COMPUTOLOGY: Journal of Applied Computer Science and Intelligent Technologies
Volume 1, Issue 1, Jan-Jun 2021, pp. 22-31
DOI: 10.17492/computology.v1i1.2103
https://www.journalpressindia.com/cjacsit

A Comparative Study of Various Classification Schemes of MRI Images of Brain Tumour

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ABSTRACT

The purpose of this study is to identify the algorithms and approaches that have been used in previous research for the classification of multiclass brain tumours in Computed Tomography (CT) or Magnetic Resonance (MR) images. The criteria for this categorization are laid out by the WHO. The precise diagnosis of tumour cells has been the focus of a great deal of research attention in recent years, and numerous new ideas and pieces of information have been generated in this area. Their study's accuracy findings imply the extent to which their concepts were discovered to provide more precise outcomes when categorizing tumour types into their appropriate groups. These findings demonstrate the efficacy of their concepts in producing more precise classifications of tumour types. Over the course of this study, we focused primarily on developing supervised classification algorithms for use on 2D MRI or CT scans of different forms of brain tumours. This study provides a comprehensive evaluation of the numerous approaches taken to assign classification labels to tumour cells.

Keywords: Brain Tumor classification, Magnetic Resonance Imaging, Computed Tomography.

1.0 Introduction

Brain tumor classification is a crucial aspect of medical diagnostics and treatment planning in the field of neurology and oncology. It involves categorizing brain tumors based on various criteria to help medical professionals make informed decisions regarding patient care. These criteria can include the type of tumor, its location within the brain, its size, and its grade or stage of malignancy. Here's an introduction to brain tumor classification:

Brain tumours can be broken down into two distinct groups: those that originate in the brain itself (primary tumours) and those that spread from the brain (secondary tumours). Secondary brain tumours develop after cancer cells have moved to the brain from elsewhere in the body, while primary brain tumours form within the brain or its surrounding tissues.

Histological Classification: One of the primary methods for classifying brain tumors is based on their histological characteristics, which involves examining the tumor cells under a microscope. The World Health Organization (WHO) provides a widely accepted classification system for brain tumors, categorizing them into various types, including gliomas, meningiomas, schwannomas, and more.

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Grade or Stage Classification: Brain tumors are also classified based on their grade or stage, which indicates their level of malignancy. The grading system typically ranges from Grade I (benign) to Grade IV (highly malignant). Gliomas, for example, are commonly graded as Grade I (low-grade) to Grade IV (glioblastoma multiforme, a high-grade tumor).

Location: The location of a brain tumor within the brain is another important aspect of classification. Tumors can occur in different regions, such as the frontal lobe, temporal lobe, parietal lobe, and occipital lobe. The location can affect the symptoms experienced by the patient and the surgical approach required for treatment.

Size and Growth Pattern: The size and growth pattern of a brain tumor can also impact its classification and treatment. Some tumors are well-defined and discrete, while others may be diffuse or infiltrative, making complete surgical removal more challenging.

Molecular and Genetic Classification: Advances in molecular and genetic research have led to a deeper understanding of brain tumors. Molecular profiling can help identify specific genetic alterations and mutations within tumors, which can guide treatment decisions and prognosis predictions.

Imaging and Diagnostic Methods: To determine the size, location, and features of a brain tumour, a variety of imaging methods, including magnetic resonance imaging (MRI) and computed tomography (CT) scans, is frequently used in the categorization process. The planning of a diagnosis and course of treatment depends on these photographs.

Treatment Planning: The best course of action for treating a brain tumour depends greatly on its categorization. Depending on the kind, grade, and other characteristics of the tumour, treatment options may include surgery, radiation therapy, chemotherapy, targeted treatments, immunotherapy, or a combination of these techniques.

In summary, brain tumor classification is a multidimensional process that considers factors such as tumor type, grade, location, size, and molecular characteristics. This classification is essential for providing patients with accurate diagnoses, personalized treatment plans, and prognostic information, ultimately improving their chances of successful outcomes and quality of life. Advances in medical research continue to refine our understanding of brain tumors and enhance classification methods for more effective patient care.

2.0 Brain Tumor Classification Methods

A brief review of brain tumor classification methods provides an overview of the various approaches and techniques used to classify brain tumors based on medical imaging data, molecular markers, and other diagnostic modalities. The classification of brain tumors is a crucial step in medical diagnosis and treatment planning.

a) Imaging-Based Classification:

MRI-Based Classification: Magnetic Resonance Imaging (MRI) remains the primary imaging modality for brain tumor classification. Researchers have developed numerous techniques, including texture analysis, machine learning, and deep learning algorithms, to improve the accuracy of classifying brain tumors based on MRI data.

Advanced Imaging Modalities: Apart from traditional MRI, newer imaging techniques like diffusion tensor imaging (DTI), perfusion-weighted imaging (PWI), and spectroscopy have been explored for their potential in enhancing brain tumor classification accuracy.

b) Histopathological Classification

Pathological Analysis: Histopathological examination of brain tumor tissue samples continues to be a gold standard for tumor classification. Advances in molecular pathology and immunohistochemistry have led to more precise classifications, including the integration of genetic markers.

Molecular Subtypes: The discovery of specific molecular markers, such as IDH mutations and MGMT promoter methylation, has allowed for the subclassification of brain tumors into different molecular subtypes. These markers have important prognostic and therapeutic implications.

c) Machine Learning and Deep Learning

Convolutional Neural Networks (CNNs): CNNs have been widely used in recent years to automate the classification of brain tumors from medical images. They can learn complex patterns and features from MRI scans, making them highly effective in distinguishing between tumor types and grades.

Ensemble Techniques: To integrate several machine learning algorithms for better brain tumour classification performance, ensemble techniques like random forests and gradient boosting have been used.

d) Integration of Multiple Data Sources

Multimodal Data Fusion: Combining data from multiple sources, such as MRI, genetic information, and clinical data, has shown promise in enhancing brain tumor classification accuracy. Integrative approaches aim to leverage the complementary information from these diverse data types.

e) Challenges and Future Directions

Data Imbalance: Addressing imbalanced datasets, where some tumor classes are underrepresented, remains a challenge in brain tumor classification. Techniques like oversampling, undersampling, and data augmentation are being explored.

Interpretable Models: Researchers are working on developing more interpretable machine learning and deep learning models to ensure that the decisions made by these algorithms can be understood and validated by medical professionals.

f) Clinical Implementation

Transitioning from research to clinical practice requires robust validation of classification models and adherence to regulatory standards.

Clinical Impact: Accurate classification of brain tumors is essential for treatment planning, including surgery, radiation therapy, and chemotherapy.

Molecular sub typing can help identify potential therapeutic targets and predict patient outcomes. Automation and AI-assisted classification can speed up the diagnostic process, leading to better patient care.

Thus brain tumor classification is a rapidly evolving field with ongoing advancements in imaging techniques, machine learning algorithms, and molecular biology. These developments hold great promise for improving diagnosis and treatment outcomes for patients with brain tumors. Researchers are continuously working on refining existing methods and exploring novel approaches to enhance classification accuracy and clinical utility.

3.0 Steps to Perform a Comparative Study for Brain Tumor Classification

A comparative study of methods for brain tumor classification involves evaluating and comparing different approaches and techniques for accurately categorizing brain tumors based on medical imaging data. This type of research is crucial for improving the diagnosis and treatment of brain tumors. Below, I outline a general framework for conducting a comparative study of brain tumor classification methods:

a) Data Collection and Preprocessing:

Collect a large number of photographs depicting various brain tumours, in terms of size, location, and type. Preprocess the data, which may include resizing, normalizing, and augmenting the images to enhance the quality and quantity of the dataset

b) Feature Extraction:

Extract relevant features from the medical images. Common features include texture, shape, intensity, and statistical measures. To automatically learn features from the photos, deep learning techniques such as Convolutional Neural Networks (CNNs) should be considered.

c) Method Selection:

Choose a set of classification methods to evaluate. These may include traditional machine learning algorithms (e.g., SVM, Random Forest, k-Nearest Neighbors) and deep learning models (e.g., CNNs, Recurrent Neural Networks, Transformers).

d) Data Splitting:

Segregate the data into a training set, a validation set, and a test set. Cross-validation can also be used to ensure robust evaluation.

e) Model Training and Tuning:

Train each selected classification model on the training data and fine-tune hyperparameters using the validation set. For deep learning models, consider transfer learning or architecture modifications to improve performance.

f) Evaluation Metrics:

Choose appropriate evaluation metrics for brain tumor classification, such as accuracy, precision, recall, F1-score, ROC curves, and AUC-ROC.

g) Comparative Analysis:

Compare the performance of each classification method using the chosen evaluation metrics. Consider visualizing results with confusion matrices, ROC curves, and precision-recall curves. Assess computational requirements, training times, and model complexity.

h) Statistical Analysis:

Use statistical tests to determine if observed differences in performance are statistically significant. Common tests include t-tests, ANOVA, and paired tests like Wilcoxon signed-rank test.

i) Generalization Testing:

Perform generalization testing by evaluating the models on an independent test dataset or through cross-validation to assess their ability to classify unseen data.

j) Discussion and Conclusion:

Summarize the findings, discussing which classification methods performed the best and why. Highlight the limitations of the study, such as dataset size and diversity, and potential biases. Suggest areas for future research and improvements in brain tumor classification methods.

k) Clinical Implications:

Discuss how the results can impact clinical practice, patient care, and the field of medical imaging. Address the potential use of the best-performing model(s) in real-world scenarios.

l) Publication and dissemination:

Share the findings through research publications, presentations, and open-access datasets to contribute to the broader medical community. The effectiveness of brain tumor classification methods may vary depending on factors like the dataset, the choice of features, and the specific algorithms used. Therefore, a comprehensive comparative study is essential to determine the most suitable approach for accurate and reliable brain tumor classification.

4.0 Related Works

Significant efforts have been undertaken recently to distinguish between different types of brain neoplasms by integrating parameters from MR/CT imaging into frameworks for pattern classification that use machine learning techniques. These investigations have been going on for a while. A classifier known as the mix technique—which combines ANN and KNN—was introduced by the authors of [5]. The work being described can be divided into three stages: discrete wavelet transformation (DWT) for feature extraction, principal component analysis (PCA) for feature selection, and the suggested ANN+KNN classifier. There are 275 MR images in the collection, with a 256 x 256 pixel resolution for each image. The dataset consists of 184 photographs of the normal brain and 181 images of the diseased brain. The shape features are extracted using GLCM, and there are around 278 distinct textures.

Neural network and KNN classifiers receive these features separately. The class label was decided by the majority vote of the two classifiers. The hybrid classifier approach performs admirably overall. To speed up the retrieval of CBIR results, the authors [6] introduced Feature Database Tree (KD-Tree) indexing. Forty of the eighty-two images were malignant, while forty were benign. Ten times, this data was processed at random. Images are segmented in each fold using wavelet transformation [28] and modified fuzzy c-means methods [29].

The tumour portion was processed using GLCM [29] for feature extraction, shape features for additional feature reduction, and PCA [29] for further feature reduction. The reduced feature set was classified by the ensemble classifier using SVM, ANN, and K-Nearest Neighbour [29]. Class labels and feature set are stored in the feature database so that KD-Tree indexing can retrieve them more quickly. The accuracy of categorisation with this method is 97%. Classification methods based on variants and ANN [7][8][12][18].

The authors used texture characteristics and intensity-based features based on GLCM [7]. PCA further minimises the dimensionality of feature vectors. Using ANN and its variants, several

scientists categorised 60–428 256 x 256 MR images. While a dataset of 273 photographs reduces classification accuracy to 64% [18] and ranges from 64% to 94% using Bayesian ANN, a short sample of 60–80 shots gives approximately 91% accuracy [7].

The author of [7] uses a huge dataset of 428 MR images to claim an accuracy of 85%. There were uses of SVM classification in [11][15–17][21]. GA and PCA choose dual intensity features, while DCT and DWT extract them [11]. 96% classification accuracy was achieved on a dataset of 120 MR images that were categorised as normal or abnormal. Using texture, shape, and ranking features reduces classifier accuracy to 88% [16]. Accuracy varies from 80% to 90% depending on how photo datasets increase or decrease, as [17][21] explains. When it comes to intensity-based features, SVM outperforms texture-based features.

A novel probabilistic neural network method is called PNN [9–10][15]. PNN attains 100% accuracy on 20 images [9] using the same texture and intensity features, but falls to 96% on 120 MR images [10]. According to the experiments, PNN performs badly for texture-based features derived using GLCM but effectively for frequency-based features extracted using DWT or DCT.

In [14], the first neuron classifier in this field, Simplified Bi-directional Associative Memory (sBAM), is described for brain tumour classification. This paper presents a comparison of three neural classifiers for MR image-based cancer categorization. The supervised and unsupervised neuron-classifier algorithms were compared using the Error Correcting Learning Algorithm, Hebbian Learning Algorithm, and sBAM.

Tumour classification using Rajasekaran and Pai's data classification technique, sBAM, has not been tested. First, the tumour image is segmented. GLCM is used by the segmented tumour region to compute texture-based features. Accuracy is measured when these produced characteristics are fed into neural classifiers. For the experiment, 200 MRI images with tumours of classes I, II, III, and IV were employed. While the accuracy of sBAM classifiers was 95% for different datasets, the performance of supervised neuron classifiers declined significantly for a sample of 50 and 200 pictures. According to the author, sBAM computes more quickly than supervised methods.

5.0 Used Dataset and Experimental Setup

This work evaluated categorization methods using a dataset of CT/MR images used by researchers. The detailed results, including tumor classes, are published here with the appropriate dataset strength. Extraction, selection, and classification of features Table 2 lists authors' algorithms and accuracy values.

6.0 Evaluation Metrics

Performance in classifying brain tumours is evaluated using F-measure, accuracy, recall, and precision. The proportion of correctly identified images to all images in the class (TP and FP) is known as precision. When compared to the total number of photos in the class, recall quantifies the proportion of correctly identified images (including True Positives and False Negatives).

F-measure integrates recall and precision. The tumour classification classifier performance is measured using the F-measure. Performance metrics can be seen in the confusion matrix table below.

Table 1: Performance Evaluation

Metric	Equation
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$

7.0 Comparative Results and Discussions

Table 2: Comparison of Previous Studies on Classification of Brain Tumors

Author- year	Brain Tumor classes/ Images per Class	Image Dataset	Feature Extraction	Feature Selection	Classifier	Accuracy Obtained (%)
Megha.P. Arakeri- Springer, 2013	1-Primary (42) 2- Malignant (40)	82	Shape+Texture (GLCM)	PCA+KD Tree indexing	SVM, ANN, K-NN	97
Jainysachdeva, vinodkr- Springer, 2013	Astocytoma, Glioblastoma, Medulloblastoma, meningioma, Metastatic	428	GLCM+LoG+IBF+RILBP	PCA	ANN+PCA-ANN	85.23
N.HemaRajni, R. Bhavani- Springer, 2013	Normal (20) Abnormal (60)	80	DWT	PCA	ANN,K-NN, SVM	91, 93, 95
D. sridhar, Murali Krishna- IEEE, 2013	Primary, Secondary	20	DCT	DCT	PNN	100
Padma Nanthagopal- Springer, 2012	Normal (40) Benign (37) Malignant (43)	120	DWT+WCT	GA	PNN	96
Padma Nanthagopal- Springer, 2012	Normal (40) Benign (37) Malignant (43)	120	DWT+WCT	GA+PCA	SVM	96
Prof. Vikas Gupta- IEEE, 2012	Class I,II,III,IV	60	GLCM	--	ANN	89
P. Rajendran, M. Madheswaran- IEEE, 2012	Nornal (151), Benign (22), Malignant (27)	200	Shape features	ASM	Decision Tree	90
DrMohd-Fauzi Bin Othman- IEEE, 2012	Normal, Abnormal	15	DWT	--	Kernel-SVM	N-98 AB- 67
Amer Al-Badarneh- IEEE/ACM 2012	1- Normal (10) 2- Abnormal (60)	70	DWT	PCA	ANN+KNN	N- 96.77 AB- 97.56
Evangelia I.	Meningioma,Glioma Grade	100	Age,shape,intensi	PCA	J48,KNN,VFI,S	85, 93.5, 95,

Zacharaki- Springer, 2011	II,III,IV,Metastatis		ty		VM,Naive Bayes	93
MohdFauzi Othman- IEEE, 2011	Normal, malignant	15	PCA		PNN	73-80
CarlosArizmendi, Alfredo Vellido- IEEE, 2011	Normal, Primary Grades, Secondary Grades	273	PCA	MWVA	Bayesian ANN	64-95
S.N.Deepa, B.Aruna Devi- IEEE, 2011	Normal, Abnormal	42	GLCM	--	RBFN	85.71
Jainysachdeva, vinodkr- IEEE 2011	1-Astrocytoma (118) 2- Glioblastoma (59) 3- Meningioma (97) 4- Medulloblastoma (88) 5- Metastatis (66)	428	GLCM+LoG+IBF+RILBP	PCA	GA-SVM	89.8, 83.3, 96, 91.8, 97.1
Dipali M. Joshi, Dr.N. K. Rana- IEEE, 2010	Normal, Abnormal	80	GLCM	--	Neuro-fuzzy	Based on segementation (75)
Evangelia I. Zacharaki- IEEE, 2009	Grade I,II,III,IV	98	Age,shape, Texture	Ranking based method	SVM	88.2
Evangelia I. Zacharaki- IEEE, 2009	1- Metastatisc (24) 2- Grade Gliomas (22) 3- Glioblastomas (34) 4- Gliomas Grade III (18)	98	Age,shape, Texture	PCA	SVM-RFE	91.7, 90.9, 41.2, 33.4

8.0 Conclusion

This paper focuses on IEEE and Springer research on brain tumor categorization from 2009 to 2013. The comparative analysis highlights the accuracy of tumor classification over the past few years. The researchers classified tumors using texture and frequency-based features retrieved using GLCM and DWT, followed by feature selection methods like PCA or Genetic algorithm. The focus was on categorization accuracy. For quicker CBIR retrieval, researchers have proposed PNN and KD-tree indexing mechanisms. Results indicate that ANN, PNN, and BPNN classifiers excel at frequency-based features, whereas KNN excels at texture-based features. The accuracy rate also changes with dataset size. Increasing the image dataset leads to diminishing accuracy. Most researchers used 80–120 MR images. New algorithms and strategies that improve efficiency on larger datasets are needed.

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