MRI-Based Brain Tumor Detection and Classification Using Deep Learning

N. Malarvizhi[1], A. Divya[1], N. Sankar Ram[2], M. Saraswathi[3], Naveen Kumar R. J.[4] and M. Nalini[5]
[1]Professor, Department of CSE, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
[2]Department of CSE, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
[3]Department of CSE, SCSVMV Deemed to be university, Kanchipuram, Tamil Nadu, India
[4]Senior Associate Engineer, Chennai, Tamil Nadu, India
[5]Associate, Professor, Department of CS&BS, S.A Engineering College, Chennai, Tamil Nadu, India

Keywords: Brain Tumor Detection, MRI Images, Brain Tumor Classification, Fully Convolutional Network (FCN), Medical Imaging, Automated Diagnosis, Radiology Assistance.

Abstract: It is obvious that the detection and classification of brain tumors in the MRI scans is an important aspect of medical imaging and so is defected in diagnosis and treatment of medical issues. This work applies a Fully Convolutional Network (FCN) model towards automatic identification of brain tumors with MRI images from Kaggle dataset. The dataset is organized into training and testing folders which have subfolders that represent categories of tumors such as glioma, meningioma, pituitary tumors, and 'no tumor' for normal cases. This lets the FCN learn to not only detect the presence of a tumor, but also which specific type it is. The model is trained to process MRI images on a pixel-by-pixel basis, allowing for precise segmentation and classification of abnormal regions. In the event that the model detects a tumor, it will determine the tumor type based on the set of features that the model has learned for each category in the dataset. The model operates in a sequence of two stages: first, it classifies an MRI scan to be tumor-positive or tumor-negative; second, if the model detects the presence of a tumor, it classifies the tumor into one of the set categories. The model performs binary classification as well as multi-class classification. The proposed system will help to assist radiologists by providing a tool that is automated and reliable for brain tumor detection and classification, which, without doubt, simplifies the diagnostics process and improves the outcome.

1 INTRODUCTION

Brain tumors are a life-threatening disease with high rates of mortality and morbidity. Precise identification and categorization of brain tumors are important in determining appropriate therapy planning and optimal outcomes. The principal imaging device applied by medical doctors to observe brain tumors is Magnetic Resonance Imaging (MRI). With its capacity to produce high-resolution, detailed images of brain structures, MRI offers significant information on the existence and nature of tumors. Yet, such human interpretation is time-consuming and necessitates specialized knowledge and is even susceptible to human fallibility or inconsistency among radiologists. Deep learning algorithms have been established as strong aids for medical image analysis automation. Of these, Fully Convolutional Networks (FCNs) have become increasingly popular because of their special feature of pixel-level image segmentation. While conventional Convolutional Neural Networks (CNNs) classify the entire images, FCNs are capable of processing images in a manner that enables fine-grained spatial analysis. This feature makes them highly appropriate for medical purposes like the detection and segmentation of brain tumors in MRI scans. FCNs not only detect if a tumor is present but also its edges and classify it into certain classes based on the nature of the tumor. The suggested work intends to utilize an FCN model to scan brain MRI images for tumor detection and classification. It employs a Kaggle dataset, which is an organized collection of MRI images divided into four classes: glioma, meningioma, pituitary tumor, and normal (no tumor). The data structure enables the FCN model to perform both multi-class classification among tumor

Malarvizhi, N., Divya, A., Ram, N. S., Saraswathi, M., J., N. K. R. and Nalini, M.
MRI-Based Brain Tumor Detection and Classification Using Deep Learning.
DOI: 10.5220/0013923200004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 5*, pages 86-91
ISBN: 978-989-758-777-1

and no tumor and multi-class classification among tumor types. The model achieves this in two steps. Firstly, the presence of a tumor, and secondly, the identification of the identified tumor into one of the specified categories. The incorporation of FCNs in brain tumor detection systems has numerous benefits. First, it provides accurate localization of tumor areas, which is critical for accurate diagnosis and planning of treatment. Second, it lightens the workload of radiologists, facilitating quicker and more uniform decision-making. Third, such automated systems can fill the gap in health care access, particularly in locations where trained radiologists are in short supply. This research sets the effectiveness of FCNs in classifying and detecting brain tumors as a potentially scalable and strong solution to medical imaging. Openly available data and deep learning methods aid in the progression of automated diagnostic equipment for brain tumor analysis.

2 LITERATURE SURVEY

A hybrid FCN approach was presented in (Kamran, A, et, al. 2020) for the classification of brain tumors. This model leverages the strength of FCNs for accurate segmentation along with ensemble classifiers for enhanced classification accuracy. The work was motivated to address challenges such as class imbalance and variation in the appearance of the tumor by combining several classifiers in an ensemble. A new FCN-based model enriched with attention mechanisms for brain tumor detection was suggested by the authors in (Bhatia, R, et, al, 2021) The research incorporated the pixelwise classification capability of FCNs and attention layers concentrating on the area of interest for the tumor. The approach made the model sensitive to small, abnormally shaped tumors and better detection accuracy than in conventional methods.

A multi-scale FCN model for segmentation of brain tumors from MRI scans was proposed in (Xu, Y2021). By combining multiple resolution levels in the segmentation process, the model could preserve both fine-grained details and large-scale tumor structures. The multi-scale method enhanced the accuracy of tumor segmentation, particularly for tumors with irregular shapes. The authors in (Gupta, A.,2022) introduced a 3D FCN-based method for brain tumor detection from volumetric MRI scans. With the utilization of 3D convolution operations, the model was able to extract spatial information from multiple slices of the brain, which enabled more precise tumor localization and detection in 3D MRI volumes. This method has proven the great benefits in utilizing 3D convolutional models compared to 2D methods in medical image analysis tasks.

A deep supervision FCN model for brain tumor segmentation was presented in (Wang, Z, 2023) In this model, more than one layer of the FCN was supervised directly during training to make sure that intermediate features were used to contribute to the final segmentation output. This process enabled the model to learn better at various abstraction levels and enhanced its segmentation accuracy, particularly for heterogeneous tumors. The authors in (Li, X, 2024) suggested a state-of-the-art multi-class segmentation FCN for the types of brain tumors (glioma, meningioma, pituitary tumors, etc.) from MRI scans. The model aimed to not only segment the tumor area but also determine the type of tumor, combining both segmentation and classification into one pipeline. The authors used a multi-task learning method to train the model for both tasks at once, which enhanced the overall performance of both tumor detection and classification.

The authors proposed a new FCN-enhanced architecture equipped with spatial attention mechanisms for the detection of brain tumors in (Cheng, H, 2024) The attention module was integrated into the FCN to target areas that were likely to hold tumor tissue, which aided the model to perform better at detecting small or inconspicuous tumors that would be missed using traditional methods. An FCN-based model using a transfer learning method for brain tumor segmentation was presented in (Khan, A, 2020). Taking advantage of pre-trained models, the research proved enhanced feature extraction and classification accuracy, particularly for small datasets. The model achieved efficient reduction of training time with high segmentation accuracy.

The authors of (Patel, R,2021) proposed a deep learning pipeline that combined FCNs with U-Net architecture for brain tumor segmentation. Their method utilized skip connections to preserve spatial information, enhancing segmentation accuracy for tumors of different shapes and sizes. The paper emphasized the benefits of employing FCN-based architectures in medical image tasks. A CNN-FCN hybrid model for brain tumor detection was implemented where a Convolutional Neural Networks (CNNs) used to extract features prior to inputting them to an FCN for pixel-wise classification. This approach enhanced small tumor region detection and minimized false positives in MRI scans. A CNN-FCN model for brain tumor segmentation and classification was proposed in

(Zhang et al, 2023). CNN was used to extract features, while FCN enhanced tumor localization. Experimented on the BraTS dataset, the model reached a Dice score of 0.87, which is superior to conventional CNN approaches.

3 PROPOSED SYSTEM

In the proposed system, a Fully Convolutional Network (FCN) is used to automatically Segment brain tumors in MRI images. Following the preprocessing step, the FCN processes the Images to distinguish between tumor regions and healthy tissue. Trained on a labeled dataset, the model detects and segments the tumors accurately, helping the radiologists by accelerating up diagnosis and improving accuracy. Figure 1 depicts the architecture diagram of the proposed system.

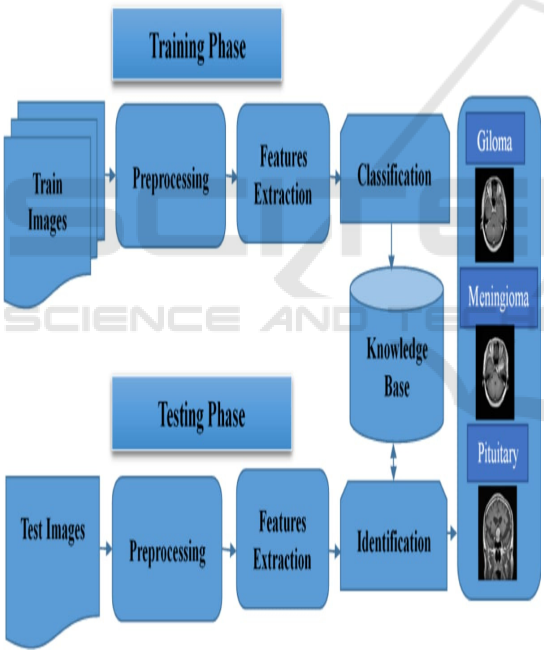


Figure 1: Architecture diagram for the proposed system.

The various steps in the Proposed System are given below:

- **Data Preprocessing**: Resize, normalize, and augment MRI images from the Kaggle dataset.
- **FCN Model Training:** Train the Fully Convolutional Network (FCN) on labeled data to segment tumor regions.
- **Tumor Detection & Segmentation:** The model classifies MRI images into tumor vs. no tumor and identifies tumor types if present.
- **Post-Processing**: Generate segmentation maps and evaluate tumor boundaries.
- **Evaluation:** Assess model performance using accuracy, precision, recall, and F1-score.
- **Testing & Deployment:** Test on unseen data and deploy the model for real-time clinical use.

3.1 Input Design

A brain tumor MRI usually contains MRI scan images classified into different types such as glioma, meningioma, pituitary tumors, and some non-tumor cases. Some of these datasets are already available to the public, such as the Kaggle Brain Tumor MRI Dataset, the Fig share Brain Tumor Dataset, or the BraTS (Brain Tumor Segmentation) Dataset, where labeled images are used in classification and segmentation tasks. Therefore, these datasets are widely deployed in deep learning research to advance the development of automated models for tumor detection, aiding in early diagnosis and medical decision support. Figure 2 shows the MRI brain images used for the proposed system.

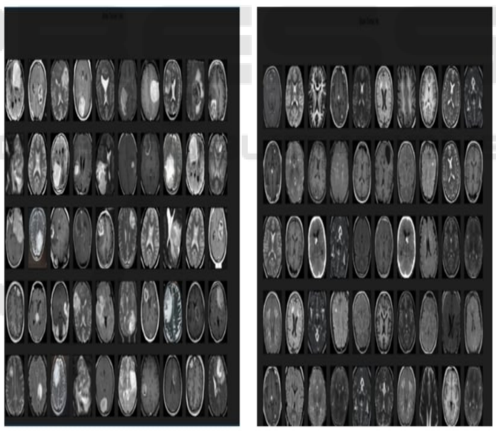


Figure 2: MRI brain images.

3.2 Output Design

The output of the proposed system is depicted from Figure 3 to 6. The results in Figure 3 shows that if a tumor is present and the type of brain tumor identified is glioma. It should also contain a suggestion like "The case should be reviewed by a neurologist." With graphical user interfaces, MRI scan images can be shown along with the results for better context. For API centrally managed systems, data can easily be processed through the use of structured JSON. This design is aimed at making things simple to understand for the users and the medical practitioners as well.

The MRI scan confirms the presence of a meningioma tumor in Figure 4. It would be best to check in with a neurologist for assessment and diagnosis. The findings can be provided in a report or as an image together with the MRI for clearer understanding. The results can also be provided via an API as a JSON for ease of use and processing of medical information. This solution is best for healthcare practitioners as well as the patients in terms of understanding the details.

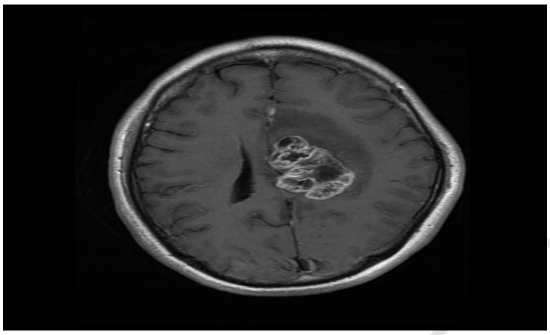


Figure 3: Found glioma tumor.

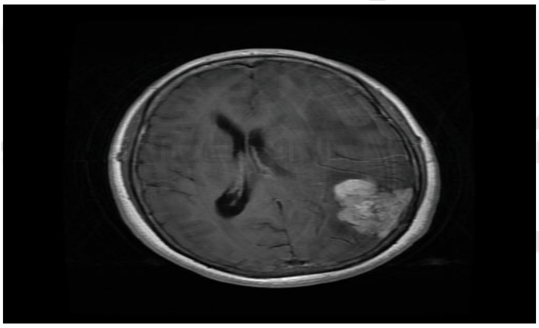


Figure 4: Found meningioma tumor.

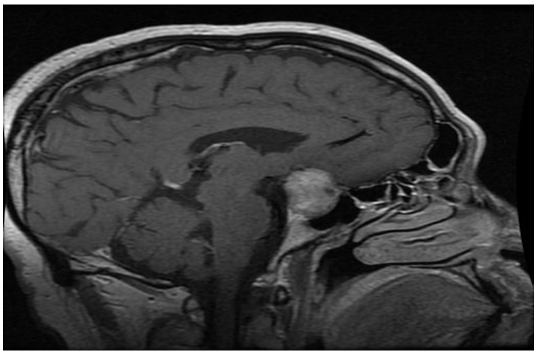


Figure 5: Found pituitary tumor.

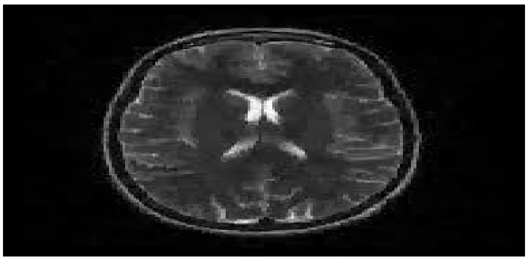


Figure 6: No tumor found.

The model has successfully detected a pituitary tumor in the MRI scan as shown in Figure 5, accurately segmenting the affected region and differentiating it from healthy brain tissue. Using the trained Fully Convolutional Network (FCN), the system classifies the tumor based on learned features with a high confidence score, ensuring reliability in diagnosis. The segmentation map visually highlights the tumor boundaries, allowing radiologists to analyze the size, shape, and location of the abnormality. This automated detection significantly reduces diagnosis time, minimizes human error, and enhances decision-making in treatment planning. The results can be further validated through clinical assessment, ensuring that the system provides a robust and efficient tool for early brain tumor detection.

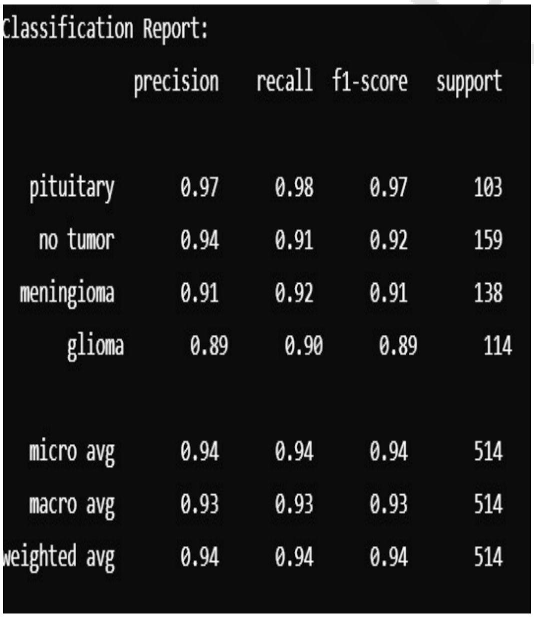
The Figure in 6 depicts no tumor found in the MRI scan. No abnormal growth on the brain or any sign. However, the patient should continue to seek attention from a neurologist because the symptoms can persist. In a structured manner, the findings can be portrayed as text, or even using a graphical user interface, accompanying the MRI for confirmation. With API-based apps, a JSON response can be very helpful to seamlessly integrate and display results clearly.

4 RESULTS AND DISCUSSIONS

The proposed Fully Convolutional Network (FCN) model for brain tumor detection and classification follows a systematic workflow.

- **Data Preparation:** The Kaggle dataset is preprocessed by resizing all MRI images to a uniform dimension, normalizing pixel values to enhance contrast, and applying data augmentation techniques such as rotation, flipping, and brightness adjustments. This helps improve model generalization and prevents overfitting.

- **Model Training:** A Fully Convolutional Network (FCN) is trained in two stages: first, performing binary classification to distinguish between tumor and non-tumor cases, and second, conducting multi-class classification to identify specific tumor types (glioma, meningioma, pituitary tumor). The model is optimized using an Adam optimizer with a carefully tuned learning rate and trained over multiple epochs.
- **Evaluation:** The model's performance is evaluated using accuracy, precision, recall, F1-score, and support as shown in Figure 7 to assess both classification and segmentation quality. A confusion matrix is used to analyze misclassifications, and segmentation results are visually inspected to validate tumor localization. Figure 8 presents a consolidated view of the confusion matrix from Figure 3 to Figure 6 and showcasing the model's classification accuracy and segmentation performance for various tumor types.
- **Testing & Deployment:** The trained model is tested on an independent test set to ensure its robustness in real-world applications. It is further validated on unseen MRI images to confirm its ability to accurately detect and classify tumors. The final model is optimized for deployment in a clinical setting, where it can assist radiologists by providing automated tumor detection and classification results.


Classification Report:

	precision	recall	f1-score	support
pituitary	0.97	0.98	0.97	103
no tumor	0.94	0.91	0.92	159
meningioma	0.91	0.92	0.91	138
glioma	0.89	0.90	0.89	114
micro avg	0.94	0.94	0.94	514
macro avg	0.93	0.93	0.93	514
weighted avg	0.94	0.94	0.94	514

Figure 7: Classification report.

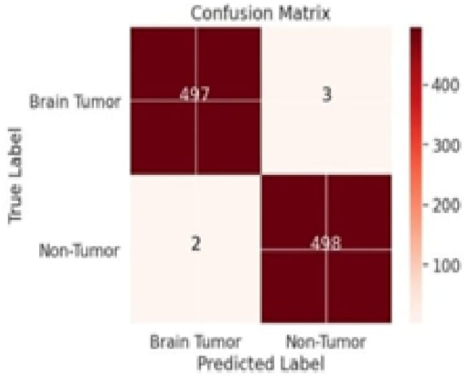


Figure 8: Confusion matrix of FCN.

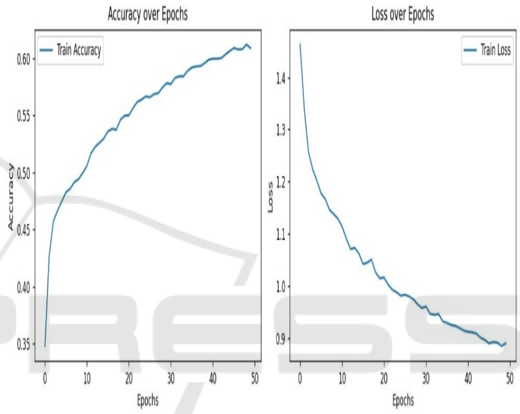


Figure 9: Accuracy and loss.

Figure 6 depicts the training accuracy and training loss for 50 epochs. As shown in Figure 9 accuracy increases from 0.35 to 0.60, and loss goes down from 1.45 to 0.85 shown in Figure 9, which is good learning. The curve of accuracy levels off after 40 epochs, which means a plateau of learning. The consistent decrease in loss indicates successful optimization. There could be room for improvement with more epochs or hyperparameter adjustments.

5 CONCLUSION AND FUTURE ENHANCEMENT

The proposed FCN-based approach for brain tumor detection and classification in MRI images, ensuring accurate segmentation and diagnosis. The proposed model, with its potential to segment and classify at the pixel level of an MRI image, ensures high accuracy in pointing out abnormal zones, hence reducing the prospect of false diagnosis. As the system runs automatically, the need to intervene is minimized and also assisting healthcare professionals in making proper and timely decisions. Future work includes expanding tumor types, integrating 3D MRI analysis, improving segmentation with attention mechanisms, and deploying the model in real-time clinical settings for practical use.

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