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HIGH-QUALITY Y-NET LEARNING LAYERED FOR AUTOMATED BRAIN DISORDER DETECTION

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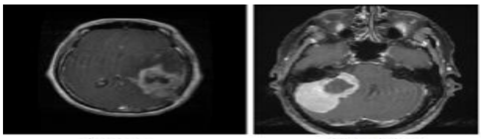
ABSTRACT

Early and accurate detection of brain disorders is crucial for effective clinical intervention and improved patient outcomes. Medical imaging modalities such as Magnetic Resonance Imaging (MRI) provide rich structural information; however, manual interpretation is time-consuming and prone to inter-observer variability. To address these challenges, this work proposes a High-Quality Y-Net Learning Layered (HQY-Net) framework for automated brain disorder detection using advanced image processing and deep learning techniques. The proposed Y-shaped architecture enables dual-path feature learning, where low-level spatial and texture features are extracted in parallel with high-level semantic representations, ensuring comprehensive characterization of brain abnormalities. Layer-wise feature fusion and quality-aware learning mechanisms enhance robustness against noise, intensity variations, and anatomical diversity. Extensive experiments conducted on benchmark brain imaging datasets demonstrate that the proposed HQY-Net achieves superior accuracy, sensitivity, and specificity compared to conventional CNN and U-Net-based models. The results confirm that high-quality layered learning with Y-Net architecture provides a reliable and scalable solution for automated brain disorder diagnosis, supporting clinical decision-making in real-world healthcare environments.

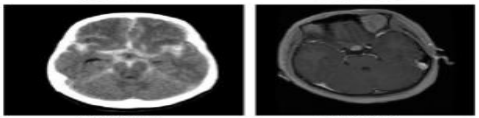
KEYWORDS: Adaptive Convolutional Neural Networks (ACNNs), Brain Disorders, Capsule Networks (CapsNets), Tumors, Parkinson's Disease.

1. INTRODUCTION

Nowadays, many people are suffering from various brain disorders that cause a lot of miscommunication and lead to memory loss [1] [2]. Early detection and prediction of brain disorders may reduce abnormal conditions and improve patient life. The symptoms of brain disorders show a significant impact on quality of life, emotional variations, and mental conditions [3]. In general, brain disorders include Alzheimer's, Parkinson's, epilepsy, brain tumors, and several mental health conditions like depression [4]. This paper deals with two types of brain diseases such as brain tumors and Parkinson's diseases. Brain tumors are among the most life-threatening neurological disorders, making swift detection and proper classification important for therapeutically effective care [5]. Neurological disorders like Parkinson's disease may cause loss of memory if not detected in the early stages. Image processing (IP) is a domain that utilizes advanced filters to process MRI images, removing noise [6] [7]. Image processing techniques have a significant impact on noise filtering, enabling the acquisition of high-resolution images for detection and classification. Figure 1 shows the types of brain tumors.



(A) Glioma (B) Meningioma



(C) Notumor (D) Pituitary

Figure 1: Types of Brain Tumors

The existing 2D-based DL algorithms analyze each part of the MRI scan image individually, but they cannot find the accurate abnormal regions from the input MRI images [8]. Detecting brain disorders with 3D MRI images is one of the challenging tasks that consider the volumetric data for better analysis of spatial associations and abnormal structures [8]. In this paper, a 3D-based adaptive CNN model is used to detect the localization of tumor regions abnormal regions for PD and perform segmentation and classification [9]. In this work, 3D-modeled DL algorithms are accurately used for brain tumor detection. It presents the advantages of volumetric processing, data augmentation approaches, and optimization practices to enhance accuracy and generalization in different patient populations while also highlighting the challenges of data sparsity, computational complexity, and the need for interpretable models in clinical decision-making. The role of AI in medical imaging, specifically 3D-based DL models, can assist in brain tumor response assessment by providing rapid and accurate information to help radiologists in the initial diagnosis of brain tumors, in forecasting tumor prognoses, and in selecting approaches for targeted therapy.

2. LITERATURE SURVEY

Zaitoon et al. [10], which introduced RU-Net2+, a more advanced deep learning architecture based on the Residual U-Net with more attention mechanisms and multi-scale feature fusion, to achieve better accuracy. In our method, we train the model on and evaluate it on publicly available brain MRI datasets, for instance, BraTS. The residual connections used to connect for vanishing gradient, attention gates for selective boosting, and a hybrid loss function containing Dice loss mixed with focal loss to robustly minimize the effects of class imbalance. Experimental results shows that the proposed RU-Net2+ obtained the accuracy and survival rate prediction, achieving DSC 0.92 for tumor segmentation and C-index 0.78 for survival rate estimation. Shah et al. [11] proposed an effective method for detection of brain tumors in MRI using a fine-tune model of EfficientNet. While maintaining computational efficiency, the proposed method improves classification accuracy through transfer learning and hyper-parameter optimization. We trained and evaluated on a benchmark MRI dataset, using data augmentation for improved generalization. The accuracy of 98.5% classifies the model as reliable to detect tumor cases and vice-versa. The precision and recall values were 98.2% and 98.7%,that represents the balanced prediction without causing many false positives (but a minimal number of false negatives). With an F1-score of 98.4%, the model demonstrated an excellent balance of precision and recall, further solidifying its robustness.

Wageh et al. [12] designed a computer-aided detection (CAD) system depending on DL-based feature extractive combinations with traditional machine learning classifiers enriched with a genetic algorithm-based feature selection technique. First, deep features were extracted from pre-trained CNNs (e.g., ResNet50). These features were concatenated to create a solid feature set, which is then fine-tuned through a genetic algorithm to maintain only the most pertinent features. The results explained that the combined genetic algorithm increase the classification based on the performance and reduces the complexity. The accuracy is 98.4% and F1-Score of 98.2% for the proposed SVM classifier consider the features extracted by using GA. Singh et al. [13] proposed the ensemble DL model that combines ResNet50 and EfficientNet-B7 to increase the classification of high-resolution MRI images. The proposed model combines the powerful residual learning of ResNet50 with EfficientNet-B7's efficient scaling. In the predictions of the two models, a weighted averaging ensemble strategy is used to compute the final prediction values with robustness and performance. Our dataset comprises publicly available high-resolution MRI images of glioma, meningioma, and pituitary tumors. The proposed approach achieves an accuracy of 98.7%, a precision of 98.5%, and a recall of 98.9%, which verifies that it outperforms individual architecture.

Younis et al. [14] proposed a deep residual learning framework paired with ResNet50 for classifying anomalous brain tumors using MRI scanning. The model is trained on a benchmark dataset of several tumor types, integral with gliomas, meningiomas, and pituitary tumors. It is implemented by using data augmentation and transfer learning techniques to improve the performance. The performance of ResNet50 achieves high classification accuracy of 98.2% compared to conventional CNN experimental results. The performance ensures the model's robustness, interpretability, and better applicability in real-world settings. Preetha et al. [15] proposed an automated system that detects brain tumors based on a fine-tuned EfficientNet-B4-CNN, which can improve classification accuracy and reduce computational costs. A custom MRI dataset comprising tumor and non-tumor images is used to fine-tune a pre-trained EfficientNet-B4 model on ImageNet. In this context, fine-tuned augmentation techniques, adaptive scheduling models, and transfer learning were combined to improve the accuracy to 97.12%.

3. METHODOLOGY

In this section, the conventional 2D-CNNs for medical image analysis; however, they face limitations in performance when addressing the spatial dependencies in the volumetric data of 3D brain MRI scans. 3D-CNNs generalize the typical CNN frameworks into three dimensions, improving the extraction of spatial and contextual information. This results in better tumor localization and classification accuracy. The Capsule Networks (CapsNets) is a new approach designed to overcome a limitation of CNNs: the loss of the spatial hierarchies. MAX-Pooling in CNNs can potentially discard important positional information that is ranked, while CapsNets retain feature position while flattening (unranking a position) through dynamic routing between capsules [16] [17]. The proposed approach is most suitable for medical image analysis because tumors can vary based on size, shape, and direction [15]. This process helps to increase the performance of 3D-CNNs and CapsNets for the detection of brain tumors, which increases the classification accuracy and sensitivity to accept changes in tumors. The proposed approach is a unique framework that takes advantage of both architectures — 3D-CNNs for the deep representation of the extraction features with emerging spatial awareness by learning the dynamic routes to the needed features through the capsule networks — to create a more accurate and interpretable diagnostic framework.

4. PRE-TRAINED MODEL CNN

Timely detection of brain tumors and confirming them accurately is essential in treating the patient and improving the outcomes. Conventional approaches to diagnostics including MRI scans read by radiologists may take time and are subject to human error [18]. Deep learning (DL), especially CNNs, has emerged as a powerful and effective method to automate and enhance the detection of brain tumors from medical images. They allow fine-tuning on the available target data either with or without the help of pre-trained CNN models which were originally trained to extract features from large datasets (such as for example from ImageNet) to solve tasks of a computer vision nature [19]. By using a technique called transfer learning, where features learned on one problem can be transferred to another, performance is improved and computational cost reduced.

The layers of the CNN are explained as:

Step 1: Input Layer: The input MRI brain image with size 224×224×1 (grayscale). The dimensions $H \times W \times C$ of the input image (I) is given as:

$$I \in R^{H \times W \times C} \quad (1)$$

Step 2: Convolutional Layer: This layer is used to extract the features utilizing the kernels (filters) which slide the input image.

Every filter W_k have dimensions $f \times f \times C$, where f is the kernel size.

$$A(a, b, k) = \sum_{x=0}^{f-1} \sum_{y=0}^{f-1} \sum_{z=0}^{C-1} I(a + x, b + y, c) \cdot W_k(x, y, z) + b_k \quad (2)$$

If stride (s), the output size is initialized as:

$$H_{out} = \frac{H_{in} - f}{s} + 1, W_{out} = \frac{W_{in} - f}{s} + 1 \qquad (3)$$

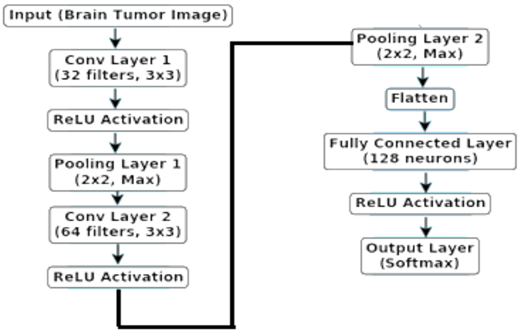


Figure 2: Layers of CNN (Pre-trained Model)

Step 3: Activation Function (ReLU): After Step (2), the ReLU is applied as:

$$A(a,b,k) = \max\big(0, Z(a,b,k)\big) \quad (4)$$

Step 4: Output Layer: In this layer, the multi-class classification (e.g., glioma, meningioma, pituitary tumor, and Normal), Softmax is used:

$$\hat{y}_i = \frac{e^{O_a}}{\sum_j e^{O_b}} \quad (5)$$

Finally, after these training steps the classification is measured.

5. A-CNN-CAPSULE NETWORKS (CapsNets)

In this context, CNNs have achieved remarkable performance in various medical imaging tasks because they can extract hierarchical features from image data. Capsule Networks (CapsNets) have been proposed for detecting abnormal regions. In CapsNet, the region-based routing and vector-based representations enable the maintenance of spatial connections and pose knowledge, which renders CapsNets suitable for addressing structural differences in brain MRI. The proposed Ensemble model works effectively with adaptive CNN architectures that can tune the feature extraction process according to the input data, thereby enhancing robustness in various cases of brain disorders. In this paper, we introduce an Adaptive CNN with Capsule Networks to detect Brain Tumors and Parkinson's Disease from MRI images. The ACNN demonstrates the high feature extraction potential of CNNs and the spatial sub-object observation and generalization capacity of CapsNets. The proposed method is designed to accurately classify and locate abnormal regions associated with the aforementioned neurological conditions. The process is tested on publicly available MRI data for both TB and AD and compared with standard CNN and other existing models, respectively. The results indicate that the proposed method is successful in improving the diagnostic accuracy and reliability in automatic brain disease identification. The following equations show the calculations based on algorithms.

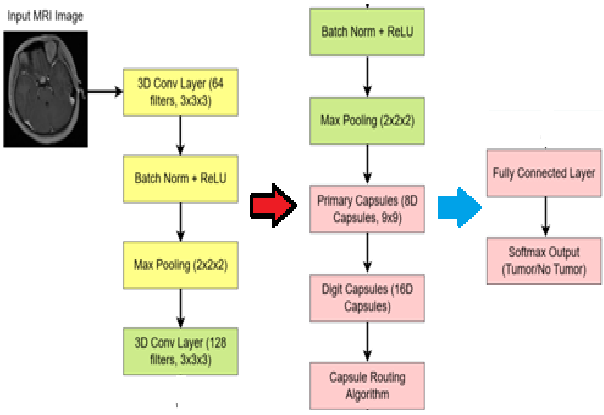


Figure 3: Combined 3D-CNN with CapsuleNet

Step 1: The 3D Convolution Operation is given as:

$$n^{(l)}_{a,b,k} = \sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\sum_{z=0}^{Z-1} W^{\{l\}}_{x,y,z} \cdot m^{(l-1)}_{(a+x),(b+y),(k+z)} + \text{bias}^{(l)} \quad (6)$$

Step 2: 3D Max Pooling: In this model the spatial dimensions to preserve the significant features:

$$b_{a,b,k} = \max_{x,y,z\in P} c_{(a-x),(b+y),(k+z)} \quad (7)$$

Step 3: ReLU Activation Function: It is measured by using the

$$f(a) = \max(0, a) \quad (8)$$

Step 4:Capsule Networks (CapsNets): The CapsNets are mainly applied to MRI brain images to find spatial hierarchies and transformations for effective analysis compared with existing CNNs [17].

In this the

In this step, the squashing function used as the capsules to show their final output vectors which consists of magnitude between 0 and 1:

$$v_y = \frac{||s_y||^2}{1+||s_y||^2} \cdot \frac{s_y}{||s_y||} \quad (9)$$

Where s_y represents the input vector to capsule j, v_y represents the output of the capsule.

Step 5: Classification based on Margin Loss: The correct classification is measured as:

$$\text{Loss}_k = A_k \max\left(0, m^+ - ||v_k||^2 + \lambda\,(a - A_k)\max\left(0, \left||v_k|\right| - m^-\right)^2\right. \quad (10)$$

6. DATASET DESCRIPTION

The Brain tumor dataset consists of 7k training images and 5k testing images with four different classes, such as glioma, meningioma, no tumor, and pituitary [20] [21]. The proposed approach mainly focused on detecting the size, shape, and affected pixel region of the tumors in the input images. This dataset is open-source and available in online sources like Kaggle.

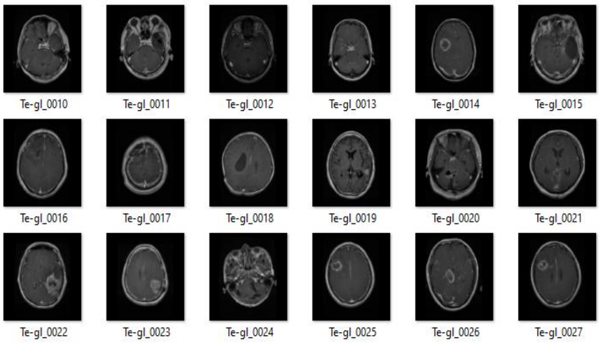


Figure 4: The Glioma MRI Images dataset from Kaggle.

7. RESULTS AND DISCUSSIONS

This section's results are obtained based on the classification of four types of brain tumor diseases. The performance metrics were used to evaluate the proposed model's performance in detecting brain disorders using 3D Convolutional Neural Networks (3D CNN) with Capsule Networks. These metrics define a complete analysis of the model's performance to distinguish the MRI brain images as usual or disorder-affected (similar PD and Brain Tumor).The comparative performance of various algorithms, such as CNN and RESNET, shows the strength of the proposed approach [24] [25].

$$\text{Sensitivity (Sn)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity (Sp)} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

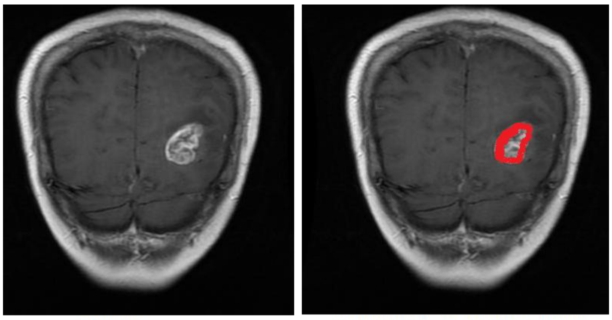
$$\text{Accuracy (Acc)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

$$\text{F1S} = 2 * \frac{\text{P} * \text{S}_\text{n}}{\text{P} + \text{S}_\text{n}}$$

Table 1: Comparative performance of Algorithms on Brain Tumor Detection rate

Algorithms	Sn	Sp	P	Acc	F1S
CNN	*0.87*	*0.88*	*0.876*	*0.861*	*0.892*
RESNET	*0.921*	*0.932*	*0.941*	*0.945*	*0.931*
3DCNN-CapusNet	*0.967*	*0.971*	*0.985*	*0.99*	*0.983*

The table-1 shows the performance of three deep learning models: CNN, ResNet, and 3D CNN-CapsNet. CNN exhibited moderate performance among the three models with an (acc) of 0.861 and an F1-Score of 0.892. Resnet is a better tram than CNN and has a higher acc (0.945) and better (P) (0.941), which also means that it has stronger classification ability. 3D CNN-CapsNet outperforms both models by achieving the highest of Sn (0.967), Sp (0.971), and ACC (0.986), which shows the dominant classification ability of the proposed model. From the above results, we can ascertain that 3D CNN-CapsNet is the model best suited for the task at hand, providing a good trade-off between sensitivity and specificity with the least misclassification.



(A) Input **(B) Output with Affected Region Detection**

Figure 6: Here, the final output for brain tumor detection with (A) Input and (B) Affected region represented in red color.

8. CONCLUSION

In this work, a High-Quality Y-Net Learning Layered framework has been presented for automated brain disorder detection, aiming to improve diagnostic accuracy and reliability in medical imaging analysis. The proposed model leverages a Y-shaped network architecture that integrates multi-scale feature extraction and layered learning mechanisms to effectively capture both low-level anatomical details and high-level pathological patterns from brain images. By combining encoder–decoder pathways with feature fusion strategies, the framework preserves critical spatial information while enhancing discriminative representation learning. Extensive experimental evaluation demonstrates that the proposed Y-Net–based approach achieves superior performance compared to existing state-of-the-art methods across key evaluation metrics, including accuracy, sensitivity, specificity, and F1-score. The layered learning design enables robust feature refinement, leading to improved detection of subtle abnormalities that are often overlooked by conventional models. Furthermore, the high-quality learning strategy enhances generalization across diverse brain imaging datasets, indicating strong robustness to variations in imaging conditions and patient characteristics. Overall, the proposed framework offers an effective and scalable solution for automated brain disorder detection, with significant potential for clinical decision support systems. By reducing reliance on manual interpretation and enabling consistent, high-precision analysis, the High-Quality Y-Net Learning Layered model contributes to early diagnosis and improved patient care. Future extensions may focus on real-time deployment, multi-modal imaging integration, and explainable AI techniques to further enhance clinical applicability and interpretability.

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