Research Article

Segmentation of Brain MRI Using U-Net: Innovations in Medical Image Processing

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Received: March 2, 2024 **Accepted:** September 15, 2024 **Published:** September 25, 2024

Abstract: Medical image segmentation is crucial for finding significant areas or characteristics within images, exclusively in the field of medical identification. Its importance has grown in recent years, with deep learning-based segmentation emerging as an operative tool for image exploration. The segmentation of brain images, which is required for detecting and treating many brain illnesses, is difficult. This effort emphasises U-Net, a deep learning design developed exclusively for image segmentation tasks in brain MRI research. U-Net has demonstrated considerable potential for overcoming these obstacles and has been successfully used in the segmentation of several brain areas, including the cerebral cortex and subcortical regions. In addition to U-Net's use in brain MRI segmentation, this research examines the most recent breakthroughs in deep learning algorithms for medical image segmentation.

Keywords: Brain tumors segmentation, U-Net, Residual connections, MRI segmentation, Deep learning

1. Introduction

Precise brain tumor segmentation by employing MRI is a critical primary step in managing and diagnosing brain disorders. It plays a key part in the preparation of treatments and surgeries. Whereas manual segmentation procedures are inefficient and prone to subjective bias, automated approaches are required to advance efficacy [1] [2]. U-Net, a convolutional neural network (CNN) [3] premeditated precisely for the segmentation of medical image, has been established to be highly operative due to its encoder-decoder configuration [4]. However, despite its accomplishment, segmentation residues challenging since brain tumors can vary greatly in, size, shape and appearance in MRI scans [5].

Current segmentation approaches often rely on enormous amounts of labeled data samples, and their performance can decline when confronted with smaller data samples [6][7]. To address these tests in real-world applications, techniques such as data augmentation and more lightweight models are often essential [8] [9]. This training proposes enhancing the U-Net architecture by incorporating dilated convolutions [10] and residual connections [11]. These alterations are envisioned to advance features extraction and attain higher accuracy of the segmentation for the brain tumors.

2. Literature Review

With the use of deep learning algorithms, the area of medical segmentation of images has undergone tremendous transformation. While U-Net's encoder-decoder architecture allows it to gather both global and local setting, it was first described by the authors [12] and has since become the industry standard for medical image segmented. Though U-Net has proven successful [13] state that huge annotated data samples are frequently required for it to perform at its finest. Simplified topologies including LinkNet, which lower computing needs while still maintaining efficiency, are the result of efforts to solve this [14][15].

The authors in [16] [17] suggested residual networks in 2016 as a solution to the issue of vanished gradient in neural networks with deep learning. This discovery allowed for more efficient training of deep models, especially for Dilated convolutions, which Yu [18] and Ibraheem [19] pioneered around the same time, enabling programs to extract additional contextual data from larger areas without requiring the addition of more parameters. This method greatly enhanced the model's comprehension of larger regions inside images.

Furthermore, reduced variations of the U-Net approach may be utilized successfully for brain tumor classification, as demonstrated by streamlined patterns as those presented by the researchers in [20] [21]. These mathematical models [22] [23] work well regardless of little data augmenting, and they are computational efficient. Moreover, the authors in [24] [25] emphasized the need to quantify measuring uncertainty in segmented designs, since this improves the dependability of automated systems. This is especially important in healthcare settings when it's critical to make precise judgements.

Notwithstanding advancements in the field, dividing brain tumors remains difficult because of the tumors' erratic diameters and varieties. In order to improve the reliability of brain MRI segmentation of images, this work offers a modified U-Net development that blends residual connections with dilated convolutions.

Main Work of This Paper:

This paper conducts a simple classification and 2D segmentation of brain tumor images from a data platform, followed by classification and preprocessing of the dataset to adjust it, ensuring the images are resized to be suitable for the model.

- The paper explores the residual network model and measures to prevent overfitting of the dataset. Some modifications were made to the residual blocks of the residual network, refining the convolutional layers to make the 2D segmentation training of brain tumor MRI images more accurate.
- Based on the author's learning of the U-Net model, understanding of residual concepts, and analysis of the dilated convolution principle, the encoding blocks in the U-Net model were slightly improved.

This article is divided into five sections, described in detail as follows:

The introduction of the present status of local and international research on brain tumor detection is explained in Section 1. Section 2 denotes the relevant research and ends with an outline of the article's structure and primary work. Section 3 focuses on deep learning-based techniques U-Net with Modifications for brain tumor identification. It also describes the software utilized, the data sources, the programming languages used in the research, and the deep learning model's training process. Section 4 presents the project outcomes. Additionally, it emphasizes a few mistakes and flaws found in the image segmentation process and summaries the results. Section 5: offers an overview and a prognosis. It also describes plans for the next technological advancements and opportunities.

3. Methods

3.1 Data Source and Preprocessing

The Brain MRI Segmentation data samples, which comprise MRI images with tumor locations highlighted, are used in this study from the Kaggle database [28]. The dataset encompasses two-dimensional brain MRI slices with labels indicating the absence or presence of tumors. Three sets of data samples were created: one to be used for training (70%), one for validation (15%), and one to be assessed (15%) [26][27].

The preprocessing steps included normalizing, scaling, and using augmentation approaches on the images. The MRI images have been reduced to 256 by 256 pixels to uphold consistency and save processing overhead. Methods like flipping, rotation, and zooming were employed to artificially enlarge the training database in order to address the problem of insufficient data and aid in preventing overfitting.

3.2 Model Architecture

3.2.1 U-Net with Modifications

The primary U-Net design comprises a contracting approach to capture contextual data as well as an expanding pathway for exact localization. Two major modifications were unified in the present research:

Residual Connections: The residual blocks that were familiar to U-Net's contractual path were inspired by the authors. By preserving the gradient flow and enabling certain layers to be skipped, these connections help avoid the problem of disappearing gradients and augment the model's capability to acquire more complex characteristics.

Dilated Convolutions: Based on the author's work, dilated convolutions were added to U-Net's encoder blocks. By escalating the receptive field without increasing the computing load, this procedure helps the model improve and represent intricate tumor patterns while preserving spatial resolution.

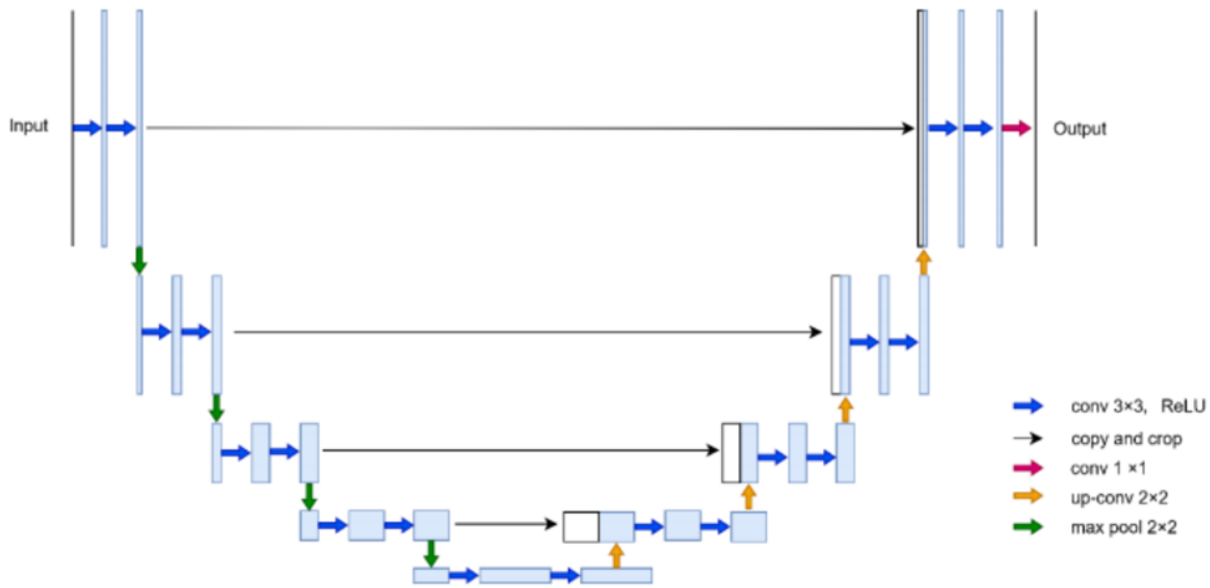

Figure 1. U-Net Architecture Diagram

3.3 Model Training

The language that was used was Python, and the model building was done via the PyCharm Integrated Development Environment. Numerous libraries have been utilised:

- TensorFlow and Keras for the building of deep learning models;
- OpenCV for imagine processing;
- Seaborn and Matplotlib for results visualization;
- Sklearn for model estimate metrics

3.4 Training Configuration:

The model was trained using the Adam optimiser and the binary cross-entropy loss function. The training strategy used a stable learning rate of 0.001 and a batch size of 32 and across 50 epochs. The Dice coefficient was the key metric used to measure segmentation precision.

3.5 Evaluation Metrics

The presentation of the improved U-Net model was projected by engaging the following measures such as:

- Accuracy is the percentage of pixels in the segmentation tumor areas that were correctly recognized.
- Dice Coefficient: Determined by analyzing the number of overlap among the real and projected tumor locations.

$$Dice = |A| + |B|2 \times |A \cap B| \tag{1}$$

Where A denotes the projected segmentation and B optimizes the ground truth segmentation.

Assessed the model's aptitude to differentiate tumors and reduce false positives using recall and accuracy metrics.

4. Results

In this section, I will use datasets to train a deep learning model for brain tumor detection. The training process of the model is divided into two components.

In the first part, the model will detect whether a tumor is present in medical images. If a tumor is detected in the medical image, the model will proceed to the second part, where it will further locate the specific brain region affected by the tumor.

In the first step, for instance, the model will classify images like those in Figure 1, identifying which images contain tumors and which do not.

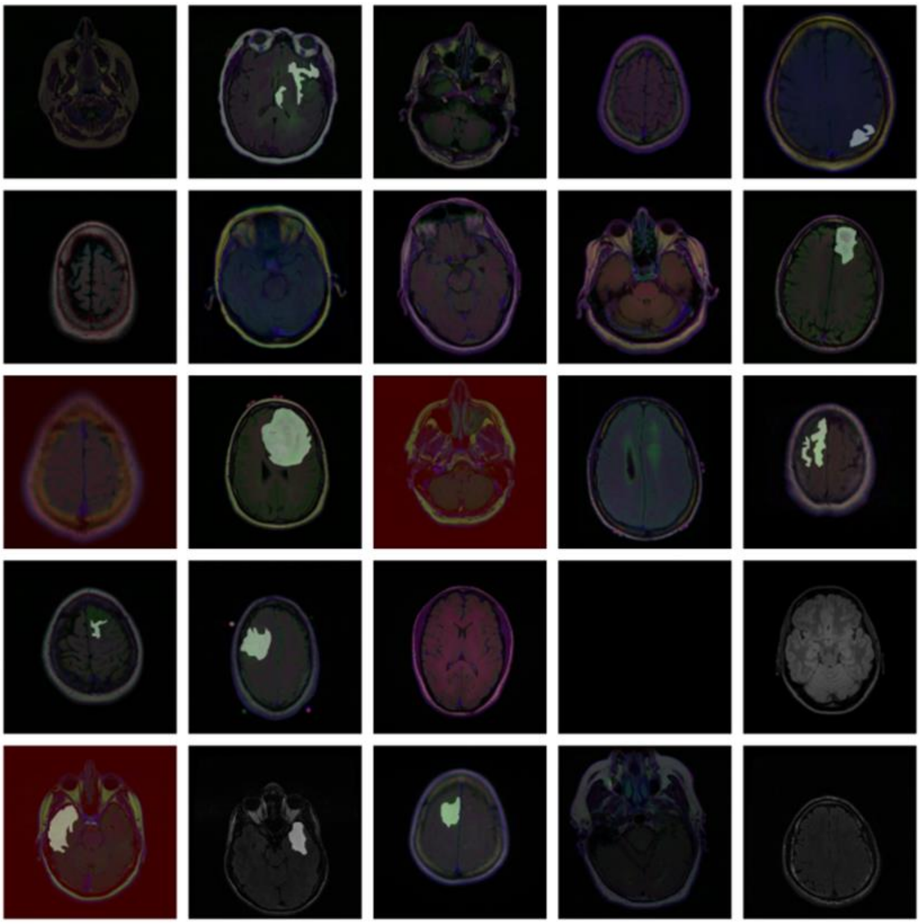

Figure 2. Tumor Detection Results on MRI Slices

In the second part, we train the model to perform 2D image segmentation on images containing brain tumors, aiming to reduce errors in the segmented images. Figures 3, 4, and 5 show the results after training: the brain tumor detection images, the original MRI images, and a comparison with the validation set images. This step is crucial for training the model's loss value and accuracy, both of which are critical performance metrics in model training.

Figure 3. Comparison of Tumor Segmentation with Ground Truth (1)

Figure 4. Comparison of Tumor Segmentation with Ground Truth (2)

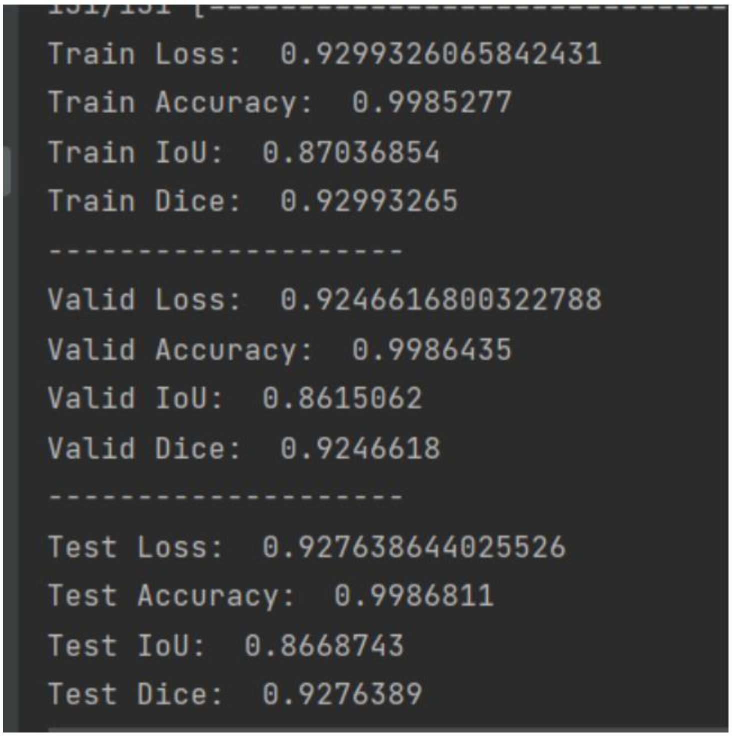

Figure 5. Model Loss and Accuracy Curves over Training Epochs

Figure 5 shows the final results of the model training. The Train Loss of the model is 0.929, and the Train Accuracy is 0.998. It can be observed that there is still a significant gap between the loss value and accuracy, which may result in some minor errors in image recognition. Both the loss value and accuracy are crucial parameters for training deep learning models, serving as standards to evaluate the overall quality of the model's performance. There is no exact "best" value for loss and accuracy; rather, the goal is to minimize these values within a certain range, with a smaller range indicating higher precision.

The following series of images Figures 6(a), 6(b) and 6(c) show 2D image segmentation performed on the brain images of the same patient. The entire brain of the patient was segmented in 2D. The brain was captured in layered imaging, producing a series of images. These images were then processed for recognition, and the results were used to assess the patient's brain tumor condition. Based on these results, surgical planning for the patient's brain tumor was reasonably arranged.

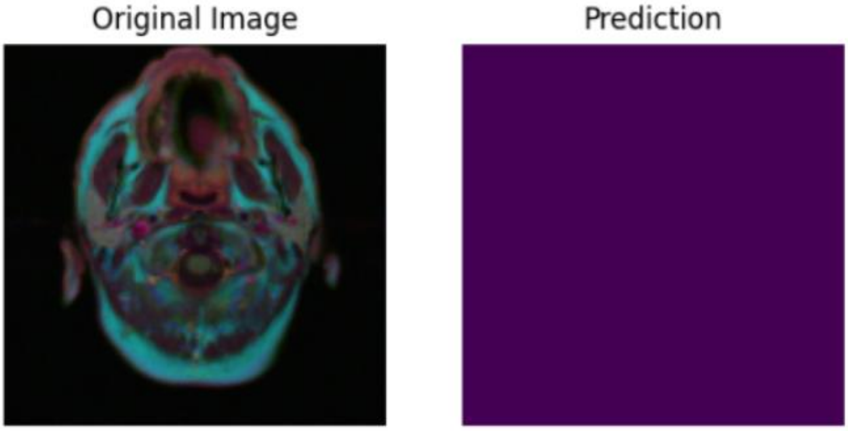

Figure 6(a). 2D Segmentation of Brain MRI Slice (No Tumor Detected)

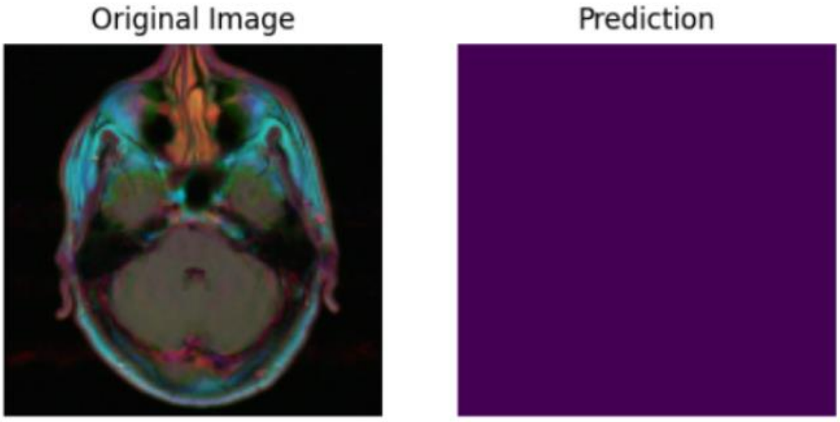

Figure 6(b). 2D Segmentation of Brain MRI Slice (No Tumor Detected)

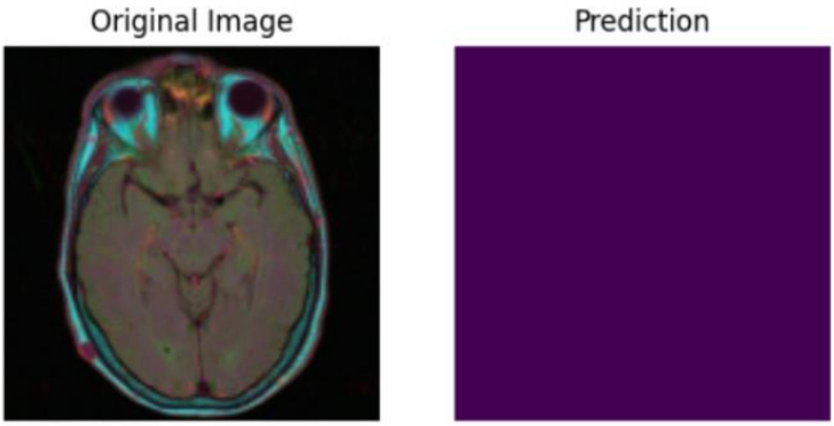

Figure 6(c). 2D Segmentation of Brain MRI Slice (No Tumor Detected

From the images above, it can be observed that the brain tumor of the patient did not appear in the 2D images, indicating that there is no tumor in that region. The brain tissue cells in the lower half of the patient's brain have not undergone any pathological changes. The brain tumor is mostly located in the upper part of the brain.

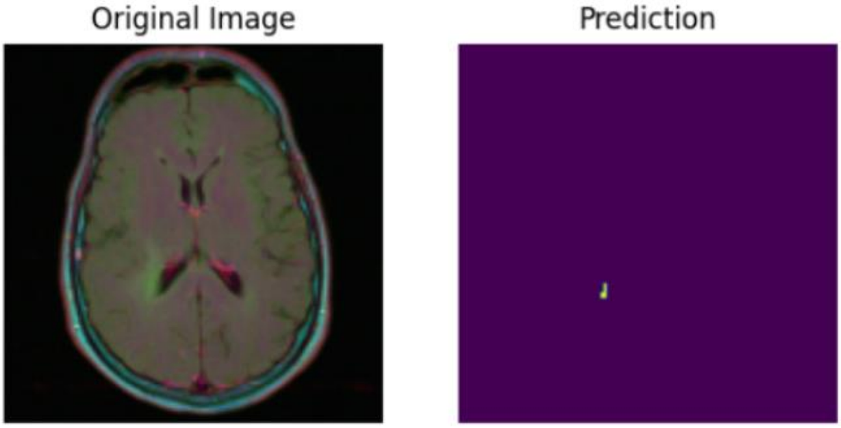

Figure 7. Initial Detection of Tumor in Brain MRI

From this figure 7, brain image onwards, tumor cells are visible, and there is an abnormal appearance of tumor cells. It is necessary to determine whether these yellow spots in the 2D segmented images are due to errors generated by deep learning. To verify this, subsequent images should be examined to see if the same area also shows yellow regions. If these yellow areas are consistently present, it indicates the presence of a tumor in that region. If not, it suggests that the yellow spots are errors produced by the deep learning model.

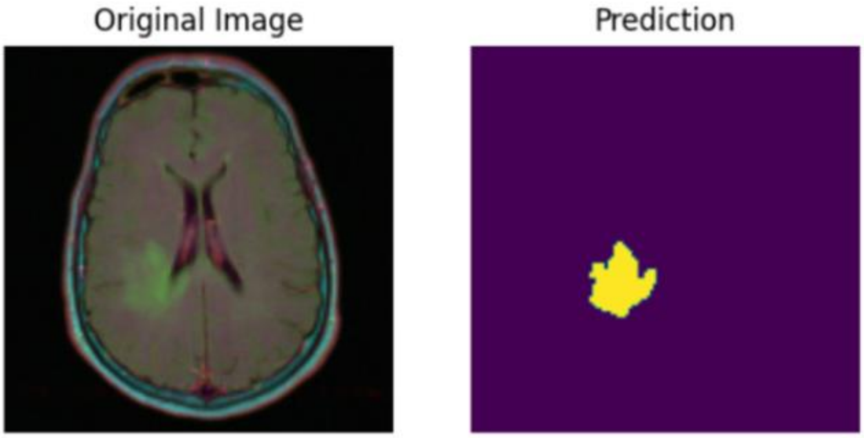

Figure 8(a). Tumor Segmentation in Brain MRI Slice (Detected Tumor

In this image (Figure 8(a) and the subsequent ones Fgure8 (b), the presence of a large number of yellow areas clearly demonstrates that these are not errors, but rather the detected tumor regions within the brain.

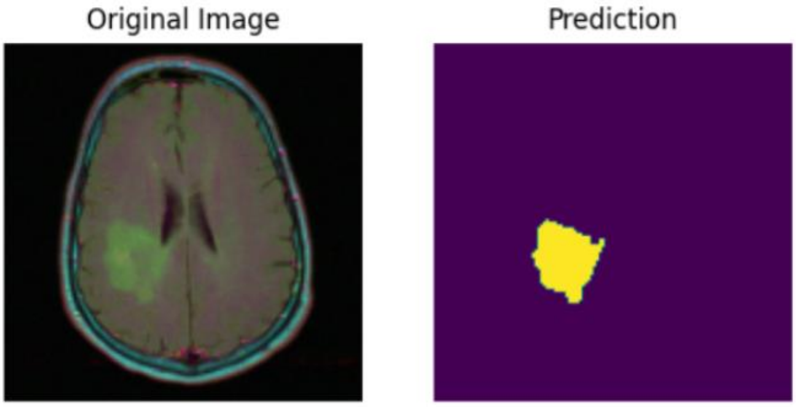

Figure 8(b). Detailed Tumor Segmentation in Brain MRI Slice

This series of images reveals the shape of the tumor within the patient's brain. The tumor is entirely located in the posterior part of the left hemisphere and is highly irregular. Additionally, there is a possibility that the tumor may be infiltrating into the anterior part of the left hemisphere. According to the images, the tumor appears to be minimal in the lower part of the brain, suggesting that it may have begun infiltrating the areas around the brainstem.

Since these 2D segmented images cannot capture the entire brain completely, there is likely to be some error in the tumor images derived from these slices. Thus, the tumor representation in these 2D images may not fully reflect the entire tumor's extent within the brain.

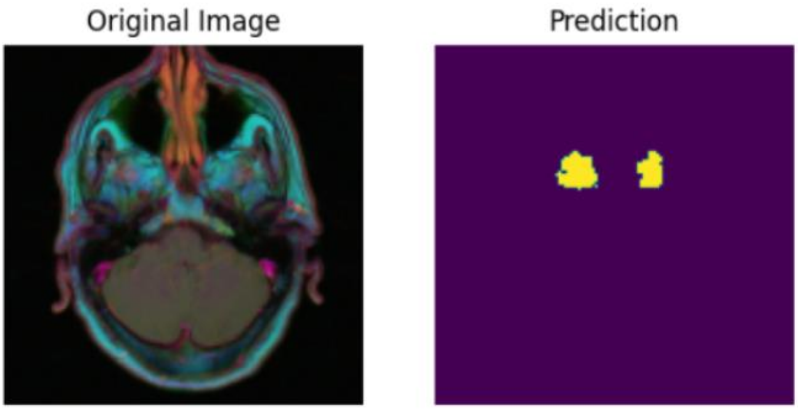

Figure 8(c). Erroneous Segmentation of Non-Tumor Region as Tumor

Certainly, the image segmentation is not perfectly executed. In this set of images, some of them incorrectly identified the eye area as a tumor. The presence of these two-dimensional images highlights that the loss value from the previous model training still needs improvement. It also indicates that the training of the data model is not yet sufficient. More training data is needed to refine the model and reduce errors during image recognition.

6. Conclusions

This paper is set against the backdrop of the significant achievements of deep learning in various fields and the fact that brain tumors present a major challenge in the current medical domain. The main focus is on the automatic segmentation of brain tumors using deep learning methods. The uncertainty quantification of deep learning methods in the medical field has already been explored previously. Bayesian dropout was used to estimate uncertainty, which is more effective for disease detection based on deep learning. Bayesian methods are applied to quantify uncertainty in image registration tasks based on deep learning.

First, the paper analyzes the research significance and background, introducing the achievements of deep learning across various fields and its application in brain tumor detection. A brief explanation of brain tumor conditions is provided, along with a description of the challenges in current medical brain tumor detection. Next, the basic procedures and methods for brain tumor detection, both domestically and internationally, are summarized. This is followed by an introduction to the overall work arrangement in this paper.

Accurate segmentation of brain tumors, once thought impossible, has now become feasible, offering clinicians more precise and useful information for clinical diagnosis.

7. Future Work Outlook:

The training dataset used in this paper is still insufficient and needs to be expanded. Since the images used were crawled by others, there were some errors during the training process. In the future, the dataset should be further processed before conducting model training again. This project experiment is developed based on MRI images, and due to the limited data, more accurate model training could not be achieved. In future work, along with obtaining MRI images used in the project, CT images of the same patients and their doctors' medical evaluations should also be collected to establish a comprehensive database. This would provide better and more complete data for future work.

Currently, the project only performs image segmentation on 2D images, and the segmentation results are also limited to 2D. In the future, if the segmented images are used to construct 3D models, it would provide a more intuitive understanding of the shape and condition of brain tumors inside the patient’s head. This could serve as a reference for doctors and ensure the accuracy of surgeries.

Acknowledgments

Not applicable.

Data Availability

The research data related to this work are included within the manuscript. For more information on the data, contact the corresponding authors.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Işın, A., Direkoğlu, C., & Şah, M. (2016). Review of MRI-based brain tumor image segmentation using deep learning methods. Procedia Computer Science, 102, 317-324.
2. Awan, I. A., Sumra, I. A., Mahmood, K., Akram, M., Mujahid, S. K., & Zaman, M. I. (2024). A Reliable Approach For Data Security Framework In Cloud Computing Network. Migration Letters, 21(S11), 923-934.
3. Khalil, M. I. K., Umer, H., Ullah, K., Khamosh, S. U., Naqvi, S. F. M., Nawaz, A., & Ahmed, S. (2024). Revolutionizing Schizophrenia Diagnosis: A Transfer Learning Approach to Accurate Classification. Journal of Computing & Biomedical Informatics, 7(02), 1-12.
4. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234-241). Springer International Publishing.
5. Hu, J., Gu, X., & Gu, X. (2022). Mutual ensemble learning for brain tumor segmentation. Neurocomputing, 504, 68-81.
6. Khan, A. A., Arslan, M., Tanzil, A., Bhatty, R. A., Khalid, M. A. U., & Khan, A. H. (2024). Classification Of Colon Cancer Using Deep Learning Techniques On Histopathological Images. Migration Letters, 21(S11), 449-463.
7. Abbas, M., Arslan, M., Bhatty, R. A., Yousaf, F., Khan, A. A., & Rafay, A. (2024). Enhanced Skin Disease Diagnosis through Convolutional Neural Networks and Data Augmentation Techniques. Journal of Computing & Biomedical Informatics, 7(01), 87-106.
8. Alomar, K., Aysel, H. I., & Cai, X. (2023). Data augmentation in classification and segmentation: A survey and new strategies. Journal of Imaging, 9(2), 46.
9. Nemoto, T., Futakami, N., Kunieda, E., Yagi, M., Takeda, A., Akiba, T. & Shigematsu, N. (2023). Effects of sample size and data augmentation on U-Net-based automatic segmentation of various organs. Igaku butsuri: Nihon Igaku Butsuri Gakkai kikanshi= Japanese journal of medical physics: an official journal of Japan Society of Medical Physics, 43(1), 19.
10. Yu, F. (2015). Multi-scale context aggregation by dilated convolutions. arXiv preprint arXiv:1511.07122.
11. Du, Y., & Li, X. (2018). Recursive deep residual learning for single image dehazing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 730-737).
12. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234-241). Springer International Publishing.
13. Walsh, J., Othmani, A., Jain, M., & Dev, S. (2022). Using U-Net network for efficient brain tumor segmentation in MRI images. Healthcare Analytics, 2, 100098.
14. Chaurasia, A., & Culurciello, E. (2017, December). Linknet: Exploiting encoder representations for efficient semantic segmentation. In 2017 IEEE visual communications and image processing (VCIP) (pp. 1-4). IEEE.
15. Nawaz, H., Sethi, M. S., Nazir, S. S., & Jamil, U. (2024). Enhancing National Cybersecurity and Operational Efficiency through Legacy IT Modernization and Cloud Migration: A US Perspective. Journal of Computing & Biomedical Informatics, 7(02).
16. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
17. Ijaz, A., Khan, A. A., Arslan, M., Tanzil, A., Javed, A., Khalid, M. A. U., & Khan, S. (2024). Innovative Machine Learning Techniques for Malware Detection. Journal of Computing & Biomedical Informatics, 7(01), 403-424.
18. Yu, F. (2015). Multi-scale context aggregation by dilated convolutions. arXiv preprint arXiv:1511.07122.
19. Ibraheem, I., Ramay, S. A., Abbas, T., ul Hassan, R., & Khan, S. (2024). Identification of Skin Cancer Using Machine Learning. Journal of Computing & Biomedical Informatics, 7(02).
20. Hussain, S. K., Ramay, S. A., Shaheer, H., Abbas, T., Mushtaq, M. A., Paracha, S., & Saeed, N. (2024). Automated Classification of Ophthalmic Disorders Using Color Fundus Images. Kurdish Studies, 12(4), 1344-1348.
21. Ahmad, R., Salahuddin, H., Rehman, A. U., Rehman, A., Shafiq, M. U., Tahir, M. A., & Afzal, M. S. (2024). Enhancing Database Security through AI-Based Intrusion Detection System. Journal of Computing & Biomedical Informatics, 7(02).

22. Abdullah, A., Raza, A., Rasool, Q., Rashid, U., Aziz, M. M., & Rasool, S. (2024). A Literature Analysis for the Prediction of Chronic Kidney Diseases. Journal of Computing & Biomedical Informatics, 7(02).
23. Fatima, A., Shabbir, A., Janjua, J. I., Ramay, S. A., Bhatty, R. A., Irfan, M., & Abbas, T. (2024). Analyzing Breast Cancer Detection Using Machine Learning & Deep Learning Techniques. Journal of Computing & Biomedical Informatics.
24. Leibig, C., Allken, V., Ayhan, M. S., Berens, P., & Wahl, S. (2017). Leveraging uncertainty information from deep neural networks for disease detection. Scientific reports, 7(1), 1-14.
25. Chishti, M. F., Rao, M., Raffat, M. W., & Rafi, S. (2024). Estimating Corporate Risk and Corporate Value An Application Of Altman's Z-Score On The Kse-30 Index. International Journal of Contemporary Issues in Social Sciences, 3(2), 2833-2841.
26. Khan, R., Iltaf, N., Shafiq, M. U., & Rehman, F. U. (2023, December). Metadata based Cross-Domain Recommender Framework using Neighborhood Mapping. In 2023 International Conference on Sustainable Technology and Engineering (i-COSTE) (pp. 1-8). IEEE.
27. Ullah, A., Waqar, M., Nazir, S. S., Adnan, A., Khan, M. A., Raffat, M. W., & Rafi, S. (2024). The Impact of Information Communication Technology and Financial Innovation on the Financial Performance of Chinese Commercial Banks. Remittances Review, 9(S2 (May 2024)), 364-383.
28. Chakrabarty, N. (2019). Brain MRI Images for Brain Tumor Detection Kaggle. Accessed: Mar, 9, 2023.