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A Preliminary Experimental Study of CNN-Based Brain Tumor Classification and U-Net-Based Segmentation from MRI

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Abstract

Accurate analysis of brain tumor regions from magnetic resonance imaging (MRI) is an important task in automated medical image analysis. Deep learning methods provide effective approaches for tumor classification and pixel-level segmentation of MRI images. This study presents a preliminary experimental investigation combining a convolutional neural network (CNN) for brain tumor classification with U-Net-based architectures for 2D brain tumor segmentation. The CNN component performs image-level tumor classification, while U-Net and Attention U-Net are employed for tumor-region segmentation. The reported CNN classification results achieved an accuracy of **94.2%**, with precision and recall values of **0.91** and **0.88**, respectively. For the segmentation models, the reported U-Net results achieved an accuracy of **96.8%**, Dice coefficient of **0.92**, precision of **0.94**, and recall of **0.91**, while Attention U-Net achieved an accuracy of **98.5%**, Dice coefficient of **0.95**, precision of **0.97**, and recall of **0.94**. These results provide a preliminary experimental assessment of CNN-based classification and U-Net-based segmentation approaches for brain tumor MRI analysis. The study is intentionally presented as a basic experimental investigation rather than a novel architectural contribution and provides a foundation for subsequent research involving advanced architectures and volumetric 3D brain tumor segmentation.

Keywords: Brain Tumor, MRI, Brain Tumor Classification, Brain Tumor Segmentation, CNN, U-Net, Attention U-Net, Deep Learning, Medical Image Analysis

1. Introduction

Brain tumors are among the critical neurological disorders that require accurate diagnosis and continuous monitoring. Magnetic Resonance Imaging (MRI) is widely used for brain tumor assessment because it provides detailed information about brain structures and tumor-related abnormalities. However, manual identification and delineation of tumor regions from MRI images can be time-consuming and may be affected by variations in tumor appearance, size, shape, and intensity. Automated image segmentation methods can assist in identifying tumor regions and provide a consistent basis for subsequent analysis. The Brain Tumor Segmentation (BraTS) benchmark has established standardized datasets and evaluation procedures for assessing automated brain tumor segmentation methods [1].

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Deep learning has become an important approach in medical image analysis because of its ability to learn hierarchical representations directly from image data. Convolutional Neural Networks (CNNs) have been widely used for extracting spatial and contextual features from medical images. In brain tumor analysis, CNN-based approaches can be employed to distinguish abnormal tissue from surrounding brain regions. However, conventional CNN architectures are often designed primarily for image-level prediction, whereas pixel-level segmentation requires preservation and reconstruction of spatial information.

The U-Net architecture was introduced specifically for biomedical image segmentation and employs an encoder-decoder structure with skip connections [2]. The encoder progressively extracts higher-level features, while the decoder reconstructs the spatial representation required to generate a segmentation map. The skip connections combine high-level semantic information with lower-level spatial information, enabling the network to retain important localization details. U-Net subsequently became a widely adopted architecture for medical image segmentation.

Although U-Net provides an effective framework for segmentation, different regions within an image may not contribute equally to the segmentation task. Attention mechanisms can therefore be incorporated to selectively emphasize relevant features. Attention U-Net extends the conventional U-Net architecture by introducing attention gates that help the network focus on salient regions while suppressing irrelevant feature responses [3]. This approach provides an extension of the conventional encoder-decoder framework without requiring a completely different segmentation architecture.

Brain tumor segmentation remains challenging because tumor regions can vary considerably in appearance and may contain different sub-regions. The BraTS benchmark evaluates tumor segmentation using regions such as the enhancing tumor (ET), tumor core (TC), and whole tumor (WT), with Dice score and other measures commonly used for evaluation [1].

In this study, a preliminary experimental investigation is conducted using three deep learning approaches with different objectives. A conventional Convolutional Neural Network (CNN) is employed for image-level brain tumor classification, while U-Net and Attention U-Net are used for pixel-level 2D brain tumor segmentation. The study focuses on evaluating the implemented approaches using appropriate performance measures for their respective tasks. The CNN provides a classification-based baseline, whereas U-Net and Attention U-Net provide segmentation-based approaches for identifying tumor regions. This preliminary investigation establishes a foundation for subsequent studies involving advanced segmentation architectures and volumetric 3D brain tumor analysis.

2. Related Work

2.1 CNN-Based Brain Tumor Classification and Feature Extraction

Convolutional Neural Networks (CNNs) have become an important approach for automated brain tumor analysis because they can learn hierarchical image representations directly from MRI data. CNN-based methods progressively extract low-level features such as edges and textures and higher-level semantic features that can assist in identifying abnormal tissue. A systematic review of MRI-based brain tumor segmentation methods reported that deep

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learning, particularly CNN-based approaches, has become an important component of automated tumor segmentation research [4].

However, conventional CNN architectures are commonly designed for image classification or feature extraction. Pixel-level segmentation requires the network to preserve spatial information and produce a prediction for each image location. Consequently, encoder-decoder architectures have been increasingly adopted to address the limitations of conventional CNN-based approaches in precise image segmentation. Recent reviews indicate that CNN-based and U-Net-based architectures continue to form an important part of the development of automated brain tumor segmentation methods [5], [6].

2.2 U-Net-Based Brain Tumor Segmentation

U-Net, introduced by Ronneberger et al., uses an encoder-decoder architecture together with skip connections to combine contextual information with spatial details [2]. The architecture was originally developed for biomedical image segmentation and has subsequently been widely adopted for medical image analysis.

In brain tumor segmentation, U-Net-based architectures have been extensively investigated because of their ability to preserve localization information while learning high-level semantic representations. A systematic review of MRI-based brain tumor segmentation identified U-Net as one of the most frequently used deep learning architectures and reported its widespread application across different MRI sequences and tumor regions [7].

More recent reviews continue to identify U-Net and its variants as dominant architectures in brain tumor segmentation research. Recent systematic reviews have continued to examine the development of deep learning approaches for MRI-based brain tumor segmentation. Bhalodiya et al. presented a systematic review of MRI-based brain tumor segmentation methods and discussed the use of different deep learning architectures, including U-Net-based approaches, for automated tumor segmentation [8].

Several experimental studies have also investigated different U-Net variants. For example, a study evaluating 3D U-Net, Attention U-Net, R2 Attention U-Net, and modified 3D U-Net on the BraTS 2020 dataset demonstrated the continued interest in improving the conventional U-Net architecture for brain tumor segmentation [9].

2.3 Attention U-Net for Brain Tumor Segmentation

Although U-Net provides an effective encoder-decoder framework, the features generated by the network may contain both relevant tumor information and irrelevant background information. Attention mechanisms have therefore been incorporated into U-Net architectures to allow the network to focus selectively on informative regions.

Oktay et al. introduced Attention U-Net by incorporating attention gates into the U-Net architecture [3]. The attention gates allow the network to suppress irrelevant feature responses and emphasize features associated with the target region. This approach has subsequently motivated numerous attention-based architectures for brain tumor segmentation.

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Attention mechanisms have been investigated specifically for MRI brain tumor segmentation. For example, Category Guided Attention U-Net incorporated supervised attention mechanisms to improve feature representation for brain tumor segmentation and was evaluated using the BraTS 2019 dataset [10]. Another study proposed a mixed-attention U-Net that combined spatial-channel attention with self-attention for multimodal brain tumor segmentation and evaluated the approach on BraTS 2019 and BraTS 2020 datasets [11].

More recent research continues to extend attention-based U-Net architectures. A 2026 study proposed a self-attention U-Net for multimodal MRI brain tumor segmentation and evaluated it on BraTS 2018 and BraTS 2020, demonstrating the continued development of attention mechanisms for improving tumor-region representation [12]. These developments demonstrate that attention mechanisms have become an important direction in the evolution of U-Net-based brain tumor segmentation.

2.4 Motivation for the Present Study

The reviewed studies demonstrate that deep learning architectures have been increasingly applied to automated brain tumor analysis using MRI images. Conventional CNNs are primarily suitable for image-level classification and feature extraction, whereas encoder-decoder architectures such as U-Net are designed to preserve spatial information and generate pixel-level segmentation maps. Attention mechanisms can further enhance segmentation by emphasizing relevant spatial features and suppressing less informative regions.

Based on these observations, the present study conducts a preliminary experimental investigation involving CNN-based brain tumor classification and U-Net-based 2D brain tumor segmentation. A conventional CNN is considered for image-level classification, while U-Net and Attention U-Net are investigated for pixel-level tumor segmentation. The purpose of this study is to establish a basic experimental foundation and examine the performance of these implemented approaches before proceeding to more advanced segmentation architectures and volumetric 3D brain tumor analysis.

3. Materials and Methods

3.1 Dataset

The study uses brain MRI data for investigating deep learning-based brain tumor classification and 2D tumor segmentation. The BraTS 2020 dataset is used as the principal source of multimodal brain MRI data for the segmentation experiments. The dataset contains multimodal MRI sequences, including T1-weighted (T1), contrast-enhanced T1-weighted (T1ce), T2-weighted (T2), and Fluid Attenuated Inversion Recovery (FLAIR) images, together with expert-provided tumor annotations [1].

For the segmentation experiments, the MRI images and corresponding tumor annotations are used to generate image-mask pairs for training and evaluation of the U-Net and Attention U-Net models. The tumor annotations represent the labeled tumor regions available in the dataset.

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The CNN component is treated separately as an image-level classification task. Accordingly, the CNN is evaluated using classification-oriented measures rather than pixel-level segmentation measures. This separation ensures that the evaluation methodology corresponds to the specific objective of each deep learning approach.

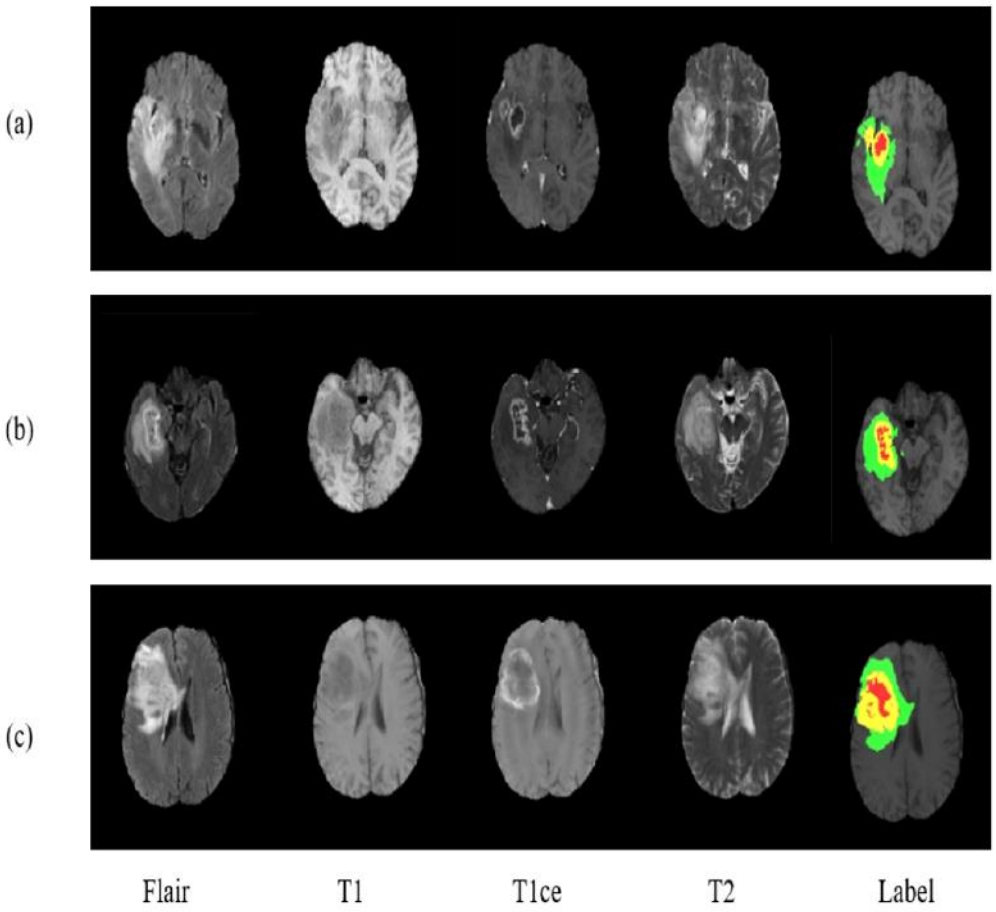


Figure 1. Representative multimodal MRI images and corresponding tumor annotations from the BraTS 2020 dataset .

For the present study, the segmentation models were investigated using a **2D image-based segmentation approach** rather than volumetric 3D processing. The MRI data were converted into suitable 2D image representations for model development and evaluation.

3.2 MRI Image Preprocessing

The MRI images were subjected to preprocessing to obtain suitable 2D image representations for the experimental models. The preprocessing procedure included image resizing and normalization to provide consistent input dimensions and intensity ranges. For the segmentation experiments, corresponding tumor masks were processed to maintain spatial correspondence with the MRI images.

The preprocessing procedure was applied before model training and evaluation to ensure that the input data were presented in a consistent format. The resulting 2D MRI images were

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subsequently used for the U-Net and Attention U-Net segmentation experiments, while the CNN classification component used appropriately prepared image inputs for image-level prediction.

3.3 CNN-Based Brain Tumor Classification

A conventional Convolutional Neural Network (CNN) was implemented as an image-level classification model. Unlike U-Net and Attention U-Net, the CNN does not generate pixel-level segmentation masks. Instead, it learns discriminative image features through successive convolutional and pooling layers and produces a class prediction at the output layer.

The implemented CNN consists of three convolutional blocks with **32, 64, and 128 filters**, respectively, with max-pooling operations following the convolutional layers. The extracted feature maps are flattened and passed through a fully connected layer containing **256 neurons**, followed by a dropout layer with a rate of **0.5**. The final dense layer uses a softmax activation function to generate the class probabilities.

The CNN was trained using the **Adam optimizer with a learning rate of 0.001**, categorical cross-entropy loss, a batch size of **32**, and **10 training epochs**. The CNN predictions were evaluated using classification-oriented performance measures, including accuracy, precision, and recall.

This CNN therefore serves as an image-level classification component in the present study, while the U-Net and Attention U-Net models described in the following sections are used specifically for pixel-level brain tumor segmentation.

3.4 U-Net Architecture

U-Net was implemented as an encoder-decoder architecture for 2D brain tumor segmentation. The encoder progressively extracts representative features from the input MRI images, while the decoder reconstructs the spatial representation required to generate the segmentation output.

Skip connections link corresponding encoder and decoder stages, allowing spatial information from earlier layers to be transferred to the decoder. This helps preserve localization information during the reconstruction process. The U-Net architecture therefore provides a structured baseline for pixel-level brain tumor segmentation [2]. The architecture used in the study is illustrated in **Figure 2**.

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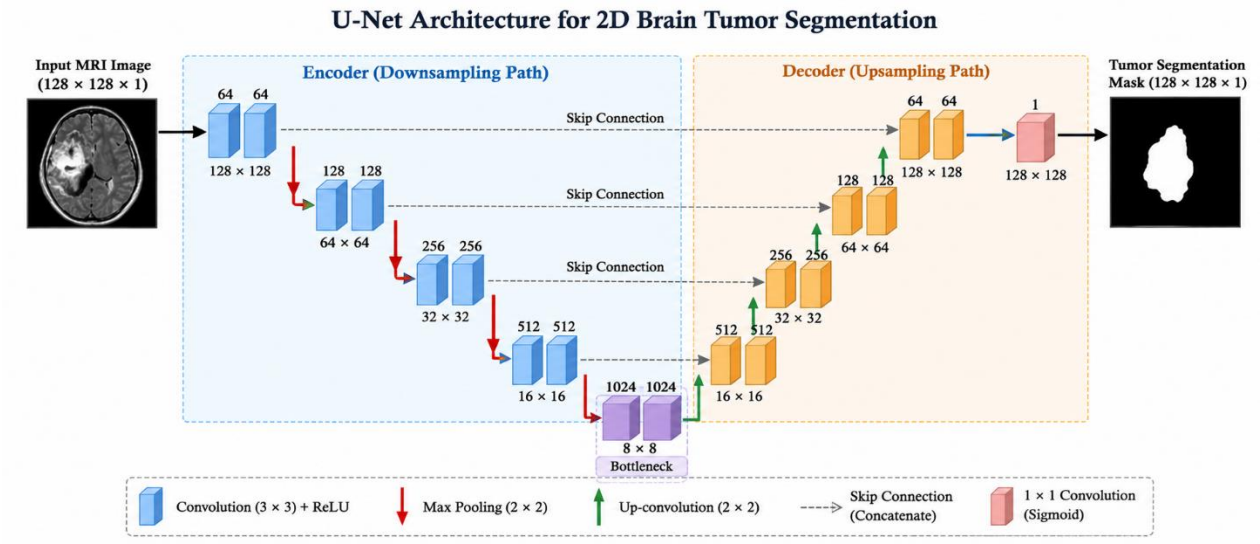


Figure 2. U-Net architecture used for 2D brain tumor segmentation.

3.5 Attention U-Net Architecture

Attention U-Net was implemented by extending the conventional U-Net architecture with attention mechanisms. Attention gates enable the network to selectively emphasize relevant feature regions while reducing the influence of irrelevant background information.

In the implemented model, attention mechanisms are incorporated into the U-Net-based segmentation pathway to improve the localization of relevant tumor regions. The architecture was investigated to examine whether selective feature emphasis provides improved segmentation performance compared with the conventional U-Net architecture [3]. The attention-gated architecture used for 2D brain tumor segmentation is illustrated in **Figure 3**.

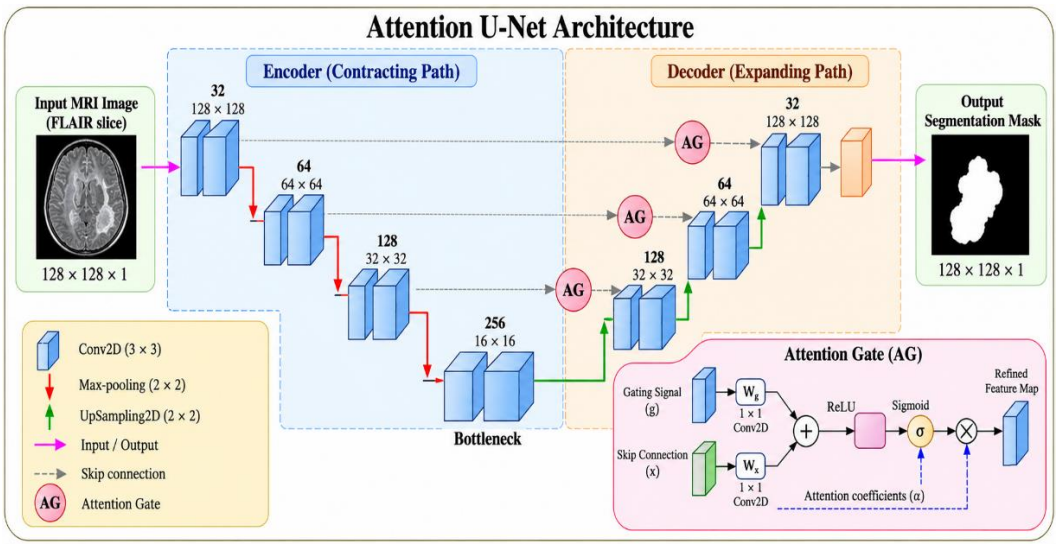


Figure 3. Attention U-Net architecture used for 2D brain tumor segmentation

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3.6 Model Training

The three models were trained according to their respective learning objectives. The CNN was trained as an image-level classification model, whereas U-Net and Attention U-Net were trained for 2D pixel-level segmentation.

CNN training: The CNN was trained using the Adam optimizer with a learning rate of **0.001** and categorical cross-entropy loss. A batch size of **32** was used for **10 epochs**. The model employed a softmax output layer for image-level class prediction.

U-Net and Attention U-Net training: The U-Net-based segmentation models were trained using the corresponding MRI image-mask pairs. The segmentation training used the Adam optimizer and segmentation-oriented loss functions. The training configurations were selected according to the respective model implementations.

3.7 Evaluation Metrics

Different evaluation metrics were used according to the specific objectives of the implemented models. Since the CNN performs image-level classification, classification-oriented metrics were used to evaluate its performance. In contrast, U-Net and Attention U-Net perform pixel-level segmentation, and therefore segmentation-oriented metrics were used.

CNN Classification Metrics: The CNN classification performance was evaluated using **Accuracy, Precision, and Recall**. Accuracy measures the proportion of correctly classified images, while Precision measures the proportion of predicted tumor cases that were correctly classified. Recall measures the proportion of actual tumor cases correctly identified by the model.

Segmentation Metrics: The U-Net and Attention U-Net models were evaluated using **Accuracy, Dice Coefficient, Precision, and Recall**. The Dice Coefficient measures the overlap between the predicted tumor region and the corresponding ground-truth mask. Precision indicates the proportion of predicted tumor pixels that correspond to actual tumor pixels, while Recall measures the proportion of actual tumor pixels correctly identified by the segmentation model.

The Dice Coefficient is expressed as:

$$\mathbf{Dice = 2|P \cap G| / (|P| + |G|)}$$

where **P** represents the predicted segmentation mask and **G** represents the ground-truth tumor mask.

The use of separate evaluation measures ensures that the CNN classification results are evaluated as an image-level task, while the U-Net and Attention U-Net results are evaluated as pixel-level segmentation tasks.

3.8 Experimental Workflow

The overall experimental workflow was designed to investigate three deep learning approaches for brain tumor MRI analysis, with separate objectives for **image-level classification** and **pixel-level segmentation**. The workflow consists of the following stages:

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BraTS MRI Dataset → Preprocessing → Task-Specific Data Preparation → CNN Classification / U-Net and Attention U-Net Segmentation → Prediction → Task-Specific Evaluation

BraTS MRI Dataset

The study begins with the **BraTS MRI dataset**, which provides multimodal MRI images together with corresponding ground-truth tumor annotations. The dataset forms the basis for the experimental investigation of brain tumor classification and segmentation.

Preprocessing

The MRI data are preprocessed to obtain suitable and consistent inputs for the deep learning models. The preprocessing stage includes preparation of the MRI images and, for the segmentation experiments, the corresponding tumor masks.

Task-Specific Data Preparation

The data are prepared according to the objective of each model. For the **CNN classification experiment**, suitable 2D MRI image inputs are prepared for image-level tumor classification. For the **U-Net and Attention U-Net segmentation experiments**, 2D MRI image-mask pairs are prepared, with the tumor masks maintaining spatial correspondence with their respective MRI images.

CNN-Based Classification

The prepared MRI images are provided to the CNN for **image-level brain tumor classification**. The CNN learns discriminative features through convolutional and pooling layers and produces a class prediction at the output layer.

U-Net and Attention U-Net Segmentation

The prepared 2D image-mask pairs are used for **pixel-level tumor segmentation** using U-Net and Attention U-Net. U-Net employs an encoder-decoder architecture with skip connections, while Attention U-Net incorporates attention mechanisms to emphasize relevant feature regions.

Prediction

After training, the CNN generates image-level class predictions, whereas U-Net and Attention U-Net generate pixel-level tumor segmentation masks. The segmentation predictions are compared with the corresponding ground-truth masks.

Task-Specific Evaluation

The CNN classification performance is evaluated using classification-oriented measures, including **Accuracy, Precision, and Recall**. The U-Net and Attention U-Net segmentation performance is evaluated using segmentation measures, including **Accuracy, Dice Similarity Coefficient (DSC), Precision, Recall, F1-Score, and Intersection over Union (IoU)**, where these measures are available from the implemented evaluation procedure.

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Thus, the CNN is investigated as an **image-level classification baseline**, while U-Net and Attention U-Net are investigated as **2D pixel-level segmentation models**. Their results are interpreted according to their respective tasks rather than treating classification and segmentation metrics as directly equivalent.

4. Results

The performance of the CNN, U-Net, and Attention U-Net models was evaluated using Accuracy, Dice Similarity Coefficient (DSC), Precision, and Recall. The results are summarized in Table 4.1.

4.1 Performance of the Models

The performance of the three implemented deep learning approaches was evaluated according to their respective objectives. The CNN was evaluated as an image-level classification model, whereas U-Net and Attention U-Net were evaluated as 2D brain tumor segmentation models.

The CNN achieved a reported accuracy of 94.2%, with precision of 0.91 and recall of 0.88 for the classification task. For the segmentation models, the reported U-Net results achieved an accuracy of 96.8%, with a Dice Similarity Coefficient (DSC) of 0.92, precision of 0.94, and recall of 0.91. Attention U-Net achieved an accuracy of 98.5%, DSC of 0.95, precision of 0.97, and recall of 0.94.

These results are presented according to the corresponding tasks of the models. The CNN result represents image-level classification performance, while the U-Net and Attention U-Net results represent pixel-level segmentation performance.

Table 4.1. Reported Performance of CNN, U-Net, and Attention U-Net

Model	Task	Accuracy (%)	Dice Score	Precision	Recall
CNN	Classification	94.2	—	0.91	0.88
U-Net	Segmentation	96.8	0.92	0.94	0.91
Attention U-Net	Segmentation	98.5	0.95	0.97	0.94

4.2 Dice Score Comparison

The Dice Similarity Coefficient (DSC) values of the **two segmentation models**, U-Net and Attention U-Net, are compared to examine their segmentation overlap performance. The U-Net model achieved a reported DSC of **0.92**, while the Attention U-Net model achieved a reported DSC of **0.95**.

The results show an increase in the reported Dice score from U-Net to Attention U-Net. Under the experimental setting of the present 2D study, the Attention U-Net configuration produced a higher reported overlap between the predicted segmentation regions and the corresponding ground-truth masks. The Dice score comparison is illustrated in **Figure 4**.

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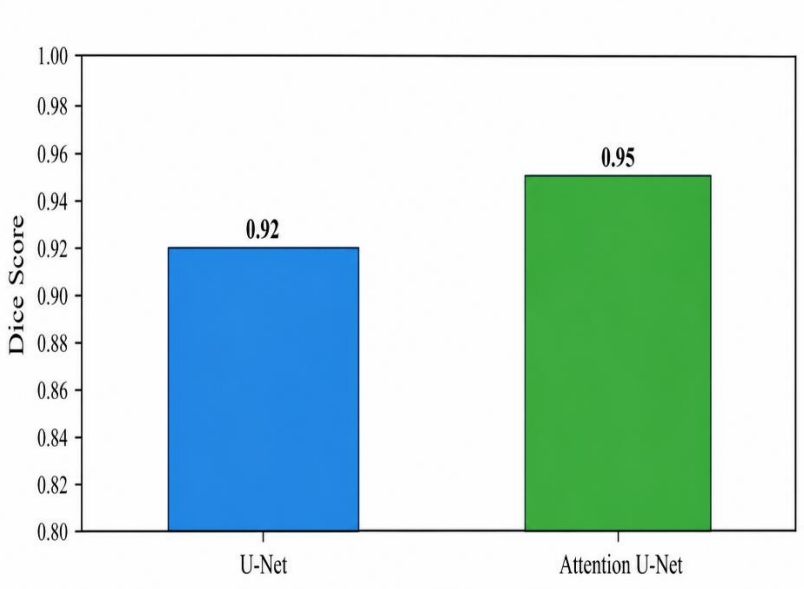


Figure 4. Dice score comparison of U-Net, and Attention U-Net.

4.3 Precision and Recall

Precision and recall provide additional information about the performance of the investigated models. The CNN model, evaluated for **image-level classification**, achieved a reported precision of **0.91** and recall of **0.88**. For the segmentation models, U-Net achieved a reported precision of **0.94** and recall of **0.91**, while Attention U-Net achieved a reported precision of **0.97** and recall of **0.94**.

The reported results show differences in precision and recall across the investigated approaches. For the segmentation models, the Attention U-Net configuration achieved higher reported precision and recall values than U-Net under the experimental conditions of this study.

The precision and recall results are considered together with the corresponding Accuracy and Dice Similarity Coefficient values presented in **Table 4.1**. The CNN precision and recall values are interpreted as **classification measures**, whereas the U-Net and Attention U-Net precision and recall values are interpreted as **segmentation measures**.

4.4 Summary of Results

The experimental results demonstrate differences in the reported performance of the three investigated 2D deep learning approaches according to their respective tasks. The CNN classification model achieved an accuracy of **94.2%**, precision of **0.91**, and recall of **0.88**. The U-Net segmentation model achieved **96.8%** accuracy, **0.92** DSC, **0.94** precision, and **0.91** recall. The Attention U-Net model achieved **98.5%** accuracy, **0.95** DSC, **0.97** precision, and **0.94** recall.

The reported values indicate differences among the investigated approaches under the experimental conditions of this study. For the two segmentation models, Attention U-Net obtained higher reported Accuracy, DSC, Precision, and Recall values than U-Net. The CNN

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results represent **image-level classification performance**, whereas the U-Net and Attention U-Net results represent **pixel-level segmentation performance**.

5. Discussion

The experimental results indicate differences in the performance of the three investigated approaches according to their respective tasks. The CNN classification model achieved an accuracy of **94.2%**, with precision of **0.91** and recall of **0.88**. The U-Net segmentation model achieved a reported Dice score of **0.92**, while Attention U-Net achieved a reported Dice score of **0.95**. The U-Net and Attention U-Net models also achieved reported accuracy, precision, and recall values of **96.8%, 0.94, and 0.91**, and **98.5%, 0.97, and 0.94**, respectively.

The CNN provides an image-level classification baseline in the present study. Although CNNs are effective in extracting hierarchical image features, the implemented CNN is designed for image-level prediction rather than pixel-level segmentation. Therefore, its classification results should be interpreted separately from the segmentation results obtained using U-Net and Attention U-Net.

The U-Net architecture provides an encoder-decoder framework with skip connections for pixel-level segmentation. The reported Dice score of **0.92** demonstrates the segmentation performance obtained under the experimental conditions of this study. The encoder-decoder structure enables the model to combine higher-level semantic information with spatial information during segmentation.

The Attention U-Net further extends the U-Net architecture through attention mechanisms. The reported Dice score increased from **0.92** with U-Net to **0.95** with Attention U-Net, while accuracy increased from **96.8% to 98.5%**. Precision and recall similarly increased from **0.94 and 0.91** to **0.97 and 0.94**, respectively. This result is consistent with the intended role of attention mechanisms in emphasizing relevant feature regions during segmentation.

The observed results demonstrate differences between the investigated classification and segmentation approaches, while the comparison between U-Net and Attention U-Net provides a direct assessment of two 2D segmentation architectures. In particular, Attention U-Net produced higher reported segmentation metrics than U-Net under the experimental setting of this study.

However, the reported results should be interpreted within the specific experimental setting of this study. The investigation focuses on **2D MRI-based processing**, and therefore the findings should not be directly generalized to 3D volumetric segmentation or clinical applications. Differences in dataset preparation, image representation, training procedures, segmentation targets, and evaluation protocols can substantially influence reported performance.

Another important consideration is the dependence of segmentation performance on MRI data quality and dataset characteristics. Variations in image quality and the availability of representative training data can influence the ability of deep learning models to generalize to unseen images. Clinical validation is also necessary before automated segmentation methods can be considered for real-world clinical deployment.

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Overall, the findings provide a preliminary experimental foundation for subsequent investigations involving more advanced architectures, multimodal learning, and **3D volumetric brain tumor segmentation**.

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6. Conclusion

This study presented a preliminary experimental investigation of three deep learning-based approaches, namely CNN, U-Net, and Attention U-Net, for brain tumor MRI analysis. The CNN was investigated for **image-level brain tumor classification**, while U-Net and Attention U-Net were investigated for **2D brain tumor segmentation**.

The CNN classification model achieved a reported accuracy of **94.2%**, with precision of **0.91** and recall of **0.88**. For the segmentation models, U-Net achieved a reported accuracy of **96.8%**, Dice score of **0.92**, precision of **0.94**, and recall of **0.91**. Attention U-Net achieved a reported accuracy of **98.5%**, Dice score of **0.95**, precision of **0.97**, and recall of **0.94**. The segmentation results therefore indicate higher reported values for Attention U-Net than U-Net under the experimental conditions of this study.

The findings indicate that the encoder-decoder structure of U-Net provides an effective framework for 2D segmentation, while the incorporation of attention mechanisms in Attention U-Net provides an additional mechanism for emphasizing relevant image features. The CNN results, however, represent an image-level classification task and are therefore interpreted separately from the segmentation results. The findings are specific to the experimental conditions and should not be directly generalized to 3D volumetric segmentation or clinical deployment.

The main contribution of this study is the establishment of a **basic experimental foundation for brain tumor MRI analysis using CNN-based classification and U-Net-based 2D segmentation**. The study provides a starting point for further investigation of advanced deep learning architectures, multimodal MRI processing, quality-aware learning, region-specific segmentation, and **3D volumetric brain tumor segmentation**.

Future work will focus on extending the segmentation framework from 2D image-based processing to volumetric 3D MRI analysis and investigating more advanced architectures and learning strategies for improving the robustness and accuracy of brain tumor segmentation.

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