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A Deep Learning Approaches for Brain and Early-Stage Cancer Detection and Classification

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Abstract: Brain cancer remains a life-threatening condition with a very high global mortality rates, affecting the human being of all ages and ethnic background across diverse populations. The rate of survival can be enhanced by detecting the brain cancer early and with the accurate assessment of the severity of brain cancer severity, the effective treatment can be avail to the patient, which can be a great help to improve survival rates. This research demonstrates the application of machine learning techniques, in specific Deep Convolutional Neural Networks (DCNN), to classify brain cancer classification cases into low & high-risk groups, which enable timely and precise decision-making in the field of biomedical sector. The suggested DCNN model is designed to process MRI (Magnetic Resonance Imaging) data and takes the advantages of MRI's advanced feature identification and matching capabilities. By analyzing key feature points in training and test images, the model delivers highly accurate classification outcomes. The dataset utilized in this research was taken from the Kaggle machine learning repository, ensuring a comprehensive and reliable foundation for experimental analysis. Extensive evaluation reveals that the DCNN model outperforms traditional methods such as K-Nearest Neighbors (KNN), Random forest (RF), Support Vector Machines (SVM), and Logic Regression (LR). It achieved higher accuracy in risk-level classification and also demonstrates superior computational efficiency, making it a robust and practical solution for real-world medical applications.

This research emphasized the potential of DCNN-based methodologies in advancing cancer diagnostics. By providing a faster, more accurate, and scalable approach, the proposed model contributes to improving early detection and risk assessment of brain cancer, ultimately enhancing patient outcomes and advancing medical research.

Keywords: Brain cancer, Deep learning, Machine learning, MRI, ResNet152.

I. Introduction

Referring to the World Health Organization (WHO) the brain and central nervous system (CNS) cancers have the highest mortality rates in the Asian continent [1]. This highlights the urgent need for early detection strategies to save lives. Accurate cancer grading is critical for targeted therapies, but traditional diagnostic methods are often invasive, time-consuming, and costly [2]. This necessitates the development of non-invasive, cost-effective, and efficient tools for characterizing and grading brain cancers. Imaging technologies such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) have proven to be fast and safe alternatives for tumor detection [3] [4].

Brain cancer, originating in the brain or spinal cord, presents diverse symptoms, including coordination problems, frequent headaches, mood swings, speech difficulties, concentration issues, seizures, and memory loss. Depending on their nature, origin, growth rate, and progression stage, brain tumors are categorized into various types, either benign or malignant. These classifications are crucial for determining the appropriate treatment approach [5]. Cancer remains one of the most devastating diseases, affecting millions of people worldwide and causing significant mortality and morbidity. Early detection and accurate classification are essential for effective treatment and improved patient outcomes [6]. However, cancers such as brain and lung cancers pose unique challenges, as they are often asymptomatic in their early stages, making traditional diagnostic approaches less effective. This underscores the need for innovative methodologies to enhance early-stage detection [7].

Deep learning-based approaches have shown significant promise in the detection and classification of complex diseases, including cancers. These advanced methodologies can analyze patterns in medical imaging data, providing accurate predictions that support diagnostic processes. In recent years, the application of deep learning for cancer detection has advanced considerably, with some models achieving high accuracy rates. Despite these advances, there is still room for improvement, particularly in the early detection of aggressive cancers such as brain and lung cancers.

The proposed system employs an enhanced deep learning-based methodology, evaluated using datasets for brain and lung cancers, including the Kaggle brain MRI dataset. Leveraging the ResNet152 architecture, the model processes input MRI images to detect cancer with high accuracy, as demonstrated in the simulation. The outcomes of this research aim to improve early-stage cancer detection and classification, offering valuable insights into the capabilities of deep learning in this domain. By enabling earlier detection and treatment, this approach has the potential to significantly enhance patient outcomes and provide an effective tool for addressing the challenges of cancer diagnosis and management.

II. Applications of Deep Learning in Various Cancer Detection

Deep learning (DL) has emerged as a transformative technology in the field of medical imaging and cancer detection. By leveraging advanced algorithms and neural network architectures, DL enables automated, accurate, and efficient analysis of complex medical data. Here are the key applications of deep learning in detecting and diagnosing various types of cancer:

- *Cervical Cancer:* Cervical cancer poses a major health challenge for women worldwide, significantly impacting their well-being and quality of life. Early detection and advanced screening methods are crucial in reducing its prevalence and improving survival rates [8]. Deep learning algorithms analyze Pap smear images to identify abnormal cells with high precision, facilitating early detection of precancerous lesions and improving screening accuracy [9].
- *Lung Cancer:* Lung cancer ranks among the deadliest diseases globally, posing significant challenges to early detection and treatment. These aggressive cancers benefit from deep learning systems trained on large medical imaging datasets. These cutting-edge algorithms empower radiologists and healthcare professionals by enabling faster, more accurate diagnoses, ultimately streamlining patient care and improving treatment outcomes [10] [11].
- *Oral Cancer:* Oral cancer, which includes malignancies of the lips, tongue, and throat, is challenging to detect in its early stages. Deep learning algorithms, applied to biopsies and CT scans, have proven highly effective in identifying and classifying these cancers. By facilitating early diagnosis—when the chances of successful treatment are highest—these models provide critical support to doctors, enabling timely interventions and significantly improving patient outcomes [12].
- *Kidney Cancer:* Diagnosing kidney cancer is particularly challenging, as the disease often presents no symptoms in its early stages. However, deep learning algorithms trained on CT and MRI scans have revolutionized detection by enabling automatic identification and classification of potential malignancies [13]. These advanced models generate critical insights that aid radiologists and oncologists in accurate diagnosis and effective treatment planning, significantly improving early intervention and patient care [14].
- *Breast Cancer:* Breast cancer remains the most prevalent cancer among women, with successful treatment heavily reliant on early detection. Deep learning algorithms have transformed mammography by enabling precise identification of potential cancerous areas. By enhancing the accuracy of early diagnoses and reducing missed cases, these advanced tools empower radiologists to deliver timely and effective care, ultimately improving patient survival rates and quality of life [15].
- *Brain Cancer:* Brain cancer encompasses a diverse range of malignancies, each with unique symptoms and detection challenges. Deep learning models designed to analyze medical images, including CT, MRI, and histopathology slides, have significantly advanced the precision of brain tumor diagnosis and classification [16] [17]. Advanced neural networks process MRI, CT, and histopathology images for precise tumor classification and boundary delineation, aiding neurosurgeons in treatment and surgical planning. These models enhance the accuracy of tumor boundary delineation, providing neurosurgeons with clearer, more detailed insights [18]. As a result, they can plan more effective therapies and surgical interventions, ultimately improving patient outcomes and reducing the risks associated with brain tumor treatment [19].

III. Traditional Methods vs Deep Learning-Based Approaches

Table I: Comparison between Traditional vs Deep Learning-Based Methods for Brain Tumor Classification

Aspect	*Traditional Methods*	*Deep Learning-Based Methods*
Approach	Uses manually crafted algorithms based on domain knowledge and statistical models.	Uses neural networks to automatically learn patterns from raw data.
Feature Extraction	Features are manually extracted using predefined rules (e.g., texture, shape).	Features are automatically learned during the training phase.
Dependency on Experts	High dependency on medical experts for defining features and preprocessing.	Minimal human intervention; relies on large datasets for training.
Data Requirements	Works on smaller datasets; preprocessing is often required to clean and normalize data.	Requires large amounts of labeled data for training; preprocessing is minimal.

Aspect	*Traditional Methods*	*Deep Learning-Based Methods*
Algorithm Complexity	Relatively simple models such as decision trees, support vector machines, or regression.	Complex models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs).
Interpretation	Outputs are interpretable due to explicit rules and statistical models.	Outputs are often opaque (“black-box”), requiring explainability tools.
Accuracy	Moderate; depends on the quality of feature engineering and data.	High; achieves state-of-the-art performance, especially with large datasets.
Specificity	Moderate; prone to false positives due to limited feature representation.	High; effectively reduces false positives with proper training.
Scalability	Limited scalability for large or high-dimensional data.	Highly scalable for large-scale, multi-modal datasets.
Speed of Prediction	Faster for smaller datasets with pre-defined algorithms.	Slower during training but fast at inference once the model is trained.
Generalization	Limited; struggles with diverse or unseen datasets.	Strong generalization with adequate training on diverse datasets.
Type of Results	Produces basic classifications or segmentation maps (e.g., benign/malignant).	Provides advanced outputs like probabilistic maps, tumor grading, and subtype classification.
Ease of Use	Simpler, easier to interpret.	Requires expertise and high resources.
Performance	Adequate for basic tasks.	Superior for complex patterns.
Output Type	Binary or simple.	Probabilistic, multi-modal insights.

IV. Framework of Deep CNNS

The following (Fig. 1) demonstrates the structure of the proposed DCNN architecture designed for brain tumor image classification [20] [21]. The architecture is organized into five main layers: an input layer to receive the data, a convolutional layer for feature extraction, a Rectified Linear Unit (ReLU) layer for activation, a pooling layer for dimensionality reduction, and a fully connected layer for classification. This DCNN-model is a specialized feedforward neural network that leverages its layered structure to learn features effectively from complex datasets. With its ability to handle large volumes of brain image data, the network is particularly suited for tasks such as medical image analysis, including classification and object detection [22] [23]. A notable advantage of the DCNN is its ability to process the three-dimensional components of an image simultaneously, enabling parallel analysis for enhanced accuracy.

The convolutional layer plays a key role by replacing traditional matrix multiplication with a linear convolution operation. In this process, filters (or kernels) are applied to the input image, extracting specific features. These filters scan the image systematically, enabling the model to identify patterns and features from the training dataset automatically. The outcome of this operation is a feature map, which represents the essential characteristics of the input image.

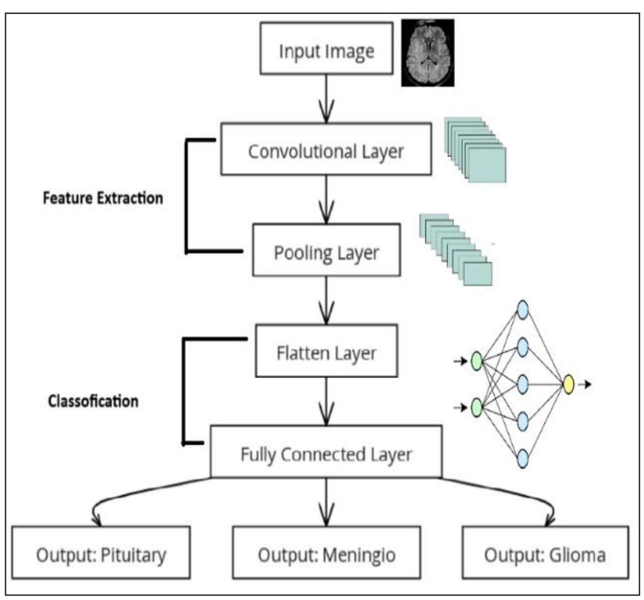

Fig. 1: Brain Tumor Classification using DCNN Architecture [16]

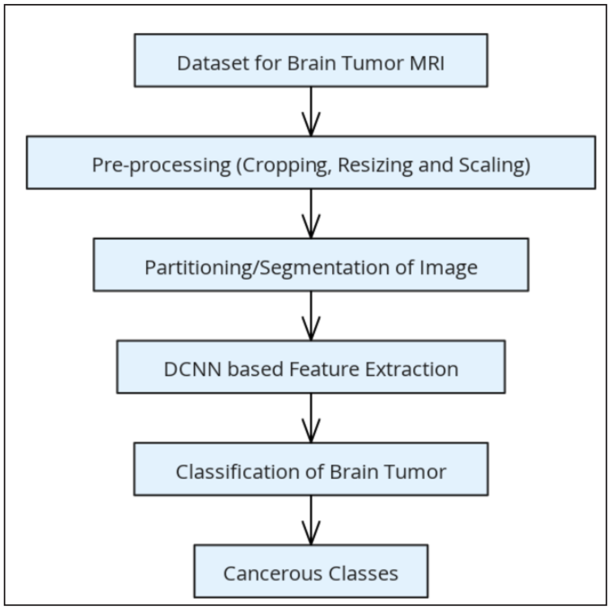

Fig. 2: DCNN Based Classification [16]

Convolution involves multiplying input data with weights to generate feature maps, which are then passed through subsequent layers. The final fully connected layer uses the extracted features to classify the brain tumor image into categories such as cancerous or non-cancerous, based on the computed classification scores. The overall framework integrates these steps into a unified system, as depicted in Fig. 2, providing an efficient and reliable method for brain tumor detection and classification.

V. Machine Learning Technique in Brain Cancer Detection

Machine learning methodology is widely used in the field medical science for early detection of brain cancer and its treatment planning. Image classification, a key branch of artificial intelligence [24], categorizes brain MRI images based on local features. These techniques help group brain cancer images into different categories, such as malignant or healthy, and assist in identifying brain tumors. Various machine learning models, including SVM, KNN, LR and RF, are applied to detect and classify cancerous nodules [25] [26]. The SURF algorithm, for example, is used to detect and match local features in cancer images, enhancing tumor classification [27]. Early detection of brain cancer is crucial, as it can improve survival rates, with early-stage cancers being more treatable. Machine learning models integrate statistical and AI algorithms to predict tumor growth and distinguish between benign and malignant nodules. In consideration to the challenges of brain cancer like lower survival rates because of the location of the tumor, the size of the tumor, and it's texture— the early diagnosis through ML-techniques can significantly increase the lifespan of patients.

VI. Proposed for Classification of Brain Tumor

The presented DCNN model is designed to classify brain tumor images into cancerous and non-cancerous categories, with specific focus on improving efficiency and accuracy in medical image analysis. By reducing the number of neurons and parameters, the DCNN effectively minimizes computational complexity and execution time.

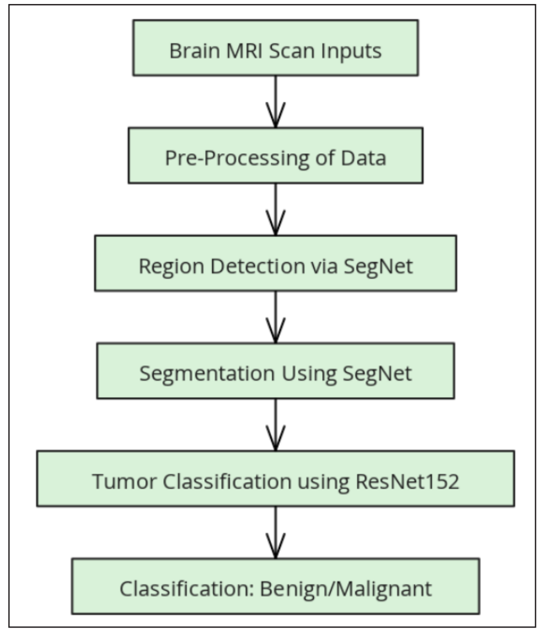

Fig. 3: Proposed Model

Fig. 3 outlines the various processes involved in the suggested model. The proposed model offers an effective and accurate method to predict the early-stage lung cancer. It uses a brain image dataset from the Brain Tumor MRI images from Kaggle to achieve precise classification.

- *Preprocessing:* Preprocessing plays a crucial role in preparing MRI images for analysis. Key steps include cropping, resizing, and scaling the images. Cropping ensures the selection of regions that contain only the brain, defined by its extreme points—left, right, top, and bottom. The images are then resized to a uniform dimension of 256×256 pixels for consistency across the network. To enhance performance, normalization is applied, scaling the pixel intensity values to a range between 0 and 1. Deep features are extracted from the processed training data, and class labels are generated. These labels and features are used as input to the ResNet152 classification model [28] [29].
- *Datasets:* The dataset comprises 7153 images representing three tumor types: pituitary, glioma, and meningioma. Additionally, 1,630 images were used for testing. To prevent overfitting or underfitting, 80% of the data was allocated for training, while the remaining 20%

was reserved for testing. This strategic data partitioning ensures higher classification accuracy and robust model performance.

- *Segmentation:* Segmentation divides the Region of Interest (ROI) within the MRI image into non-overlapping regions for feature extraction. Using a pre-trained SegNet model, segmentation masks are generated for the tumor regions. The SegNet architecture, based on an efficient encoder-decoder framework, creates feature maps while conserving memory usage. The segmented ROI serves as a critical input for subsequent stages of the classification pipeline.
- *Feature Extraction:* From the segmented tumor regions, the hidden features are extracted to aid in tumor classification and prediction. Texture-based descriptors are applied to the ROI, capturing the unique tissue characteristics that differentiate various tumor types. These features form the foundation for further analysis by the DCNN.
- *Convolutional Layers:* The preprocessed brain images are fed into the convolutional layers for feature extraction. The pixel intensity of the input image is represented as a matrix, which is multiplied with a kernel matrix to generate feature maps. The proposed system includes 30 convolutional layers, with a pooling layer added after every two convolutional layers to down sample the input size. This structure ensures efficient feature extraction and reduces computational complexity. At the end of these layers, a fully connected layer with 64 neurons is introduced to flatten the feature data into a one-dimensional format for classification.
- *Pooling Layers:* Pooling layers reduce the dimensionality of feature maps, minimizing the number of variables and preventing overfitting. Max pooling operations are employed to retain the most prominent features by calculating the maximum value within each feature map patch. This approach not only reduces training time but also enhances the accuracy of the classification model.
- *Fully Connected Layers:* The fully connected layer, situated at the end of the convolutional network, flattens the feature map into a one-dimensional structure for classification. It assigns the images into multiple classes, including benign and malignant tumors. The softmax function is utilized within this layer to perform the final classification, producing accurate predictions for brain tumor diagnosis.

VII. Result Analysis

The proposed DCNN was designed and tested using an MRI brain-tumor dataset to analyze its performance in brain tumor classification. The system's accuracy was assessed using cross-validation techniques, and its results were compared with existing models. Specifically, the pre-trained ResNet152 model was utilized to implement the deep convolutional layer network, processing the input MRI brain images effectively. To ensure a robust evaluation, a two-fold cross-validation method was employed, providing a reliable measure of the classification model's accuracy. The Fig. 4 shows the value of the Test Accuracy, Recall, Precision, and F1-Score.

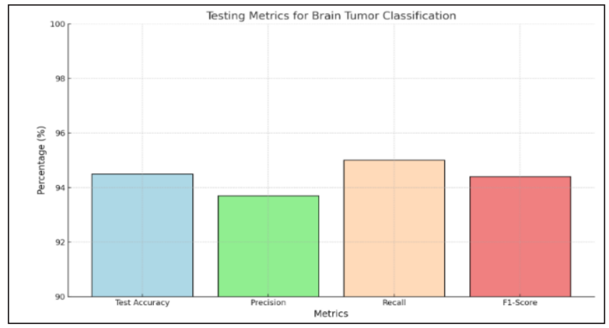

Fig. 4: Testing Metrics for Brain Tumor Classification

For the performance evaluation, the confusion matrix plays as a valuable tool for evaluating the performance of the proposed deep learning classification model. Key performance metrics such as precision, accuracy, recall & F1-score are analyzed to assess the effectiveness of the brain cancer classification system. The Fig. 5 illustrated the confusion matrix for the simulated ResNet152-based brain tumor classification, showing the relationship between actual and predicted labels for Pituitary, Glioma, and Meningioma tumor types.

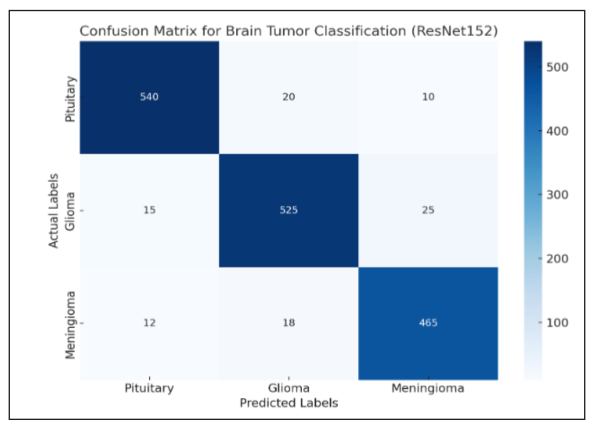

Fig. 5: Confusion Matrix for Brain Tumor Classification (ResNet152)

The classification performance of ResNet152 was then compared against other popular CNN architectures, including VGG-16 and MobileNet. As in Fig. 6, shows the a comparison the performance of ResNet152 with other methods existing methos like ResNet50, VGG16, InceptionV3, and MobileNet based on accuracy, establishing its effectiveness for brain tumor diagnosis. This improvement highlights the advantages of the proposed approach in handling complex medical imaging tasks.

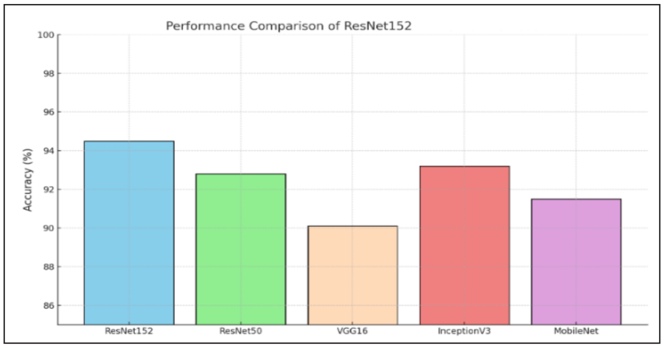

Fig. 6: Performance Comparison of ResNet152 with Other Methods

The Fig. 7 presents the comparison of the performance of ResNet152 with other classification methods such as Random Forest, SVM, KNN, and Logistic Regression based on the accuracy.

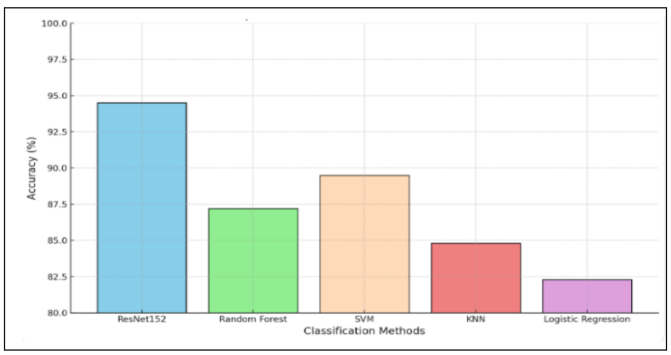

Fig. 7: Performance Comparison of ResNet152 with Other Classification Methods

VIII. Conclusion

Accurate classification of the brain tumor MRI-images is a critical requirement in modern healthcare systems. The deep CNN model demonstrates its significance in achieving high precision in medical image diagnostics. By leveraging ResNet152, the proposed system effectively extracts essential features from MRI image data, facilitating the accurate classification of tumor types such as meningioma, pituitary, and glioma. This high-performing model enhances the reliability of brain tumor classification, contributing significantly to medical IoT-based healthcare systems. In the future, this approach can be expanded to incorporate risk assessment alongside classification, further advancing its utility in brain tumor analysis using MRI data.

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