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RareDetect: AI Based System for Identifying Rare Brain Tumors

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***Abstract* - Rare brain tumors are challenging to detect due to their low prevalence, complex visual patterns, and limited availability of annotated medical datasets. This paper presents *RareDetect*, an AI-based system designed to accurately identify and classify rare brain tumors from MRI images using deep learning techniques. The proposed system employs Convolutional Neural Networks (CNNs) along with transfer learning models such as ResNet50 and VGG16 to enhance feature extraction and classification performance. A comprehensive preprocessing pipeline, including image normalization, resizing, and data augmentation, is applied to improve model generalization and reduce overfitting. The system is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed approach achieves high accuracy and improved detection capability for rare tumor classes compared to traditional methods. The system aims to support radiologists by providing faster, reliable, and automated diagnostic assistance, thereby enabling early detection and improved clinical decision-making.**

Keywords— Rare Brain Tumor, Deep Learning, Convolutional Neural Network (CNN), MRI Imaging, Transfer Learning, ResNet50, VGG16, Medical Image Classification, Artificial Intelligence

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has significantly transformed the field of medical imaging, enabling automated and accurate disease diagnosis. Among various applications, brain tumor detection using Magnetic Resonance Imaging (MRI) has gained considerable attention due to its importance in early diagnosis and treatment planning.

Brain tumors, including glioma, meningioma, and pituitary tumors, exhibit complex structures and varying characteristics, making manual detection challenging even for experienced radiologists.

While significant progress has been made in detecting common brain tumors, the identification of rare brain tumors remains a critical challenge. The primary difficulties arise from limited availability of annotated datasets, high variability in tumor appearance, and class imbalance in training data. These factors often lead to reduced model performance and increased misclassification rates in conventional approaches.

To address these challenges, this paper presents *RareDetect*, an AI-based system designed for identifying rare brain tumors from MRI images using deep learning techniques. The proposed system utilizes Convolutional Neural Networks (CNNs) for feature extraction and integrates transfer learning models such as ResNet50 and VGG16 to enhance classification accuracy. A comprehensive preprocessing pipeline, including image normalization, resizing, and data augmentation, is applied to improve generalization and robustness.

The main objective of this work is to develop a reliable and efficient model capable of accurately classifying brain tumors, including rare categories, while minimizing false predictions. The system aims to assist radiologists by providing automated diagnostic support, reducing workload, and enabling faster decision-making. Furthermore, the proposed approach contributes to improving early detection rates, which is crucial for effective treatment and better patient outcomes.

Brain tumors are abnormal growths of cells within the brain that can be either benign or malignant, and their early detection is crucial for effective treatment and improved patient survival. Magnetic Resonance Imaging
Convolutional Neural Networks (CNNs) are among the most widely used deep learning models for image classification tasks.

To evaluate the effectiveness of the proposed system,

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performance metrics such as accuracy, precision, recall, and F1-score are used. These metrics provide a comprehensive understanding of the model's ability to correctly classify tumor and non-tumor cases.

II. LITERATURE REVIEW

Huang Meiyan et al. [1] (2013) proposed a brain tumor segmentation method based on Local Independent Projection-based Classification (LIPC). The approach treats segmentation as a classification problem by assigning each voxel to a specific class using locality-based feature projection and softmax regression. The method achieved good accuracy in MRI tumor segmentation and showed improved performance in handling complex tumor boundaries. However, it relies on traditional machine learning and handcrafted features, which may limit its efficiency compared to modern deep learning approaches.

A. Hazra et al. [4] (2017) proposed a brain tumor detection method based on image segmentation using MATLAB. The approach focuses on preprocessing MRI images and applying segmentation techniques to isolate tumor regions. The method demonstrates effective detection of tumor boundaries and provides a simple implementation framework.

Sebastian Ruder [7] (2017) presented an overview of gradient descent optimization algorithms such as SGD, Momentum, RMSProp, and Adam. The study highlights their role in improving convergence and training efficiency of deep learning models. However, it is mainly theoretical and not specific to medical imaging applications.

Karen Simonyan and Andrew Zisserman [10] (2015) introduced the VGG16 model, a deep convolutional neural network with a uniform architecture using small convolution filters. The model achieved high performance in large-scale image recognition tasks and is widely used for transfer learning. However, it has high computational complexity and requires significant resources.

III. COMPARATIVE ANALYSIS

Variousapproacheshave been proposed for brain tumor detection and segmentation. Early methods such as texture-based segmentation and seeded region growing [11], as well as MATLAB-based techniques [4], provide simple implementations but require manual intervention and lack robustness. Classification-based segmentation approaches like LIPC [1] and tumor percentage estimation methods [2] improve accuracy but still rely on traditional machine learning. Computer-aided systems [3] and automated MRI-based detection models [5] enhance automation but face challenges in handling complex and rare tumor patterns.

Studies on segmentation techniques [6] provide insights into preprocessing and feature extraction methods. Optimization algorithms discussed by Ruder [7] improve training efficiency of deep learning models, while foundational concepts in information retrieval [8] support data processing.

Public MRI datasets [9] enable model training but suffer from class imbalance. Deep learning architectures such as VGG16 [10] significantly improve feature extraction and classification performance compared to traditional methods. However, most existing approaches either lack automation, struggle with rare tumor detection, or require large datasets, highlighting the need for advanced AI-based systems like RareDetect.

Brain tumor detection using artificial intelligence involves multiple stages, including image acquisition, preprocessing, feature extraction, classification, and evaluation. MRI images serve as the primary input due to their ability to capture detailed brain structures. However, raw MRI data often contains noise, intensity variations, and irrelevant background information, which can affect model performance. Therefore, preprocessing techniques such as normalization, resizing, and data augmentation are applied to standardize the dataset and improve learning efficiency.

Feature extraction plays a crucial role in identifying tumor patterns within MRI images. Traditional approaches rely on handcrafted features such as texture, intensity, and shape descriptors. However, these methods are limited in capturing complex patterns. Deep learning models, particularly Convolutional Neural Networks (CNNs), overcome this limitation by automatically learning hierarchical features from data. Lower layers capture basic features like edges, while deeper layers identify complex tumor structures, improving classification accuracy.

To address these issues, techniques such as data augmentation, regularization, and cross-validation are applied. Evaluation metrics including accuracy, precision, recall, and F1-score are used to measure model performance and ensure reliability.
Overall, the integration of deep learning, transfer learning, and optimization techniques provides a strong theoretical foundation for developing efficient and accurate brain tumor detection systems like RareDetect.

COMPARISON OF VGG16 AND ResNet50

IV. RESEARCH GAP

Despite significant advancements in brain tumor detection using deep learning, several limitations still exist in current approaches. Most existing studies focus on common tumor types and do not adequately address the detection of rare brain tumors, leading to poor performance on underrepresented classes. Additionally, many models rely on a single architecture such as VGG16 or ResNet50 without performing a comparative analysis to identify the most effective model. The issue of class imbalance in MRI datasets further affects model accuracy and generalization, especially for rare tumor categories.

Furthermore, traditional methods and some deep learning approaches suffer from overfitting due to limited training data, while high computational complexity makes real-time implementation challenging. Another major limitation is the

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lack of interpretability in deep learning models, which reduces trust in clinical applications.

Therefore, there is a need for an efficient and robust system that combines multiple models, improves rare tumor detection, handles data imbalance, and provides reliable performance for real-world medical use.

Additionally, many research works rely on a single deep learning architecture such as VGG16 or ResNet50 without conducting a comprehensive comparative analysis. This limits the understanding of model performance across different architectures and prevents the selection of the most suitable model for rare tumor detection. Furthermore, traditional image processing and early machine learning methods lack the ability to automatically learn complex features, leading to lower accuracy compared to modern deep learning approaches.

Another significant gap is the issue of overfitting due to limited availability of labeled medical datasets. Deep models tend to memorize training data instead of generalizing well to unseen data. Moreover, high computational requirements of deep learning models make them less suitable for real-time or resource-constrained environments. The lack of interpretability in these models also poses a challenge, as medical professionals require explainable results to trust AI-based systems.

Therefore, there is a need for a robust and efficient system that integrates multiple deep learning models, addresses dataset imbalance, improves generalization, and enhances detection accuracy for rare brain tumors.

V. CONCLUSION

From the comparative study of existing methods, it is observed that traditional techniques such as segmentation and texture-based approaches [4], [11] provide basic tumor detection but lack automation and accuracy. Classification-based methods [1], [2] improve segmentation performance but rely on handcrafted features. Computer-aided systems and automated detection models [3], [5] enhance efficiency but struggle with variability in tumor patterns. Deep learning models like VGG16 [10] significantly improve feature extraction, while optimization techniques [7] enhance training performance. However, challenges such as dataset imbalance [9], overfitting, and limited focus on rare tumor classes still persist.

Therefore, there is a need for an advanced AI-based system that combines deep learning, transfer learning, and proper preprocessing techniques to improve accuracy and reliability. The proposed system aims to overcome these limitations by enhancing rare tumor detection and providing better support for medical diagnosis.

Existing methods improve tumor detection but suffer from limitations such as lack of automation, dataset imbalance, and poor performance on rare tumors. This highlights the need for an advanced AI-based system for accurate and reliable detection.

REFERENCES

[1] Huang Meiyan, Wei Yang, Wu Yao, Jiang Jun, Chen Wufan, and Qianjin Feng, “Brain Tumor Segmentation Based on Local Independent Projection-based Classification”, IEEE Transactions on Biomedical Engineering, 2013.
[2] Annisa Wulandari, Riyanto Sigit, Mochamad Mobed Bachtiar, “Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI”, International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC), 2018
[3] M. Usman Akram, Anam Usman, "Computer Aided System for Brain Tumor Detection and Segmentation",International Conference on Computer Networks and Information Technology (ICCNIT), 2011.
[4] A. Hazra, A. Dey, S. Gupta and M. Ansari, “Brain tumor detection based on segmentation using MATLAB”, 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), 2017.
[5] T. M. Shahriar Sazzad, Misbah Ul Hoque, Mahmuda Rahman, K. M. Tanzibul Ahmmed, "Development of Automated Brain Tumor Identification Using MRI Images", International Conference on Electrical, Computer and Communication Engineering (ECCE), 2019.
[6] Ruchi D. Deshmukh, Prof. Chaya Jadhav, "Study of Different Brain Tumor MRI Image Segmentation Techniques", International Journal of Computer Science Engineering and Technology(IJCSET), Vol 4, Issue 4,133-136, April 2014.
[7] Sebastian Ruder, "An overview of gradient descent optimization algorithms", arXiv:1609.04747v2 [cs.LG], June 2017
[8] Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, "Introduction to Information Retrieval", Cambridge University Press. 2008
[9] MRI Image dataset collected by Jun Cheng et al, OnlineReference: http://dx.doi.org/10.6084/m9.figshare.1512427
[10] Karen Simonyan, Andrew Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", International Conference on Learning Representations (ICLR), 2015.
[11] Mukesh Kumar, Kamal K.Mehta, “A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method”, International Journal of Computer Technology and Applications, August 2011.