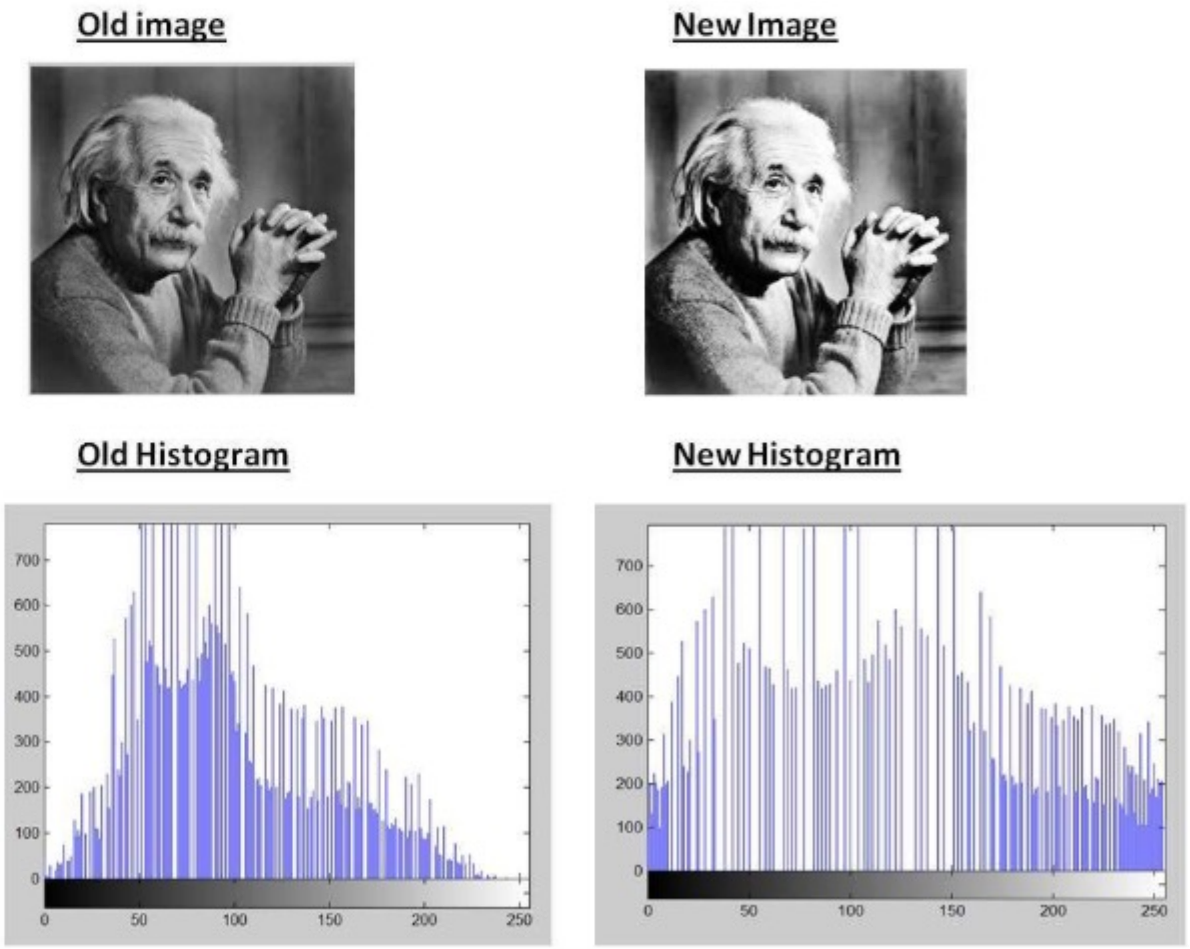

Fig. 1. Histogram equalization of an image[12]

HISTOGRAM IS A GRAPHICAL REPRESENTAION OF THE INTENSITY DISTRIBUTION OF AN IMAGE[13]

HISTOGRAM EQUALIZATION IS A METHOD TO PROCESS IMAGES IN ORDER TO ADJUST THE CONTRAST OF THE IMAGE BY MODIFYING THE INTENSITY DISTRIBUTION OF THE HISTOGRAM[13]

SPREAD OUT THE MOST FREQUENT INTENSITY VALUES [13]

PRE-PROCESSING

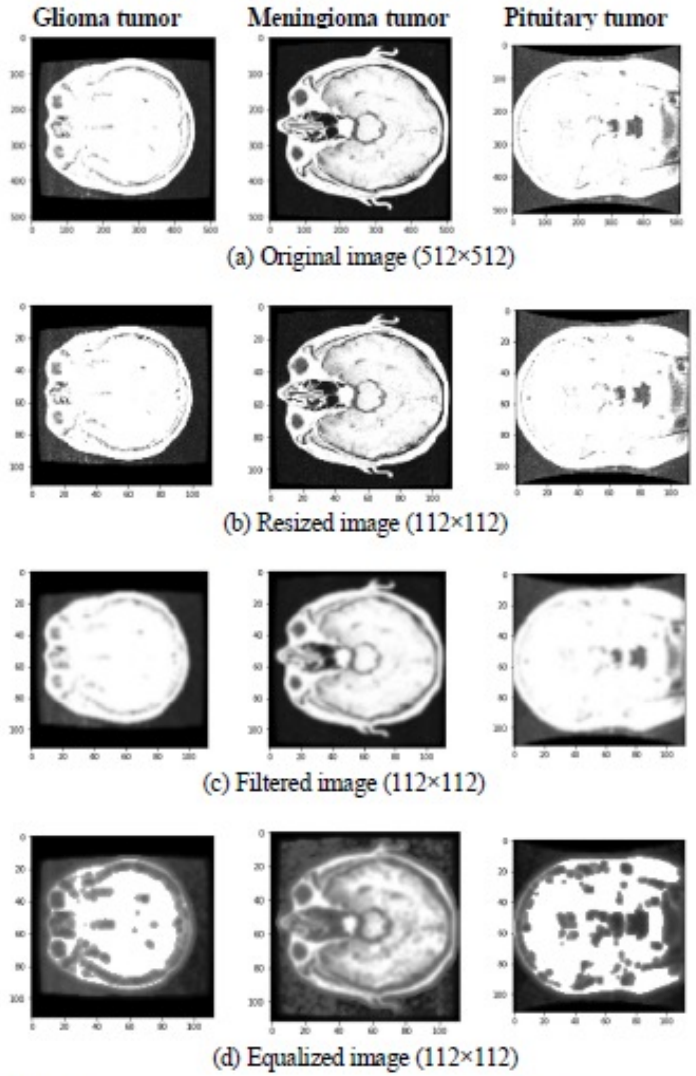

Fig. 2. Stepwise pre-processing outcome for tumor classification

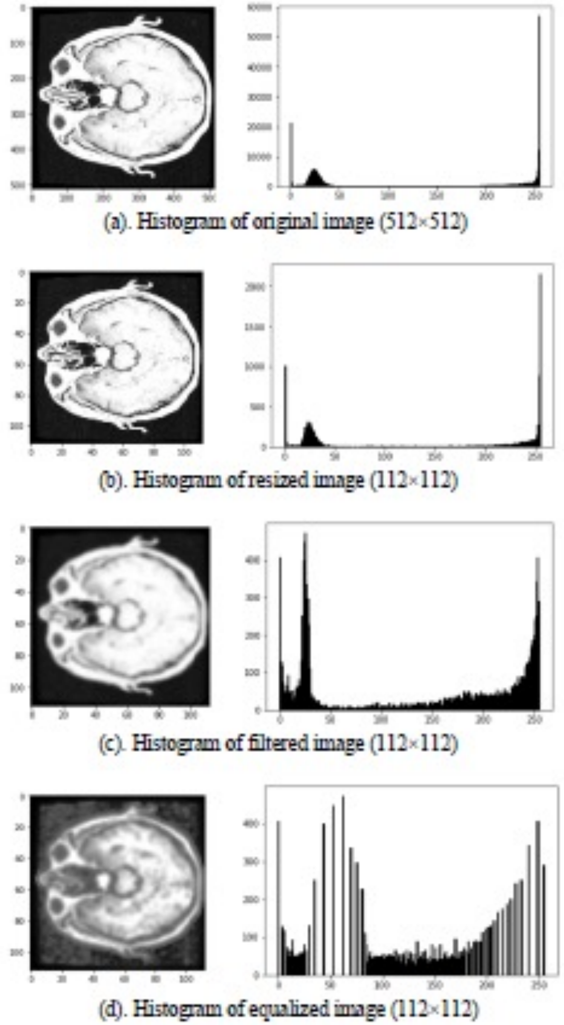

Fig. 3. Histogram of different pre-processing step image

CLASSIFICATION USING CNN

CONVOLUTIONAL NEURAL NETWORK

- ❖ MULTI-LAYER NEURAL NETWORK
- ❖ AN EFFECTIVE RECONGINTION ALGORITHM APPLIED IN PATTERN RECOGNITION & IMAGE PROCESSING [8]
- ❖ DECREASE THE NUMBER OF PARAMETERS NEEDED FOR THE MODEL COMPARED TO ANN

- ❖A SEQUENCE OF CONVOLUTION & POOLING OPERATION FOLLOWED BY A FULLY CONNECTED LAYER.

- ❖CONVOLUTIONAL FILTER (C1) ON INPUT IMAGE(I) TO GENERATE A FEATURE MAP.

- ❖FEAUTERS GENERATED BY C1 FED IN FIRST SUBSAMPLING LAYER S1.

- ❖MAX POOLING IS USED IN SUBSAMPLING LAYER WITH A WINDOW SIZE OF 2x2.

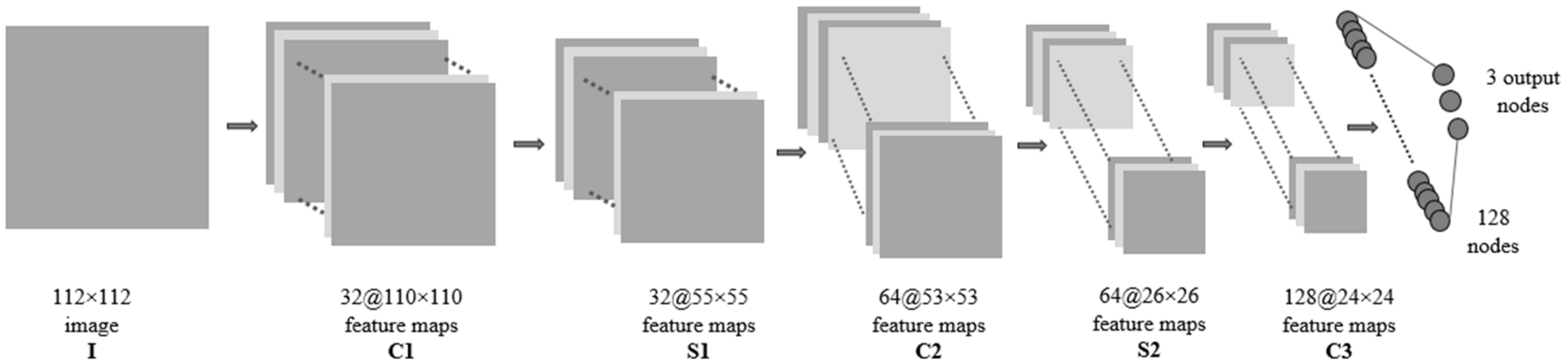

Fig. 4. CNN architecture of the model (**I, C, S represent input image, convolution and subsampling respectively)**

CLASSIFICATION USING CNN

- ❖ IN C2 , 64 CONVOLUTIONAL FILTERS ARE USED & RESULT IS FED TO S2 WITH 2x2 WINDOW SIZE.

- ❖IN C3, 128 FILTERS ARE USED & RESULT IS FED TO A DENSE LAYER WITH 128 NODES.

- ❖FINALLY A DENSE LAYER WITH SOFTMAX ARE USED FOR THE CLASSIFICATION.

- ❖A DROPOUT LAYER IS USED AFTER EACH SUBSAMPLING TO REDUCE OVERFITTING[9].

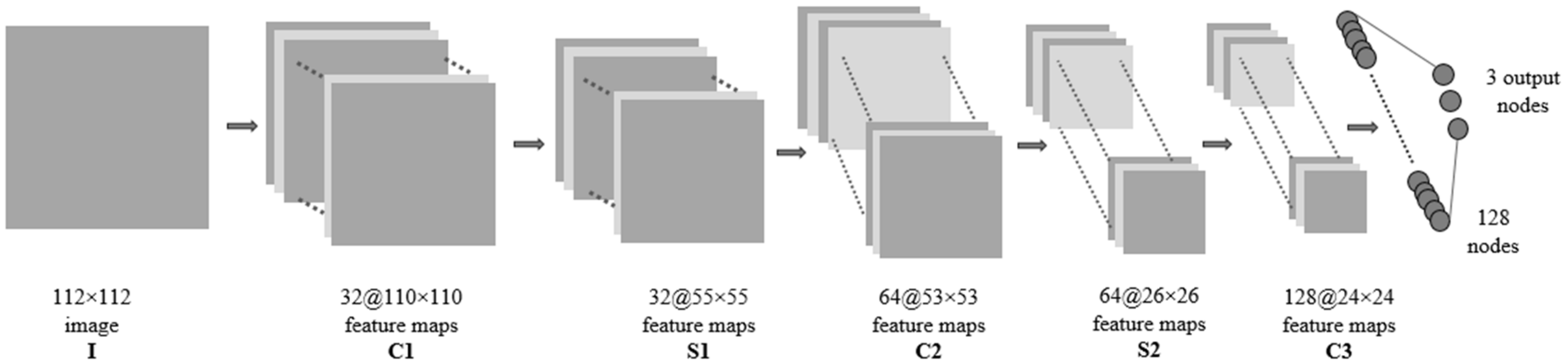

Fig. 5. CNN architecture of the model (**I, C, S represent input image, convolution and subsampling respectively)**

PERFORMANCE EVALUATION

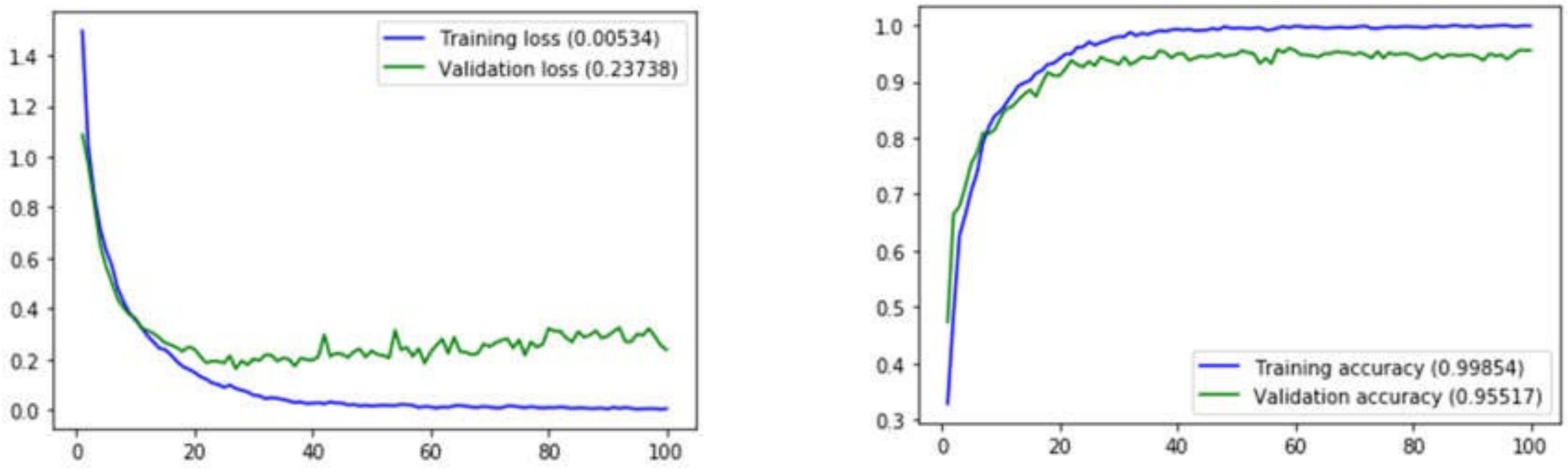

Fig. 6. Loss and Accuracy curve for 100 epochs

- **ADAM OPTIMIZER IS USED AFTER DEVELOPING THE CNN MODEL.**
- **A BATCH SIZE OF 256 AND 100 EPOCHS ARE USED.**
- **AFTER EVALUATING THE MODEL ON TEST DATA , 28.16% LOSS & 94.39% ACCURACY WAS ACHIEVED.**

PERFORMANCE EVALUATION

Table 1. Confusion matrix for the model

	Class 1 (Glioma)	Class 2 (Meningioma)	Class 3 (Pituitary)
Class 1 (Glioma)	88	12	3
Class 2 (Meningioma)	13	213	0
Class 3 (Pituitary)	0	1	170

- ❖**500 IMAGES ARE USED FOR TESTING.**
- ❖**MODEL IDENTIFIES 3 CLASSES.**
- ❖**PITUITARY IS IDENTIFIED MORE ACCURATELY.**

Table 2. Performance measure indices

Class	Precision	Recall	F1-score	Support
Class 1 (Glioma)	0.88	0.85	0.87	103
Class 2 (Meningioma)	0.94	0.95	0.94	226
Class 3 (Pituitary)	0.98	0.99	0.99	171

$$Precision = \frac{True\ Positive}{True\ positive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ positive + False\ Negative}$$

$$F1\text{-}score = 2\times\frac{Precision \times Recall}{Precision + Recall}$$

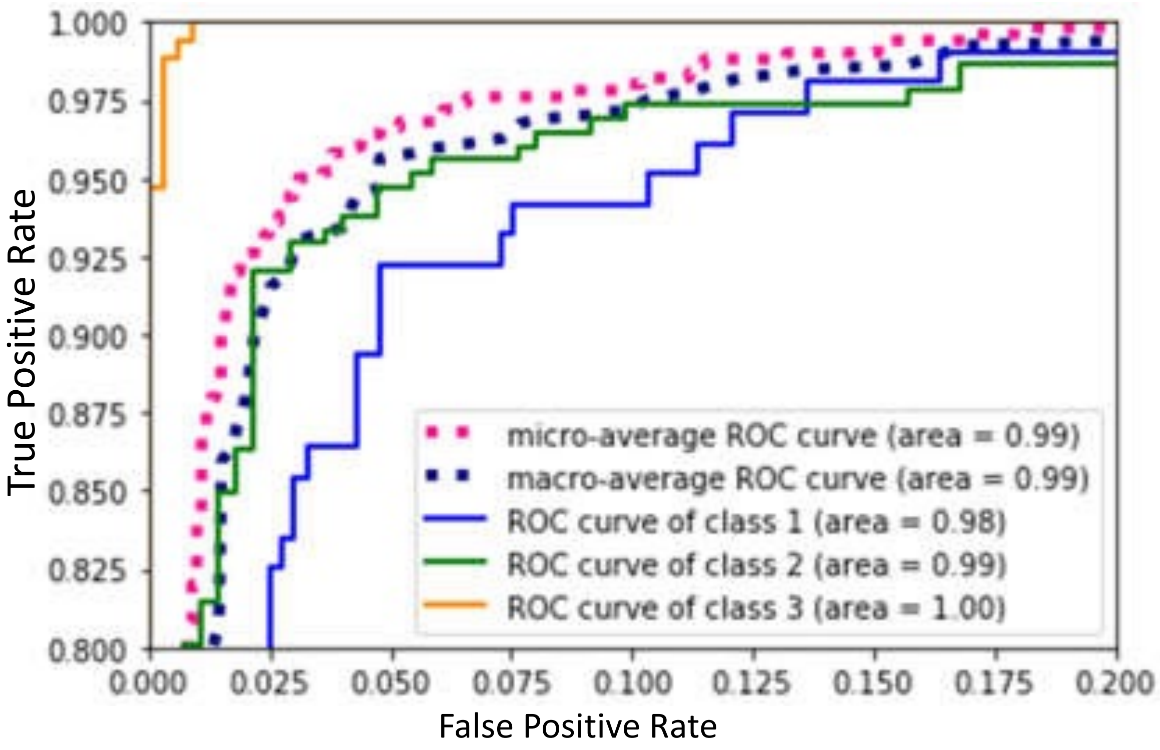

Fig. 5. ROC (Receiver Operating Characteristic) curve of the system

PERFORMANCE EVALUATION

- REPRESENTS A PLOT OF THE TRUE POSITIVE RATE (Sensitivity) VERSUS THE FALSE POSITIVE RATE (100-Specificity).
- AREA UNDER THE ROC CURVE(AUC) IS A MEASURE OF HOW WELL THE MODEL IS DISTINGUISHING BETWEEN DIFFERENT.
- THE CLOSER THE ROC IS TO THE UPPER LEFT CORNER, THE HIGHER THE OVERALL ACCURACY[11].

PERFORMANCE EVALUATION

Table 3. Comparison with existing methods in testing phase

Methods	Average Precision (%)
CBIR [4]	89.3
CBIR with BoVW [5]	91
CBIR with BoVW and REML [6]	93.1
Proposed model using CNN	**93.33**

- **COMPARED WITH SEVERAL METHODS PROPOSED IN DIFFERENT PAPERS USING SAME DATASET.**
- **HIGHER ACCURACY IS OBTAINED BY OUR PROPOSED METHOD.**

CONCLUSION

- THIS METHOD SIGNIFICANTLY CLASSIFIES AMONG THREE IMPORTANT TUMOR CLASSES.
- THIS MODEL CONCENTRATE ON THE MOST IMPORTANT PATTERNS DURING TRAINING PHASE.
- ACQUIRED 94.39% ACCURACY & AN AVERAGE OF 93.33% PRECISION.
- THIS MODEL CAN BE GENERALIZED TO USE ON DATASET WITH MORE TUMOR CLASSES.

REFERENCES

[1] cancer.org, ‘Key Statistics for Brain and Spinal Cord Tumors’, January, 2019. [Online]. Available: https://www.cancer.org/cancer/brain-spinal-cord-tumorsadults/about/key-statistics.html, [Accessed: Jan. 9, 2019].

[2] Q. T. Ostrom, H. Gittleman, J. Xu, C. Kromer, Y. Wolinsky, C. Kruchko, and J. S. Barnholtz-Sloan, “Cbtrus statistical report: primary brain and other central nervous system tumors diagnosed in the united states in 2009–2013,” *Neuro-oncology, vol. 18, no.* suppl5, pp. v1–v75, 2016.

[3] mayoclinic.org, ‘Brain tumor’. [Online]. Available: https://www.mayoclinic.org/diseases-conditions/braintumor/symptoms-causes/syc-20350084, [Accessed: Dec. 15, 2018].

[4] W. Yang, Q. Feng, M. Yu, Z. Lu, Y. Gao, Y. Xu, and W. Chen, “Content-based retrieval of brain tumor in contrast-enhanced mri images using tumor margin information and learned distance metric,” *Medical physics, vol. 39,no. 11, pp. 6929–6942, 2012.*

[5] M. Huang, W. Yang, M. Yu, Z. Lu, Q. Feng, and W. Chen, “Retrieval of brain tumors with region-specific bag-of visual-words representations in contrast-enhanced mri images,” *Computational and mathematical methods in medicine, vol. 2012, 2012.*

[6] M. Huang, W. Yang, Y. Wu, J. Jiang, Y. Gao, Y. Chen, Q. Feng, W. Chen, and Z. Lu, “Content-based image retrieval using spatial layout information in brain tumor t1-weighted contrast-enhanced mr images,” *PloS one, vol. 9, no. 7, p. e102754, 2014.*

REFERENCES

[7] J. Cheng, ‘brain tumor dataset’, 2017. [Online]. Available: https://figshare.com/articles/brain_tumor_dataset/1512427,[Accessed: Oct. 5, 2018].

[8] T. Liu, S. Fang, Y. Zhao, P. Wang, and J. Zhang, “Implementation of training convolutional neural networks,” *arXiv preprint arXiv:1506.01195, 2015.*

[9] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov,“Dropout: a simple way to prevent neural networks from overfitting,” *The Journal of Machine Learning Research, vol.* 15, no. 1, pp. 1929–1958, 2014.

[10] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” *arXiv preprint arXiv:1412.6980, 2014.*

[11] M. H. Zweig and G. Campbell, “Receiver-operating characteristic (roc) plots: a fundamental evaluation tool in clinical medicine.” *Clinical chemistry, vol. 39, no. 4, pp. 561–577,* 1993.

[12] tutorialspoint.com, ‘Histogram Equalization’. [Online]. Available: https://www.tutorialspoint.com/dip/histogram_equalization.htm, [Accessed: April 25, 2019].

[13] towardsdatascience.com, ‘Histogram Equalization’. [Online]. Available: https://towardsdatascience.com/histogram-equalization-5d1013626e64, [Accessed: April 25, 2019].

THANK YOU

ANY QUESTION?