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A Survey on Brain Tumor Detection Using Deep Learning Techniques

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Abstract*— Brain tumor is an abnormal growth of cells within the brain that can interfere with critical functions such as cognition, movement and sensation. It can be either cancerous or non-cancerous depending on its cellular characteristics. Brain tumors can adversely affect the brain decision-making processes, operational efficiency and overall control capabilities. Brain tumor detection (BTD) is critical for early diagnosis and effective treatment. To prevent the deaths of millions of people due to brain tumor, we must come up with a solution that allows us to diagnose the condition early. This study presents survey on the research works done on development of deep learning (DL) technologies for the BTD from 2019-2024. The current trends and difficulties in the BTD using DL and modern imaging techniques are evaluated. Additionally, we examined different DL networks and evaluated each technique's effectiveness. The results of this comparison suggest the hybrid neural network is more effective in detection of brain tumor. MobileNetv3, CNN, ResNet-50 and hybrid models have overall detection accuracy between 92% to 99.75%. The MobileNetv3 model achieves success rate of 99.75% than other DL frameworks for detection of brain tumor. This demonstrates that DL algorithms can accurately detect brain tumor on its early stage.

Index Terms: Brain tumor, Machine learning, Deep learning, MobileNetv3.

I. INTRODUCTION

A human brain controls the functions of all other organs and plays an important role in decision-making. It is responsible for regulating both voluntary and involuntary activities carried out by the central nervous system [1]. The development of a brain tumor in the tissues surrounding the brain or within the skull can significantly impact a person's life [2]. Cancer cells that have spread from other parts of the body can potentially create tumors in the brain [3]. Brain tumors can be classified into benign and malignant. A benign tumor has a uniform structure and contains no cancerous cells, while a malignant tumor contains cancerous cells. Grade I and II tumors are classified as benign, whereas Grade III and IV tumors are classified as malignant, according to a tumor grading system created by the American brain tumor association and the world health organization (WHO) [4].

It is possible to fully examine brain structures using various imaging modalities includes positron emission tomography (PET), computed tomography (CT) and magnetic resonance imaging (MRI) [5]. Enhancing patient outcomes requires accurate and timely detection through MRI scans [6]. By providing crucial details about the tumor's size, location and shape, MRI images assist doctors in making well-informed treatment decisions. In some cases, MRI images cannot detect certain types of brain tumors [7]. Medical imaging patterns was identified and classified using machine learning (ML) particularly DL [8]. The main purpose of image processing and DL algorithms is to analyse medical images and classify brain tumors into different subcategories, aiding professionals in their diagnosis [9]. High variability and intrinsic features of the MRI data, including variations in tumor sizes, forms, detection, area calculations, segmentation, classification and the capacity to identify ambiguity in segmented regions, pose a problem when it comes to brain tumors [10]. The main objectives of the paper are as follows:

a) Researching all advanced DL networks on the detection of brain tumor with the gathered images.
b) To provide an in-depth survey of many trustworthy data sources on brain tumor.
c) Discussing the shortcomings of the existing survey papers on BTD, a review of current studies was carried out in the area of BTD using image processing techniques, and

The paper is organized as follows: Section 2 presents an analysis of BTD, while section 3 explores CNN architectures, specifically ResNet, U-Net, and MobileNet. Section 4 provides a discussion of the survey results and section 5 concludes the study.

II. STUDY ON BRAIN TUMOR DETECTION

In recent years, numerous studies have investigated the brain tumor detection with DL and ML methods. The following section provides a brief overview of some recent research works.

A. U-Net:

In 2024, Khan et al., [11] suggested a technique that combines ensemble learning techniques with an improved U-net algorithm to detect and classify brain cancers. By addressing uncertainty issues in MRI image segmentation and reducing computational cost, the proposed technique enhances lesion detail detection accuracy. This model uses

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the extraction of color, shape, and texture information to improve brain tumor diagnostics by attaining faster and more precise detection. With a 96% accuracy rate, the suggested model's accuracy produces very useful outcomes.

In 2023, Mallampati et al., [12] suggested a ML-based technique that uses features from MRI to detect brain tumors. With 2D-UNet segmentation features, the model's accuracy of 64% is produced. By training it using 3D-UNet segmentation data, they obtain a remarkable accuracy rate of 71%, surpassing existing state-of-the-art models that utilize these features.

B. Support Vector Machine:

In 2024, Anantharajan et al., [13] suggested a DL and ML based MRI technique for BTD. Simulations are run to assess the model execution and efficacy. It provides an accuracy of 97.93% in correctly identifying the tumor image. The data provide a number of advantages, indicating the value of this model combination. The numerical results demonstrate improved specificity (98%) and sensitivity (92%) in distinguishing among normal and aberrant tissue from brain MRI images, validating the efficiency of the suggested method.

In 2024, Asiri et al., [14] suggested a dual-module system for classifying tumors and improving MRI images. The first module, called the Image Enhancement Technique, normalizes images and addresses problems like noise and fluctuating low area contrast by employing three ML and imaging techniques: independent component analysis, adaptive Wiener filtering and neural networks. Tumor segmentation and classification are carried out by the second module, which also makes use of SVM to verify the results of the first module. It obtained a Dice score (DSC) of 0.981, accuracy of 0.989.

C. Inception V3:

In 2024, Agarwal et al., [15] suggested an DL approach for BTD. It contains limited dataset for training, the system makes use of transfer learning's capabilities to get the best possible performance for the DL-based system. When the suggested system was put to the test against the most advanced models available such as ResNet-50, DenseNet-201, AlexNet, GoogLeNet, VGG-16, VGG-19. In a publicly available dataset of MRI images with diverse levels of contrast and brightness, an accuracy of 98.89% was achieved, marking the highest performance.

In 2023, Rastogi et al., [16] suggested a DL technique for brain tumor analysis that enhances segmentation and classification. DL is practical for BTD using Inception-V3 and RESUNET. Include an additional layer as a classification head on the Inception V3 model. The Inception-V3 model with an additional classification layer has a test accuracy of 0.9996 and a loss value of 0.0025. The model has an accuracy of 0.9700, and its detection and localization tversky value of 0.9688.

D. Extreme Learning Machine:

In 2024, Bhimavarapu et al., [17] proposed a ML classifier and segmentation of an enhanced unsupervised clustering strategy for the BTD. The tumors are classified by the upgraded Extreme Learning machine with a precision of 99.14%, a recall of 99.25%, and an accuracy of 98.56%. The enhanced method outperformed other algorithms, especially in glioma grade classification with accuracy of 99.28% on Kaggle dataset and 98.47% on Fig sharing dataset. Related to existing models, the suggested technique improves accuracy by about 5.39% in the Fig sharing dataset and 6.22% in the Kaggle dataset.

E. Xception:

In 2024, Khan and Park [18] suggested a CNN technique for MRI-Based Multiclass BTD. The model's impressive diagnostic accuracy is demonstrated through comprehensive evaluations on three distinct datasets, achieving an a F1-score of 97.36%, precision of 97.63%, accuracy of 97.52%, a recall of 97.18% and specificity of 98.32%. These results outperform state-of-the-art models like ResNet50, DenseNet121 and other advanced techniques. Moreover, its versatility across several MRI modes highlights its potential for wide clinical use, providing a noteworthy breakthrough in BTD and radiological diagnostics.

In 2024, Kaur et al., [19] suggested an Xception model design to divide images of brain tumor disease into two groups. Combining Adam and Adamax optimizers allows for the model is optimized during the training process. The outcomes demonstrate the model's proficiency, as it achieved a remarkable accuracy rate of 96%. The findings of this study are potentially significant since they show how the Xception model can advance the field of medical diagnosis.

F. Hybrid VGG16–Resnet50:

In 2024, Dhakshnamurthy et al., [20] suggested an approach for classifying and classifying the brain tumors using transfer learning models. This study examines three key models in computer vision like AlexNet, VGG16 and ResNet-50. The VGG16 and ResNet-50 models exhibited outstanding operation, leading to their combination into a combined VGG16–ResNet-50 model. After the combined model was applied to the dataset, it produced impressive results such as sensitivity of 99.98%, accuracy of 99.98%, F1 score of 99.98% and specificity of 99.98%.

G. YOLOv5:

In 2024, Almufareh et al., [21] suggested a YOLO-based DL structure for automated brain tumor segmentation and classification in MRI images. Gliomas, pituitary and meningiomas are the three kinds of brain tumors included in the dataset. Advanced mask alignment algorithms are incorporated during the preprocessing phase to guarantee accurate segmentation of the tumor regions. Based on the YOLOv5 numerical findings, it was observed that the box

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identification and mask segmentation tasks had recall scores of 0.905 and 0.906 and precision scores of 0.94 and 0.936. In both box detection and mask segmentation, mAPs are 0.947 at IoU thresholds of 0.5, but 0.666 and 0.657 at IoU thresholds of 0.5 to 0.95.

In 2022, Paul et al., [22] proposed a brain cancer segmentation using YOLOv5. The Brats 2021 dataset, which comes from the RSNA-MICCAI brain tumor radio genomic classification, was used in the study. Meningioma, pituitary, and glioma are the three groups represented in the study paper model. The outcomes demonstrate that, when it comes to the runtime consumption of an M2 10 core GPU, our model reaches competitive accuracy.

H. CNN:

In 2023, Mahmud et al., [23] suggested a DL technique for the identification of brain tumors from MRI data. The study also compares the suggested architecture with several models includes Inception V3, VGG16 and ResNet-50. It contains variety of metrics like recall, accuracy, loss and AUC to analyse the models' performance. The CNN model achieved an accuracy of 93.3%, a recall of 91.19%, AUC of 98.43% and a loss of 0.25 when tested on a dataset of 3,264 MRI images.

In 2022, Lamrani et al., [24] suggested a technique for BTD using CNN and MRI images. The proposed study employs a CNN to detect brain tumors and assesses its effectiveness in this task. The primary goal is to conduct BTD and classification using CNN as a ML technology. The pre-trained architecture model attained an accuracy of 96% based on training and testing data. Based on the given dataset, CNN is the more accurate technique for predicting brain tumors.

In 2024, Martínez-Del-Río-Ortega et al., [25] suggested an image classifier for MRI that uses CNN to identify brain malignancies. To maximize the identification of brain tumors, several CNN architectures were put into practice and assessed. The optimal model outperformed earlier research with a sensitivity of 99.2%, accuracy of 97.5% and binary accuracy of 98.2%. These findings highlight the DL methods can be used in clinical settings to greatly improve diagnostic precision and dependability.

I. Efficientnet:

In 2022, Shah et al., [26] proposed method utilizing optimized efficientNet for brain tumor identification in MRI. Image enhancement techniques were used to enhance image quality using various filters. The overall classification and detection accuracy of an EfficientNet-B0 model was 98.87%. In terms of recall, precision, accuracy and AUC it outperformed other CNN models.

In 2021, Guan et al., [27] suggested an effective brain tumor classification model that is capable of classifying brain MRI images of cancers. The experiment shows that the proposed method outperformed current methods on the same dataset, achieving overall accuracy of 98.04%, with specificity rates of 98.55%, 99.38%, and 99.25% and sensitivity rates of 96.89%, 97.82%, and 99.24% for Glioma, Meningioma and Pituitary classes.

III. MATERIALS AND METHODS

DL models for BTD have developed the field of dermatology by offering powerful tools for early analysis and classification of brain tumor. These models primarily rely on CNN, a class of DL architectures ideally suited for image analysis. CNNs can automatically identify key structures in brain tumor images, making them highly effective at differentiating between the presence and absence of tumors.

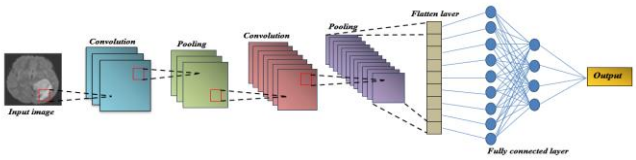


Figure 1. Architecture of CNN

The DL models for identifying brain tumor provide details about some CNN variations, including Alex Net, ResNet, Google Net, Mobile Net, U-Net and GAN. Advanced networks that can accommodate different resource limits and scalability requirements include Alex Net, ResNet, Google Net, Mobile Net, U-Net and GAN. CNN architecture is shown in Figure 1. The CNN [15,23,28,29,25] model utilizes Fig sharing, Kaggle, BRATS 2018, BRATS, Br35H datasets for the recognition and categorization of brain tumor through success rates of 98.89%, 93.30%, 92.03%, 97.87% and 97.5%. Comparing CNN to traditional feed-in neural networks, the need for fewer neurons and hyperparameters is a significant advantage. To tackle challenging visual imaging issues for image recognition applications, a number of CNN baseline designs have been developed. In the present study ResNet, U-Net and Mobile Net are suggested pre-trained models.

A. ResNet

ResNet, developed by Kaiming and his team at Microsoft Research in 2015, allows for the training of very deep neural networks through residual connections. These connections allow certain layers to be bypassed, helping gradients flow during training and overcoming the vanishing gradient problem. Models such as ResNet-50, ResNet-101, and ResNet-152 demonstrate that deep networks can achieve high accuracy in tasks such as image recognition and segmentation. The ResNet [31] detect the brain tumor in humans with high reliability rate utilizing kaggle dataset at an accuracy rate of 99%.

B. U-Net

A CNN design termed U-Net was created for challenges involving semantic picture segmentation. It is composed of a decoder network that up samples and fine-tunes the feature

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maps to generate pixel-wise segmentation masks, and an encoder network that progressively lowers the dimension of space using convolution and pooling layers. The U-Net architecture is particularly popular in medical image analysis and other tasks where precise pixel-level segmentation is required, thanks to its ability to capture fine details and spatial information. The U-Net [33] detect the brain tumor in humans with high reliability rate utilizing TCIA dataset at an accuracy rate of 92%.

C. Mobile Net

Mobile Net uses depth-wise separable convolutions in its layers, which are made up of point-wise (PC) and depth-wise convolutions (DWC). In DWC, the channels of the input tensor are filtered independently, reducing computations, whereas in PC, the results are combined. This plan decreases the quantity of constraints and computations compared to traditional convolutional layers, making Mobile Net suitable for embedded and mobile applications with limited computational resources. The MobileNet [35] detect the brain tumor in humans with high reliability rate utilizing kaggle dataset at a success rate of 99.75%.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The methodologies for classifying and identifying brain tumor are briefly compared in the section below.

A. Experimental Results

In this section, a DL approaches for detecting brain tumor is mentioned and discussed. The pre-process models and various datasets that were utilized to identify brain tumor are discussed. When contrasted with the models given below, MobileNetv3 model performs well and beats other models with a reliability of 99.75%.

Table 1: Comparison of various methods for detecting brain tumor.

Author& year	Dataset	Data description	Pre-processing methods	Network model	Partitioning	Validation results
Guan et al., 2021 [27]	MRI dataset	MRI dataset contains 3064 images	min-max normalization and data augmentation	Efficient-Net	70% and 30% for training and validation,	Accuracy (98.04%)
Ranjbarzadeh et al., 2021 [28]	BRATS 2018 dataset	BRATS 2018 dataset contains 285 images	remove unimportant information	Cascade CNN	training (80%), validation (10%), and testing (10%).	Accuracy (92.03%)
Hossain et al., 2019 [29]	BRATS dataset	BRATS dataset contains 217 Images	Gaussian blur filter	CNN	70 to 30 in terms of training to testing images,	Accuracy (97.87%)
Abdusalomov (2023) [30]	Kaggle dataset	Kaggle dataset Contains 10,288 images	Gaussian blur filter and Data augmentation	YOLOv7	80% and 20% of the training and testing.	Accuracy (99.5%)
Agarwal et al., 2024 [15]	Fig sharing dataset	Fig sharing dataset contains 3064 images	ODTWCHE technique	CNN	training 735 MRI images and testing 219 MRI images	Accuracy (98.89 %)
Mahmud et al., 2023 [23]	Kaggle dataset	Kaggle dataset Contains 3264 MR images	Gaussian and Laplacian filters, data augmentation	CNN	training (80%), validation (10%) and testing (10%)	Accuracy (93.30)
Asad et al., 2023 [31]	Kaggle dataset	Kaggle dataset contains 3762 MRI images	Noise reduction	ResNet-50	Training (80%) and testing (20%)	Accuracy (99%)
Tseng and Tang 2023 [32]	Kaggle dataset	Kaggle dataset contains 250 images	CLAHE and segmentation	XGBoost	150 images for training and 100 images for the testing	Accuracy (97%)
Naser and Deen 2020 [33]	TCIA	TCIA dataset Contains 815 images	resizing, Image cropping, padding, intensity normalization	U-Net	80% training and 20% testing	Accuracy (92%)
Raza et al., [34]	CE-MRI dataset	CE-MRI dataset contains 3064 images	Normalization and resize function	DeepTumorNet	70% training and 30% testing	Accuracy (99.67%)
Mathivanan 2024 [35]	Kaggle dataset	Kaggle dataset contains 7,023 images	image augmentation	MobileNetv3	80% training and 20% testing.	Accuracy (99.75%)

Author& year	Dataset	Data description	Pre-processing methods	Network model	Partitioning	Validation results
Martínez-Del-Río-Ortega 2024 [25]	Br35H dataset	Br35H dataset contains 4600 images	Normalization and segmentation	CNN	training 70%, validation 20% and testing 10%	Accuracy (97.5%)

CNN [23], YOLOv7 [30], ResNet-50 [31], XGBoost [32] and MobileNetv3 [35] networks employ Kaggle dataset for the detection of brain tumor with a success rate of 93.30%, 99.5%, 99%, 97% and 99.75 respectively. Kaggle dataset provide best result to the MobileNetv3 model for BTD. From this overall review, MobileNetv3 model [35] yield more reliability rate related with other advanced approaches.

V. CONCLUSION

The paper presents a survey of the research work about recognition and detection of brain tumor using DL methods presented over the period from 2019 to 2024. This work supports the concept that DL algorithms to enhance the approaches for detecting brain tumor. A DL model analyzes complex visual data using neural networks, and it provides an effective and scalable solution to brain tumor. To improve generalization and usability of detection, DL models for brain tumor should avoid overfitting. Kaggle dataset has a success rate of 99.75% than MRI, BRATS (2018), BRATS, Fig sharing, TCIA, CE-MRI and Br35H dataset. The MobileNetv3 model achieves success rate of 99.75% for the BTD, which is comparatively higher than the other advanced approaches. The entire study examines the success rates between 92% to 99.75% for the identification of brain tumor using advanced DL models. Using DL, the prevention of brain tumor is facilitated through early detection and precise monitoring. Early BTD is significantly improving the chances of effective action and decrease the risk of problems. Regular brain tumor screenings and early diagnosis lead to less invasive treatments, higher survival rates and better quality of life for affected individuals.

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