Paper -2

* The brain tumor is an urgent malignancy caused by unregulated cell division.
* In this paper, transfer-learning-based models in addition to a Convolutional Neural Network (CNN) called BRAIN-TUMOR-net trained from scratch are introduced to classify brain magnetic resonance images into tumor or normal cases.
* The main objective of the proposed approach is to combine image batch identification with a fine-tuned classifier to classify many instances as tumor or normal cases (30).
* However, the CNN model trained from scratch using k-fold validation has the longest runtimes of 376, 3418, and 16284.818 s on the first, second, and third datasets, respectively.
* Anaraki AK, Ayati M, Kazemi F. Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms.

This paper proposes an efficient framework for brain tumor detection using different deep learning techniques on MRI images. The key points are:

* Three publicly available MRI datasets are used for evaluation, with tumor and normal cases.
* Transfer learning models (InceptionResNetv2, Inceptionv3, ResNet50) are applied by fine-tuning the pretrained models.
* A custom CNN called BRAIN-TUMOR-net is designed and trained from scratch using stratified k-fold cross-validation.
* BRAIN-TUMOR-net achieves the highest accuracy of 100% on the largest dataset, outperforming transfer learning.
* Transfer learning models still produce good results even on small datasets, with ResNet50 giving 93.48% accuracy on the smallest dataset.
* Segmentation is performed using techniques like K-means, fuzzy c-means, and watershed algorithm.
* Comprehensive evaluation using metrics like sensitivity, specificity, precision, F1-score, ROC, etc. is presented.
* BRAIN-TUMOR-net with cross-validation achieves state-of-the-art performance, demonstrating the potential of CNNs for brain tumor diagnosis.

In summary, this paper provides a deep learning framework for brain tumor classification and segmentation, leveraging both transfer learning and custom CNN models to achieve excellent accuracy on MRI data.

Paper -7

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Title

Current Trends on Deep Learning Models for Brain Tumor Segmentation and Detection

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This paper reviews current deep learning techniques for brain tumor segmentation and detection using MRI images. The key points are:

* MRI is useful for detecting abnormalities like brain tumors. Segmentation and classification of tumors from MRI is challenging.
* The typical workflow involves pre-processing, segmentation, feature extraction, and classification.
* Deep learning models like CNNs, ANNs, and SVM have shown good performance for brain tumor analysis tasks.
* 3D CNNs leverage volumetric MRI data but can be computationally expensive. Recent work focuses on efficient 3D architectures.
* Transfer learning using pretrained models can be beneficial given limited medical training data.
* Multi-modal data fusion improves accuracy over single modal approaches.
* Top techniques highlighted include cascaded CNNs, deep supervision, attention mechanisms, and generative adversarial networks.
* Current research directions include interpretability of models, robustness, and clinical integration of automated methods.

In summary, the paper surveys the state-of-the-art in deep learning based approaches for brain tumor segmentation and classification from MRI scans, analyzing the techniques, trends, and key challenges in this area.

Explain the Objective of the Research Paper

The objective of the research paper is to review the current trends in deep learning models for accurately and reliably segmenting and detecting brain tumors using MRI scans. The paper aims to explore the challenges faced by deep neural networks in segmenting critical organs from 3D medical MR images and focuses on 3D-based Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Multi-class Support Vector Machines (MCSVM) for deeper segmentation. The goal is to provide an overview of the current development in image segmentation and classification techniques for tumor detection, with a specific focus on gliomas. The paper also discusses the importance of processing input images at multiple scales simultaneously and addresses the imbalance present in the data. Overall, the objective is to provide insights into the present status of segmentation and detection of brain tumors using deep learning models. [\*](https://cite.petal.org/document/328681/view?organizationId=55282#/page/0)

Explain About the Research Paper Dataset:

The research paper does not provide specific information about the dataset used. It focuses more on the current trends and techniques in deep learning models for brain tumor segmentation and detection. Therefore, there is no information available about the dataset used in the research paper.

Data Preprocessing Insights:

The research paper mentions that data preprocessing plays an important role in the segmentation and classification of brain tumor images. It states that preprocessing techniques are implemented on the MR images to remove non-brain portions, correct nonuniform properties, and bring the images into a common spatial and intensity space. This preprocessing step is crucial for improving the clarity and quality of the images, which in turn facilitates more accurate segmentation and classification.

Some specific preprocessing techniques mentioned in the paper include noise removal, converting color images to grayscale, salt and pepper noise reduction, and improving contrast to enhance image clarity. The paper also mentions that developing new architectures that resemble neural networks can reduce hardware requirements and processing time for large-sized images.

Overall, the research paper emphasizes the importance of proper data preprocessing in order to facilitate more accurate and reliable brain tumor segmentation and classification

Machine Learning/Deep Learning Models:

The research paper discusses various machine learning and deep learning models used for brain tumor segmentation and detection. Specifically, it focuses on deep neural networks (NNs) and machine learning techniques.

For 2D image segmentations, deep neural networks and machine learning techniques have shown good achievements. However, segmenting organs from 3D MR images is a challenging task for neural networks. The paper highlights the use of 3D-based Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Multi-class Support Vector Machines (MCSVM) for deeper segmentation.

The paper also mentions the use of efficient and effective image processing techniques for tumor-infected human brain MRI adjacent image patches. It discusses the use of discriminative 3D NNs and computational machine learning to process input images at multiple scales simultaneously.

Overall, the research paper explores the current trends in deep learning models for brain tumor segmentation and detection, highlighting the use of various machine learning and deep learning techniques to achieve accurate and reliable results.

Paper -13

This paper proposes a hybrid deep learning and machine learning approach for brain tumor classification from MRI images. The key points are:

* The dataset contains 6321 MRI images across 4 tumor classes - glioma, meningioma, pituitary and no tumor.
* As preprocessing, techniques like augmentation, resizing and grayscale conversion are applied.
* Three CNN models - GoogLeNet, ShuffleNet and NasNet Mobile - are used for feature extraction from the MRI images.
* The extracted features are fed into 3 conventional ML classifiers - SVM, KNN and LDA.
* ShuffleNet + SVM achieves the best performance with 98.4% accuracy, 97% precision, 96.75% recall and F1-score.
* The lightweight ShuffleNet architecture extracts more discriminative features compared to GoogLeNet and NasNet Mobile.
* The results are compared to recent papers, and the proposed hybrid approach provides superior tumor classification accuracy.

In summary, the key contribution is combining CNN feature extraction with traditional ML classification to leverage their complementary strengths for improved brain tumor diagnosis from MRI scans. The proposed pipeline outperforms previous approaches.

Explain the Objective of the Research Paper:

The objective of the research paper is to develop a method for classifying brain tumors using MRI images. The traditional approaches for distinguishing brain cancers are time-consuming and prone to human error. The researchers aim to utilize Artificial Intelligence (AI) techniques, specifically Convolutional Neural Network (CNN) and supervised machine learning algorithms, to improve the accuracy and efficiency of brain tumor classification. They propose a hybrid method that combines pre-trained deep learning CNN models with supervised classifiers such as k-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA). The research focuses on four brain tumor classes: glioma, meningioma, pituitary, and no tumor. The goal is to extract features from MRI images using CNN models and achieve high performance in terms of accuracy, precision, recall, and F1-Score. The results of the proposed method are compared with other state-of-the-art papers to demonstrate its superiority.

Explain About the Research Paper Dataset

The research paper utilizes an image dataset of MRI scans for brain tumor classification. The dataset consists of 6,321 MRI images, which are categorized into four distinct classes: glioma, meningioma, pituitary, and no tumor. Specifically, there are 1,621 images of glioma, 1,645 images of meningioma, 2,000 images of pituitary tumors, and 1,055 images of normal brain scans without tumors. The dataset used in the research is publicly available on Kaggle and is sourced from FigShare, SARTAJ dataset, and Br35H. The researchers gathered the dataset from these sources to conduct their analysis.

Data Preprocessing Insights

The research paper mentions several data preprocessing techniques that were applied to the MRI image dataset before training the models. These techniques aim to enhance the training process and improve the performance of the models.

1. Augmentation Techniques: Image rotation, sharing, scaling, and reflection were employed as augmentation techniques to increase the diversity and variability of the dataset. These techniques help in reducing overfitting and improving the generalization ability of the models.
2. Resizing Images: The MRI images in the dataset have different dimensions, so they were resized to a uniform dimension of 224 × 224 × 3 pixels. This resizing ensures that all images have the same size, which is necessary for optimal performance when using pre-trained deep learning models.
3. Grayscale Conversion: The MRI images were converted to grayscale, resulting in a single-channel representation of the images. This conversion simplifies the data and reduces the computational complexity of the models.

Overall, these preprocessing techniques aim to standardize the dataset, increase its diversity, and make it suitable for training the deep learning and machine learning models used in the research.

Machine Learning/Deep Learning Models

The research paper utilizes a combination of deep learning and machine learning models for the classification of brain tumors in MRI images.

Deep Learning Models:

1. GoogleNet: GoogleNet is a deep learning convolutional neural network (CNN) model consisting of 22 learning layers. It is used in the research paper for feature extraction from the MRI images.
2. NasNet-Mobile: NasNet-Mobile is another deep learning CNN model used for feature extraction. It is employed to extract meaningful features from the MRI images.
3. ShuffleNet: ShuffleNet is a deep learning CNN model used for feature extraction as well. It helps in extracting significant features from the MRI images.

Machine Learning Classifiers:

1. k-Nearest Neighbor (KNN): KNN is a supervised machine learning algorithm used for classification. It is applied to the extracted features from the deep learning models to classify the brain tumor images.
2. Supporting Vector Machines (SVM): SVM is another supervised machine learning algorithm used for classification. It is employed as a classifier for the extracted features from the deep learning models.
3. Linear Discriminant Analysis (LDA): LDA is a dimensionality reduction technique that is also used as a supervised machine learning classifier in the research paper. It helps in classifying the extracted features from the deep learning models.

These deep learning models and machine learning classifiers are combined to create a hybrid approach for brain tumor classification in the research paper. The extracted features from the deep learning models are fed into the machine learning classifiers to make predictions and classify the brain tumor images.

Experimental Details:

The research paper used an image dataset of MRI scans consisting of 6,321 images. The dataset includes four distinct types of brain tumors (glioma, meningioma, pituitary) and a category for images with no tumor. The dataset was obtained from various sources, including Kaggle, FigShare, SARTAJ dataset, and Br35H [p. 3](https://cite.petal.org/document/328692/view?organizationId=55282#/page/3).

To enhance the training process and improve model performance, data augmentation techniques were applied to the MRI images. These techniques included image rotation, image sharing, image scaling, and image reflection [p. 4](https://cite.petal.org/document/328692/view?organizationId=55282#/page/4).

The MRI images were resized to a uniform dimension of 224 × 224 × 3 pixels to ensure optimal performance [p. 4](https://cite.petal.org/document/328692/view?organizationId=55282#/page/4).

The deep learning models (GoogleNet, NasNet-Mobile, and ShuffleNet) were used for feature extraction from the MRI images [p. 4](https://cite.petal.org/document/328692/view?organizationId=55282#/page/4).

The extracted features were then fed into the machine learning classifiers, including k-Nearest Neighbor (KNN), Supporting Vector Machines (SVM), and Linear Discriminant Analysis (LDA) [p. 4](https://cite.petal.org/document/328692/view?organizationId=55282#/page/4).

To evaluate the performance of the models, several metrics were used, including accuracy, precision, recall, and F1-score. Cross-validation with k=5 was employed to mitigate overfitting [p. 5](https://cite.petal.org/document/328692/view?organizationId=55282#/page/5).

The experimental results showed that the combination of ShuffleNet with SVM achieved the highest accuracy of 98.40%, precision of 97%, recall of 96.75%, and F1-score of 96.75% [p. 2](https://cite.petal.org/document/328692/view?organizationId=55282#/page/2).

Overall, the experimental details involved preprocessing the dataset, applying data augmentation techniques, extracting features using deep learning models, and utilizing machine learning classifiers for classification. The performance of the models was evaluated using various metrics

Explain the Results

The results of the study showed that the combination of ShuffleNet with SVM achieved the highest performance in classifying brain tumors using MRI images. The accuracy of this model was 98.40%, indicating that it correctly classified 98.40% of the images. The precision, which measures the proportion of correctly classified positive cases, was 97%. The recall, which measures the proportion of actual positive cases correctly classified, was also 96.75%. The F1-score, which combines precision and recall, was also 96.75% [p. 2](https://cite.petal.org/document/328692/view?organizationId=55282#/page/2).

Comparisons were made with other state-of-the-art papers, and the proposed method outperformed them in terms of accuracy, precision, recall, and F1-score [p. 2](https://cite.petal.org/document/328692/view?organizationId=55282#/page/2). The results were also compared with studies that used different deep learning architectures and classic methodologies like SVM. The proposed method achieved higher accuracy compared to LeNet, ResNet, AlexNet, and SVM [p. 3](https://cite.petal.org/document/328692/view?organizationId=55282#/page/3).

The results were presented in confusion matrices for each model and classifier. The highest accuracy achieved by ShuffleNet with SVM was 98.40%, while the lowest accuracy achieved by NasNet-Mobile with SVM was 95.05% [p. 6](https://cite.petal.org/document/328692/view?organizationId=55282#/page/6). The F1-scores for the different models and classifiers ranged from 93.5% to 96.75% [p. 6](https://cite.petal.org/document/328692/view?organizationId=55282#/page/6).

The study also compared the proposed method with other published papers that used MRI images for brain tumor classification. The proposed method showed higher accuracy and F1-score compared to these studies [p. 6p. 6](https://cite.petal.org/document/328692/view?organizationId=55282#/page/6).

Overall, the results demonstrated the effectiveness of using a combination of deep learning models for feature extraction and machine learning classifiers for brain tumor classification. The ShuffleNet model with SVM classifier achieved the highest accuracy and performed better than other models and classifiers