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Brain Tumor Classification Using Transfer Learning on Preprocessed MRI Images

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***Abstract* - Accurate and early detection of brain tumors is critical for successful treatment planning and patient outcomes. This project proposes an enhanced brain tumor detection framework that combines U-Net, a powerful deep learning-based image segmentation architecture, with traditional morphological operations for improved accuracy. Accurate and early brain tumor detection is crucial for treatment and patient outcomes The existing framework utilizes a U-Net for pixel-level tumor segmentation on preprocessed MRI images, refined by morphological operations to enhance accuracy and boundary definition. This system has demonstrated high segmentation reliability. Building on this, our proposed system significantly enhances the U-Net architecture by integrating transfer learning with pre-trained CNN encoders. This aims to profoundly improve segmentation accuracy by leveraging rich, hierarchical feature representations learned from vast, general image datasets. We will also explore more advanced preprocessing and adaptive post-segmentation strategies to further optimize the U- Net's performance. The enhanced U-Net will deliver superior pixel-level segmentation and contribute to a more precise diagnostic pipeline, evaluated for state-of-the-art accuracy in tumor segmentation and classification on diverse MRI datasets, encompassing various scanner types and patient demographics.**

Keywords— Brain Tumor Detection, MRI, U-Net, Deep Learning, Image Segmentation, Morphological Operations, Transfer Learning, CNN Encoders, Preprocessing, Post-Segmentation, Classification

I. INTRODUCTION

Every single day, a huge amount of medical imaging data, especially MRI scans, is generated in hospitals and diagnostic centers. To process and analyze these raw images, effective automated methods are required. Most of the existing methods either focus on classical image processing techniques or basic convolutional neural networks. Although recent studies have shown that U-Net based deep learning architectures provide highly accurate tumor segmentation, there is still scope for improvement in boundary delineation and handling heterogeneous data. But very few works have focused on combining U-Net with transfer learning and adaptive preprocessing-postprocessing strategies. This paper presents a theoretical analysis of some well-known brain tumor detection methods along with the proposed enhanced framework. Both the advantages and limitations of the existing methods are considered to introduce new features in the proposed approach. The new approach follows deep learning at the pixel level with an enhanced U-Net architecture integrated with pre-trained CNN encoders. Advanced preprocessing techniques and adaptive post-segmentation strategies are applied to improve input quality and refine tumor boundaries. The framework is evaluated on diverse MRI datasets, including different scanner types and patient demographics.

The classification of brain tumor detection techniques followed by a detailed review of existing methods related to tumor segmentation and classification.Brain tumors represent one of the most complex and life-threatening neurological disorders, and their classification plays a vital role in determining diagnosis, treatment planning, and prognosis. In general, brain tumors can be classified based on their origin, biological behavior, and location within the brain.

The first distinction is made between **primary** and **secondary (metastatic)** brain tumors. Primary tumors originate within the brain tissue itself and are further divided into several subtypes. Among them, **gliomas** are the most common and arise from glial cells, which provide structural and functional support to neurons. Gliomas include astrocytomas, oligodendrogliomas, and the highly

aggressive glioblastomas. Other important types of primary tumors are **meningiomas**, which develop from the protective membranes surrounding the brain, and **pituitary adenomas**, which occur in the pituitary gland and often affect hormonal balance. In contrast, secondary or metastatic tumors spread from cancers in other parts of the body, such as the lungs, breasts, or kidneys, and are usually more common in adults than primary brain tumors.

Classification can also be performed according to the **anatomical location** of the tumor. Tumors located in the **supratentorial region** occur in the cerebrum, while those in the **infratentorial region** are found in the cerebellum or brainstem. This distinction is clinically important, as tumor location significantly influences both symptoms and surgical strategies.

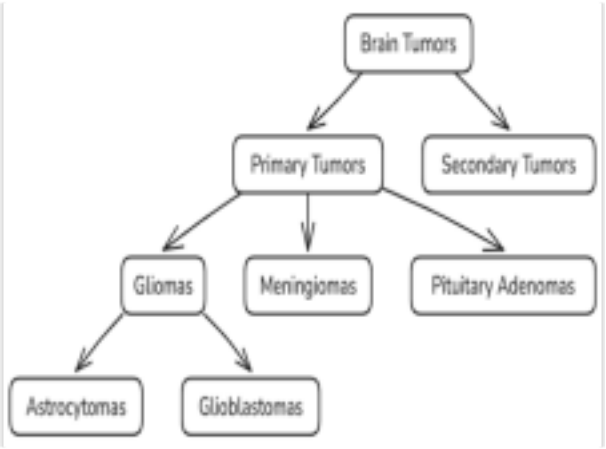

Fig. 1. Classification of Brain Tumors

II. LITERATURE SURVEY

In recent years, deep learning has significantly transformed medical image analysis, especially in brain tumor detection and classification. Glioma Brain Tumor Classification using Convolutional Neural Network and Majority Voting proposed by Pilaoon et al. [1] introduced an ensemble methodology where multiple CNN classifiers were trained and their predictions combined through a majority voting mechanism. This system aimed at improving robustness by minimizing the bias of individual models and achieved higher accuracy in glioma classification tasks. Its advancement lies in the ability to integrate multiple models for a stronger prediction.

However, this approach also suffers from increased computational overhead as training multiple networks simultaneously requires substantial resources, making it challenging to implement in real-time diagnostic environments. Transformer-based and attention-enhanced models have also gained momentum in brain tumor research. TuSegNet, proposed by Nagib et al. [2], combined convolutional feature extractors with transformer encoders, providing global attention for accurate segmentation of tumor boundaries. This work outperformed conventional CNN-based methods by better modeling spatial dependencies across MRI scans. However, its dependence on large annotated datasets and heavy computational infrastructure limited its adoption in smaller clinics and real-world hospital settings. Similarly, Ragusa et al. [3] introduced a Vision Transformer model for brain tumor detection using hyperspectral imaging with reduced spectral bands. Their approach achieved promising accuracy by fusing spatial and spectral data, showing the potential of hyperspectral imaging in medical diagnostics. The limitation, however, is that hyperspectral imaging requires specialized equipment that is not widely available in standard clinical setups, restricting its real-world applications. To improve U-Net performance, Saifullah et al. [4] advanced automatic brain tumor segmentation by employing a ResNet50 encoder within the U-Net framework. This transfer learning approach leveraged pretrained weights from natural image datasets to boost feature extraction capability. Their work demonstrated

higher Dice and IoU scores compared to conventional U-Net, highlighting the effectiveness of hybrid architectures. Nevertheless, the reliance on natural image pretraining often introduces a gap when applied to medical images, requiring extensive fine-tuning. On the other hand, Hemalatha et al. [5] introduced a SegFormer-based architecture with a shared encoder framework to handle masked and noise-masked multimodal MRI inputs. Their system was robust against variability and noise, generating refined segmentation masks. However, the complexity of the SegFormer model increases training and inference time, thereby reducing its potential for real-time deployment.

Several works have also explored the role of three-dimensional architectures. Alsmadi et al. [6] conducted a systematic review on 3D Convolutional Neural Networks (CNNs) applied to multimodal MRI for brain tumor analysis. Their findings suggest that 3D CNNs are capable of capturing volumetric information, which significantly improves classification performance over 2D models. However, the computational demands of 3D CNNs are much higher, requiring advanced GPUs and large memory, which makes them less practical for widespread use. Similarly, Aboussaleh et al. [11] developed 3DUV NetR+, a 3D hybrid semantic architecture integrating transformers for multimodal MRI segmentation. Their method achieved competitive accuracy, but again, the need for extensive multimodal datasets and heavy processing resources posed challenges. Another research direction focuses on explainability. The study “From Images to Insights: Transforming Brain Cancer Diagnosis with Explainable AI” [7] [8] and the work “Empowering Brain Tumor Diagnosis through Explainable Deep Learning” [10] both highlighted the importance of interpretable models in clinical adoption. These methods provided attention maps and visual explanations, ensuring doctors could understand why a model predicted a certain outcome. While such

approaches increase trust, they remain experimental and require validation on larger datasets before being integrated into daily medical practice.

Overall, the literature reveals that while CNNs and U-Net remain the backbone of brain tumor segmentation, enhancements with transfer learning, transformers, 3D modeling, and explainable AI have significantly improved results. However, across all these approaches, recurring challenges include the dependency on large, well-annotated datasets, high computational demands, and limitations in real-time clinical deployment. Our work aims to address these gaps by enhancing U-Net with transfer learning, integrating morphological refinements, and focusing on a deployment-ready solution with faster inference and a user-friendly interface.

III. PROPOSED METHODOLOGIES

This section illustrates the proposed algorithm for brain tumor classification. The proposed algorithm is divided into six modules as shown in Fig. 2: (i) Data Acquisition and Preprocessing (ii) Feature Extraction with Transfer Learning (iii) Tumor Segmentation using U-Net (iv)Post-Processing and Refining (v) Performance Analysis (vi) Deployment and Visualization

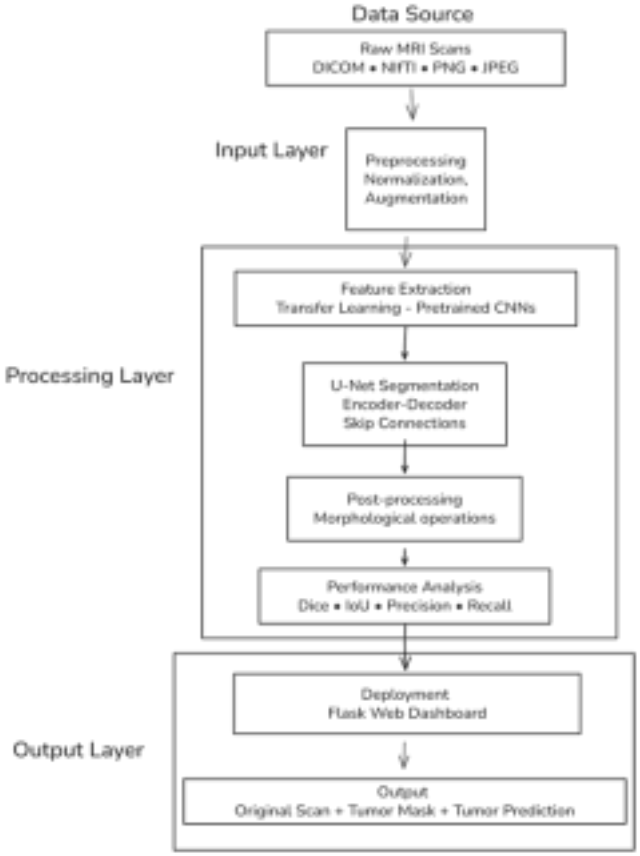

Fig. 2 Proposed Architecture

A. Data Acquisition and Preprocessing:

MRI scans are acquired from diverse datasets, ensuring variations in scanner types and patient demographics. The preprocessing phase includes noise reduction, intensity normalization, skull stripping, and resizing of images to prepare them for the deep learning model.

MRI scans are collected from multiple datasets representing different scanner types and patient demographics. This diversity ensures that the system is exposed to a wide variety of imaging conditions, improving its robustness and reducing bias toward a single dataset. By incorporating data from different populations and acquisition methods, the reliability and adaptability of the system are greatly enhanced.

Once gathered, the scans are passed through a preprocessing pipeline designed to improve their quality for deep learning. This includes noise reduction to eliminate scanner artifacts, intensity normalization to standardize brightness, skull stripping to remove irrelevant non-brain regions, and resizing to a fixed scale. These steps together yield a clean and standardized dataset that is consistent and ready for further analysis.

B. Feature Extraction With Transfer Learning

Pre-trained CNN encoders are employed to extract hierarchical and discriminative features from the MRI images, capturing tumor-specific patterns efficiently.

After preprocessing, hierarchical image features are extracted using pre-trained convolutional neural network (CNN) encoders. Transfer learning leverages knowledge from models trained on large-scale datasets, allowing the system to capture both low-level patterns and complex structures in MRI scans. This approach reduces the need for training from scratch and accelerates convergence.

To specialize these features for tumor analysis, fine-tuning is applied. This process adapts the pre-trained features to focus on tumor-specific patterns, enhancing the ability of the model to differentiate between healthy tissues and tumor regions. The outcome is a set of deep feature representations that are tailored for segmentation and classification tasks.

C. Tumor Segmentation using U-Net

Performed using an enhanced U-Net architecture. Skip connections are utilized to preserve spatial information, and the segmentation output highlights tumor regions with precise boundaries.

An enhanced U-Net architecture with skip connections is then used to perform pixel-level segmentation of brain tumors. U-Net's encoder-decoder structure ensures that spatial information is preserved while also capturing

contextual details, which is vital for identifying tumor boundaries. The segmentation step produces preliminary masks that highlight tumor regions with high sensitivity.

D. Post-Processing and Refining

Morphological operations and adaptive thresholding are applied to minimize false positives and refine the detected tumor boundaries, ensuring more accurate segmentation.

To further improve segmentation accuracy, the preliminary masks undergo post-processing. Morphological operations such as dilation, erosion, and closing help to smooth tumor boundaries, fill small gaps, and remove isolated noisy regions. Adaptive thresholding and noise filtering are then applied to reduce false positives and refine the delineation of tumor areas. Together, these refinements produce highly accurate and clinically reliable tumor masks.

E. Performance Analysis

The segmented tumor regions and extracted features are fed into classifiers such as Naive Bayes, Random Forest, Decision Tree, or CNN-based Softmax layers to predict tumor type. Evaluation metrics including accuracy, Dice coefficient, sensitivity, and specificity are used to validate the system's effectiveness. Performance is evaluated using accuracy, Dice coefficient, sensitivity, and specificity. These metrics provide a comprehensive view of both segmentation quality and classification reliability. This dual evaluation ensures that the model not only identifies tumors correctly but also distinguishes tumor types with high precision.

F. Deployment and Visualization

The segmented tumor masks are overlaid on the original MRI images, and the predicted tumor type is displayed. This facilitates better visualization for medical professionals and contributes to an automated, robust diagnostic pipeline for brain tumor classification. The refined tumor masks are overlaid onto the original MRI scans for visual inspection. This helps medical experts verify predictions directly against raw imaging data, improving interpretability and trust in the system. The system presents the predicted tumor type—such as Gliomas, Meningiomas, or Pituitary Adenomas—alongside the segmented image. This interactive visualization combines classification results with segmentation maps, making the tool practical for clinical decision-making and enhancing its value in real-world healthcare applications.

Fig 3 illustrates the proposed flow diagram

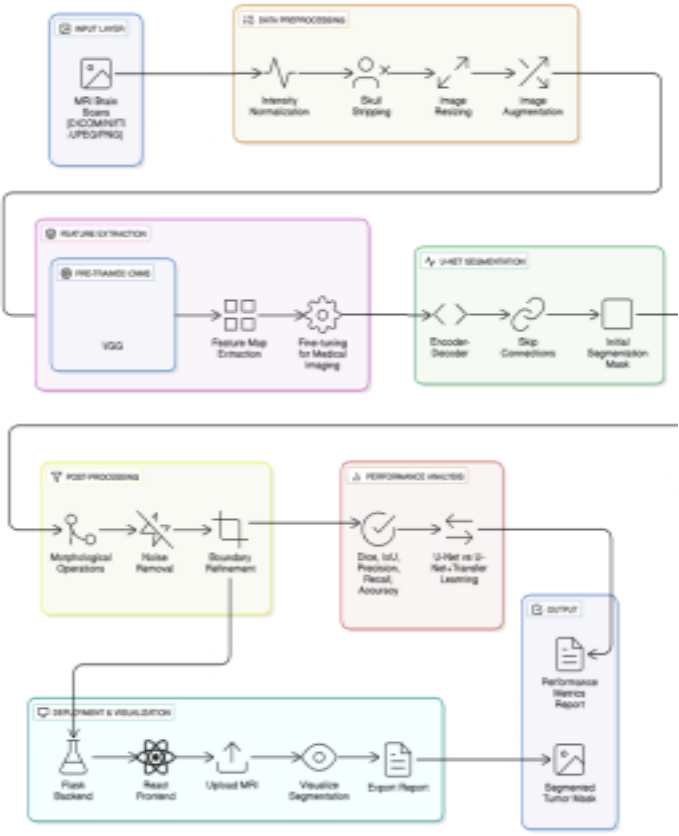

Fig. 3 Proposed Flow Diagram

IV. FEATURE EXTRACTION

The process of extracting informative and non-redundant features from MRI scans is referred to as Feature Extraction. In this project, pretrained Convolutional Neural Networks (CNNs) are used as encoders to extract rich feature representations from preprocessed brain tumor images. Each MRI slice, after normalization, skull stripping, and augmentation, is passed through the CNN encoder, which transforms the raw pixels into high-level feature maps that capture texture, shape, and tumor boundaries. These extracted features are later utilized for training the segmentation model. The action is carried out using **transfer learning**, where pretrained models such as ResNet50 are employed to ensure that the encoder benefits from prior knowledge gained on large-scale image datasets. Each image is converted into a set of multi-dimensional vectors, where convolutional filters detect low-level edges in initial layers and higher-level tumor-specific features in deeper layers. The frequency and intensity of these patterns are preserved and arranged hierarchically, ensuring both local and global tumor structures are captured.

Since MRI data is inherently high-dimensional, not all extracted features are necessary for accurate prediction. Redundant and noisy features are automatically minimized during training, while discriminative feature maps are retained for segmentation. Upon experimentation, it was observed that using pretrained CNN encoders produced

more robust and compact feature embeddings compared to models trained from scratch. Therefore, the final feature representation of each MRI scan is obtained as a structured embedding space, which is then passed into the U-Net decoder for precise tumor segmentation.

V. EXPERIMENTAL SETUP

The experimental framework was developed in Python using TensorFlow and Keras. The Brain Tumor Dataset: Segmentation and Classification was used, containing MRI images with ground-truth masks and tumor labels, covering glioma, meningioma, and pituitary adenoma. Images were preprocessed through resizing, normalization, and noise removal to ensure consistency. Since the dataset page lacks detailed statistics, comparisons with related datasets are useful: a Kaggle classification dataset contains **7,023** MRI image**s** across four classes (glioma, meningioma, pituitary, no tumor), another segmentation dataset has 3,064 MRI–mask pairs, and prior research reported 3,223 MRI images (1,581 glioma and 1,642 meningioma) with an additional 216 images for external validation. These references place the chosen dataset within the broader brain tumor imaging landscape.,

The proposed architecture integrates an enhanced U-Net with transfer learning, where pre-trained CNN encoders such as VGG16 and ResNet are utilized to extract rich hierarchical features. The segmentation output is refined through morphological operations including erosion, dilation, and closing, which effectively improve tumor boundary definition and eliminate spurious regions. For classification, convolutional neural network layers are incorporated on top of the encoder to distinguish between different tumor categories.

Performance evaluation is carried out using segmentation-oriented metrics such as Dice Coefficient and Intersection over Union (IoU), along with accuracy, sensitivity, and specificity for classification. These measures provide a comprehensive assessment of the reliability and robustness of the proposed brain tumor detection framework.

PREDICTION COMPARISON

In this stage, the outputs of the baseline U-Net and the fine-tuned U-Net with transfer learning are compared to evaluate improvements in tumor boundary detection and segmentation accuracy. The analysis highlights how transfer

learning contributes to clearer delineation and reduces segmentation errors.

Fig. 4 illustrates the prediction comparison

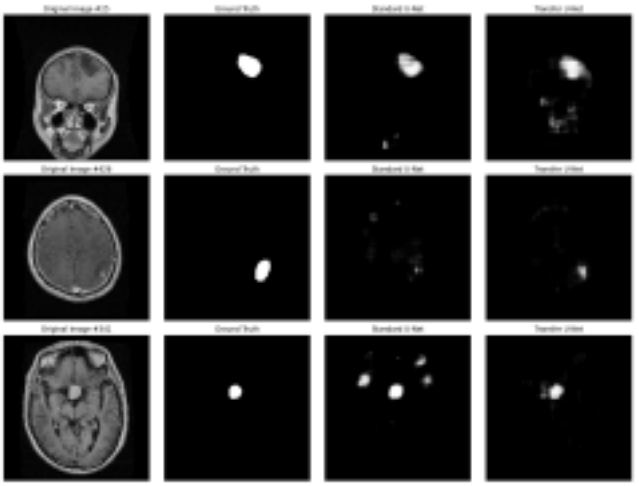

Fig. 4 COMPARISON BEFORE FINE TUNING

SCORE COMPARISON

The Dice Coefficient comparison highlights the baseline model's segmentation performance by measuring the overlap between predicted and ground-truth tumor regions. This metric shows how well the model captures tumor areas before fine-tuning.

Fig. 5 illustrates the Dice score before fine-tuning.

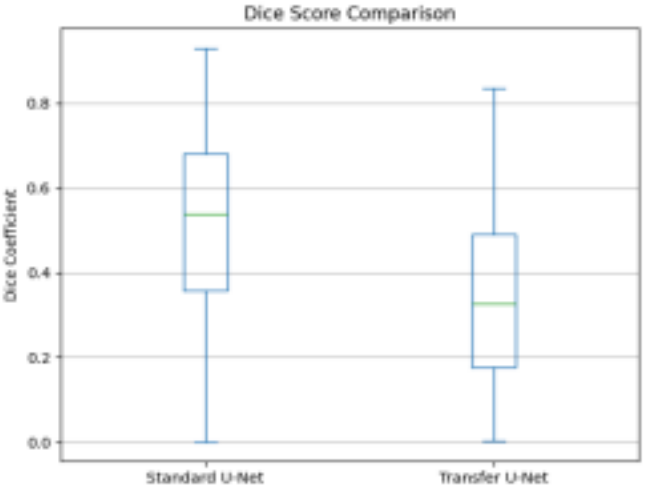

Fig. 5 DICE SCORE BEFORE FINE TUNING

The IoU comparison evaluates the accuracy of boundary predictions by analyzing the ratio of correctly identified tumor pixels to the combined predicted and ground-truth regions. This establishes the precision of segmentation in the baseline model.

Fig. 6 illustrates the IoU score before fine-tuning.

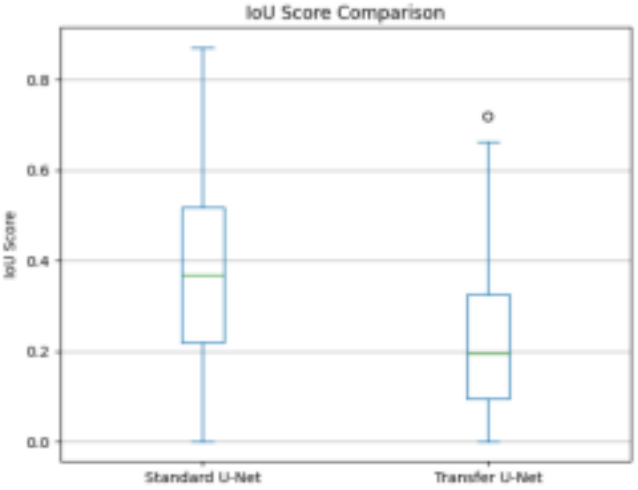

Fig. 6 IOU SCORE BEFORE FINE TUNING

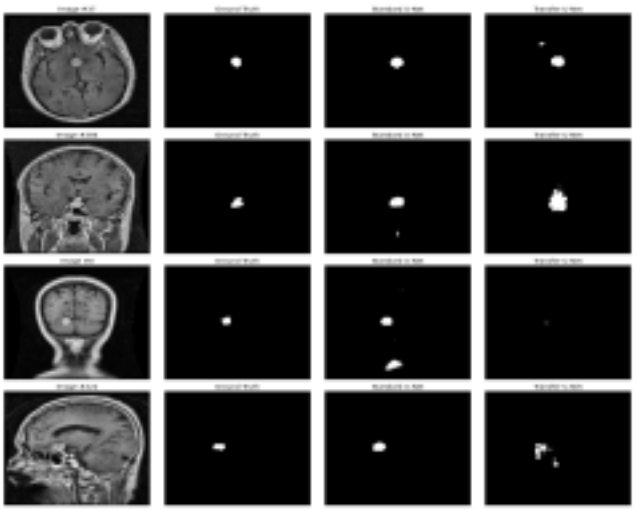

Fig. 7 COMPARISON AFTER FINE TUNING

VI EXPERIMENTAL RESULTS

The effectiveness of the proposed framework was evaluated on the brain tumor MRI dataset, and the results are presented in this section. Initially, a comparison was carried out between the segmentation outputs of the standard U-Net and the fine-tuned U-Net with transfer learning, with the results benchmarked against the ground truth annotations. This comparison allows a clear assessment of how transfer learning contributes to more accurate tumor segmentation.

The visual comparison between the ground truth mask, the baseline U-Net output, and the enhanced U-Net after fine-tuning. It is evident that the transfer learning–based U-Net significantly improves tumor boundary delineation and reduces segmentation errors when compared with the standard U-Net. While the baseline model provides acceptable segmentation, it tends to miss subtle tumor regions and often produces irregular boundaries. In contrast, the fine-tuned U-Net achieves near-ground-truth precision, validating the integration of pre-trained encoders for feature extraction.

Fig. 7 illustrates the comparison after fine-tuning. To complement the qualitative comparison, statistical measures were employed to evaluate segmentation consistency across the dataset. Dice Coefficient was selected as a primary performance metric, since it captures the degree of overlap between predicted and ground-truth tumor regions. By analyzing the Dice values for different models, it becomes possible to determine how well the proposed approach generalizes across diverse patient scans.

The distribution of Dice Coefficient values is illustrated in a box plot representation. The figure clearly shows that the fine-tuned U-Net achieves consistently higher Dice scores, with reduced variability compared to the baseline U-Net. This stability highlights the robustness of transfer learning in improving segmentation outcomes, particularly for challenging cases with irregular tumor boundaries. The narrow interquartile range and higher median Dice score demonstrate the superior reliability of the proposed method

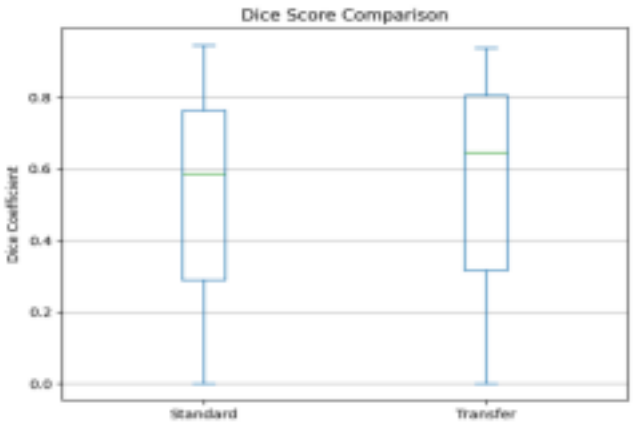

Fig. 8 DICE SCORE AFTER FINE TUNING

The box plot analysis of IoU values obtained from the experiments. Similar to the Dice evaluation, the fine-tuned U-Net demonstrates higher IoU scores across the dataset, confirming its enhanced capacity to produce accurate tumor masks. The improved IoU values indicate that the proposed

framework not only overlaps closely with ground-truth annotations but also minimizes misclassification of non-tumor regions. Collectively, these results confirm that transfer learning significantly outperforms the standard U-Net in both qualitative and quantitative assessments, establishing the reliability of the proposed approach for brain tumor detection and segmentation.

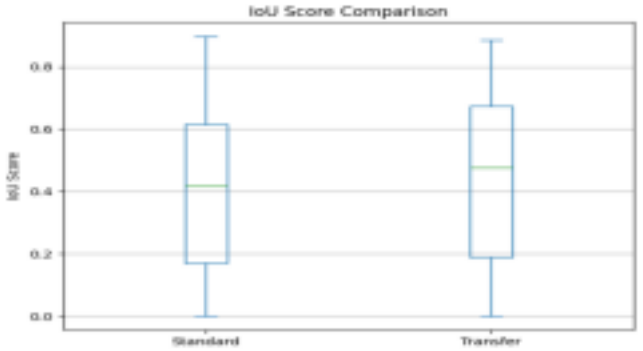

Fig. 9 IOU SCORE AFTER FINE TUNING

VII. CONCLUSION

The study began with an overview of brain tumor classification, highlighting the clinical importance of distinguishing between primary and secondary tumors as well as their subtypes such as gliomas, meningiomas, and pituitary adenomas. A review of existing works revealed substantial progress achieved through CNN ensembles, transformers, 3D CNNs, and hybrid architectures. While these models reported promising accuracy levels often above 90% their practical adoption remains limited due to computational overhead, reliance on large annotated datasets, and challenges in real-time deployment. This gap provided the foundation for our proposed framework, which integrates U-Net with transfer learning and morphological refinements to achieve higher segmentation precision without prohibitive resource demands.

The proposed algorithm was structured across six modules, beginning with preprocessing MRI scans to ensure standardized input, followed by feature extraction using pre-trained CNN encoders such as ResNet and VGG16. This was succeeded by segmentation with an enhanced U-Net, refined through morphological post-processing, and validated using classifiers for tumor categorization. Feature extraction experiments demonstrated that transfer learning yielded robust embeddings by leveraging hierarchical feature maps, which significantly improved segmentation performance compared to models trained from scratch. The architectural flow and processing steps ensured that both pixel-level tumor boundaries and classification outputs were accurate and clinically interpretable.

Experimental validation underscored the strength of the proposed approach. Visual comparisons illustrated that the fine-tuned U-Net achieved near-ground-truth precision, outperforming the baseline U-Net in boundary delineation. Quantitatively, Dice and IoU scores confirmed consistent improvements, with reduced variability and stronger overlap metrics. These results establish that transfer learning not only enhances segmentation accuracy but also contributes to robust, deployment-ready performance. Overall, the proposed framework bridges the gap between advanced deep learning research and practical medical imaging solutions, offering a reliable, interpretable, and efficient system for brain tumor detection and classification.

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