A CNN-based Approach to Automate Brain Tumor Classification

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***Abstract*—Brain tumors require an assessment to ensure timely diagnosis and effective patient treatment. Morphological factors such as size, location, texture, and variable appearance complicate tumor inspection. Medical imaging presents challenges, including noise and incomplete images. This research article presents a methodology for processing Magnetic Resonance Imaging (MRI) data, encompassing techniques for image classification and denoising. The effective use of MRI images allows medical professionals to detect brain disorders, including tumors. This research aims to categorize healthy brain tissue and brain tumors by analyzing the provided MRI test data. Unlike alternative methods like Computed Tomography (CT), MRI technology offers a more detailed representation of internal anatomical components, making it a suitable option for studying data related to brain tumors. The MRI picture is first subjected to a denoising technique utilizing an Anisotropic diffusion filter. Subsequently, the MRI picture undergoes segmentation with the application of Morphological operations aimed at enhancing the classification of images associated with the illness. A hybrid method utilizing Convolution Neural Networks (CNN) has been created, consisting of five separate sets of layers that include pooling and convolution layers. This method has superior performance relative to other existing techniques. The dataset employed for the model's development is a publicly available and validated Brain Tumor Classification (MRI) database, which consists of brain MRI scans, achieved an accuracy of 98%.**

***Index Terms*—MRI, CNN, BRAIN TUMOR, CT**

I. INTRODUCTION

The brain and spinal cord, collectively referred to as the Central Nervous System (CNS), are essential for the regulation of various biological functions. The functions include organization, analysis, decision-making, directive issuance, and information integration [1]. The human brain exhibits extraordinary complexity owing to its distinctive physical architecture. Stroke, infection, brain tumors, and migraines represent a minor fraction of central nervous system (CNS) illnesses that pose significant obstacles in diagnosis, evaluation, and the formulation of effective treatment methods [3]. Early detection of brain tumors, caused by the abnormal proliferation of brain cells, is a considerable challenge for neuropathologists and radiologists. The detection of cerebral malignancies by magnetic resonance imaging (MRI) is an intricate manual procedure prone to inaccuracies. Brain tumors are defined by the atypical growth of nerve cells, resulting in the formation of a mass. Approximately 130 unique tumor types can arise in the brain and central nervous system, encompassing both benign and malignant forms. The prevalence of various tumors differs, with some being exceptionally rare and others often observed [4].Approximately 700,000 individuals in the United States have been diagnosed with primary brain tumors. In the United States, around 85,000 new instances of brain tumors were documented in 2021. The patient's age is only one factor affecting prognosis and survival rates in brain tumor instances. Research referenced in [5] indicates that patients aged 55–64 had a one-year survival rate of 46.1%, but those aged 65–74 showed a survival rate of 29.3%. Imaging segmentation is utilized in the medical imaging field to divide the image into two pieces. A visual representation can be improved by extraction for analytical purposes. This transpires when the image is partitioned into multiple distinct segments. Medical diagnosis primarily relies on the scientific analysis of images. The existence of nuanced differences, specific types of noise, and the absence of evidence concerning impediments in medical imaging complicates the resolution of this issue. Computed tomography (CT) and magnetic resonance imaging (MRI) can be employed to investigate the interior architecture of the brain. Furthermore, it is more beneficial than employing an autonomous computed tomography (CT) apparatus. Owing to its absence of radiation, it has no effect on the human body. The magnetic field and radio waves are fundamental elements. Magnetic resonance imaging (MRI) is a frequently utilized technique for identifying brain tumors. It is a widely utilized non-invasive imaging modality that offers accurate distinction between tissues. The imaging of structures of interest in human brain tumors can be improved by MRI's ability to normalize frequently afflicted tissue. Researchers have lately encountered a significant obstacle in the manual segmentation of brain MRI images [7]. Abnormal brain tumors have frequently been identified by image segmentation. Various approaches require a patient-specific training dataset to conduct customized MRI tumor imaging studies. This dataset exacerbates the challenges for experts. These strategies generally rely on alternative imaging techniques, such as T1-weighted contrast-enhanced images. A continual challenge is the full automation of extract segmentation, which relates to accurate image segmentation. Capelle et al. presented two-dimensional T2-weighted magnetic resonance imaging (2D-T2MRI) [8].

II. RELATED WORKS

We have assessed multiple previous research efforts related to machine learning-based supervised, semisupervised, and unsupervised algorithms relevant to time series analysis. We conducted a thorough analysis to identify the shortcomings of the current system.This research improved the classification framework we developed for brain cancers.

- Pendela Kanchanamala et al. [9] developed an optimization-enhanced hybrid deep learning model for the detection and classification of brain tumors utilizing MRI, achieving scores of 0.929, 0.934, and 0.939 for brain tumor identification.
- Emrah Irmak [10] attained an accuracy of 92.66% utilizing a bespoke CNN model for the classification of normal, glioma, meningioma, pituitary, and metastatic brain tumors.
- Ayadi et al. [11] proposed a CNN-based computer-assisted diagnosis (CAD) method for the classification of brain cancers. Experiments performed on three separate datasets using the 18-weighted layered CNN model achieved a classification accuracy of 94.74% for brain tumor type classification and 90.35% for tumor grading.
- Khan et al. [12] (2020) presented a deep learning methodology for classifying brain tumors as malignant or benign, employing 253 authentic brain MRI scans with data augmentation.Edge detection was utilized to delineate the region of interest in the MRI image prior to feature extraction with a fundamental CNN model. The attained classification accuracy was 89%.
- Banerjee et al. [13] examined the potential use of deep learning techniques for glioma classification by MR imaging. The researchers assessed the effectiveness of transfer learning employing VGGNet and ResNet architectures, attaining accuracies of 84% and 90% for 2D images, respectively.
- In a distinct study [14], researchers presented two approaches for glioma grading, which included brain tumor segmentation with a modified U-Net model. A regional convolutional neural network (R-CNN) was utilized for the classification task in each two-dimensional image slice of the MRIs.Their proposed 2D Mask R-CNN attained an accuracy of 96%. The classification efficacy of the 2D model demonstrated that data augmentation improved the results [6].

In a specific application, certain machine learning models exhibit greater efficacy than others. However, the effectiveness of these models in classifying cardiovascular illnesses has not yet reached parity. Additional progress is necessary to improve the current state of the art.

III. METHODOLOGY

The methodology of this study involves a systematic approach to analyzing the Brain Tumor dataset to perform the most accurate classification of brain tumors using various deep learning models. The process is outlined in the accompanying structural outline, figure 1 illustrates the key steps and stages of the analysis.

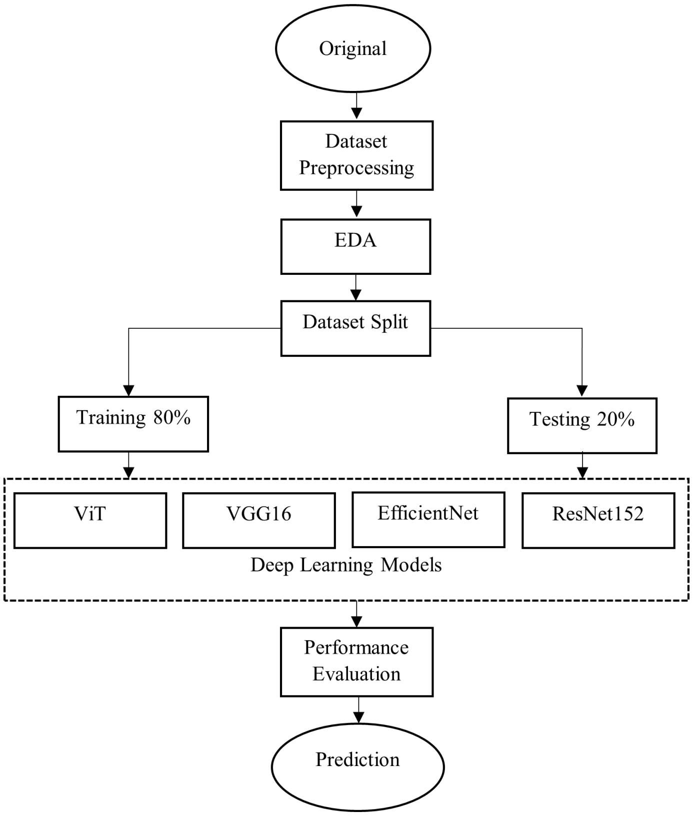


Fig. 1. The proposed methodology of the system.

Figure 1 illustrates the process of deep learning by using four neural networks, namely ResNet152, VGG, ViT, and EfficientNet models. Every model separately processes the supplied data and produces predictions. The models are subsequently compared to determine the most accurate prediction.

Utilizing a deep learning methodology, models are developed to calculate accuracy and assess predictions of different classes of brain tumors. This study incorporates four deep learning models, ViT (Vision Transformer), ResNet152, VGG16, and Efficient. The models can incorporate the distinctive characteristics and performance measurements that are pertinent to each position by classifying the tumors. In addition, the evaluation of the models involves the analysis of the f1 score, confusion matrix, and Receiver Operating Characteristic (ROC) curves.

IV. DATASET

The pipeline begins with feeding the image data into the ensemble system. These input images can be part of any image classification dataset. This study's dataset comprises four classes of various types of tumors, which are used to train and evaluate the models. The classes are Glioma Tumor, No Tumor, Meningioma Tumor, and Pituitary Tumor.

A. *Exploratory Data Analysis*

Exploratory Data Analysis (EDA) is applied to summarize the main features of the data, discover patterns, and identify any potential issues such as faulty images or outliers. Figure 2 shows the distribution of the training dataset across four different classes of brain tumors. Glioma Tumor forms 29% of the dataset used for training. Furthermore, meningioma tumors constitute 29% of the training sample. The Pituitary Tumor class covers an additional 29% of the training data. The No Tumor category comprises the smallest fraction, accounting for 14% of the training sample.

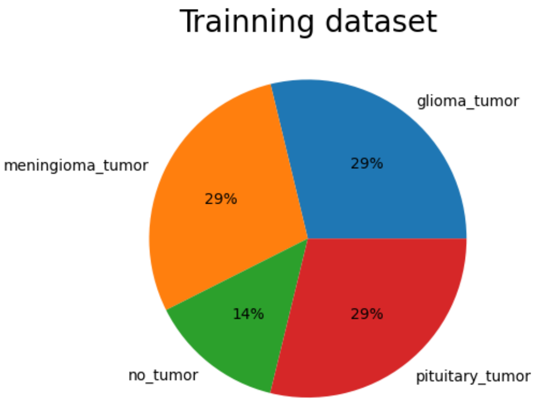


Fig. 2. The distribution of the training dataset.

Figure 3 illustrates a grid consist of twelve MRI brain scans, each annotated with a specific category of brain tumor: glioma, pituitary, or meningioma. The images are monochromatic and depict cross-sections of the human brain acquired from various perspectives and planes. Based on the variations in the placement and size of the tumors throughout the photos, each row appears to depict a distinct patient or case study. Multiple scans reveal the presence of glioma and pituitary tumors, as well as the meningioma tumor. The aforementioned images have significance in the fields of medical diagnosis, treatment planning, and research about brain tumors.

Figure 4 shows that the training dataset maintains an equitable distribution of around 800 photos for each type of tumor (meningioma, glioma, and pituitary), but has a smaller sample size (around 500) for the category of ”no tumor”. The test set shows a comparable trend, with approximately 100 photos allocated to each tumor group and a somewhat smaller number (roughly 70) for the ”no tumor” category. This implies that a well-balanced dataset is necessary for the successful training of a machine learning model, taking into account the presence of a somewhat under-represented ”no tumor” class, especially in the training set.

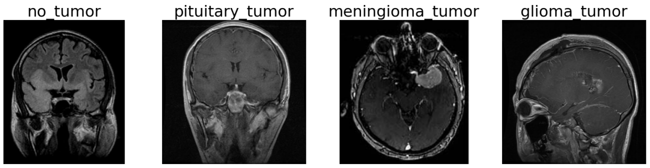


Fig. 3. Train image data from data augmentation.

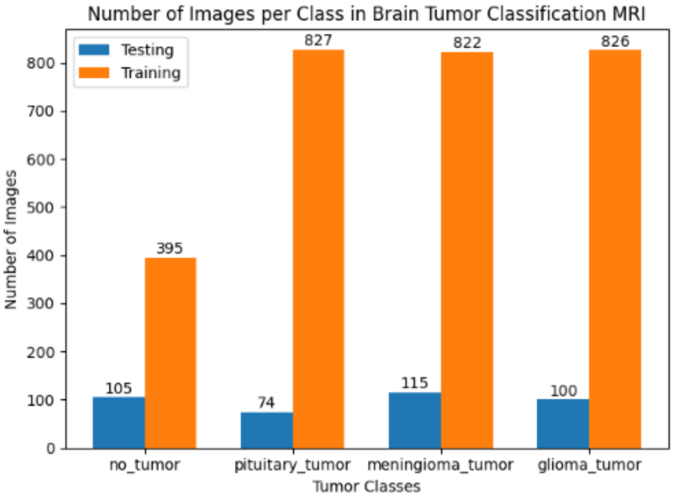


Fig. 4. Class distribution in train and test sets.

B. *Dataset Preprocessing*

A ratio of 80:20 is used to divide the training and test datasets. The training dataset is used to train the model, whereas the test dataset is used to evaluate the model's performance during training. Neural networks require inputs of a fixed size, requiring dimensional image adjustment. The size is reliant upon the architecture of the model being applied. It requires images with exactly 224x224 pixel size. Proper scaling ensures uniformity across the dataset. The implementation of data augmentation serves to augment the model's ability to generalize. Augmentation is the process of artificially creating several versions of images by applying transformations such as rotations, flips, zooms, or shifts. This method is especially beneficial when the dataset is modest in size or displays an imbalance. The dataset undergoes normalization. Because the pixel values of images often range from 0 to 255. However, neural networks demonstrate exceptional performance when the inputs are normalized, sometimes rescaled to a range of 0 to 1, or sometimes standardized to have a mean of zero and a standard deviation of one. Also, this ensures that the model attains accelerated convergence throughout the training phase. Label encoding is a technique used to convert string labels into numerical values. This includes one-hot encoding, which converts them into a specific binary vector representation. In addition, shuffling is implemented to ensure the random assortment of data, thereby improving the learning skills of the model and reducing the detection of organized patterns in the dataset. Before partitioning the data into training and validation sets, it is imperative to restructure it.

V. RESULT AND DISCUSSION

The preprocessed data is used to train various deep-learning models, utilizing the chosen classes. This study utilizes Vision Transformer, ResNet152, VGG16, and EfficientNet. Confusion matrix and ROC curves are developed to obtain optimal outcomes and provide a visual representation. Subsequently, the models are assessed utilizing diverse measures.

Figure 5 displays the effectiveness of four deep learning models VGG16, EfficientNet, ResNet152, and Vision Transformer in categorizing various types of brain tumors using ROC curves. Each graph plots the true positive rate (sensitivity) against the false positive rate to demonstrate the model's capacity to differentiate across tumor classifications. An AUC is a measure of the accuracy of a model, where values closer to 1 indicate superior performance.

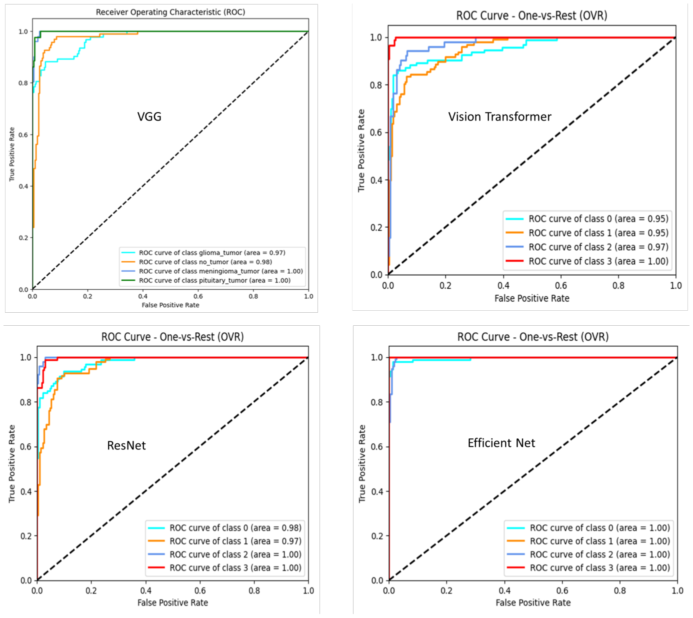
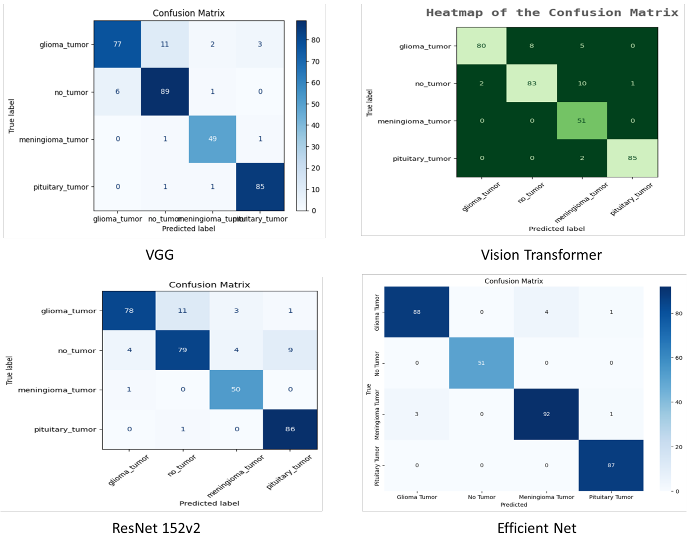


Fig. 5. ROC curves for all models.

In Figure 5, a constant pattern of excellent classification performance is observed across the models, as shown by ROC curves located in the upper-left corner of each plot. This indicates a high true positive rate and a low false positive rate. All models exhibit robust capabilities in accurately classifying various tumor types, with AUC values ranging from 0.97 to 1.00. As evidenced by their AUC values of 1.00, Efficient Net and Vision Transformer provide near-perfect classification accuracy for all tumor classifications, demonstrating flawless model performance with no false positives. These models systematically generate ROC curves that are closely grouped in the upper left corner of the graph, indicating exceptionally high sensitivity and accuracy for all types of tumors. VGG16 and ResNet152 display outstanding performance, with AUC values near 1.00, with minimal deviation from EfficientNet and Vision Transformer. Although the dissimilarities are small, both models have remarkable classification abilities, as evidenced by their ROC curves constantly indicating robust performance. The tiny variations in certain curves indicate that, although being very precise, there may be particular difficulties in differentiating between different types of tumors in comparison to the impeccable performance of the other two models.

Each confusion matrix in the figure 6 depicts the classification performance of four deep learning models, VGG16, EfficientNet, ResNet152, and ViT in categorizing brain cancers into four groups: glioma tumor, no tumor, meningioma tumor, and pituitary tumor. The matrices quantify the performance of the models by displaying accurate and inaccurate predictions for each class. In each matrix, the diagonal values correspond to accurate classifications.



VGG

Vision Transformer

ResNet 152v2

Efficient Net

Fig. 6. Confusion matrix for all models.

In Figure 6, EfficientNet demonstrates the best level of accuracy among the models, with nearly flawless classification rates for all types of tumors. Precision in differentiating between glioma and no tumor cases is very high, and there are no instances of misclassification in the meningioma and pituitary tumor categories. In addition to their strong performance in distinguishing between glioma and pituitary tumors, Vision Transformer and VGG16 demonstrate excellent accuracy in detecting meningioma tumors without any errors. While ResNet152 generally efficient, grapples with the challenge of differentiating between glioma tumors and the no tumor category, exhibiting the greatest frequency of misclassifications in this domain. The classification accuracy of meningioma tumors is consistently high across all models, with no instances of misclassifications detected. Confusion predominantly arises in glioma tumors and no tumor cases, especially within ResNet152, which erroneously classifies several glioma instances as no tumor and vice versa. Although there are occasional errors, all models exhibit robust overall performance. Among them, EfficientNet stands out as the most precise, while ResNet152 must undergo considerable refining to minimize misclassifications across specific tumor types.

In summary, the models display strong performance in differentiating various categories of brain tumors, with EfficientNet achieving the highest level of accuracy. Despite their great accuracy, especially in detecting meningioma and pituitary tumors, Vision Transformer and VGG16 have significant difficulty in differentiating glioma tumors from other types. While ResNet152 remains quite effective, it exhibits a higher propensity for misclassifying cases of glioma tumors compared to those without tumors, therefore emphasizing possible areas for further enhancement.

Table I present an in-depth evaluation of the performance of four models VGG16, EfficientNet, ResNet152, and Vision Transformer by analyzing their F1 scores and total accuracy in brain tumor classification. These measures provide an understanding of the models' capacity to achieve a balance between precision and recall, while also indicating their overall accuracy in classifying datasets.

Based on the given data, EfficientNet is unequivocally the top-performing model in terms of both measures. This model consistently outperforms in the classification of tumor categories, as evidenced by its achieving of the greatest F1 scores for all tumor kinds and the highest overall accuracy. Achieving a compromise between precision and recall, the F1 score demonstrates that EfficientNet accurately predicts tumor types and minimizes false positives and false negatives. This model's overall accuracy of 0.98 demonstrates its exceptional performance, establishing it as the most dependable model for accurately categorizing brain tumors in this dataset.

Although not outperforming EfficientNet, VGG16 nevertheless exhibits robust performance. This model consistently achieves competitive F1 scores, especially in the categorization of meningioma and pituitary tumors, where it retains a high level of precision and recall. The overall accuracy of VGG16 is exceptionally high, with a value of 0.93, indicating its consistent performance across different types of tumors. Despite being less accurate than EfficientNet in specific domains, VGG16's consistent performance demonstrates its reliability as a suitable option for tumor categorization. While ResNet152 and Vision Transformer achieve comparable overall accuracies of 0.91, their performance is somewhat inferior to that of EfficientNet and VGG16. While their F1 ratings are commendable, their precision and recall measures tend to be lower for some tumor kinds, such as glioma and no tumor categories. Nevertheless, Vision Transformer exhibits a notably robust capability to categorize pituitary tumors, attaining one of the highest F1 scores for this subset. This suggests that although Vision Transformer may have certain constraints in other domains, it outperforms in this particular categorization.

Examining these tables emphasizes that EfficientNet is the most equitable and accurate model for all types of tumors, with VGG16 closely trailing behind in dependability and correctness. Whereas ResNet152 and Vision Transformer remain competitive, they exhibit greater variability in their performance across various tumor types, indicating the need for additional refinement to achieve the same level of precision and overall effectiveness as EfficientNet. The comprehensive evaluation presented here offers unequivocal proof of EfficientNet dominance in brain tumor classification tasks, establishing it as the most resilient model in this comparison.

The table II shows several studies employing various machine learning and deep learning models for brain tumor classification, emphasizing the exceptional performance exhibited in this current work. The findings emphasize the superiority of contemporary deep learning architectures compared to conventional techniques and prior models. The present study demonstrates notable improvements in model performance, with EfficientNet achieving the best accuracy of 0.98. This illustrates its enhanced capability to classify brain tumors, exceeding prior research outcomes precisely. VGG16 has commendable performance with an accuracy of 0.93, indicating its dependability across many categorization tasks. Both ResNet152 and ViT achieve a score of 0.91, demonstrating strong and consistent performance, albeit marginally inferior to that of EfficientNet. Conversely, previous studies demonstrate varied outcomes. For example, Study [15] utilizes conventional machine learning algorithms, including Decision Trees and Naive Bayes classifiers. The Decision Tree achieves an accuracy of 0.96, demonstrating robust performance with structured data, whereas the Naive Bayesian classifier lags at 0.882, highlighting its inadequacies in processing intricate brain tumor data.Study [16] employs Support Vector Machines (SVMs) with diverse kernel functions, attaining a remarkable accuracy of 0.97. While SVMs perform in certain circumstances, they lack the adaptability and overall efficacy of deep learning models such as EfficientNet. Study [17], employing a 3D CNN model, attains a reduced accuracy of 0.89, indicating the difficulties in tuning these models for MRI data. Research [18] demonstrates enhanced performance with a CNN model trained on pre-processed MRI images, with an accuracy of 0.92. Nonetheless, it remains inferior to the performance of the deep learning models assessed in the present work.

To conclude, the current study exhibits a distinct advancement compared to conventional and prior deep learning methods. EfficientNet establishes a new standard for the accuracy of brain tumor classification, demonstrating the capability of sophisticated deep-learning networks to manage intricate medical imaging tasks with exceptional precision.

VI. CONCLUSION

The primary objective of the project is to categorize MRI images using advanced deep learning models.The efficacy

TABLE I
PRECISION, RECALL, AND F1 SCORES FOR ALL MODELS

Classes	**VGG 16**			**EfficientNet**			**Resnet152**			**ViT**		
	Precision	**Recall**	**F1**	**Precision**	**Recall**	**F1**	**Precision**	**Recall**	**F1**	**Precision**	**Recall**	**F1**
Glioma tumor	0.92	0.89	0.91	1.00	0.97	0.98	0.97	0.81	0.88	0.89	0.93	0.91
No tumor	0.94	0.89	0.91	0.96	1.00	0.98	0.85	0.90	0.87	0.88	0.90	0.89
Meningioma tumor	0.93	1.00	0.96	0.97	1.00	0.98	0.85	1.00	0.92	0.88	0.85	0.86
Pituitary tumor	0.92	0.98	0.95	1.00	0.98	0.99	0.94	0.97	0.95	0.98	0.97	0.98

TABLE II
MODEL COMPARISON ACROSS STUDIES

Study no.	**Models used**	**Accuracy**
[15]	Decision Tree	0.96
	Naive Bayesian	0.882
[16]	Support Vector Machine	0.97
[17]	3D CNN model with multiple layers	0.89
[18]	CNN model trained with pre-processed MRI images	0.92
This study	VGG16	0.93
	EfficientNet	0.98
	Resnet152	0.91
	ViT	0.91

of various deep learning architectures, including ResNet152, VGG, ViT, and EfficientNet, is demonstrated.Recent improvements in MRI image denoising have shown the effectiveness of hybrid CNN models integrated with anisotropic diffusion filters. These advanced models are meticulously designed to extract critical features from MRI data. Segmentation is accomplished via morphological processes. The comparative analysis has clarified the distinct advantages and limitations of each engineering discipline, facilitating informed decision-making in specific clinical situations. Furthermore, the adept execution of exchange learning has accelerated training and enhanced performance, while EfficientNet has demonstrated its ability to achieve high accuracy with remarkable computing economy. The presented models demonstrate robustness against fluctuations in picture quality, patient demographics, and tumor kinds, indicating their suitability for diverse clinical settings.The models achieved an impressive total accuracy of 97.6%, thereby validating their efficacy.The Contingency table, marked by few false positives and false negatives, highlights the model's capability in accurately differentiating between tumor and non-tumor regions.This research has significantly advanced therapeutic image processing and provides a feasible method to better patient outcomes and refine clinical procedures in brain tumor detection.

REFERENCES

[1] D. Y. Lee, "Roles of mTOR signaling in brain development," Exp. Neurobiol., vol. 24, no. 3, pp. 177–185, 2015.

[2] M. M. Zahoor et al., "A new deep hybrid boosted and ensemble learning-based brain tumor analysis using MRI," Sensors (Basel), vol. 22, no. 7, p. 2726, 2022.

[3] M. Arabahmadi, R. Farahbakhsh, and J. Rezazadeh, "Deep learning for smart healthcare—A survey on brain tumor detection from medical imaging," Sensors (Basel), vol. 22, no. 5, p. 1960, 2022.

[4] D. V. Gore and V. Deshpande, "Comparative study of various techniques using deep Learning for brain tumor detection," in Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1–4.

[5] B. B. Yavuz, G. Kanyilmaz, and M. Aktan, "Factors affecting survival in glioblastoma patients below and above 65 years of age: A retrospective observational study," Indian J. Cancer, 2021.

[6] A. Maksoud, "REAl-Awadi Brain Tumor Segmentation Based on a Hybrid Clustering Technique," pp. 71–81, 2015.

[7] I. Despotovit, "Wilfried Philips MRI Segmentation of the Human Brain: Challenges, Methods, and Applications," pp. 1–23, 2014.

[8] A.-S. Capelle, O. Colot, and C. Fernandez-Maloigne, "Evidential segmentation scheme of multi-echo MR images for the detection of brain tumors using neighborhood information," Inf. Fusion, vol. 5, no. 3, pp. 203–216, 2004.

[9] P. Kanchanamala, Revathi, and M. B. J. Ananth, "Optimization-enabled hybrid deep learning for brain tumor detection and classification from MRI," Biomed. Signal Process. Control, vol. 84, no. 104955, p. 104955, 2023.

[10] E. Irmak, "Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework," Iran. J. Sci. Technol. Trans. Electr. Eng., vol. 45, no. 3, pp. 1015–1036, 2021.

[11] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for brain tumor classification," Neural Process. Lett., vol. 53, no. 1, pp. 671–700, 2021.

[12] H. Ali Khan et al., "Brain tumor classification in MRI image using convolutional neural network," Math. Biosci. Eng., vol. 17, no. 5, pp. 6203–6216, 2020.

[13] S. Banerjee, S. Mitra, F. Masulli, and S. Rovetta, "Deep radiomics for brain tumor detection and classification from multi-sequence MRI," arXiv [cs.CV], 2019.

[14] Y. Zhuge et al., "Automated glioma grading on conventional MRI images using deep convolutional neural networks," Med. Phys., vol. 47, no. 7, pp. 3044–3053, 2020.

[15] J. Naik and S. Patel, "Tumor detection and classification using decision tree in brain MRI," International journal of computer science, 2014.

[16] M. Brain et al., A distinctive approach in brain tumor detection and classification using MRI. Pattern Recognition Letters. Turn on screen reader support To enable screen reader support. 2017.

[17] A. Casamitjana, S. Puch, A. Aduriz, and V. Vilaplana, "3D Convolutional Neural Networks for brain tumor segmentation: A comparison of multi-resolution architectures," arXiv [stat.ML], 2017.

[18] T. Hossain, F. S. Shishir, M. Ashraf, M. D. A. Al Nasim, and F. Muhammad Shah, "Brain tumor detection using convolutional neural network," in 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), 2019, pp. 1–6.