

## **Brain Tumour Classification Into High Grade & Low-Grade Gliomas: A Comparative Study**

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### **ABSTRACT**

With The Rapid Development In Bio Imaging Technology, Much Emphasis Has Been Placed On The Automation Of MRI-Based Brain Tumour Identification, Characterization, And Diagnostic Systems. The Most Common Form Of Primary Brain Tumour Is Gliomas. According To World Health Organization (WHO) Recommendations, They Are Divided Into Four Categories: Grade I, Grade II, Grade III, And Grade IV. The Precise Grading Of Gliomas Has Therapeutic Implications For Diagnosis, Surveillance, And Prognostic Procedures. The Primary Objective Of This Research Study Is To Compare And Evaluate The Diagnostic Efficiency Of Supervised And Unsupervised Learning-Based Classifiers In Recognizing The Difference Between High Grade Gliomas (Higgs) And Low Grade Gliomas (Lggs) By Extracting Histo-Pathological Features From MRI(Magnetic Resonance Imaging) Scanned Images. This Paper Explores Merits And Demerits Of Classification Algorithms Used For Grading In Recent Years. The Paper Also Highlights The Algorithms Used In Classification Stages Such As Preprocessing And Feature Extraction.

**Keywords:** Brain Tumour, MRI Images, Classification, Gliomas Grading, Supervised Learning, Unsupervised Learning

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### **INTRODUCTION**

A Large Amount Of Cells Make Up The Human Body. When Uncontrollable Cell Growth Occurs, The Excess Mass Of Cells Becomes A Tumour. Brain Tumours Are The Tenth Leading Cause Of Mortality In India. The Location Of The Tumour In The Brain, The Type Of Tissue Involved, And The Tumour's Initial Status Are All Factors In Determining The Classification Of Brain Tumours. Benign Tumours (Harmless Growth) And Malignant Tumours (Harmful Growth) Are The Two Most Common Forms Of Tumours. Malignant Tumours Are Cancerous Tumours That Can Spread Cancer Cells Throughout The Body Via The Bloodstream Or Lymphatic System. Malignant Tumours Can Be Further Break Down Into Primary And Secondary Type Of Tumours. Primary Tumours Grow Within The Brain, And Secondary Tumours, Also Known As Brain Metastasis Tumours, Begin Elsewhere In The Body But Spread Throughout The Body And To The Brain. Primary Brain Tumours Are Given Names Based On The Type Of Cells Or The Area Of The Brain Where They Originate Or Are Located. Gliomas, For Example, Is A Type Of Brain Tumour That Starts With In Glial Cells. There Are Several Various Forms Depending On Which Part Of The Brain The Tumour Originates In. Gliomas Are One Of The Most

Common Form Of Brain Tumour. Gliomas Account For About 80% Of All Malignant Brain Tumours (Lasocki Et Al. 2015). Many Factors Influence The Clinical Outcome Of Patients With Glial Tumours. Gliomas Tissue Is Studied Histologically In Order To Identify And Grade The Tumour.

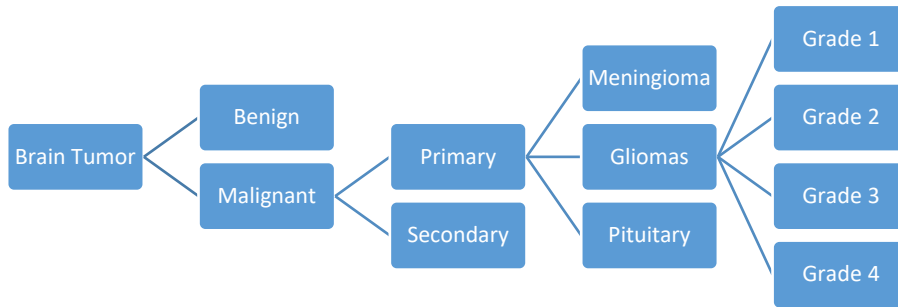


Fig 1 Forms Of Brain Tumours And Their Classification

The World Health Organization (WHO) Grades And Categorises Brain Tumours (Upadhyay And Waldman 2011). On A Scale Of I To IV, Brain Tumours Are Classified As Malignant Or Cancerous, Depending On How Irregular Their Cells Look Under A Microscope. The Least Malignant Grade Is I And The Most Malignant Grade Is IV. The Main Objective Of Brain Tumour Grading System Is To Assess The Tumour's Possible Growth Rate And Distribution Throughout The Brain, Which Can Be Used To Forecast Outcomes And Schedule Treatment. Grades I And II Gliomas Are Referred To As Low-Grade Gliomas Because Their Cells Are Clearly Differentiated, Have Less Violent Impulses, And Have A Stronger Prognosis. Gliomas In Grades III And IV Are Considered High-Grade Because Their Cells Are Undifferentiated And Extremely Malignant, And Their Prognosis Is Low. Table 1 Compares The Function Of LGG And HGG Tumours.

Table 1

*Comparison Of LGG And HGG Functions*

S.No.	LGG (Low Grade Gliomas)	HGG (High Grade Gliomas)
1	<ul style="list-style-type: none"> <li>Initial Stages Of A Tumour's Growth</li> <li>Not Cancerous (Upadhyay And Waldman 2011)</li> </ul>	<ul style="list-style-type: none"> <li>Cancerous Tumours At Their Most Advanced Stages (Upadhyay And Waldman 2011)</li> </ul>
2	<ul style="list-style-type: none"> <li>Don't Spread To Other Areas Of The Body</li> <li>Expand Slowly (Abd-Ellah Et Al. 2019)</li> </ul>	<ul style="list-style-type: none"> <li>Spread To Other Organs Multiply Quickly (Abd-Ellah Et Al. 2019)</li> </ul>
3	<ul style="list-style-type: none"> <li>Does Not Cause Death</li> <li>Can Be Treated By Surgery Alone</li> </ul>	<ul style="list-style-type: none"> <li>Can Causes Instant Death (Abd-Ellah Et Al. 2019)</li> <li>Chemotherapy And Radiation Therapy, Are Needed For Treatment</li> </ul>

Gliomas Grading Accuracy Is Critical For Tumour Identification, Treatment And Recovery Preparation. The Growth Of Radiological Imaging Methods For Identification And Classification Of Brain Tumours Has Improved In Recent Years. MRI Is A Radiation-Free And Hence Better Imaging Tool Than CT. It Offers Clearer Descriptions Of The Brain, Spinal Cord, And Vascular Anatomy. The

Basic Planes Of MRI To Visualise The Structure Of The Brain Are Axial, Sagittal, And Coronal. T1-Weighted, T2-Weighted, And FLAIR Are The Most Widely Used MRI Sequences For Brain Research (Aquino Et Al. 2017). Based On Only An MR Image Scan, A Radiologist Cannot Singularize If The Patient Had A Low-Grade Gliomas Or A High-Grade Gliomas. Surgery Or Biopsy For Diagnosis And Tumour Grading Remains The Standard Procedure. However, Due To The Heterogeneous Nature Of Gliomas, A Biopsy May Cause Issues Including Taking Samples That Do Not Represents The Entire Tumour Problem And Interpreting The Results Inconsistently (Abd-Ellah Et Al. 2019). Furthermore, Because Of The Tumour's Position, These Operations Are Invasive And Potentially Dangerous, An Automatic Application For Brain Tumour Classification Is Of Great Interest For Tumour Surgeons. Advances In Bio Imaging Strengthened The Non-Invasive Identification Of Tumours Tumour Sizes, Shapes, Anatomical Structure And Other Pathological Characteristics Of Brain Tumours Which Help In Suggesting The Proper Treatment To The Patients.

### CLASSIFICATION TECHNIQUES

The Method Of Obtaining Information Groups From Multi - Standard Raster Images Is Known As Image Classification. Many Researchers Have Adopted Various Brain Tumour Classification Methods Towards Characterising The Input MRI, Which Are Primarily Categorized Into Two Broad Groups: Supervised Techniques And Unsupervised Techniques (Subashini Et Al. 2016). The Domain Knowledge Directs Supervised Methods In Determining The Right Class. The Empirical Similarity That Group The Images Into Distinct Clusters Are Used In Unsupervised Approaches To Segment Them. These Two Methods Include Several Approaches Dependent On Their Characteristics. Common Algorithms Involved In Gliomas Grading Include Convolutional Neural Network (CNN), Naïve Bays Classifier, Fuzzy C-Mean Clustering, Support Vector Machine (SVM). Table 2 The Advantages And Limitations Of Some Of These Classifier Algorithms Used For Brain Tumour Classification.

Table 2

*Merits And Limitations Of Various Classification Algorithms*

CLASSIFICATION TECHNIQUE	SUPERVISED / UNSUPERVISED LEARNING	MERITS	LIMITATION
Naïve Bays Classifier (Subashini Et Al. 2016)	Supervised	<ul style="list-style-type: none"> <li>• For Categorical Data, The Algorithm Performs Exceptionally Well</li> <li>• Some Training Data Is Necessary To Estimate The Classification Parameters</li> </ul>	<ul style="list-style-type: none"> <li>• It Assumes That All The Features Are Independent</li> <li>• Dependencies Among These Cannot Be Modelled By This Classifier</li> </ul>
Support Vector Machine (SVM)(Kabir Anaraki Et Al. 2019;	Supervised	<ul style="list-style-type: none"> <li>• Transform Linear Classifier Into Nonlinear With The “Kernel Trick”</li> <li>• Often Makes High Accurate Prediction</li> <li>• Low Overfitting</li> </ul>	<ul style="list-style-type: none"> <li>• It Presumes That Data Is Distributed Equally And Independently, Which Is Inappropriate For Segmenting Noisy Medical Scans.</li> </ul>

Vamvakas Et Al. 2019)			
Convolutional Neural Network (CNN) (Khan Et Al. 2020; Mehrotra Et Al. 2020)	Supervised	<ul style="list-style-type: none"> <li>• Ability To Function With Any Number Of Inputs And Layers</li> <li>• Back Propagation Technique To Automate Training Features Is Highly Beneficial</li> <li>• Less Susceptible To Over Fitting And Easy To Train</li> </ul>	<ul style="list-style-type: none"> <li>• Needs High Amount Of Data Set To Perform Well</li> <li>• Computationally Expensive</li> </ul>
Artificial Neural Network (ANN) (Mehrotra Et Al. 2020)	Supervised	<ul style="list-style-type: none"> <li>• Perform Best With High Quality Labelled Data</li> <li>• Ability To Model Critical Dependencies</li> <li>• Fast Computation</li> </ul>	<ul style="list-style-type: none"> <li>• Overfitting Problem</li> <li>• Blackbox Modelling</li> </ul>
K-Nearest Neighbour (KNN) (Gupta Et Al. 2016)	Supervised	<ul style="list-style-type: none"> <li>• It Is Easy To Implement. Training Is Done In Faster Manner</li> <li>• Data Does Not Have To Be Separable With A Linear Boundary</li> <li>• Suited For Multimodal Data</li> <li>• Robust With Regards To Noisy Training Data</li> </ul>	<ul style="list-style-type: none"> <li>• Requires Large Storage Space</li> <li>• Performance Reduced On Large Data Sets</li> <li>• Sensitive To Noise</li> <li>• Expensive While Choosing The Value Of K</li> </ul>
Decision Tree (Usman And Rajpoot 2017)	Supervised	<ul style="list-style-type: none"> <li>• It Can Efficiently Process Data With Many Dimensions</li> <li>• Both Numerical And Categorical Data Are Handled By The Decision Tree</li> </ul>	<ul style="list-style-type: none"> <li>• Its Output Is Contingent On The Dataset Sort.</li> </ul>
Fuzzy C-Mean Clustering (Raju, Suresh, And Rao 2018)	Unsupervised	<ul style="list-style-type: none"> <li>• It Defines Sharp Boundaries For Segmented Region</li> </ul>	<ul style="list-style-type: none"> <li>• Due To The Unpredictability Of The Preliminary Membership Values Sometimes It Produces Inconsistent Results.</li> <li>• It Considers Only The Image's Intensity, Which Produces Inadequate Results For Noisy MR Images.</li> <li>• Outlier Problems</li> <li>• Provide More False Positives In Brain Image</li> </ul>

K-Mean Clustering (Vamvakas Et Al. 2019)	Unsupervised	<ul style="list-style-type: none"> <li>• The Cluster Are Not Hierarchical And They Do Not Overlap.</li> <li>• Its Implementation Is Simple, And It Executes Quickly In Real Time And With A High Number Of Variables</li> </ul>	<ul style="list-style-type: none"> <li>• It Is Very Sensitive To The Initial Choice Of The Number Of K</li> <li>• On Their Own They Aren't Enough For Classification Can Also Be Used To Create Clusters As Features To Improve Classification Models</li> </ul>
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**RELATED WORK**

Recognition Of Tumour In Brain Plays A Curial And Extreme Occupation In The Medical Image Processing Field. For The Appropriate Treatment Direction, The Need For An Automated And Well-Organized Method Of Gliomas Classification And Diagnosis Has Risen. Many Experiments Have Been Suggested For This Reason By Various Researchers, All Of Which Have Produced Positive Findings With Precision. To Classify Malignant And Non-Cancerous Brain MR Images, (Khan Et Al. 2020)Uses A Convolutional Neural Network Technique Combined With Data Augmentation. Efficiency Of The Proposed CNN Based Model Was Compared To Pre-Trained Models, Using The Transfer Learning Method. Model Accuracy Outcome Had A Very Low Complexity Rate Despite The Fact That The Experiment Was Conducted On A Very Small Dataset. (Usman And Rajpoot 2017)Extracted Intensity Difference And Wavelet Features On Multi-Modality MRI Data, And Used With RF Classifier That Provides Improved Classification Precision. Cross-Validation Method Got A Dice Overlap Of 75 Percent For The Central Tumour Region, While The Enhancing Tumour Region Had A Dice Overlap Of 95 Percent For. The Intensity-Invariant Local Texture On MRI Images Was Converted By (Li-Chun Hsieh, Chen, And Lo 2017)Into A Local Binary Pattern (LBP). Histogram Moment And Textures Obtained From The LBP Were Used In A Logistic Regression Classifier To Design A Malignancy Prediction Model. The Precision Of The System Was 93 Percent, Which Was Slightly Higher Than The Performance Of Traditional Texture Features. Using A VGG-19 Deep Convolutional Neural Network, (Ahammed Muneer Et Al. 2019)Introduces Automated Glioma Tumour Grading. Windchrm Tool Was Used To Extract And Classify The Features.VGG-19 Deep Convolutional Neural Network Classifier Had A Classification Accuracy Of Approximately 98 Percent. Table 3 Compares The Classification Methods That Has Been Used In The Recent Times With Their Performance Evaluation And Limitations.

Table 3

*Overview Of Recent Classification Techniques Used For LGG & HGG Grading*

Paper	Pre-Processing	Feature Extraction	Classification	Performance (%)	Limitation	Tumour Type	Modalities
(Subashini Et Al.	PCNN Median Filter	GLCM Shape Intensity & Texture	LVQ (Learned Vector Quantization ) And Naïve Bayes	Accuracy: 91	Smaller Dataset	LGG And HGG	T2 W

(2016)		Based Features					
(Vamvakas Et Al. 2019)	Otsu Binarization, Thresholding	DWT(Discrete Wavelet Transforms), K-Means Clustering,	SVM (Support Vector Machine)	Accuracy: 99 Sensitivity:100 Specificity:98.03	Extraction Of More Appropriate Features Was Limited	LGG And HGG	T2 W
(Kabir Anaraki Et Al. 2019)	Region-Of-Interest Definition	Automatically	Convolutional Neural Networks (Cnns) And Genetic Algorithm (GA)	Accuracy: 90.9	Difficult To Assess All Potential Cases	Gliomas Grade II/Grade III/Grade IV	T1 Axial
(Choi And Park 2017)	-	Histogram, Shape Graylevel Co-Occurrence Matrix (GLCM)	Logistic Regression Based On LASSO Coefficient	Accuracy: 89.8 Sensitivity:88.8 Specificity:90.7	Additional Clinical Parameters Required For Better Classification	HGG And LGG	FLAIR, T1, T1C(Contrast), T2
(Gupta Et Al. 2016)	Adaptive Histogram Equalization (CLAHE), Thresholding	Texture Based Features Using GLCM, Shape Based Features Using Region Props	K-Nearest Neighbour (Knn)	Accuracy: 93	Performance Reduced On Large Data Sets	HGG And LGG Astrocytoma	T1, T1C, T2, FLAIR
(Yang Et Al. 2018)	Noise Reduction, Inhomogeneity Correction, And Rigid Intra-Subject Registration	Invariant Texture	SVM (Support Vector Machine)	Accuracy: 87 Sensitivity:83 Specificity:96	Failed To Classify Grade III Gliomas	HGG And LGG	Axial 3D T1 W(Weighted), Sagittal 3D T2 W, FLAIR,

(Raju Et Al. 2018 )	-	Scattering Transform, Wavelet Transform	Bayesian Fuzzy Clustering , HCS(Harmony -Crow Search)-- Multi- SVNN	Accuracy: 93 Sensitivity:96 Specificity:99	Smaller Dataset	Non-Tumour Region.	T1, T2, T1C, FLAIR
(Mzoughi Et Al. 2020 )	Intensity Normalization/Contrast Enhancement	Automatically	Deep CNN(Convolutional Neural Network )	Accuracy: 96.4	The Dataset Does Not Include Enough MR Images To Train A Deep CNN	LGG And HGG	Hole Volumetric T1-Gado
(Özcan Et Al. 2021 )	Cropping	Texture And Shape	Deep CNN (Convolutional Neural Network )	Accuracy: 93.3 Sensitivity:98 Specificity:88.9	Retrospective Design And A Small Dataset	LGG And HGG	T2 W, FLAIR
(Pan Et Al. 2015 )	Resizing, Intensity Normalization	Automatically	Deep CNN(Convolutional Neural Network )	-	Training Samples For LGG Data, Are Relatively Small Than HGG	HGG And LGG	T1 , T1 C, T2, T2, FLAIR

## CONCLUSION

With The Advent Of Emerging Technology, The Dataset Size Has Grown Significantly, Making Machine Learning And Traditional Data Analysis Approaches Very Difficult To Manage. Furthermore, Analysing Noisy, High-Dimensional, And Dynamic Datasets Such As MRI Images Is A Significant Task. With The Rapid Advancement In Medical Image Modalities, New Methods Are Frequently Discovered And Presented. This Paper Provides A Detailed Study Of The Gliomas Classification System, Including Information About Feature Extracted, Tumour Segmentation And Classification Approach That Help To Specifically Categorise Low Grade Gliomas And High Grade Gliomas, And The Effectiveness Of These Approaches. The Primary Purpose Of This Comparison Study Is To Investigate And Provide A Brief Overview Of Various Classification Techniques Using An MRI Dataset. From This Comparative Study, It Is Observed That Each Algorithm Produces Significant Results In Terms Of Accuracy But At The Same Time They Have Their Own Benefits And Limitations. Supervised Learning Based Classification Approaches Face Difficulties Such As Massive Dataset Sizes, Overfitting Of Training Results, And An Apparent Lack Of Flexibility. CNN Has The Advantage Of Convolved Features For Automated Learning For Tumours Directly From Multi-Modal MRI Images. With SVM Methods Integration Of Multi-Sequence MRI For Classification Is Challenging. Such Mechanisms Are Incapable Of Dealing With Matters Of A High Dimension. As A



Result, Hybrid Methods Are Necessary For Certain Complex Situations. This Study May Be Expanded In The Future To Use A Combination Of Each Of These Classifiers To Assess Their Efficiency.

## REFERENCES

1. Abd-Ellah, Mahmoud Khaled, Ali Ismail Awad, Ashraf A. M. Khalaf, And Hesham F. A. Hamed. 2019. "A Review On Brain Tumor Diagnosis From MRI Images: Practical Implications, Key Achievements, And Lessons Learned." *Magnetic Resonance Imaging* 61(August 2018):300–318. Doi: 10.1016/J.Mri.2019.05.028.
2. Ahammed Muneer, K. V., V. R. Rajendran, And K. Paul Joseph. 2019. "Glioma Tumor Grade Identification Using Artificial Intelligent Techniques." *Journal Of Medical Systems* 43(5). Doi: 10.1007/S10916-019-1228-2.
3. Alhassan, Afnan M., And Wan Mohd Nazmee Wan Zainon. 2020. "BAT Algorithm With Fuzzy C-Ordered Means (BAFCOM) Clustering Segmentation And Enhanced Capsule Networks (ECN) For Brain Cancer MRI Images Classification." *IEEE Access* 8:201741–51. Doi: 10.1109/Access.2020.3035803.
4. Aquino, Domenico, Andrea Gioppo, Gaetano Finocchiaro, Maria Grazia Bruzzone, And Valeria Cuccarini. 2017. "MRI In Glioma Immunotherapy: Evidence, Pitfalls, And Perspectives." *Journal Of Immunology Research* 2017. Doi: 10.1155/2017/5813951.
5. Cho Hwan-Ho, And Hyunjin Park. 2017. "Classification Of Low - Grade And High - Grade Glioma Using Multi - Modal Image Radiomics Features." 39th Annual International Conference Of The IEEE Engineering In Medicine And Biology Society (EMBC), 2017: 3081-84, Doi: 10.1109/EMBC.2017.8037508.
6. El-Dahshan, E. A. S., Heba M. Mohsen, Kenneth Revett, And Abdel Badeeh M. Salem. 2014. "Computer-Aided Diagnosis Of Human Brain Tumor Through MRI: A Survey And A New Algorithm." *Expert Systems With Applications* 41(11):5526–45. Doi: 10.1016/J.Eswa.2014.01.021.
7. Gupta, Sheifali, Prabhpreet Walia, Chaitanya Singla, Shivani Dhankar, Tanvi Mishra, Ayush Khandelwal, And Mohit Bhardwaj. 2016. "Segmentation, Feature Extraction And Classification Of Astrocytoma In MR Images." *Indian Journal Of Science And Technology* 9(36). Doi: 10.17485/Ijst/2016/V9i36/102154.
8. Kabir Anaraki, Amin, Moosa Ayati, And Foad Kazemi. 2019. "Magnetic Resonance Imaging-Based Brain Tumor Grades Classification And Grading Via Convolutional Neural Networks And Genetic Algorithms." *Biocybernetics And Biomedical Engineering* 39(1):63–74. Doi: 10.1016/J.Bbe.2018.10.004.
9. Kaur, Taranjit, Barjinder Singh Saini, And Savita Gupta. 2017. "Quantitative Metric For MR Brain Tumour Grade Classification Using Sample Space Density Measure Of Analytic Intrinsic Mode Function Representation." *IET Image Processing* 11(8):620–32. Doi: 10.1049/Iet-Ipr.2016.1103.
10. Khan, Hassan Ali, Wu Jue, Muhammad Mushtaq, And Muhammad Umer Mushtaq. 2020. "Brain Tumor Classification In MRI Image Using Convolutional Neural Network." *Mathematical Biosciences And Engineering* 17(5):6203–16. Doi: 10.3934/MBE.2020328.
11. Lasocki, Arian, A. Tsui, M. A. Tacey, K. J. Drummond, K. M. Field, And F. Gaillard. 2015. "MRI Grading Versus Histology: Predicting Survival Of World Health Organization Grade II-IV Astrocytomas." *American Journal Of Neuroradiology* 36(1):77–83. Doi: 10.3174/Ajnr.A4077.
12. Li-Chun Hsieh, Kevin, Cheng Yu Chen, And Chung Ming Lo. 2017. "Quantitative Glioma



- Grading Using Transformed Gray-Scale Invariant Textures Of MRI.” *Computers In Biology And Medicine* 83(November 2016):102–8. Doi: 10.1016/J.Compbimed.2017.02.012.
13. Maximov, Ivan I., Aram S. Tonoyan, And Igor N. Pronin. 2017. “Differentiation Of Glioma Malignancy Grade Using Diffusion MRI.” *Physica Medica* 40:24–32. Doi: 10.1016/J.Ejmp.2017.07.002.
  14. Mehrotra, Rajat, M. A. Ansari, Rajeev Agrawal, And R. S. Anand. 2020. “A Transfer Learning Approach For AI-Based Classification Of Brain Tumors.” *Machine Learning With Applications* 2(October):100003. Doi: 10.1016/J.Mlwa.2020.100003.
  15. Mzoughi, Hiba, Ines Njeh, Ali Wali, Mohamed Ben Slima, Ahmed Benhamida, Chokri Mhiri, And Kharedine Ben Mahfoudhe. 2020. “Deep Multi-Scale 3D Convolutional Neural Network (CNN) For MRI Gliomas Brain Tumor Classification.” *Journal Of Digital Imaging* 33(4):903–15. Doi: 10.1007/S10278-020-00347-9.
  16. Özcan, Hakan, Bülent Gürsel Emiroğlu, Hakan Sabuncuoğlu, Selçuk Özdoğan, Ahmet Soyer, And Tahsin Saygı. 2021. “A Comparative Study For Glioma Classification Using Deep Convolutional Neural Networks.” *Mathematical Biosciences And Engineering* 18(2):1550–72. Doi: 10.3934/MBE.2021080.
  17. Pan, Yuehao, Weimin Huang, Zhiping Lin, Wanzheng Zhu, Jiayin Zhou, Jocelyn Wong, And Zhongxiang Ding. 2015. “Brain Tumor Grading Based On Neural Networks And Convolutional Neural Networks.” *Proceedings Of The Annual International Conference Of The IEEE Engineering In Medicine And Biology Society, EMBS 2015-Novem*:699–702. Doi: 10.1109/EMBC.2015.7318458.
  18. Qin, Jiang Bo, Zhenyu Liu, Hui Zhang, Chen Shen, Xiao Chun Wang, Yan Tan, Shuo Wang, Xiao Feng Wu, And Jie Tian. 2017. “Grading Of Gliomas By Using Radiomic Features On Multiple Magnetic Resonance Imaging (MRI) Sequences.” *Medical Science Monitor* 23:2168–78. Doi: 10.12659/MSM.901270.
  19. Raju, A. Ratna, P. Suresh, And R. Rajeswara Rao. 2018. “Bayesian HCS-Based Multi-SVNN: A Classification Approach For Brain Tumor Segmentation And Classification Using Bayesian Fuzzy Clustering.” *Biocybernetics And Biomedical Engineering* 38(3):646–60. Doi: 10.1016/J.Bbe.2018.05.001.
  20. Resmi, Ananda, And Tessamma Thomas. 2010. “Texture Description Of Low Grade And High Grade Glioma Using Statistical Features In Brain Mris.” *J. Of Recent Trends In Engineering And Technology* 4(3):27.
  21. Subashini, M. Monica, Sarat Kumar Sahoo, Venika Sunil, And Sudha Easwaran. 2016. “A Non-Invasive Methodology For The Grade Identification Of Astrocytoma Using Image Processing And Artificial Intelligence Techniques.” *Expert Systems With Applications* 43:186–96. Doi: 10.1016/J.Eswa.2015.08.036.
  22. Upadhyay, N., And A. D. Waldman. 2011. “Conventional MRI Evaluation Of Gliomas.” *British Journal Of Radiology* 84(SPEC. ISSUE 2):107–11. Doi: 10.1259/Bjr/65711810.
  23. Usman, Khalid, And Kashif Rajpoot. 2017. “Brain Tumor Classification From Multi-Modality MRI Using Wavelets And Machine Learning.” *Pattern Analysis And Applications* 20(3):871–81. Doi: 10.1007/S10044-017-0597-8.
  24. Vamvakas, A., S. C. Williams, K. Theodorou, E. Kapsalaki, K. Fountas, C. Kappas, K. Vassiou, And I. Tsougos. 2019. “Imaging Biomarker Analysis Of Advanced Multiparametric MRI For Glioma Grading.” *Physica Medica* 60(February):188–98. Doi: 10.1016/J.Ejmp.2019.03.014.
  25. Yang, Yang, Lin Feng Yan, Xin Zhang, Yu Han, Hai Yan Nan, Yu Chuan Hu, Bo Hu, Song Lin Yan, Jin Zhang, Dong Liang Cheng, Xiang Wei Ge, Guang Bin Cui, Di Zhao, And Wen Wang. 2018. “Glioma Grading On Conventional MR Images: A Deep Learning Study With

Transfer Learning.” *Frontiers In Neuroscience* 12(NOV):1–10. Doi: 10.3389/Fnins.2018.00804.

26. Zacharaki, Evangelia I., Sumei Wang, Sanjeev Chawla, Dong Soo Yoo, Ronald Wolf, Elias R. Melhem, And Christos Davatzikos. 2009. “Classification Of Brain Tumor Type And Grade Using MRI Texture And Shape In A Machine Learning Scheme.” *Magnetic Resonance In Medicine* 62(6):1609–18. Doi: 10.1002/Mrm.22147.