

Smart Neuro-Vision: A Deep Learning Framework for Brain Tumor Segmentation and Classification Using U-Net and ResNet-101

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Abstract: Brain tumor is one of the highly critical neurological problems which needs early and precise diagnosis to achieve better survival rate and prognosis. This explains the importance of intelligent computer-aided diagnostic systems. MRI Manual interpretation is time-consuming as it depends on radiological expertise. This study presents novel DL based framework named Smart Neuro Vision. It is for automated brain tumor segmentation and classification using U-Net and ResNet-101 architecture. The proposed scheme is divided into four distinct main blocks namely image preprocessing, tumor segmentation, tumor classification and performance evaluation. Firstly the MRI images are preprocessed to get better quality images. Then a U-net model segments the tumor regions from MRI scans. The segmented tumor images are then classified to these four categories namely Glioma, Meningioma, Pituitary Tumor and No Tumor using ResNet-101. Experiments were carried out using an open source brain MRI dataset provided by Kaggle with four tumor classes. The segmentation model attained Dice Coefficient of 96.8%, IoU score of 94.5% and segmentation accuracy of 97.2%. Moreover, the classification model achieved 98.4% accuracy. This indicates good detection performance of tumor and reduced overfitting. The obtained results validate proposed framework of combining U-Net segmentation with ResNet-101 classification for automated brain tumor diagnosis, which offers a powerful, reliable, and efficient solution. The proposed system could aid radiologists in making clinical decisions and has great potential to be implemented in actual healthcare settings.

Key Words: MRI, Deep Learning, Brain Tumor Detection, U-Net Segmentation, ResNet-101, Transfer Learning.

1. Introduction

Brain tumor is abnormal cell mass in central nervous system which can impair the functioning of the body's neurons, including memory, vision, speech, and movement [7]. It can be either benign (non-cancerous) or malignant (cancerous). It can threaten human life depending on the nature of the tumor [5]. MRI is most common imaging method for diagnosis of brain tumors. Traditionally radiologists manually analyze MR imaging to determine tumor location, size and type. But process requires more time and is prone to inter-observer variation [4, 9]. The recent in Deep Learning (DL) have paved the way for building automated systems that can extract significant information from medical images [7]. CNNs have demonstrated excellent performance in medical image analysis. U-Net architectures have been broadly applied to accurately segment medical images [1]. Likewise, transfer learning models like ResNet-101 have proven to be more efficient to classify images using knowledge gained from large scale datasets [3].

There has been several research on deep learning in brain tumor analysis. Javed et al [1] used transfer learning based

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classification models and U-Net with an accuracy of 96.06%. Shamshad et al [3] tested different transfer learning architectures and achieved 97% classification accuracy by using VGG-16. Wageh et al. [4] used deep feature extraction and classifiers with 99.8% accuracy. Nassar et al. [9] suggested hybrid “deep learning” technique which has got classification accuracy of 99.31%. Gundogan [2] also introduced the Explainable Artificial Intelligence (XAI) methods and obtained 99.77% classification accuracy. These studies prove the efficacy of DL techniques towards detection and classification of a tumor from MRI images. Yet, variations in data sets, model sophistication, computational needs, or the method for validating the models remain issues that impact the trustworthiness and transferability of these approaches.

While there has been a huge progression with the automated diagnosis of brain tumors, there are still a few drawbacks. Most of the previous works are only interested in classification and fail to precisely localize the tumors' regions [3, 5]. In some methods, due to ensemble learning and feature optimization mechanisms, extensive computational resources are required [4, 9, 10] and in others insufficient validation and real time applicability are achieved [2, 8]. Moreover, the combination of accurate tumor segmentation and high performance of the classification is still limited. Hence, it is desirable to have a single model to accurately segment tumor regions and correctly classify various tumor classes with high efficiency, good computational speed, and good generalization performance.

In this proposed research, attention is given to brain tumor analysis from MRI by utilizing publicly available datasets that consist of classes like Meningioma, Glioma, Pituitary Tumor and No Tumor. The study only considers MRI diagnosis and excludes clinical data, multimodal medical data and genetic information. The framework highlights automated segmentation and classification based on deep learning approaches and is tested in controlled experimental conditions. The current work is not intended for real time clinical deployment and cross hospital validation.

The remaining part of paper goes as follows. Section II gives detailed overview of previous studies on brain tumor segmentation and classification. The proposed methodology is detailed in Section III, comprising of pre-processing, U-Net Segmentation and ResNet-101 classification modules. The experimental setup, implementation details and performance evaluation metrics are explained in Section IV. The results and comparative analysis are provided in Section V. Section VI, at last, ends the paper with some suggestions for further research.

2. Literature Review

The brain tumors detection and classification by MRI is an important research field, because the number of brain tumors is increasing and early detection is required. The techniques of medical image processing (MIP) have been progressed to improve accuracy of brain tumor. To improve the performance of tumor detection and classification, researchers have suggested the following methods like CNNs, hybrid DL models, ensemble learning technique, transfer learning architecture, and semi-supervised framework. In the following section, the most relevant studies regarding brain tumor segmentation and classification are reviewed and their major contributions and limitations are pointed out.

Javed et al. [1] presented a DL framework for the prediction of AD in IoMT environment. The framework used U-Net for MRI image segmentation and ResNet-101 with transfer learning for classification. The experiments were carried out on a Kaggle Alzheimer's MRI dataset which consists of nearly 6400 MRI images. The proposed model showed high classification performance and an accuracy of 96.06%. The study, however, was constrained by the small number of patients in the data set, the absence of external validation, and inadequate model interpretability, potentially impacting its clinical implementation.

Gundogan [2] gives a new hybrid multi class classification model with MRI dataset which is also powered by the XAI. The framework comprised a customized CNN for feature extraction, XGBoost for classification and Grad-CAM for explainability. Image categories were classified with an accuracy of 99.77%. The model was found to have good performance, but the research had no validation with external data sets, and was not tested in real clinical settings.

In this regard, Shamshad et al. [3] conducted an extensive survey on transfer learning approaches for classification based on MRI data. Several pre trained models were tested. VGG-16 model was found to have the best accuracy of 97% with much less training time when compared with all other models. The study reported, however, problems with variability in the data sets, imaging variability and lack of model interpretability.

Wageh et al. [4] have presented a CAD system for brain tumor detection using ML classifiers. Then the concatenation of features and feature selection using genetic algorithm was performed. The experiments were performed on Br35H datasets, where the accuracy of 99.7% and 99.8% was obtained respectively. Although this approach was of high performance, it was also very complex in terms of computation since features were concatenated together and optimization steps were performed.

Aamir et al [5] created an optimized CNN model for brain tumour detection. The framework was tested on three datasets of MRI images hosted on Kaggle, with an average accuracy score of around 97%. The drawback of the model was, however, that there were no explainability mechanisms and no investigation of real-time clinical implementation.

Atha and Chaki [6] have proposed SSBTCNet which is a combination of Autoencoder-based feature learning and MLP classifiers. Fuzzy logic based augmentation, along with unlabeled MRI data, was used to enhance the classification performance in the framework. The experimental results proved that proposed method was more accurate than the previous methods with about 97.55% accuracy. However the performance was largely affected by quality of the Autoencoder reconstruction and the model was prone to noisy data.

Solanki et al. [7] has given a detailed survey over the techniques of brain tumor detection and classification. The survey results highlighted the main difficulties: tumor heterogeneity, image variability, insufficient data set availability. The study was however, only an analytical one and no specific detection framework was suggested or validated.

To categorize and retrieve the brain tumor, Chaki and Woźniak [8] have proposed Deep Brain Incep-Res Architecture

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(DBIRA2.0-RLN) which is based on RL network. The framework combined the blocks of Inception, residual connection, for the blocks of feature extraction and classification. The meningioma, glioma, pituitary and no-tumor classes were classified with 97.1% accuracy, 98.7% accuracy, 94.3% accuracy and 100% accuracy, respectively. But the model was highly computation-intensive and not validated during real-time deployment.

Nassar et al. [9] introduced strong hybrid DL model. Authors used majority voting approach between pre trained CNN models. The model was tested on dataset of 3064 T1-weighted contrast enhanced MRI images obtained from 233 patients which was 99.31% overall accurate. The ensemble architecture was very accurate but was complex and not easily interpretable.

Talukder et al. [10] presented optimized ensemble DL framework using transfer learning and Weighted Optimization Technique. The framework used Xception, ResNet50V2, ResNet152V2 and InceptionResNetV2 models. When experiments were conducted on the Figshare CE-MRI dataset of 3064 images an accuracy of 99.76% was obtained. The framework, however, required a lot of computation resources and was complicated in construction of ensemble.

From the literature surveyed, it is observed that the performance of brain tumor classification has been improved substantially using deep learning, transfer learning, hybrid model, and ensemble model. But a few issues are still not resolved. Many studies have concentrated on accurate classification of the tumor, ignoring the localization and segmentation of the tumor. Some methods are very accurate but are also expensive and complex in terms of the ensemble structure. In addition, some of the methods are not externally validated, explainable nor real-time applicable for clinical settings. Moreover, obtaining accurate tumor segmentation and classification in a fast manner is not yet well investigated in the literature.

To overcome these challenges, the proposed work aims to create a unified deep learning framework with the mix of both the tumor segmentation using U-Net and classification using ResNet-101 transfer learning. The framework focuses on accurate segmentation of tumor regions, enhancing the classification performance, minimizing irrelevant background information, and offering a solution that can be implemented efficiently and automatically for brain tumor diagnosis. The proposed system aims to provide reliable performance and facilitate early detection and clinical decision-making through an integrated segmentation and classification.

3. Proposed Methodology

The suggested framework is designed to give an automated and accurate solution for brain tumor segmentation as well as classification using MRI. It consists of four main components: image preprocessing, tumor segmentation using U-Net, transfer learning using ResNet-101 and performance evaluation. The fig. 1 shows complete architecture diagram.

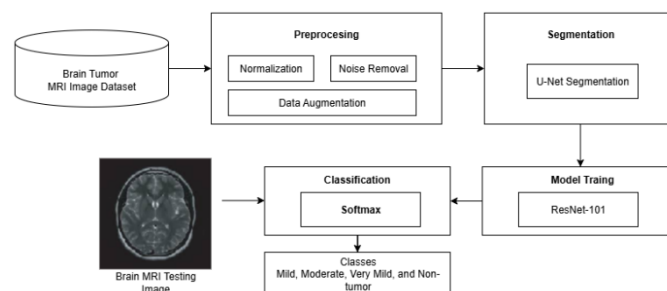


Fig. 1. Proposed Architecture Diagram

The MRI images are initially pre-processed to increase quality of images. It remove unwanted variations. The preprocessed images are then given to U-Net segmentation model which successfully detects and segments the tumor area from the brain MRI images. The segmented tumour segments are then classified into predefined classes using ResNet-101 transfer learning model. Finally, the framework performance is measured by using traditional segmentation and classification measures.

A. Image Preprocessing Module

The goal of the image preprocessing module is to improve the quality of MRI images and to preprocess the image sets in a way that they can be easily used for deep learning analysis. In the first place, all MRI images are converted to 224×224 pixels for consistency in the images. To improve the stability of the training, pixel intensity normalization is performed. Moreover, Gaussian filtering and contrast enhancement techniques are used to get rid of noises and enhance the tumors. In eq.1 the normalization process is shown in eq.1

$$I_{norm} = (I - I_{min}) / (I_{max} - I_{min}) \quad (1)$$

Where I is Original image intensity, I_{min} is Minimum intensity value, I_{max} is Maximum intensity value, I_{norm} is Normalized image. Data augmentation is also performed to enhance the generalisation performance of the model and prevent it from overfitting such as rotating and horizontally flipping images, zooming and shifting.

B. Tumor Segmentation Using U-Net

A U-Net model is used to precisely define tumor boundaries within MRI images. U-Net is made up of an encoder-decoder

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architecture, along with skip connections. The encoder learns features from MRI images and the decoder learns to reconstruct pixel-level tumor masks. With the skip connections, spatial information is maintained and a precise localisation of the tumour areas is possible. The segmented output separates the tumor tissue from the normal brain tissue and removes the irrelevant background information. This will enhance feature extraction and enhance classification accuracy. Table 1 specifies parameters details used in the U-Net Training.

Parameter	Value
Image-Size	224 × 224
Optimizer	Adam
Learning-Rate	0.0001
Batch-Size	16
Epoch	50
Loss-Function	Dice Loss
Activation-Function	ReLU

Table 1. U-Net Training Parameters

The segmented tumor regions obtained by the U-Net model were fed to the ResNet-101 classification network. Transfer learning was used by the means of the ImageNet pre-trained weights. Details are given in table 2. The last fully connected layer was replaced to classify MRI images.

Parameter-Name	Value
ImageSize	224 × 224
Weights	ImageNet
PoolingMethod	Average Pooling
Optimizer	Adam
LearningRate	0.0001
BatchSize	16
Epochs	50

Table 2. ResNet-101 Configuration

The results of the Segmentation and Classification, performance analysis and comparative study along with the discussion of the obtained results is presented in the next chapter.

C. Brain Tumor Classification

The ResNet-101 classification model is fed with extracted tumor regions after the segmentation. ResNet-101 is a 101 layer deep CNN with skip connection to mitigate the issues of network degradation and vanishing gradients. The transfer learning approach is used by leveraging pre-trained model parameters from ImageNet to efficiently extract features from small medical image datasets. This can be formulated as a residual learning mechanism as in eq. 2:

$$H(x) = F(x) + x \quad (2)$$

Here x = feature map and $F(x)$ = learned residual mapping, $H(x)$ = final output representation. The deep features achieved from the extraction process are passed through fully connected layers and classified according to four classes. The Softmax classifier calculates class probabilities as in eq. 3:

$$P(y_i) = e^{z_i} / \sum e^{z_j} \quad (3)$$

Where z_i is Output score of class i , N is total classes. The class that has the maximum is finally chosen as the prediction class. The next section describes the implementation details, experimental setup and description of the dataset, training configuration and evaluation procedures used to validate the proposed framework.

4. Results and Discussion

Experimental Setup

The publicly available multiclass brain MRI dataset is used to from kaggle. The MRI images are of varying types and anatomical structures, suitable for assessing deep learning based classification systems. The dataset was split into training, validation and testing sets. Stratified splitting strategy was used to maintain the class distribution in every split. The python along with deep learning libraries are used to develop the framework. Experiments were performed with a high-performance GPU for fast model training and inference. The experiments were performed on a Windows operating system that runs on Intel Core i7 processors, and an NVIDIA GPU to speed up the training and inference of deep learning models.

Results and Discussion

Segmentation Performance Analysis

Dice Coefficient, IoU and Segmentation Accuracy were used to evaluate the proposed U-Net segmentation model. The model was able to accurately segment tumor boundaries and produce correct segmentation masks for various tumor categories.

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The segmentation outcome shows that model is capable to segment the tumor tissue and healthy brain tissue and hence increase the quality of the classification stage. Table 3 gives segmentation performance Results.

Metric	Value (%)
Dice Coefficient	96.8
IoU Score	94.5
Segmentation Accuracy	97.2

Table 3. Segmentation Performance Results

As shown in Fig 2, the Dice coefficient obtained is very high (96.8%), which indicates very high overlap between predicted tumor region and ground truth mask. Likewise, IoU value of 94.5% also demonstrates the ability of the segmentation model to precisely localize the tumor boundaries.

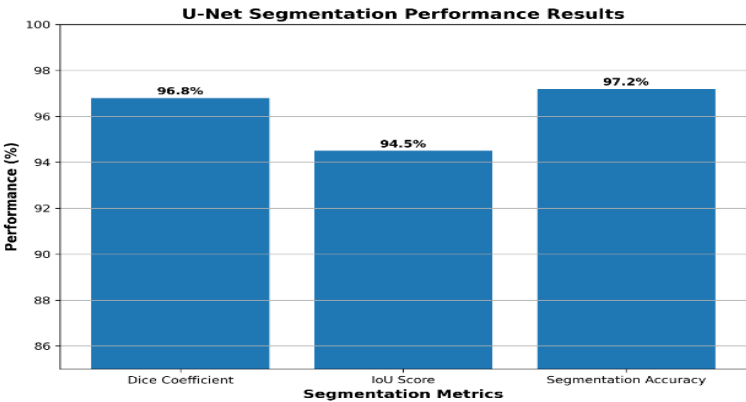


Fig. 2. U-Net Segmentation Performance Comparison Graph

Classification Training Performance

To classify the segmented MRI images into four classes, transfer learning was applied to the ResNet-101 model. System indicates that training and validation accuracy continuously improved demonstrating the model's convergence and the effectiveness of the feature learning.

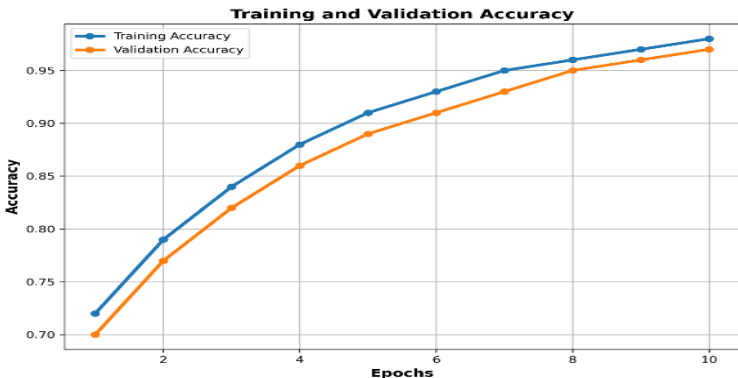


Fig. 3. Training and Validation Accuracy Graph

With the training accuracy as in fig 3 being ~98% and validation accuracy ~97%, it showed that it had great generalization ability and minimal overfitting. Table 4 mentions details of training performance statistics.

Parameter	Value
Training Accuracy	98.0%
Validation Accuracy	97.0%
Epochs	20
Batch Size	16

Table 4. Training Performance Statistics

Loss Function Analysis

Loss curves as in fig 4 will give insight about the convergence of model. Both curves show a consistent downward trend over epochs, which suggests that the model is learning effectively without any significant issues.

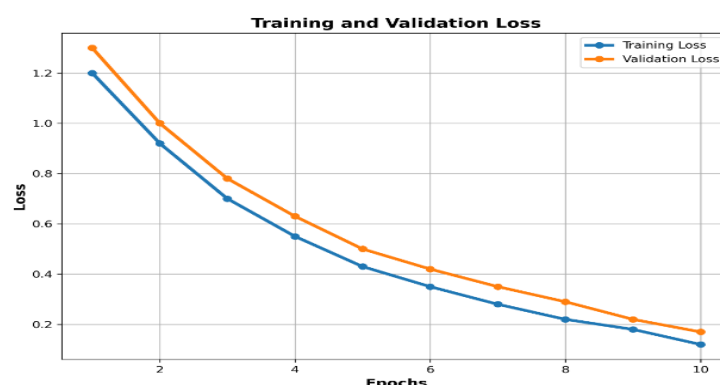


Fig. 4. Training and Validation Loss Graph

The minimal difference between the training and validation losses indicates that the model is not overfitting the training data and performs well on unseen MRI data.

4.5 Class-wise Performance Analysis

To further assess the effectiveness of classification, class-wise results were calculated as shown in table 5.

Tumor Class	Precision (%)	Recall (%)	F1-Score (%)
Glioma Tumor	98.2	97.6	97.9
Meningioma Tumor	97.1	96.5	96.8
Pituitary Tumor	98.9	98.4	98.6
No Tumor	97.8	97.2	97.5

Table 5. ClassWise Classification Performance

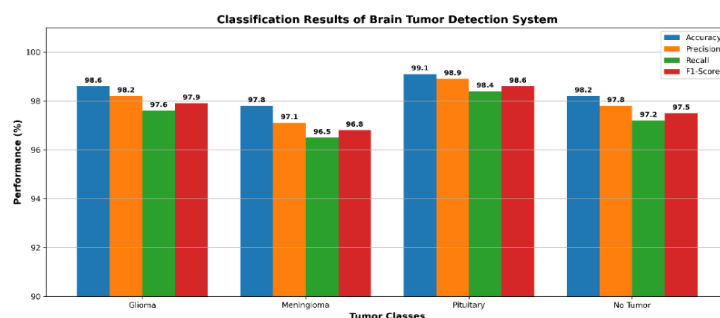


Fig.5. Class-wise Performance Metrics Graph

The results of fig 5 show consistent high performance for all tumour categories. The Pituitary Tumor class had the best performance, and the Meningioma class performed a little worse owing to the fact that it had more intra-class variation. The proposed framework of Smart NeuroVision framework is working well for the proposed system with high accuracy and reliability. The main findings of this study are summarized and their significance is discussed along with some directions for further study in the next chapter for the further enhancement of the proposed framework.

5. Discussion

The experimental results demonstrate the effectiveness of proposed Smart NeuroVision framework for brain tumor segmentation and classification by implementing U-Net and ResNet-101. The U-Net model showed a Dice Coefficient of 0.968, an IoU of 0.945 and an accuracy of 0.972, suggesting a high level of accuracy in localizing the tumor boundaries. The ResNet-101 model achieved an overall classification accuracy of 98.4%, highlighting its ability to learn features and predict multiple classes with high accuracy. Stable convergence of the training and validation curve, without much overfitting, is observed, demonstrating good model generalization. Evaluation was also performed on a class level and also resulted in high Precision, Recall and F1-Score for each of the tumor categories with the highest performance being the Pituitary Tumor class. The results validate that incorporating classification architecture based on transfer learning ResNet-101 and segmentation architecture U-Net into a single network boosts diagnostic accuracy by filtering out the background noise and extracting features for the classification task. Thus, the proposed framework can be an effective computer-aided diagnosis (CAD) system used to assist the radiologists to accurately detect brain tumor at early stage. (10)

6. Conclusion

The proposed work suggested smart NeuroVision based deep learning framework which together enhances the accuracy of diagnosis. Experimental results showed excellent performance with Dice Coefficient of 96.8%, IoU of 94.5% and Segmentation accuracy of 97.2%. The model gave accuracy of 98.4% for tumor classification. The findings validate the accuracy and classification of brain tumors using the proposed framework and minimize extensive manual diagnosis. Hence, the system can also be used as a good computer-aided diagnostic tool to help radiologists in clinical decision making and early detection of the disease.

Future work could be directed to further develop the framework by using larger and more varied MRI data from the different health care centers. To increase performance of feature extraction and classification, advanced architectures like Vision.

Transformer and attention based networks can be integrated. To enhance transparency and interpretability explainable Artificial intelligence (XAI) can be incorporated, for example, Grad-CAM. Further, the framework can be adapted for tumor grading, prediction of survival and assessment of treatment response. The combination of clinical and genomic information with MRI images could further enhance the accuracy of diagnosis. Last but not least, the proposed system can be implemented as an online clinical decision support system (CDSS) for real-time applications in healthcare.

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