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A Comprehensive Survey on Deep Convolutional Neural Networks for Brain Tumor Detection

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***Abstract* — The evolution of medical imaging technology has sparked revolutionary progress in neuroimaging, particularly in the domain of brain tumor diagnostics. This survey paper navigates through cutting-edge methodologies in brain tumor classification, centering on the transformative impact of deep convolutional neural networks (CNNs). The integration of deep learning techniques, specifically CNNs, has reshaped the land- scape of brain tumor classification by automating the extraction of intricate features from medical imaging data, notably magnetic resonance imaging (MRI) scans. The review critically evaluates key studies that leverage CNN architectures for brain tumor classification, emphasizing diverse datasets, model architectures, and evaluation metrics. Furthermore, the review explores the integration of CNNs with traditional architectures, underscoring the innovative approaches to enhance classification accuracy. As a synthesis of contemporary research, this survey paper aims to furnish a comprehensive understanding of the current landscape of brain tumor classification using deep convolutional neural networks. By critically assessing methodologies, achievements, and challenges, it endeavors to guide future research directions, aspiring to refine diagnostic accuracy, optimize model performance, and ultimately advance personalized treatment strategies for individuals grappling with brain tumours.**

Keywords — Brain tumor, Magnetic resonance imaging (MRI), Deep learning, convolutional neural networks (CNN)

I. INTRODUCTION

The advent of advanced medical imaging technologies has paved the way for revolutionary developments in the field of diagnostic medicine, particularly in the domain of neurology. Among the myriad neurological disorders, brain tumors rep- resent a significant health challenge, demanding precise and swift diagnostic approaches for effective treatment. In recent years, there has been a paradigm shift in the utilization of deep learning techniques, specifically deep convolutional neural networks (CNNs), to enhance the accuracy and efficiency of brain tumor classification.[1] This novel approach capitalizes on the capacity of CNNs to automatically learn intricate hierarchical features from medical imaging data, thereby providing a powerful tool for automated tumor classification.

The classification of brain tumors using deep CNNs involves the extraction of complex patterns and features from medical images such as magnetic resonance imaging (MRI) scans. These neural networks, inspired by the human visual system, can discern subtle differences in tumor characteristics, aiding in the differentiation of various tumor types and grades.[2]

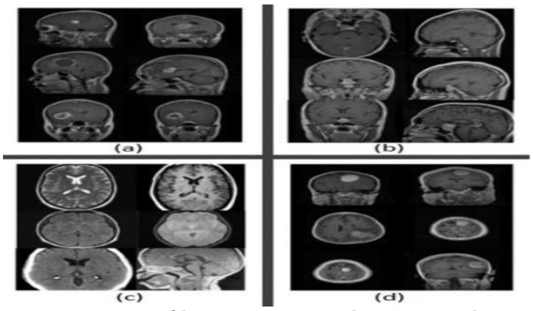

Fig.1- MR images of brain tumors. (a) Glioma tumor (b) Pituitary tumor (c) No tumor (d) Meningioma tumor

This sophisticated approach holds promise for not only expediting the diagnostic process but also improving the overall accuracy of tumor classification, thus facilitating personalized treatment strategies. Several studies have demonstrated the effectiveness of deep CNNs in brain tumor classification. For instance, the work by [3] showcased the potential of deep learning models in automatically classifying brain tumors with high accuracy, even outperforming traditional machine learning methods. Additionally, the research conducted by [4] emphasized the significance of deep CNNs in not only identifying tumor presence but also providing valuable insights into tumor subtypes, aiding clinicians in tailoring treatment plans for optimal patient outcomes.

As the integration of deep CNNs in medical imaging gains momentum, it is crucial to explore the challenges and opportunities associated with this innovative approach. This introduction sets the stage for a comprehensive exploration of brain tumor classification using deep convolutional neural networks, delving into the technical intricacies, clinical implications, and the future prospects of this transformative methodology. Through an in-depth analysis of existing literature and emerging research trends, this study aims to contribute to the growing body of knowledge that seeks to harness the potential of artificial intelligence in improving neurological diagnostics and patient care.

The remaining part of the paper is organized as follows; Section 2 illustrates related works to this survey work. In

Section 3, the commonly used neural network models and in section 4, their performance metrics in evaluating the performance of brain tumor classification methodologies is highlighted. In Section 5, Finally, the paper presents a discussion on different models and a conclusion in Section 6.

II. LITERATURE SURVEY

In this section, we review pertinent research on the detection of brain tumors utilizing machine learning (ML) models. In [5], a deep educational model leveraging an MRI dataset for brain tumor detection. Their study incorporated four additional transfer learning models—VGG16, MobileNet, ResNet-50, and Inception V3. The dataset, comprising 10,000 MR images with a resolution of 200 × 200 pixels, was categorized into brain tumors and non-brain tumors, each containing 5000 images. Notably, their deep educational model outperformed others, achieving a training accuracy of 100% and a test accuracy of 98%.

In [6] introduced a deep convolutional neural network (DCNN) model for brain tumor detection using an MRI dataset. Their proposed model, characterized by a lightweight architecture with minimal convolutions, max-pooling, and iterations, was compared with VGG16, VGG19, and CNN- SVM. Analyzing 3394 MR images across four subcategories—Glioma (934), Meningioma (945), No Tumor (606), and Pituitary (909)—their model demonstrated an impressive overall accuracy of 97.72%. Additionally, it achieved a detection rate of 99% for Glioma, 98.26% for Meningioma, 95.95% for Pituitary, and 97.14% for normal images.

In [7], pioneered a cutting-edge Correlation Learning Method (CLM) that integrates a convolutional neural network (CNN) with a conventional architecture for brain tumor classification. Investigating 3064 brain cancer images, including Meningioma (708 images), Glioma (1426 images), and Pituitary (930 images), their CLM model exhibited an accuracy of approximately 96%, precision of about 95%, and a recall of around 95%.

In [8], proposed a comprehensive approach for detecting brain tumors, involving naive Bayes, random forest, neural network, KNN, and decision tree machine learning models. Additionally, they introduced a hybrid ensemble classifier (KNN-RF-DT). The evaluation of these machine learning models, conducted on a dataset comprising 2556 images, highlighted their efficacy in brain tumor detection. The study focused on brain tumor detection using machine learning models, employing an 85%-15% split for training and testing, respectively. Feature extraction through Stationary Wavelet Transform (SWT), Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM) yielded thirteen distinctive features for classification. The proposed approach demonstrated robust performance with an accuracy of 97.305%, precision of 97.73%, specificity of 97.60%, sensitivity of 97.04%, and reliability of 97.41%.

In [9], introduced dense EfficientNet, a CNN-based net-work, for brain tumor image detection using MRI. Comparative analysis with ResNet-50, MobileNet, and MobileNetV2 favored the dense EfficientNet, achieving a remarkable 98.78%

accuracy and a 98.0% F1-score after training on a dataset of 3260 MR images featuring four types of MRI.

In [10], proposed a CNN-based residual network for early brain tumor detection, utilizing the BRATS 2015 MRI dataset. The model achieved an accuracy of 97.05%, along with other notable metrics, including a mean accuracy of 97.05%, global accuracy of 94.43%, mean IoU of 54.21%, weighted IoU of 93.64%, and mean BF score of 57.027%, after one-hundred epochs of training.

In [11], presented a modified two-step dragonfly algorithm for brain tumor segmentation in 3D MR images, demonstrating enhanced accuracy (98.20%), recall (95.13%), and precision (93.21%) compared to other models. Notably, limitations included a focus on the entire tumor segment without considering multiple tumors per slice.

In [12], proposed a hybrid CNN model for brain tumor detection using BRATS MR images, integrating a two-phase training method and regularization approaches. The model exhibited promising performance, with a Dice score of 86%, sensitivity of 86%, and specificity of 91%.

In [13], introduced a KNN classifier for early detection of fetal brain abnormalities, achieving an accuracy of 95.6% and an AUC of 99%. Attallah et al. [41] proposed a deep-learning-based machine learning architecture for the early diagnosis of embryonic neurodevelopmental abnormalities, showing promising results.

In [14], explored a physiological MRI approach combined with nine machine learning models for early brain tumor detection, considering various performance indicators. Aamir et al. [43] proposed an automated method for brain tumor detection, achieving a superior 98.95% accuracy compared to existing approaches.

In their research, the authors collected diverse brain tumor MR images and assessed their CNN model against various machine learning models, outperforming transfer learning models. Despite challenges like low GPU resources initially, the study utilized a substantial dataset of 3264 MRI scans, addressing limitations and optimizing system performance for future research.

III. NEURAL NETWORK MODELS

A. VGG16

In [15], pioneered the VGG16 deep convolutional neural network (DCNN) model, achieving notable success by securing a top 5 test accuracy of 92.7% in the ImageNet competition organized by the Oxford Visual Geometry Group. Transfer learning efficiency assessments revealed that a pre-trained and fine-tuned VGG16 model outperformed a fully trained network. The substantial depth of the VGG model proved advantageous, facilitating the learning of more intricate and complex features by the kernels.

B. VGG19

The VGG19 model, an extension of the original VGG architecture, incorporates a total of 19 layers. This model concludes with three fully connected (FC) layers, summing up to a total of 19 layers. These FC layers consist of 4096, 4096, and 1000 neurons, respectively. Additionally, the model includes five Maxpool layers and a Softmax layer. Notably, layers with convolutional characteristics incorporate the Rectified Linear Unit (ReLU) activation feature [16].

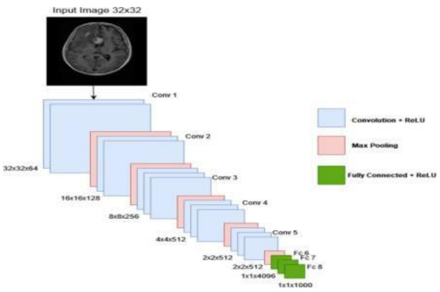

Fig.2- VGG16 Model Architecture

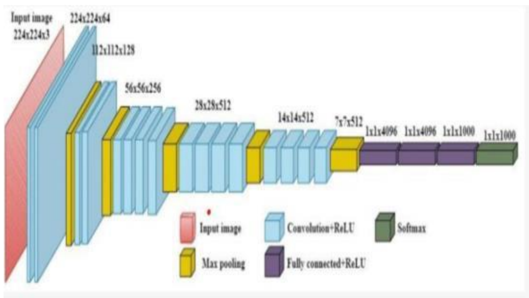

Fig.3- VGG19 Model Architecture

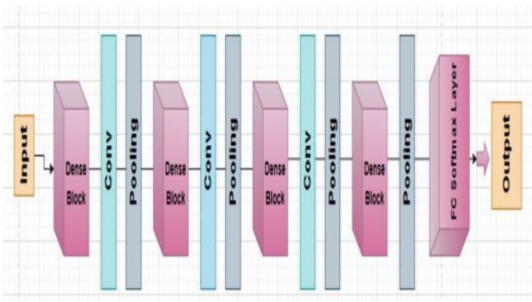

Fig.4- DenseNet 121 Model Architecture

C. DenseNet 121

The convolutional neural network architecture of DenseNet121 emphasizes dense connections between layers. Developed by researchers at Facebook AI Research, DenseNet121 is a 121-layer neural network that incorporates convolutional, pooling, and fully connected layers. In contrast to traditional CNN designs, DenseNet121 establishes dense connections between every layer in a feed-forward manner, facilitating a direct flow of both data and gradients across the network. This dense connectivity enhances gradient-based optimization, elevates model performance through enhanced feature reuse, reduces the number of parameters, and improves overall gradient flow. Renowned for its outstanding performance in tasks such as picture categorization and object identification, DenseNet121 stands as a preferred choice in numerous computer vision applications [17].

D. ResNet50

ResNet50, a profound convolutional neural network architecture, has emerged as a breakthrough in computer vision. Comprising 50 layers and introducing residual blocks, ResNet50 effectively addresses challenges associated with training highly deep neural networks. Renowned for its exceptional performance, ResNet50 excels in diverse tasks such as image segmentation, object identification, and classification.

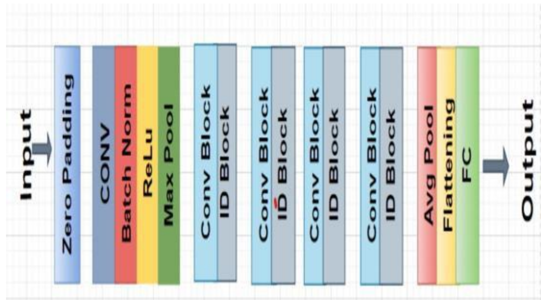

Fig.5- ResNet50 Model Architecture

The inclusion of skip connections in ResNet50 enhances gradient flow, preventing a decline in network performance as depth increases. This mechanism enables information to flow directly from early levels to subsequent layers. ResNet50 has become a favored choice in cutting-edge deep learning applications due to its potent feature extraction capabilities [18].

E. YOLO V4

YOLOv4, an advanced object identification algorithm, is renowned for its remarkable precision and speed. Standing for "You Only Look Once," it is widely employed in numerous computer vision tasks. YOLOv4 boasts sophisticated features, including a CSPDarknet53 backbone and diverse scale predictions, enabling it to effectively identify objects of varying sizes and scales. Implementing the Mish activation function and incorporating optimizations like spatial pyramid pooling (SPP) and panoptic feature pyramid networks (PFPN), YOLOv4 has garnered a stellar reputation for its reliable real-time object detection performance [19].

F. Inception V3

The Inception v3 model stands as a prominent deep learning network primarily utilized for image categorization and detection [20-23]. Notably, training Inception V3 poses challenges on systems with limited computational capabilities, often necessitating several days for model training [24-26]. An improvement over Inception V1 released by GoogLeNet in 2014, Inception V3 was introduced in 2015 with 42 layers and demonstrated minimal error rates compared to its predecessors. The Inception process encompasses steps such as convolution, pooling, dropout, fully connected, and softmax [27-28]. Figure 7 provides a visual representation of the Inception V3 architecture [29].

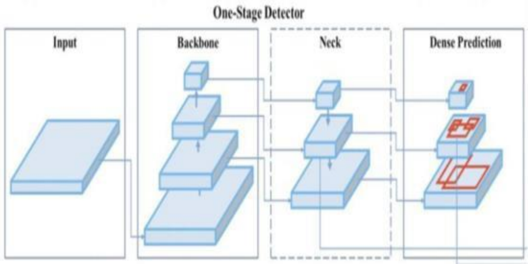

Fig.6- YOLO V4 Model Architecture

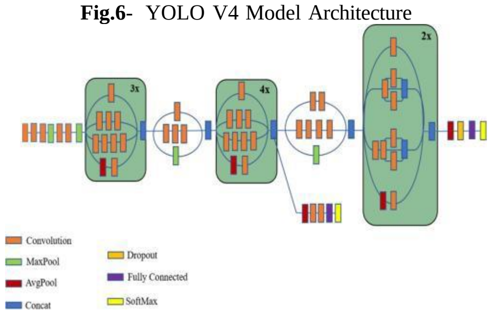

Fig.7- Architecture of Inception V3

IV. METHODOLOGY

A. Architecture

In our investigation, an initial convolutional layer processed an input image of dimensions 32 × 32 pixels using 16 filters, resulting in a 32 × 32 × 16 feature map and a 3 × 3 kernel size, aimed at identifying fundamental features. Subsequently, the output from this convolutional layer underwent max- pooling, generating a 15 × 15 × 16 feature map to reduce spatial data dimensions by half for the subsequent layer. The subsequent process involved another convolutional layer with 32 filters, producing a 13 × 13 × 32 feature map with a 3 × 3 kernel size, followed by a max-pooling layer resulting in a 6 × 6 × 32 feature map. This sequence continued with additional convolutional and pooling layers, culminating in a final convolutional layer generating a 4 × 4 × 64 feature map. The final pooling layer produced a 2 × 2 × 64 feature map. The flattened output of the last convolutional layer was fed into a fully connected dense layer with 4160 dimensions, which, in turn, connected to the ultimate output layer featuring a softmax activation function. While the final layer utilized softmax activation without dropout, all preceding layers employed a 0.5 dropout and ReLU activation function. Figure 2 illustrates the CNN architecture configuration proposed above. Model training involved 80 epochs, a batch size of 18, and a learning rate of 0.01, utilizing the Adam optimizer and a categorical cross-entropy-based loss function to calculate loss values.

The methodology comprised several key stages. Initially, data collection occurred from an online repository (kaggle.com, accessed on 10 November 2022), followed by dataset pre-processing. The validation stage employed a holdout validation system, and various machine learning models were applied to train the images. Dataset partitioning allocated 80% for training, 10% for testing, and 10% for validation. The study focused on validating four brain image types: glioma tumors, meningioma tumors, no tumor, and pituitary tumors. To corroborate the findings, multiple metrics such as accuracy, recall, AUC, and loss were considered. Figure 3 provides a comprehensive step-by-step breakdown of the research methodology.

B. Environment Setup

Our experimental setup utilized the Google Colab Pro+ plat- form, which is entirely cloud-based. Developed with NVIDIA Tesla K80, T4, and P100 GPUs, this platform also featured a substantial 52 GB high-RAM runtime. Leveraging this highly customized environment, the training of machine learning models was not only expedited but also significantly more efficient compared to conventional setups.

C. Dataset Collection

Our dataset, aimed at detecting brain tumors, was sourced from publicly available data on kaggle.com. The dataset was curated using images obtained from magnetic resonance imaging (MRI), selected for their efficacy in brain tumor detection. Meningioma (937 photos), no tumor (500 images), pituitary tumor (900 images), and glioma tumor (926 images) constituted the four distinct types of brain tumor data considered in our study. The dataset comprised a total of 3264 MRI images.

D. Pre-Processing of the Dataset

Pre-processing stands as a crucial phase in rendering data suitable for training purposes. Given that the MR images were sourced from a patient database and exhibited unclear and low- quality attributes, normalization was a key step to ready the images for subsequent processing. To enhance image clarity and eliminate blurriness, Gaussian and Laplacian filters were applied during this stage. This preparatory phase aimed to optimize the quality of the images for subsequent analysis.

E. Data Division and Augmentation

Despite its limited size comprising solely MR images, our dataset posed a challenge as deep neural networks typically thrive on expansive datasets for optimal outcomes. The dataset consisted of 3264 MR images, where 80% of the data facilitated training, while the remaining images were allocated for testing and validation at rates of 10% each. Recognizing the potential of data augmentation to bolster the original dataset and refine training, we implemented techniques such as mirroring, rotation, width and height shifting, and zooming. These augmentation strategies not only expanded the dataset but also heightened the model's learning capacity. Subsequently, the datasets underwent validation using the holdout validation method.

F. Validation Process

Selecting an optimal validation procedure was imperative for the dataset comprising 3264 scan images. Employing the widely adopted holdout validation process, we allocated 80% of the data for training purposes and reserved the remaining 20% for testing [30]. This technique, recognized for its effectiveness, involves the division of the dataset into two parts: a training set and a testing set, expediting the model training process. The training set played a pivotal role in deep learning model training, while the testing set served to assess the model's performance. Within the holdout method, 80% of the dataset underwent random selection for training, leaving the remaining 20% for testing. This approach facilitated robust model training, leveraging a substantial amount of data for enhanced generalization to new, unseen data. However, it is essential to acknowledge that the testing set might not be entirely representative of the overall data, potentially introducing bias to the performance estimate.

G. Performance Metrics

In assessing the machine learning models and scrutinizing their performances, we took into account key metrics including accuracy, recall, and the area under the curve (AUC).

Accuracy: Accuracy is calculated by dividing the number of correct predictions by the total number of samples, and this can be computed using Equation (1)

$$\text{Accuracy} = \frac{TN+TP}{TP+TN+FP+FN} \times 100\ \% \quad (1)$$

where: TP = True positive; TN = True negative; FN = False negative; FP = False positive.

Recall: Recall is one of the another most important metrics to evaluate machine learning model. The recall can be calculated as:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Area under the Curve: AUC stands for the area under the curve. The AUC evaluates how effectively the model distinguishes between both positive and negative categories. Higher AUC values indicate a better performance of the model.

TABLE I
NEURAL NETWORK MODEL'S PERFORMANCE ON BRAIN TUMOR DETECTION

Models	Accuracy (%)	AUC (%)	Recall (%)	Loss
CNN	93.30	98.43	91.13	0.25
ResNet-50	81.10	94.20	81.04	0.85
VGG16	71.60	89.60	70.03	1.18
Inception V3	80.00	89.14	79.81	3.67

V. RESULTS AND DISCUSSION

An analysis of the performance of various deep learning models—namely, VGG16, CNN, ResNet-50, and Inception V3 classification algorithms—on the brain tumor MR image dataset, with visual comparisons shown in Figure 8. The table showcases model performance metrics, including accuracy, area under the curve (AUC), recall, and loss function results. Upon careful examination of the CNN, VGG16, ResNet-50, and Inception V3 methods, it became evident that the CNN outperformed other deep learning models, as indicated in Table-1. The CNN achieved an impressive validation accuracy of 93.3%, a validation AUC of 98.43%, a validation recall of 91.1%, and a validation loss of 0.260.

To further illustrate the validation accuracy, corresponding training accuracy graphs for CNN, ResNet-50, Inception V3, and VGG16 are presented. The blue lines represent training accuracy, while the orange lines represent validation accuracy. Notably, the CNN exhibited the highest validation accuracy at 93.30%, coupled with a training accuracy value of 90.50%. In comparison, ResNet-50 achieved a validation accuracy of 81.10%, with the highest training accuracy value of 98.43%. Inception V3 achieved a validation accuracy of 80% and a training accuracy of 91.79%. However, VGG16 exhibited the lowest validation accuracy at 71.60% and the lowest training accuracy at 79.20%.

During model implementation, 80 epochs and a batch size of 18 were selected, and the Adam optimizer was employed. The accuracy graph analysis emphasized the superiority of the CNN, demonstrating a significant output curve in validation accuracy concerning training accuracy, without encountering over-fitting or under-fitting issues.

VI. CONCLUSION

The early detection of brain tumors plays a crucial role in mitigating higher mortality rates on a global scale. The intricacies of tumor form, dynamic size changes, and structural variations make accurate detection challenging. The classification of MR images significantly influences clinical diagnosis and therapy decisions for brain tumor patients. While early identification of brain tumors using MR images and segmentation methods holds promise, achieving precise recognition and categorization of tumor locations remains a formidable task.

In our study on early brain tumor detection, diverse MRI brain tumor images were utilized. Deep learning models, particularly CNN, have proven instrumental in classification and detection. Our proposed CNN model demonstrated promising results, leveraging a substantial volume of MR images. To ensure the efficiency of the ML models, various indicators were employed during the evaluation process. Additionally, we considered alternative ML models to comprehensively assess our outcomes. Acknowledging the limitations of our research, the training process for the CNN was time-consuming due to numerous layers and inadequate GPU capacity. Subsequent improvements to our GPU system resulted in reduced training times. Future work could enhance brain cancer identification by incorporating individual patient information from diverse sources.

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