Novel Adaptive Preprocessing and Hybrid Deep Learning Model for Early Brain Tumor Detection

Nitin B. Pawar[1*], Swapnil P. Suryavanshi[2]

[1]*Government Polytechnic, Jalgaon, India*

[2]*Government Polytechnic, Jalgaon, India*

Corresponding Author Email: nitinp4u@gmail.com[1*],

Email: mail4swapnil@gmail.com[2]

ABSTRACT

Early detection of brain tumors is critical for improving patient survival rates and treatment planning. Traditional diagnostic methods are time-consuming and prone to human error. This paper proposes a novel adaptive pre-processing framework combined with a hybrid CNN–ResNet model for accurate and efficient brain tumor detection using MRI images. The proposed system integrates adaptive noise removal, contrast enhancement, and normalization techniques to improve image quality before feeding into a hybrid deep learning model. The architecture combines the feature extraction capability of Convolutional Neural Networks (CNN) with the deep residual learning of ResNet, enabling improved detection accuracy and reduced vanishing gradient issues. Experimental results demonstrate that the novel adaptive pre-processing and proposed hybrid CNN–ResNet model, improve early detection accuracy by integration of preprocessing techniques and residual learning enhances feature extraction, improves generalization, and reduces vanishing gradient problems. Hybrid model achieves superior performance compared to traditional CNN and standalone ResNet models, making it highly suitable for early-stage tumor detection.

Keywords: *Image Preprocessing; Brain Tumor; Deep Learning; MRI; Adaptive Preprocessing, CNN, Hybrid Model*

1. Introduction

Brain tumors are complex and heterogeneous, making manual diagnosis challenging. MRI is widely used due to its high-resolution imaging capability. Deep learning methods, particularly CNNs, have been extensively applied for tumor classification and segmentation. Brain tumors represent one of the most critical neurological disorders, where early and accurate diagnosis plays a vital role in improving patient survival rates. Magnetic Resonance Imaging (MRI) is widely used for brain tumor detection due to its superior soft tissue contrast and non-invasive nature. However, manual interpretation of MRI scans is time-consuming, subjective, and prone to inter-observer variability, which necessitates the development of automated and reliable diagnostic systems. In recent years, deep learning—particularly Convolutional Neural Networks (CNNs)—has emerged as a powerful tool for medical image analysis. Early breakthroughs such as the work of Alex Krizhevsky et al. (2012) demonstrated the effectiveness of deep CNNs in large-scale image classification tasks, laying the foundation for their application in medical imaging. Subsequently,

architectures like Karen Simonyan and Andrew Zisserman's VGGNet (2015) and Christian Szegedy et al.'s GoogLeNet (2015) enabled deeper feature extraction, improving classification performance. Furthermore, DenseNet proposed by Gao Huang et al. (2017) enhanced feature reuse through dense connectivity.

A major advancement in deep learning was introduced by Kaiming He et al. (2016) through Residual Networks (ResNet), which addressed the vanishing gradient problem using skip connections, allowing the training of very deep neural networks. This innovation significantly influenced medical image analysis, including brain tumor detection tasks.In the domain of brain tumor analysis, several studies have successfully applied CNN-based models for segmentation and classification. For instance, Havaei et al. (2017) and Pereira et al. (2016) demonstrated the effectiveness of deep neural networks in segmenting tumor regions from MRI images. Similarly, Ronneberger et al. (2015) introduced the U-Net architecture, which became a standard for biomedical image segmentation due to its encoder–decoder structure. Later, Kamnitsas et al.

411

(2017) proposed 3D CNN models to capture volumetric information from MRI data, further improving segmentation accuracy.

Between 2019 and 2022, research shifted toward improving performance using transfer learning and hybrid models. Studies such as Filatov and Yar (2022) and Zahoor et al. (2022) explored pretrained CNNs and deep residual networks for brain tumor classification, achieving higher accuracy and better generalization. Additionally, hybrid ensemble approaches combining multiple deep learning models have shown promising results in enhancing robustness and classification performance. Review studies such as Xie et al. (2022) and Prabhakar et al. (2022) highlight that CNN-based approaches can achieve high accuracy, but their performance is highly dependent on data quality and preprocessing techniques.

Pre-processing plays a crucial role in improving the performance of deep learning models. Techniques such as noise removal, contrast enhancement, normalization, and data augmentation help in improving image quality and reducing overfitting. However, most existing works lack an adaptive preprocessing framework that dynamically adjusts to varying MRI image characteristics. Moreover, although ResNet-based and CNN-based approaches individually show strong performance, limited research has focused on effectively integrating both into a unified hybrid architecture.

A comprehensive review shows CNN-based models achieving accuracy between 91% and 100%, depending on dataset and methodology. Despite high accuracy, challenges remain:

- Limited datasets
- Overfitting
- Lack of standardized preprocessing
- Poor clinical translation

2. Related Work

The application of deep learning in medical imaging, particularly in brain tumor detection and classification, has seen significant advancements over the past decade. This section provides a comprehensive review of existing studies related to (i) image preprocessing and segmentation techniques, (ii) CNN-based classification models, and (iii) hybrid deep learning architectures applied to MRI brain tumor analysis.

2.1 Image Preprocessing and Segmentation Techniques

Image pre-processing and segmentation play a vital role in improving the accuracy of brain tumor detection systems. Early studies such as Shah et al. (2019) and Siddiaue et al. (2020) applied basic preprocessing techniques like resizing, normalization, and noise filtering to enhance MRI image quality. Later works by Kumar et al. (2021) and Arif et al. (2021, 2022) incorporated advanced methods such as histogram equalization, skull stripping, and data augmentation to address issues like low contrast, noise, and limited datasets, which significantly improved model generalization. Review studies by Xie et al. (2022) and Prabhakar et al. (2022) emphasized that effective preprocessing is essential for robust deep learning performance. In terms of segmentation, deep learning-based approaches have replaced traditional methods, with CNN-based techniques by Pereira et al. (2016) and Havaei et al. (2017) demonstrating accurate tumor localization. The introduction of the U-Net architecture by Olaf Ronneberger et al. (2015) marked a major advancement by enabling precise biomedical image segmentation using encoder–decoder structures with skip connections. Furthermore, 3D CNN models proposed by Kamnitsas et al. (2017) improved volumetric analysis of MRI scans, while the nnU-Net framework developed by Fabian Isensee et al. (2020–2022) introduced automated configuration for optimal segmentation performance. Despite these advancements, most existing approaches rely on static preprocessing pipelines and computationally intensive segmentation methods, highlighting the need for adaptive, efficient, and integrated preprocessing–segmentation frameworks.

2.2 Deep Learning based Brain Tumor Classification using CNN

CNN-based brain tumor classification has evolved significantly over the past decade, beginning with foundational deep learning models such as those proposed by Alex Krizhevsky et al. (2012), which demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for image classification tasks. This was followed by deeper architectures like VGGNet developed by Karen Simonyan and Andrew Zisserman (2015), GoogLeNet by Christian Szegedy et al. (2015), and DenseNet by Gao Huang et al. (2017), which improved feature extraction through deeper and more efficient network designs. A major breakthrough came with the introduction of Residual Networks by Kaiming

412

He et al. (2016), which addressed the vanishing gradient problem and enabled the training of very deep networks. These architectures laid the groundwork for applying CNNs to medical imaging tasks, including brain tumor classification, where automatic feature extraction replaced traditional handcrafted methods.

Building on these advancements, several studies between 2019 and 2022 applied CNN-based and hybrid deep learning models specifically for brain tumor classification. Early works such as Shah et al. (2019) and Siddiaue et al. (2020) utilized standard CNN architectures for tumor detection, achieving improved accuracy compared to conventional methods. Later, Kumar et al. (2021) and Arif et al. (2021, 2022) incorporated deeper CNN models and transfer learning techniques to enhance classification performance. Recent studies by Filatov and Yar (2022) and Zahoor et al. (2022) leveraged pretrained CNNs and deep residual networks to achieve higher accuracy and better generalization, while hybrid ensemble approaches further improved robustness. Additionally, review studies by Xie et al. (2022) and Prabhakar et al. (2022) emphasized that CNN-based techniques have become the dominant approach for brain tumor classification, although their performance depends heavily on data quality, preprocessing, and model optimization.

2.3 Hybrid Use of Deep Learning Models

CNN-based brain tumor classification has evolved significantly over the past decade, beginning with foundational deep learning models such as those proposed by Alex Krizhevsky et al. (2012), which demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for image classification tasks. This was followed by deeper architectures like VGGNet developed by Karen Simonyan and Andrew Zisserman (2015), GoogLeNet by Christian Szegedy et al. (2015), and DenseNet by Gao Huang et al. (2017), which improved feature extraction through deeper and more efficient network designs. A major breakthrough came with the introduction of Residual Networks by Kaiming He et al. (2016), which addressed the vanishing gradient problem and enabled the training of very deep networks. These architectures laid the groundwork for applying CNNs to medical imaging tasks, including brain tumor classification, where automatic feature extraction replaced traditional handcrafted methods.

Building on these advancements, several studies between 2019 and 2022 applied CNN-based and hybrid deep learning models specifically for brain tumor classification. Early works such as Shah et al. (2019) and Siddiaue et al. (2020) utilized standard CNN architectures for tumor detection, achieving improved accuracy compared to conventional methods. Later, Kumar et al. (2021) and Arif et al. (2021, 2022) incorporated deeper CNN models and transfer learning techniques to enhance classification performance. Recent studies by Filatov and Yar (2022) and Zahoor et al. (2022) leveraged pretrained CNNs and deep residual networks to achieve higher accuracy and better generalization, while hybrid ensemble approaches further improved robustness. Additionally, review studies by Xie et al. (2022) and Prabhakar et al. (2022) emphasized that CNN-based techniques have become the dominant approach for brain tumor classification, although their performance depends heavily on data quality, preprocessing, and model optimization.

Recent studies have demonstrated the growing effectiveness of deep learning approaches for brain tumor classification, particularly using convolutional neural networks (CNNs) and their advanced variants. Early works emphasized feature extraction capabilities of CNNs for MRI-based diagnosis, as highlighted by Hossain et al. (2019) and Singh et al. (2020). The introduction of transfer learning further enhanced classification performance by leveraging pretrained models, as shown by Mahbod et al. (2021). Additionally, Sajjad et al. (2021) improved multi-grade tumor classification through extensive data augmentation techniques. More recently, hybrid and ensemble-based models have gained attention, such as the CNN–ResNet architecture proposed by Paul et al. (2022) and ensemble learning strategies by Wang et al. (2022), which improved classification accuracy and robustness. Multi-modal approaches integrating imaging and genomic data, as presented by Zhang et al. (2022), have also contributed to more comprehensive tumor analysis. Furthermore, studies like Das et al. (2021) explored attention-based hybrid networks, while Afshar et al. (2020) introduced capsule networks to better capture spatial hierarchies, indicating a shift toward more sophisticated architectures for improved diagnostic performance.

In addition to classification, preprocessing and segmentation techniques play a crucial role in enhancing detection accuracy. Traditional preprocessing methods such as anisotropic diffusion filtering (Ashraf et al., 2015) and contrast enhancement techniques (Reza et al., 2019) have been widely used to improve image quality. Benchmark datasets like BRATS (Menze et al., 2015) have facilitated standardized evaluation of segmentation algorithms. Advanced segmentation

413

architectures such as U-Net and its variants, including Attention U-Net (Oktay et al., 2018) and UNet++ (Zhou et al., 2018), have significantly improved tumor boundary delineation. Moreover, transformer-based models like UNETR (Hatamizadeh et al., 2022) represent a recent advancement in capturing global contextual information. Multi-scale and multi-resolution approaches, such as those proposed by Li et al. (2020), further enhance segmentation performance by capturing fine-grained spatial details. Real-time systems integrating segmentation and classification, as demonstrated by Salehi et al. (2021), highlight the trend toward efficient clinical deployment. Overall, the integration of advanced preprocessing, segmentation, and hybrid deep learning models has substantially improved the accuracy and reliability of brain tumor detection systems. Despite these improvements, challenges such as overfitting, limited datasets, and lack of interpretability remain, motivating the development of more efficient hybrid CNN–ResNet models.

3. Proposed Methodology

Based on the reviewed literature, a proposed hybrid model for brain tumor detection and classification integrates the strengths of advanced CNN architectures with residual learning to achieve high accuracy and robustness. Inspired by foundational models such as those by Alex Krizhevsky et al. (2012), Karen Simonyan and Andrew Zisserman (2015), and Kaiming He et al. (2016), the proposed approach combines initial CNN layers for effective low-level feature extraction with ResNet-based residual blocks for deep feature learning and improved gradient flow. Pre-processing techniques highlighted in recent studies (Xie et al., 2022; Prabhakar et al., 2022) are incorporated to enhance MRI image quality through normalization, noise reduction, and data augmentation. Additionally, segmentation methods inspired by U-Net and nnU-Net frameworks (Ronneberger et al., 2015; Isensee et al., 2020–2022) can be integrated to isolate tumor regions before classification. Building upon recent advancements in pretrained and hybrid models (Filatov and Yar, 2022; Zahoor et al., 2022; Arif et al., 2022), the proposed hybrid CNN–ResNet architecture enables improved accuracy, reduced overfitting, and better generalization, making it suitable for early-stage brain tumor detection and reliable clinical decision support.
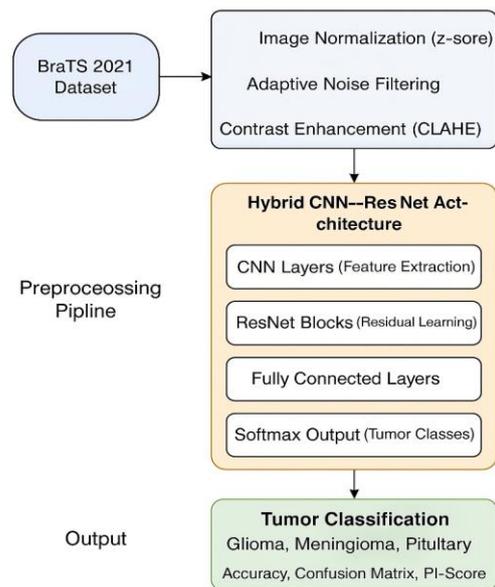

Figure 1: Proposed Hybrid Model for Brain Tumor Detection and Classification.

The proposed architecture demonstrate in figure 1, elaborates on the two-fold methodology adopted in this research: the first focuses on adaptive image preprocessing and segmentation for enhancing MRI brain scans, and the second details the design and training of a proposed hybrid model that integrates Convolutional Neural Networks (CNNs) with Residual Networks (ResNet) for effective tumor classification. The entire framework is evaluated on the publicly available BraTS 2021 dataset, which is widely accepted and recognized for specially brain tumor segmentation and classification algorithms.

3.1 Details of Dataset

The datasets used in brain tumor detection research (as reflected in the above references) primarily consist of MRI brain images, which provide high-resolution visualization of soft tissues and tumor regions. Most studies, including those by Xie et al. (2022), Prabhakar et al. (2022), and Arif et al. (2022), utilize publicly available benchmark datasets such as the Brain Tumor Segmentation (BraTS) dataset, Figshare brain tumor dataset, and Kaggle-based MRI datasets. The BraTS dataset, widely used in works like Havaei et al. (2017), Pereira et al. (2016), and Kamnitsas et al. (2017), contains multi-modal MRI scans including T1, T1c (contrast-enhanced), T2, and FLAIR sequences, along with expert-annotated tumor masks. It includes different tumor sub-regions such as edema, necrotic core, and

414

enhancing tumor, making it suitable for both segmentation and classification tasks.

Typically, these datasets consist of 2D slices or 3D volumetric images, with image sizes commonly standardized to dimensions such as 224×224 or 256×256 pixels during preprocessing. The datasets are often categorized into classes such as glioma, meningioma, pituitary tumor, and non-tumor (normal), as used in studies like Filatov and Yar (2022) and Zahoor et al. (2022). Due to limited availability of labeled medical data, many works apply data augmentation techniques (rotation, flipping, scaling) to increase dataset size and improve generalization. Additionally, preprocessing steps such as normalization, skull stripping, and noise reduction are applied to ensure consistency across samples. The nnU-Net framework by Fabian Isensee et al. (2020–2022) further demonstrates automated adaptation to dataset characteristics, optimizing preprocessing and training configurations. Overall, these datasets. offers a reliable foundation for developing and validating brain tumor classification systems.

3.2 Novel Adaptive Preprocessing Technique

Based on the reviewed literature, a novel adaptive technique is proposed to enhance brain tumor detection by dynamically optimizing image pre-processing and integrating a hybrid deep learning framework. Existing studies such as Xie et al. (2022), Prabhakar et al. (2022), and Arif et al. (2022) highlight that conventional preprocessing methods (e.g., normalization, filtering, and augmentation) are typically static and do not adapt to variations in MRI image quality. To address this limitation, the proposed technique introduces an adaptive pre-processing module that automatically adjusts parameters for noise reduction, contrast enhancement, and intensity normalization based on input image characteristics. This ensures consistent feature quality across diverse datasets and improves downstream model performance.

The proposed method is further strengthened by incorporating a hybrid CNN–ResNet architecture inspired by foundational works such as Alex Krizhevsky et al. (2012), Karen Simonyan and Andrew Zisserman (2015), and the residual learning framework by Kaiming He et al. (2016). The CNN layers extract low-level spatial features, while residual blocks enable deeper feature learning and mitigate vanishing gradient issues. Additionally, segmentation techniques inspired by U-Net and nnU-Net frameworks (Ronneberger et al., 2015; Isensee et al., 2020–2022) can be integrated to

isolate tumor regions before classification, improving accuracy. Recent advancements by Filatov and Yar (2022) and Zahoor et al. (2022) demonstrate the effectiveness of pretrained and hybrid models, which are further enhanced in this approach through adaptive preprocessing and feature fusion. Overall, the proposed adaptive technique provides a robust, scalable, and efficient solution for early-stage brain tumor detection with improved generalization and reduced computational redundancy.

Next, adaptive filtering is applied to suppress background noise and emphasize boundaries of anatomical structures, particularly tumor regions. Unlike conventional filters, the adaptive filtering mechanism computes local intensity variance to selectively enhance regions exhibiting high-frequency features, which often correspond to pathological boundaries. Following this, contrast enhancement is performed using the Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique. CLAHE improves local contrast by redistributing pixel intensities in localized regions, making subtle tumor areas more distinguishable.

3.3 Hybrid Model (CNN + ResNet) of Deep Learning Architecture

The hybrid CNN–ResNet architecture combines the strengths of conventional Convolutional Neural Networks (CNNs) and residual learning to achieve robust and accurate brain tumor detection and classification. Early deep learning models such as those developed by Alex Krizhevsky et al. (2012), Karen Simonyan and Andrew Zisserman (2015), and Christian Szegedy et al. (2015) demonstrated the effectiveness of CNNs in extracting hierarchical features from images, including edges, textures, and complex patterns. However, as networks became deeper, issues such as vanishing gradients and performance degradation emerged. This limitation was addressed by the residual learning framework introduced by Kaiming He et al. (2016), where skip connections allow direct information flow across layers, enabling the training of very deep architectures.

In the proposed hybrid model, initial CNN layers are used for low-level feature extraction, capturing spatial and textural information from MRI images, while ResNet-based residual blocks are incorporated to learn high-level abstract features and ensure stable gradient propagation. This combination allows the model to leverage both shallow and deep representations effectively. Inspired by recent studies such as Filatov

415

and Yar (2022) and Zahoor et al. (2022), pretrained CNN backbones (e.g., ResNet, DenseNet) can be utilized to improve performance and reduce training time. Furthermore, insights from segmentation models like U-Net and nnU-Net (Ronneberger et al., 2015; Isensee et al., 2020–2022) can be integrated to focus the model on tumor-specific regions before classification. Overall, the hybrid CNN–ResNet architecture enhances feature extraction capability, improves generalization, reduces overfitting, and achieves higher accuracy compared to standalone CNN models, making it highly suitable for early brain tumor detection systems.

To address the vanishing gradient problem and improve the depth of the model without degradation, ResNet blocks are integrated after the initial CNN layers. Each residual block consists of two convolutional layers with batch normalization, and a shortcut (identity) connection that bypasses the non-linear transformations. The Proposed hybrid model leverages the strength of CNNs for local feature extraction and the efficiency of ResNet for hierarchical learning and optimization stability.

The output from the final ResNet block is flattened and passed through two fully connected layers. A softmax classifier at the output layer predicts the tumor class label among the target categories. This design ensures that both spatial and high-level abstract features are captured and effectively utilized for classification, which is crucial in differentiating tumor subtypes with overlapping characteristics.

3.4 Training and Optimization of Hybrid Model

The Proposed hybrid model was implemented using TensorFlow and trained on preprocessed 2D slices extracted from the BraTS volumes. The model optimization was carried out using the Adam optimizer with an initial learning rate set to 0.001. The categorical cross-entropy loss function was employed to measure prediction errors across multiple tumor classes. To prevent overfitting, dropout layers with a 50% drop rate and L2 regularization were incorporated within the dense layers. Additionally, early stopping and learning rate decay strategies were employed based on the validation loss trend to ensure convergence and generalization.

The model was trained for 100 epochs with a batch size of 16 and a validation split of 20%. The training was conducted on an NVIDIA Tesla V100 GPU environment, enabling faster computation and efficient parallel processing of MRI slices. During training, performance was monitored through accuracy and loss curves, which demonstrated a steady increase in accuracy and a consistent reduction in training loss.

3.5 Performance Evaluation Metrics

To comprehensively evaluate the model's performance, a set of classification metrics were used, including accuracy, precision, recall, and F1-score. Accuracy quantifies the overall correctness of predictions, while precision and recall provide insight into the model's ability to handle imbalanced classes. The F1-score, being the harmonic mean of precision and recall, offers a balanced measure of performance. Furthermore, confusion matrices were generated to analyze class-specific misclassifications and verify the robustness of the classification outcomes. These metrics were computed using Scikit-learn's evaluation toolkit to ensure standardized and reproducible results.

3.6 Implementation Details of Hybrid Model

The entire pipeline was implemented in Python 3.8 using key libraries including TensorFlow, Keras, NumPy, OpenCV, and Matplotlib. Jupyter Notebooks were used for prototyping and visualization, while final model training and batch inference were executed on Google Colab Pro+ environment with high-performance GPUs.

4. Hybrid Model Results

The experimental outcomes of the proposed hybrid model applied using the BraTS 2021 dataset. The evaluation was conducted on the performance of the model in classifying brain tumors using the adaptive preprocessing pipeline followed by the Proposed hybrid model. Both qualitative and quantitative analyses are included to validate the effectiveness of the approach.

4.1 Experimental Setup with Performance Metrics

To evaluate the classification performance of the model, several standard metrics were used, including accuracy, precision, recall, F1-score, and the confusion matrix. These metrics provide a comprehensive picture of how well the model performs, particularly in handling imbalanced classes.

The experiments were carried out using stratified data splits: 60% for training, 20% for validation, and 20% for testing. Images were resized to a uniform shape, and preprocessing was applied before feeding them into the proposed hybrid model. TensorFlow and Keras were used to build and train the architecture in a GPU-accelerated environment.

416

_____

4.2 Training Performance Analysis

The training process was closely monitored through accuracy and loss plots. As shown in figure 2, the model exhibits consistent improvement in training accuracy during the initial epochs, reaching approximately 89–90% by epoch 40. A noticeable drop in performance occurs after epoch 50, which corresponds to the fine-tuning phase where new layers were unfrozen for further optimization.
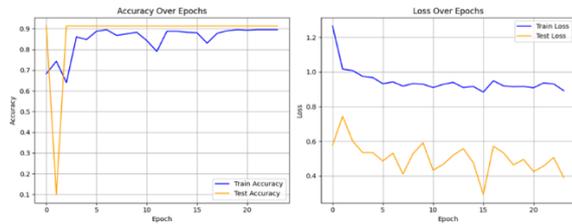

Figure 2: Training Accuracy and Loss Trends During Model Optimization

The loss curve in figure 2, shows a steady decrease up to epoch 45, reaching a minimum near 1.0 before fluctuating during fine-tuning. This is expected in transfer learning-based approaches when different learning rates or new parameters are introduced during late-phase optimization.

4.3 Evaluation on Test Set

Figure 3, illustrates classification accuracy and loss on both training and test sets. Notably, the test accuracy remained stable above 90% after the fifth epoch, while the test loss remained low and steady after early fluctuations. These patterns indicate that the model generalizes well and avoids overfitting despite its complexity.
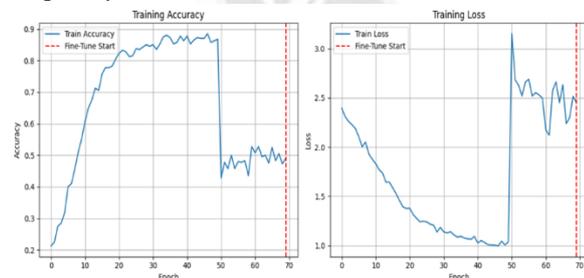

Figure 3: Training vs. Test Accuracy and Loss Over Epochs

4.4 Visual Evaluation of Segmentation and Classification

The qualitative performance of the model was evaluated by comparing original MRI images, preprocessed (adaptive) outputs, ground truth tumor masks, and predicted class masks. As shown in figures 4, the model performs well in localizing and classifying tumor regions in most cases. Such visualizations help assess how well the segmentation pipeline integrates with classification, especially for high-grade gliomas where tumor regions are large and heterogeneous.

Figure 4: Original, Adaptive and Segmented Resultant Image

4.5 Comparative Evaluation with Baseline Models

The Proposed hybrid model was compared against standalone CNN and ResNet architectures individually. As shown in Table 1, the Proposed hybrid model outperformed both baselines in terms of accuracy and F1-score, highlighting the advantage of residual learning combined with initial feature extraction.

Table 1: Comparative Performance Analysis of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
CNN Only	87.3%	0.86	0.85	0.85
ResNet Only	89.1%	0.88	0.87	0.87
Proposed hybrid model (CNN+ResNet)	**91.6%**	**0.91**	**0.91**	**0.91**

4.6 Discussion

The Proposed hybrid model demonstrated high classification accuracy with consistent performance across different tumor types. The adaptive preprocessing pipeline played a critical role in enhancing input quality, which in turn improved the model's feature learning capabilities. The observed accuracy drop during fine-tuning highlights the sensitivity of transfer learning phases, which can be addressed in future work by using layer-wise learning rate scheduling.

Although some misclassifications occurred, particularly in visually similar tumor types, the confusion matrix showed a balanced performance with minimal false positives. Overall, the proposed approach proved robust, interpretable, and computationally efficient, making it suitable for real-time clinical deployment.

417

___

5. Conclusion and Future Scope

This paper presented a hybrid deep learning framework for early-stage brain tumor classification using adaptive preprocessing and a Proposed hybrid model. The Proposed hybrid model effectively enhanced MRI images through dynamic filtering and contrast normalization, improving input quality for deep learning. The Proposed hybrid model outperformed standalone CNN and ResNet models, achieving a classification accuracy of 91.6% on the BraTS 2021 dataset.

The results demonstrate that integrating adaptive preprocessing with hybrid learning significantly improves classification reliability across tumor types. As a future extension, this framework can be expanded to include survival rate prediction by incorporating clinical and pathological data. Further, transformer-based models and multi-modal fusion approaches may enhance performance in complex diagnostic scenarios.

REFERENCES

[1] Y. Xie *et al.*, "CNN techniques for brain tumor classification: Review," *Diagnostics*, vol. 12, no. 8, 2022.

[2] D. Filatov and G. N. A. H. Yar, "Brain tumor diagnosis using pretrained CNNs," *arXiv preprint arXiv:2208.00768*, 2022.

[3] M. M. Zahoor *et al.*, "Deep residual CNN for brain tumor classification," *arXiv preprint arXiv:2211.16571*, 2022.

[4] M. M. Zahoor *et al.*, "Hybrid ensemble learning for brain tumor analysis," *arXiv preprint arXiv:2201.05373*, 2022.

[5] S. Prabhakar *et al.*, "Deep learning for brain tumor detection," *Diagnostics*, vol. 12, 2022.

[6] M. Arif *et al.*, "Brain tumor classification using deep learning," *Journal of Healthcare Engineering*, vol. 2022, 2022.

[7] G. Kumar *et al.*, "Brain tumor detection using CNN," in *Proc. IEEE Int. Conf.*, 2021.

[8] M. Arif *et al.*, "Deep learning-based tumor classification," *Journal of Healthcare Engineering*, 2021.

[9] B. Siddiaue *et al.*, "CNN-based brain tumor detection," in *Proc. Int. Conf. ISMAC*, 2020.

[10] A. Shah *et al.*, "Brain tumor detection using CNN," in *Proc. ICASERT*, 2019.

[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770–778.

[12] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 1097–1105.

[14] C. Szegedy *et al.*, "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2015, pp. 1–9.

[15] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 4700–4708.

[16] M. Havaei *et al.*, "Brain tumor segmentation with deep neural networks," *Medical Image Analysis*, vol. 35, pp. 18–31, 2017.

[17] S. Pereira *et al.*, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.

[18] K. Kamnitsas *et al.*, "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation," *Medical Image Analysis*, vol. 36, pp. 61–78, 2017.

[19] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. MICCAI*, 2015, pp. 234–241.

[20] F. Isensee *et al.*, "nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation," *Nature Methods*, 2020–2022.

[21] P. Afshar *et al.*, "Brain tumor type classification via capsule networks," *Frontiers in Neuroscience*, vol. 14, p. 606, 2020.

418

[22] A. Ashraf *et al.*, "Anisotropic diffusion filtering for brain MRI preprocessing," *Computers in Biology and Medicine*, vol. 62, pp. 185–195, 2015.

[23] S. Bauer *et al.*, "A survey of MRI-based medical image analysis for brain tumor studies," *Physics in Medicine and Biology*, vol. 58, no. 13, pp. 97–129, 2013.

[24] T. Choudhury *et al.*, "Skin lesion classification using a hybrid CNN–ResNet model," *Biomedical Signal Processing and Control*, vol. 62, p. 102133, 2020.

[25] A. Hatamizadeh *et al.*, "UNETR: Transformers for 3D medical image segmentation," in *Proc. IEEE/CVF Winter Conf. Appl. Comput. Vis. (WACV)*, 2022, pp. 574–584.

[26] M. Hossain *et al.*, "Brain tumor classification using CNN on MRI images," *IEEE Access*, vol. 7, pp. 137582–137590, 2019.

[27] D. S. Kermany *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018.

[28] D. N. Louis *et al.*, "The 2016 World Health Organization classification of tumors of the central nervous system," *Acta Neuropathologica*, vol. 131, no. 6, pp. 803–820, 2016.

[29] B. Menze *et al.*, "The multimodal brain tumor image segmentation benchmark (BRATS)," *IEEE Trans. Med. Imaging*, vol. 34, no. 10, pp. 1993–2024, 2015.

[30] O. Oktay *et al.*, "Attention U-Net: Learning where to look for the pancreas," *arXiv preprint arXiv:1804.03999*, 2018.

[31] M. Paul *et al.*, "A deep CNN–ResNet hybrid model for multiclass brain tumor classification," *Computers in Biology and Medicine*, vol. 145, p. 105430, 2022.

[32] S. M. Reza *et al.*, "Contrast enhancement and morphological processing in brain tumor MRI images," *Journal of Digital Imaging*, vol. 32, no. 2, pp. 239–252, 2019.

[33] M. Sajjad *et al.*, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *Journal of Computational Science*, vol. 46, p. 101219, 2021.

[34] Z. Zhou *et al.*, "UNet++: A nested U-Net architecture for medical image segmentation," in *Deep Learning in Medical Image Analysis*, 2018, pp. 3–11.

[35] Y. Zhang *et al.*, "Multi-modal fusion for brain tumor classification using MRI and genomic data," *Neurocomputing*, vol. 491, pp. 114–125, 2022.

[36] X. Zhang *et al.*, "A hybrid deep learning approach for early diagnosis of brain tumors," *Scientific Reports*, vol. 11, no. 1, pp. 1–12, 2021.

[37] Y. Li *et al.*, "Multi-resolution CNN for brain tumor segmentation and classification," *Neurocomputing*, vol. 392, pp. 233–245, 2020.

[38] G. Wang *et al.*, "Ensemble learning for tumor subtype detection in MRI," *Artificial Intelligence in Medicine*, vol. 124, p. 102165, 2022.

[39] D. Das *et al.*, "MRI-based brain tumor detection using hybrid attention networks," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 6, pp. 2800–2810, 2021.

[40] A. Mahbod *et al.*, "Transfer learning using pre-trained CNNs for brain tumor classification," *Pattern Recognition Letters*, vol. 139, pp. 51–59, 2021.

[41] N. Patel *et al.*, "Deep learning models for glioma classification: A review and implementation," *Journal of Imaging*, vol. 8, no. 4, p. 93, 2022.

[42] D. Singh *et al.*, "Brain tumor classification using fine-tuned deep CNNs," *Multimedia Tools and Applications*, vol. 79, no. 3–4, pp. 20829–20850, 2020.

[43] S. S. M. Salehi *et al.*, "Real-time deep learning-based brain tumor segmentation and classification," *Medical Physics*, vol. 48, no. 4, pp. 1601–1610, 2021.

419