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| SL | Name | Year | Description | Method | Result |
| 1 | Brain Tumor Classification Using Deep Learning. Vishal K. Waghmare, Maheshkumar H. Kolekar . | 2020 | This study uses Convolutional Neural Networks (CNNs), including basic CNN and VGG-16 architectures, to automatically classify brain tumors from MRI images, achieving a detection accuracy of 95.71% on an online dataset. The research highlights CNN's effectiveness in tasks like image classification, recognition, and segmentation for medical imaging. | Convolutional Neural Networks (CNNs), including basic CNN and VGG-16 architectures. | detection accuracy of 95.71% |
| 2. | BrainNet: Optimal Deep Learning Feature Fusion for Brain Tumor Classification, Usman Zahid , Imran Ashraf | 2022 | This study uses ResNet101 with transfer learning for brain tumor classification, optimizing features through differential evolution, particle swarm optimization, and PCA. The proposed technique achieves a prediction speedup of 25.5x with an accuracy of 94.4%, reducing computational overhead while maintaining high accuracy. | ResNet101 with transfer learning, differential evolution, particle swarm optimization, and PCA for feature optimization. | Achieved a prediction speedup of 25.5x and an accuracy of 94.4%, with reduced computational overhead. |
| 3. | Deep CNN for Brain Tumor Classification, Wadhah Ayadi, Wajdi Elhamzi | 2021 | This research employs a novel deep Convolutional Neural Network (CNN) model for automated brain tumor classification from MRI images, addressing limitations of manual techniques. Experimental evaluation on three datasets demonstrates superior performance compared to existing methods. | A proposed novel Convolutional Neural Network (CNN) model with multiple layers for automated classification. | The model outperformed existing methods, demonstrating convincing classification performance on the evaluated datasets. |
| 4. | Deep Learning Techniques for the Classification of Brain Tumor: A Comprehensive Survey. AYESHA YOUNIS, QIANG L | 2023 | This study reviews state-of-the-art deep learning methods for brain tumor classification and segmentation from MRI images, highlighting their powerful feature representation and performance. It identifies gaps in current literature, compares deep learning approaches, and provides future directions for enhancing automated classification techniques. | Deep learning-based methods, including hierarchical feature learning and data representation techniques for classification and segmentation. |  |
| 5. | Brain Tumor Classification Using Convolutional Neural Network. Nyoman Abiwinanda, Muhammad Hanif | 2019 | This study employs a simple Convolutional Neural Network (CNN) architecture to classify Glioma, Meningioma, and Pituitary tumors from T1-weighted CE-MRI images, without region-based preprocessing. It achieved a training accuracy of 98.51% and a validation accuracy of 84.19%, comparable to more complex segmentation algorithms. | Convolutional Neural Network (CNN) with a simple architecture consisting of convolution, max-pooling, flattening layers, and one hidden full connection layer. | Achieved a training accuracy of 98.51% and validation accuracy of 84.19%, comparable to more complex region-based segmentation algorithms. |
| 6. | Brain Tumor Classification Using Convolutional Neural Networks J. Seetha1 and S. Selvakumar Raja2 | 2018 | This paper focuses on automatic brain tumor classification using Convolutional Neural Networks (CNNs). MRI images from Radiopaedia and the BRATS 2015 dataset were used to achieve an accuracy of 97.5%, demonstrating high performance with reduced computational complexity compared to traditional methods. | Convolutional Neural Networks (CNN) with pre-trained models like ImageNet. | 97.5% Accuracy, highlighting low computational complexity. |
| 7. | Brain Tumor Classification Using Deep Learning  Himank Dave, Nikhil Kant, Nishank Dave, Divya Ghorui | 2021 | This study introduces a hybrid segmentation and classification approach utilizing the VGG-16 CNN model on a Kaggle MRI dataset. The proposed method effectively classified tumors and non-tumors. The features of the segmented images were further classified into various types of tumors, including Glioma tumor, Meningioma tumor, Pituitary tumor, and no tumor using one-hot encoding. | VGG-16 CNN model, One-hot encoding | Accuracy achieved using VGG-16 was not explicitly quantified but suggested effective classification of tumor types. |
| 8. | A Hybrid DeepLearning-Based Approach for Brain Tumor Classification  Asaf Raza, HumaAyub1,Javed Ali Khan Yousef Ibrahim Daradkeh, Danish Javeed, Ijaz Ahmad, Ahmed S. Salama, Ateeq Ur Rehman and Habib Hamam | 2022 | This paper proposes a hybrid DeepTumorNet model, modified from GoogLeNet, for brain tumor classification for three types of brain tumors (BTs)—glioma, meningioma, and pituitary tumor classification. Using the CE-MRI dataset, the model achieved a 99.67% accuracy, surpassing other deep learning models in performance and robustness. | Hybrid DeepTumorNet based on GoogLeNet architecture, Leaky ReLU activation functions. | Achieved the highest classification accuracy of 99.67% on the CE-MRI dataset. |
| 9. | Brain Tumor Classification Using Convolutional Neural Network  Nyoman Abiwinanda, Muhammad Hanif, S. Tafwida Hesaputra, Astri Handayani, and Tati Rajab Mengko | 2019 | The study explores a simple Convolutional Neural Network (CNN) architecture to classify brain tumors into three types: Glioma, Meningioma, and Pituitary without requiring prior region-based segmentation. Using a dataset of T1-weighted contrast-enhanced MRI images, the method achieves a training accuracy of 98.51% and a validation accuracy of 84.19%, demonstrating comparable performance to more complex segmentation-based algorithms. | Convolutional Neural Network (CNN) with five variations in architecture. Architecture 2 was the most effective, with two convolution layers, ReLU activation, max-pooling, and a fully connected layer of 64 neurons. | Training accuracy: 98.51%. Validation accuracy: 84.19% (best for Architecture 2). |
| 10. | Brain Tumor Classification Method Based on Segmented Uniformity Measure and Spatial Shift Information Fusion  Xiaorui Zhang, Peisen Lu,Wei Sun, Rui Jiang | 2024 | The proposed method enhances brain tumor classification by combining segmented uniformity-based Local Ternary Pattern (SULTP) feature extraction with Spatial Shift Fuse-MLP (SSF-MLP). This hybrid approach achieves superior classification accuracy of 97.26% on benchmark datasets. | Segmentation-based Uniform Local Ternary Patterns (SULTP), Spatial Shift Fuse-MLP (SSF-MLP), GELU & ReLU activation functions. | Sa Dataset: 97.26%  SfB Dataset: 95.32% |
| 11. | Convolutional Neural Network Techniques for Brain Tumor Classification | 2022 | The study leverages BRATS2018 and BRATS2019 datasets to develop a robust brain tumor classification system. Using a fine-tuned DenseNet201 model, feature selection techniques (EKbHFV and MGA), and feature fusion, the system achieves exceptional accuracy—99.7% and 98.8% for HGG and LGG on BRATS2018, and 99.8% and 99.3% on BRATS2019—while reducing computational time. It offers a decision support system for radiologists. | CNN architectures like AlexNet, VGG, ResNet, GoogLeNet, DenseNet, and EfficientNet. | 99.8% accuracy for High-Grade Glioma and 99.3% for Low-Grade Glioma |
| 12. | A decision support system for multimodal brain tumor classification using deep learning | 2021 | This study utilizes BRATS2018 and BRATS2019 datasets to develop a brain tumor classification system with high accuracy and efficiency. Leveraging a fine-tuned DenseNet201 model, advanced feature selection techniques (EKbHFV and MGA), and feature fusion, the method achieves remarkable classification accuracies of up to 99.8% while reducing computational time. | DenseNet201 model, EKbHFV and MGA for feature selection and feature fusion, multiclass cubic SVM classifier | Accuracy (up to 99.8%) and reduced computational time |
| 13. | Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection | 2020 | This study introduces a deep learning-based framework for multimodal brain tumor classification using BRATS 2015, 2017, and 2018 datasets. Leveraging transfer learning with pre-trained VGG16 and VGG19 models, robust feature selection (via correntropy) and fusion (PLS-based) significantly enhance classification accuracy and computational efficiency. The proposed method achieves accuracies of 98.16%, 97.26%, and 93.40% across the datasets, outperforming traditional classifiers and addressing challenges in multimodal MRI data classification. | CNNs (VGG16, VGG19), transfer learning, ELM, PLS-based feature fusion and correntropy-driven hybrid approach | BRATS 2015: 98.16%, BRATS 2017: 97.26%, and BRATS 2018: 93.40%. |
| 14. | Brain Tumor Classification Using Dense EfficientNet  Dillip Ranjan Nayak 1 , Neelamadhab Padhy 1 , Pradeep Kumar Mallick 2 , Mikhail Zymbler 3  and Sachin Kumar | 2022 | This study proposes a Dense EfficientNet CNN model for brain tumor classification, using 3260 T1-weighted MRI images categorized into glioma, meningioma, pituitary, and no tumor classes. The approach incorporates min-max normalization and data augmentation, achieving 99.97% training accuracy and 98.78% testing accuracy, surpassing existing deep-learning models. | Dense EfficientNet CNN, a variant of EfficientNetB0 dense layers and dropout layers with probabilities (0.25, 0.25, and 0.5) for improved generalization. | Training Accuracy: 99.97% Testing Accuracy: 98.78% |
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1.

**Year:**

**Name:**

**Summarized Abstract:**

This study uses Convolutional Neural Networks (CNNs), including basic CNN and VGG-16 architectures, to automatically classify brain tumors from MRI images, achieving a detection accuracy of 95.71% on an online dataset. The research highlights CNN's effectiveness in tasks like image classification, recognition, and segmentation for medical imaging.

**Accuracy Rate:** 95.71%

**Dataset Info:** Online dataset of brain MRI images.

**Algorithms or Models:** Convolutional Neural Networks (CNNs), including basic CNN and VGG-16 architectures.

**Metrics:** Training accuracy and validation accuracy.

**Results:** Achieved a detection accuracy of 95.71%, showcasing CNN's capability in image classification, recognition, and segmentation.

2.

This study uses ResNet101 with transfer learning for brain tumor classification, optimizing features through differential evolution, particle swarm optimization, and PCA. The proposed technique achieves a prediction speedup of 25.5x with an accuracy of 94.4%, reducing computational overhead while maintaining high accuracy.

**Dataset Info:** FLAIR, T1, T2, and T1CE brain tumor MRI images.

**Algorithms or Models:** ResNet101 with transfer learning, differential evolution, particle swarm optimization, and PCA for feature optimization.

**Results:** Achieved a prediction speedup of 25.5x and an accuracy of 94.4%, with reduced computational overhead.

3.

This research employs a novel deep Convolutional Neural Network (CNN) model for automated brain tumor classification from MRI images, addressing limitations of manual techniques. Experimental evaluation on three datasets demonstrates superior performance compared to existing methods.

**Dataset Info:** Three brain tumor MRI datasets (details unspecified in the abstract).

**Algorithms or Models:** A proposed novel Convolutional Neural Network (CNN) model with multiple layers for automated classification.

**Results:** The model outperformed existing methods, demonstrating convincing classification performance on the evaluated datasets.

4.

This study reviews state-of-the-art deep learning methods for brain tumor classification and segmentation from MRI images, highlighting their powerful feature representation and performance. It identifies gaps in current literature, compares deep learning approaches, and provides future directions for enhancing automated classification techniques.

**Dataset Info:** Not explicitly mentioned in the abstract.

**Algorithms or Models:** Deep learning-based methods, including hierarchical feature learning and data representation techniques for classification and segmentation.

**Results:** Comprehensive review of recent deep learning approaches, highlighting their effectiveness, performance comparisons, and recommendations for future research and adoption.

5.

This study employs a simple Convolutional Neural Network (CNN) architecture to classify Glioma, Meningioma, and Pituitary tumors from T1-weighted CE-MRI images, without region-based preprocessing. It achieved a training accuracy of 98.51% and a validation accuracy of 84.19%, comparable to more complex segmentation algorithms.

**Dataset Info:** 3064 T-1 weighted CE-MRI images from the Brain Tumor Dataset, 2017, publicly available via figshare.

**Algorithms or Models:** Convolutional Neural Network (CNN) with a simple architecture consisting of convolution, max-pooling, flattening layers, and one hidden full connection layer.

**Metrics:** Training accuracy and validation accuracy.

**Results:** Achieved a training accuracy of 98.51% and validation accuracy of 84.19%, comparable to more complex region-based segmentation algorithms.

6.

2022,Convolutional Neural Network Techniques for Brain Tumor Classification (from 2015 to 2022)

The study leverages BRATS2018 and BRATS2019 datasets to develop a robust brain tumor classification system. Using a fine-tuned DenseNet201 model, feature selection techniques (EKbHFV and MGA), and feature fusion, the system achieves exceptional accuracy—99.7% and 98.8% for HGG and LGG on BRATS2018, and 99.8% and 99.3% on BRATS2019—while reducing computational time. The method outperforms existing models like VGG and AlexNet, offering a decision support system for radiologists. Future work aims to improve feature retention and extend applicability to newer datasets.

The proposed approach demonstrates high accuracy and efficiency in brain tumor classification, achieving 99.8% accuracy for High-Grade Glioma and 99.3% for Low-Grade Glioma. Combining feature selection techniques with feature fusion significantly improved performance

**Dataset Info:** TCGA-GBM, TCGA-LGG, Brain Tumor Dataset (Cheng et al., 2017), BraTS, Harvard Medical School Data, and others were used.

**Algorithms or Models:** CNN architectures like AlexNet, VGG, ResNet, GoogLeNet, DenseNet, and EfficientNet.

**Metrics:** Accuracy, F1 Score, Specificity, Sensitivity, Precision, and Area Under the Curve (AUC).

**Results:** Accuracy: 99.8% accuracy for High-Grade Glioma and 99.3% for Low-Grade Glioma

7.

2021,A decision support system for multimodal brain tumor classification using deep learning

This study utilizes BRATS2018 and BRATS2019 datasets to develop a brain tumor classification system with high accuracy and efficiency. Leveraging a fine-tuned DenseNet201 model, advanced feature selection techniques (EKbHFV and MGA), and feature fusion, the method achieves remarkable classification accuracies of up to 99.8% while reducing computational time. The approach outperforms existing models like VGG and AlexNet, showcasing its potential as a robust decision support tool for radiologists.

The proposed system effectively addresses multiclass classification challenges with superior accuracy and efficiency. Feature selection and fusion techniques significantly enhance performance

**Dataset Info:** **BRATS2018** and **BRATS2019** datasets were used

**Algorithms or Models:** uses a DenseNet201 model for multiclass brain tumor classification, employing EKbHFV and MGA for feature selection and feature fusion for optimal performance. A multiclass cubic SVM classifier ensures high accuracy, outperforming models like VGG, AlexNet, ResNet101, and InceptionV3.

**Metrics:** Accuracy, recall, precision, F1-Score, area under the curve (AUC), false-negative rate (FNR), and computational time.

**Results:** Accuracy (up to 99.8%) and reduced computational time

8.

2020,Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection:

This study introduces a deep learning-based framework for multimodal brain tumor classification using BRATS 2015, 2017, and 2018 datasets. Leveraging transfer learning with pre-trained VGG16 and VGG19 models, robust feature selection (via correntropy) and fusion (PLS-based) significantly enhance classification accuracy and computational efficiency. The proposed method achieves accuracies of 98.16%, 97.26%, and 93.40% across the datasets, outperforming traditional classifiers and addressing challenges in multimodal MRI data classification.

The proposed approach effectively improves brain tumor classification accuracy while reducing computational time, providing a reliable decision support tool for radiologists. Future work aims to tackle challenges like low-contrast images and extend the methodology to newer datasets for broader clinical applications.

**Dataset Info:** BRATS 2015, BRATS 2017, and BRATS 2018 datasets.

**Algorithms or Models:** The study employs pre-trained CNNs (VGG16, VGG19) with transfer learning for feature extraction and ELM for robust feature selection and classification. A PLS-based feature fusion and correntropy-driven hybrid approach enhance classification accuracy.

**Metrics:** Accuracy, false-negative rate (FNR), testing time, and statistical metrics (variance, standard deviation, SEM).

**Results:** Accuracies of BRATS 2015, 2017, and 2018- 98.16%, 97.26%, and 93.40%.

9.  
**2018, Brain Tumor Classification Using Convolutional Neural Networks**

This paper focuses on automatic brain tumor classification using Convolutional Neural Networks (CNNs). MRI images from Radiopaedia and the BRATS 2015 dataset were used to achieve an accuracy of 97.5%, demonstrating high performance with reduced computational complexity compared to traditional methods.

Demonstrates the effectiveness of CNNs for automatic brain tumor classification. Reduced complexity compared to traditional methods, with an accuracy rate of 97.5%.

**Dataset Info:** MRI brain images From Radiopaedia and BRATS 2015 testing dataset.

**Algorithms or Models:** Convolutional Neural Networks (CNN) with pre-trained models like ImageNet.

**Metrics:** Training accuracy, validation accuracy, and validation loss.

**Results:** Accuracy: 97.5%, highlighting low computational complexity.

10.

**2021, Brain Tumor Classification Using Deep Learning**

This study introduces a hybrid segmentation and classification approach utilizing the VGG-16 CNN model on a Kaggle MRI dataset. The proposed method effectively classified tumors and non-tumors, emphasizing improvements in preprocessing and segmentation for better accuracy.

Demonstrates the success of hybrid segmentation methods combined with deep learning (VGG-16) for tumor classification. Suggests improvements in preprocessing for better detection accuracy.

**Dataset Info:** Kaggle MRI dataset.

**Algorithms or Models:** VGG-16 CNN model used for tumor vs. non-tumor classification.

**Metrics:** Accuracy for both detection and classification.

**Results:** Accuracy achieved using VGG-16 was not explicitly quantified but suggested effective classification of tumor types.

11.

**2022, A Hybrid Deep Learning-Based Approach for Brain Tumor Classification**

This paper proposes a hybrid DeepTumorNet model, modified from GoogLeNet, for brain tumor classification. Using the CE-MRI dataset, the model achieved a 99.67% accuracy, surpassing other deep learning models in performance and robustness.

Proposes a novel DeepTumorNet hybrid model that outperformed existing state-of-the-art approaches. Achieved the highest classification accuracy on the CE-MRI dataset, emphasizing its robustness in tumor classification.

**Dataset Info:** CE-MRI dataset, publicly available on Figshare,

from Nanfang Hospital and Tianjin Medical University, China.

**Algorithms or Models:** A hybrid DeepTumorNet based on GoogLeNet architecture, Leaky ReLU activation functions for improved performance.

**Metrics:** Accuracy, precision, recall, and F1-score.

**Results:** Accuracy: 99.67%.

12.

**2019, Brain Tumor Classification Using Convolutional Neural Network**

The study explores a simple Convolutional Neural Network (CNN) architecture to classify brain tumors into three types: Glioma, Meningioma, and Pituitary. Using a dataset of T1-weighted contrast-enhanced MRI images, the method achieves a training accuracy of 98.51% and a validation accuracy of 84.19%, demonstrating comparable performance to more complex segmentation-based algorithms.

**Dataset Info:** Brain Tumor Dataset (2017), provided by Jun Cheng, available on Figshare.

**Algorithms or Models:** Convolutional Neural Network (CNN) with five variations in architecture:

Architecture 2 was the most effective, with two convolution layers, ReLU activation, max-pooling, and a fully connected layer of 64 neurons.

**Metrics:** Accuracy, Validation Loss.

**Results:** Training accuracy: 98.51%. Validation accuracy: 84.19% (best for Architecture 2).

13.

**2019, Brain Tumor Classification Using Convolutional Neural Network**

The proposed method enhances brain tumor classification by combining segmented uniformity-based Local Ternary Pattern (SULTP) feature extraction with Spatial Shift Fuse-MLP (SSF-MLP). This hybrid approach achieves superior classification accuracy of 97.26% on benchmark datasets.

**Dataset Info:** Sa Dataset: Provided by Sartaj from MIT, SfB Dataset: Contains diverse MRI images from Figshare and Br35H.

**Algorithms or Models:** Segmentation-based Uniform Local Ternary Patterns (SULTP), Spatial Shift Fuse-MLP (SSF-MLP), GELU & ReLU activation functions.

**Metrics:** Classification accuracy, true positive rate (TPR), false positive rate (FPR), F-measure, and ROC area.

**Results:** **Sa Dataset:** 97.26% **SfB Dataset:** 95.32%

14.

**2022, Brain Tumor Classification Using Dense EfficientNet**

This study proposes a Dense EfficientNet CNN model for brain tumor classification, using 3260 T1-weighted MRI images categorized into glioma, meningioma, pituitary, and no tumor classes. The approach incorporates min-max normalization and data augmentation, achieving 99.97% training accuracy and 98.78% testing accuracy, surpassing existing deep-learning models.

**Dataset Info:** Brain Tumor Dataset (2017) from Kaggle (T1-weighted contrast-enhanced MRI images)

**Algorithms or Models:** Dense EfficientNet CNN, a variant of EfficientNetB0 dense layers and dropout layers with probabilities (0.25, 0.25, and 0.5) for improved generalization.

**Metrics:** Accuracy, precision, recall, F1-score.

**Results:** **Training Accuracy:** 99.97% **Testing Accuracy:** 98.78%