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Brain Tumor Detection Using Machine Learning and Deep Learning

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Abstract: This paper proposes a method to detect and classify gliomas using Magnetic Resonance Imaging (MRI)... Brain tumors are severe diseases affecting over 200 varieties and have increased by 300% in the last three decades. Early detection and treatment are crucial for patient survival. Magnetic Resonance Imaging (MRI) is the most commonly used method for diagnosing brain tumors. Advances in machine learning, particularly deep learning, have led to the identification and classification of medical imaging patterns. Convolutional Neural Networks (CNNs) and autoencoders are successful techniques in image processing for high diagnostic accuracy. Various deep learning and machine learning algorithms have been used to identify tumors and detect cardiovascular stenosis, with high diagnostic accuracy. However, many studies have limitations, such as a lack of performance comparison between proposed models and traditional machine learning methods. Brain tumors are diseases caused by abnormal cell growth in the brain, with non-cancerous and malignant types.
Keywords: Image segmentation, CNN, Augmentation, Image classification, MRI

I. INTRODUCTION

Brain tumors, primarily gliomas, are caused by uncontrolled cell growth, affecting normal brain activities, and destroying normal cells. Despite advancements in medical treatments like surgery, chemotherapy, and radiotherapy, malignant brain tumor cases remain untreatable. MRI is a useful tool for validating gliomas, providing detailed structure about the human brain. Accurate segmentation is crucial for brain tumor detection, but manual segmentation is time-consuming for radiologists. Automated techniques, such as machine learning methods, can improve diagnosis abilities in radiology. This work aims to present an automated method to increase tumor detection performance, including lesion enhancement, lesion segmentation, and feature extraction. In a variety of medical image processing tasks, including brain tumor detection, deep learning approaches, and CNNs in particular, showed outstanding efficacy. When compared to other machine learning classifiers, the results from using deep learning approaches to classify and segment brain tumors were superior. The system is designed to automate brain tumour detection from medical imaging data (e.g., MRI, CT scans) using a pipeline that involves data pre-processing, feature extraction, classification, and evaluation. The proposed method will use deep learning models for feature extraction and machine learning classifiers for final decision-making. This research paper has discussed the different stages of brain tumours. Cerebrum cancer division is a significant assignment in clinical picture handling. Early determination of mind cancers assume a significant part in further developing therapy prospects and expands the endurance pace of the patients. Manual division of the mind growths for disease finding, from the enormous measure of MRI pictures produced in clinical daily practice, is a troublesome and tedious errand. Additionally, mind growth analysis requires an acute level of precision, where a minor mistake in decision making may result in a calamity. Consequently, cerebrum cancer division is difficult for clinical purposes. Among the right now proposed mind division strategies, cerebrum cancer division techniques dependent on conventional picture handling isn't sufficiently ideal. In customary strategy, an MRI is produced by utilizing attractive field radiation through which a two-dimensional picture (predominantly dependent on a particular dark scale) is created and afterwards that picture is handled and inspected by a clinical expert.

II. RESEARCH BACKGROUND

Detecting brain tumors in their early stages is crucial. Brain tumors are classified by biopsy, which can only be performed through definitive brain surgery. Computational intelligence-oriented techniques can help physicians identify and classify brain tumors. Herein, we proposed two deep learning methods and several machine learning approaches for diagnosing three types of tumor, i.e., glioma, meningioma, and pituitary gland tumors, as well as healthy brains without tumors, using magnetic resonance brain images to enable physicians to detect with high accuracy tumors in early stages.

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A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumors, and healthy brains were used in this study. First, pre -processing and augmentation algorithms were applied to MRI brain images. Next, we developed a new 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network, both of which were already trained by our assigned hyperparameters. Then 2D CNN includes several convolution layers; all layers in this hierarchical network have a 2*2 kernel function. This network consists of eight convolutional and four pooling layers, and after all convolution layers, batch-normalization layers were applied. The modified auto-encoder network includes a convolutional auto-encoder network and a convolutional network for classification that uses the last output encoder layer of the first part. Furthermore, six machine-learning techniques that were applied to classify brain tumors were also compared in this study.

III. METHEDOLOGY

Brain tumor detection using machine learning (ML) and deep learning (DL) has become a prominent research area due to its potential to aid in early diagnosis and treatment. Here's a comprehensive methodology that incorporates both ML and DL techniques for detecting brain tumors from medical images like MRI or CT scans:

A. Data Collection and Pre-processing

Data Collection: The first step involves collecting datasets, such as MRI or CT scans of brain images. Public datasets like the Brain Tumor Dataset (BRATS) or The Cancer Imaging Archive (TCIA) are often used. These datasets typically include labelled images with tumor types, such as gliomas, meningiomas, and pituitary tumors.

Pre-processing:

Image normalization: Standardize pixel values to a specific range (e.g., 0 t) .

Resize images to a fixed dimension (e.g., 224x224 pixels) to feed into neural networks.

Augmentation: Perform data augmentation techniques like rotation, zoom, and flipping to enhance dataset diversity.

Noise reduction: Apply filters (e.g., Gaussian or median filters) to reduce noise and enhance image clarity.

B. Feature Extraction

Traditional ML Approach:

Manual Feature Extraction: Using techniques like texture analysis, histogram-based methods, and edge detection (e.g., using Gabor filters, wavelet transforms, or Gray-level co-occurrence matrices (GLCM)).

Statistical Features: Extract features such as intensity, shape, and texture from images, which could be used to distinguish between tumor and non-tumor regions.

Deep Learning Approach:

Convolutional Neural Networks (CNNs): Instead of manual feature extraction, DL methods (especially CNNs) learn hierarchical features directly from images. The CNNs automatically extract low- to high-level features (edges, textures, shapes, etc.) and are ideal for image classification tasks.

Transfer Learning: Pretrained models like VGGNet, ResNet, or InceptionNet can be fine-tuned on the brain tumor dataset, saving computational time and resources.

C. Model Training

Supervised Learning: Typically, supervised learning is employed, where the model is trained using labelled datasets (tumor or non-tumor images).

Loss Function

Optimization: Use optimizers like Adam, SGD (Stochastic Gradient Descent), or RMSprop for minimizing the loss function.

D. Model Evaluation

Metrics

Cross-validation: Apply k-fold cross-validation to assess the robustness of the model and prevent overfitting.

E. Tumor Localization and Segmentation (Optional)

For more advanced systems, tumor localization and segmentation are performed using deep learning methods like U-Net, Fully Convolutional Networks (FCN), or Mask R-CNN.

F. Post-processing

Refinement: Apply post-processing techniques like morphological operations (dilation, erosion) to refine the predicted tumor boundaries in segmentation. 3D Reconstruction: For volumetric MRI images, the detection and segmentation process can extend to 3D to analyze the entire brain volume.

G. Result Visualization and Diagnosis

Visualize the detection and segmentation results on the original MRI or CT scan for easier interpretation by medical professionals.
Heatmaps or Grad-CAM (Gradient-weighted Class Activation Mapping) can be used to show the regions where the model focuses during classification, aiding in explainability.

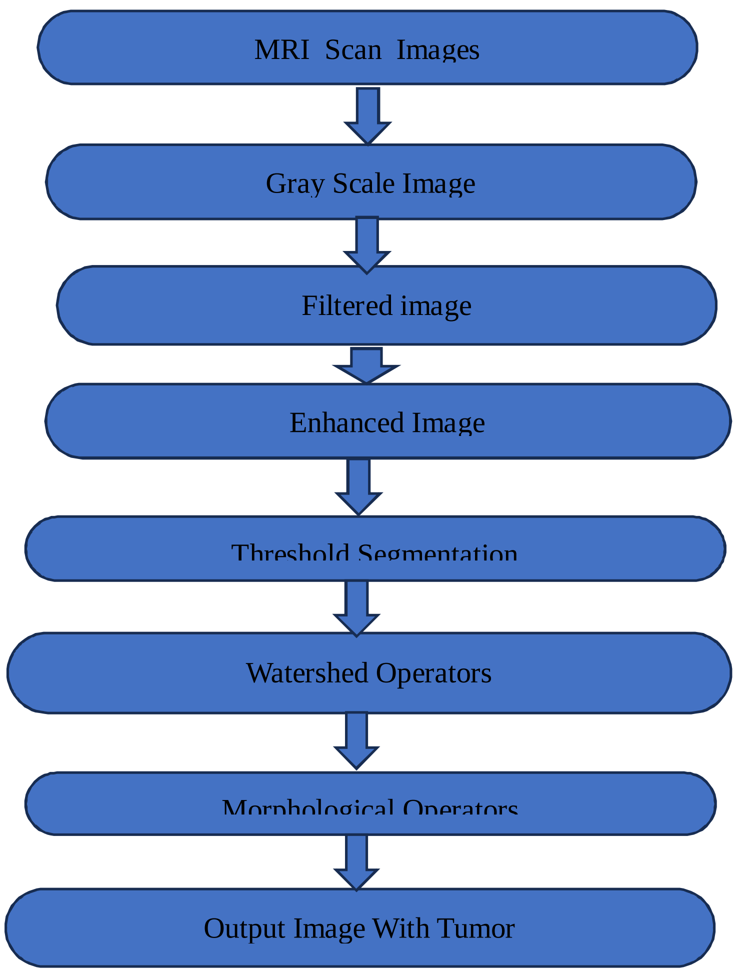
H. Model Deployment and Integration

Once the model is trained and validated, it can be deployed as part of a medical image processing tool, integrated with hospital systems or PACS (Picture Archiving and Communication Systems).
Real-time prediction: The trained model can be used to predict brain tumor presence in real-time clinical environments.

I. Clinical Validation

Clinical Testing: After training and validation, models should undergo real-world clinical testing on fresh patient data to ensure their generalizability and reliability in clinical settings.
Human-in-the-loop: In real-world applications, radiologists and medical experts may use the model predictions as a secondary opinion, ensuring that the technology complements, rather than replaces, human expertise.

IV. FLOW CHART

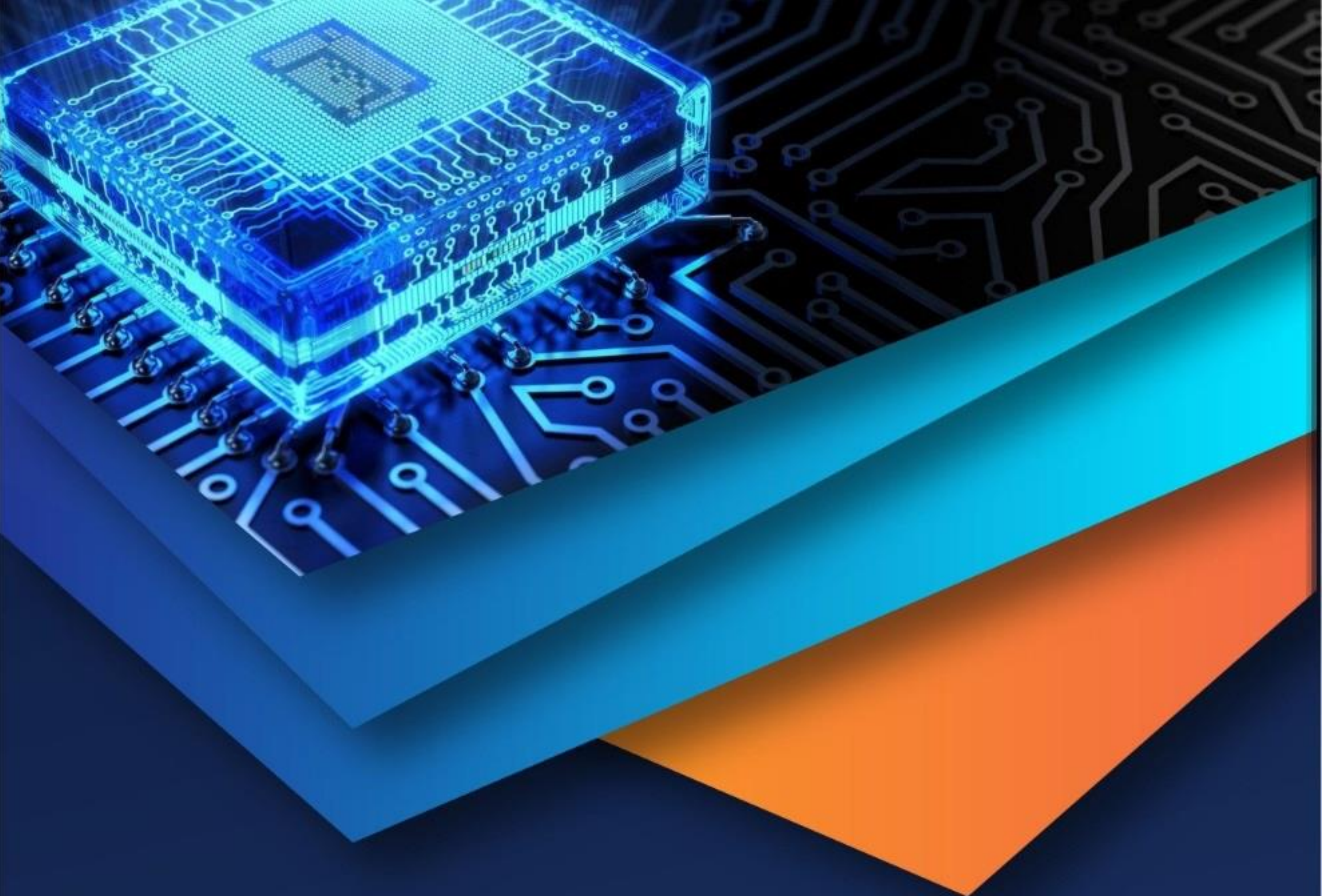


V. CONCLUSION

To reduce global death rates, diagnosis of brain cancers is essential. Brain tumors can be difficult to identify because of their complex architecture, size variability, and unusual forms. In our research, we used a large collection of MRI scans of brain tumors to overcome this obstacle. We showed that a state-of-the-art YOLOv7 model could be improved by transfer learning and fine tuning in order to detect gliomas, meningioma, and pituitary brain tumors in MRI data. Our suggested CNN model demonstrates the substantial influence of deep learning models in tumor identification and demonstrates how these models have changed this field. Using a huge collection of MRI images, we found some encouraging findings in the diagnosis of brain cancers. We used a wide range of performance measures to measure the effectiveness of our deep learning models. When compared to standard techniques of categorization, the proposed technology not only detects the existence of brain tumors, but also pinpoints their precise location within the MRI images. This localization allows for fine-grained categorization without laborious human interpretation. The proposed solution, in contrast to segmentation techniques, uses a little amount of storage space and has a low computational cost, making it portable across a variety of systems. Not only did the suggested approach achieve better accuracy than prior efforts using bounding box detection techniques, it also outperformed those techniques when applied to meningioma, glioma, and pituitary brain cancers. The results were improved, and the problem was tackled with the help of picture data augmentation, even though the dataset was relatively small. Using the available data, we obtained an accuracy of 99.5% in our analysis. The proposed method for detecting brain cancers in medical images has achieved this accuracy.

REFERENCES

[1] Shenbagarajan Anantharajan, Shenbagalakshmi Gunasekaran a, Thavasi Subramanian a, Venkatesh R b Measurement: Sensors [2024]
[2] Md Ishtyaq Mahmud 1, *ORCID, Muntasir Mamun 2 and Ahmed Abdel Gawad 1ORCID A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks [2023]
[3] Mahsa Arabah Madi 1†, Reza Farah bakhsh 2,† and Javad Rezazadeh 1,3,*: Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging [2022]
[4] P Gokila Brindha et al 2021 Brain tumor detection from MRI images using deep learning techniques [2021]
[5] Sneha Gram purohit; Venkamma Shilavati; Vaishnavi R. Dharavi; Megha Kudari; Soumya Jo Brain Tumor Detection Using Deep Learning Models [2020]
[6] A Novel Approach for Brain Tumor Detection Using MRI Images Abd El Kader Isselmou, Shuai Zhang, Guozhi Xu Province-Ministry Joint Key Laboratory of Electromagnetic Field and Electrical Apparatus Reliability, Department of Biomedical Engineering, Hebei University of Technology, Tianjin, China, [2016]
[7] Muhammad Usman Brain tumors detection using MRI [2015]



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