An Experimental Study on Brain Tumor Detection Using Deep Learning Techniques

Gogineni Sai Rohith
Department of Computer Science and Engineering
SRM University – AP, Andhra Pradesh, India
goginenisairohith@gmail.com

Ritesh Jadhav
Department of Computer Science and Engineering
SRM University – AP, Andhra Pradesh, India
riteshvasanthjadhav@gmail.com

Chaitanya Sai Nutakki
Department of Computer Science and Engineering
SRM University – AP, Andhra Pradesh, India
csnutakki@gmail.com

Teja Siva Kumar Paleti
Department of Computer Science and Engineering
SRM University – AP, Andhra Pradesh, India
paletiteja4321@gmail.com

Hemantha Kumar Kalluri
Department of Computer Science and Engineering
SRM University – AP, Andhra Pradesh, India
hemanth_mtech2003@yahoo.com

***Abstract*—The increasing incidence of brain tumors has underscored the critical need for accurate diagnosis and effective treatment strategies. This study explores advanced methodologies to enhance brain tumor detection and classification. We introduce an innovative convolutional model designed to significantly improve identification accuracy. The performance of several deep learning algorithms, including Inception V3, GoogLeNet, and VGG-19, is meticulously evaluated in the context of brain tumor image classification.**

A key novelty of this study is the implementation of decision-level fusion, a method not previously explored in this domain. By combining the classification outputs of multiple models, our approach enhances the overall decision-making process, leading to improved accuracy and robustness. This technique allows for the aggregation of diverse perspectives from different models, thereby mitigating individual model weaknesses and capitalizing on their strengths. Our results indicate that these approaches markedly enhance the accuracy (with Inception V3 reaching 98.25%, GoogLeNet 95.36%, and VGG-19 91.24%) and resilience of brain tumor detection and classification systems, laying the foundation for a reliable diagnostic tool.

***Keywords*—Brain Tumour, Machine Learning, Deep Learning, Transfer Learning, Fusion, Otsu Thresholding, CLAHE**

I. INTRODUCTION

Brain tumors are a critical medical condition arising from the abnormal growth of brain cells or tissues, disrupting the normal cell turnover process. Degeneration of brain tissue can result from the uncontrolled and aggressive proliferation of cells, which manifests as lesions or neoplastic growth [1].

There are two main categories of brain tumors: primary and metastatic tumors. Primary tumors, such as gliomas, develop within the brain from glial cells. In comparison, metastatic brain tumors result from cancers that spread to the brain from other body parts through the bloodstream. Brain tumor cancer remains a critical and severe health concern. In 2015, approximately 23,000 individuals in the United States received a diagnosis of brain tumor cancer [2]-[4].

However, it's not limited to a specific age group, affecting both adults and children, with approximately 80,000 fresh cases of primary brain tumors reported in 2018 [5]. These tumors encompass various types, such as Meningioma, Gliomas, Pituitary tumors, and others like Malignant, Medulloblastoma, and Lymphomas. The causes of this disease are multifaceted, often related to cancer-related ailments and morbidity. Effectively managing this ailment hinges on its timely and accurate detection [6].

Understanding the gravity of the situation necessitates looking at the intricacies of the brain, one of the most complex and vital parts of the human body, where tissues and nerve cells orchestrate critical bodily functions, from breathing to sensory perception and muscle control [7]. In this intricate system, some cells develop normally, while others lose their capabilities, cease growth, and become abnormal [8]. This assembly of irregular cells gives rise to a tumor, making brain tumors an uncontrolled and irregular proliferation of brain cells [9].

These abnormal cells multiply uncontrollably, leading to severe impairment of brain function and often fatal outcomes. Early detection of brain tumors is paramount for saving patients' lives, and examining brain tumor images plays a crucial role in this process [10]. To address this, deep learning (DL) methods, particularly those based on transfer learning and finetuning, have gained widespread popularity for brain tumor classification [11].

For neurologists, analyzing, classifying, and identifying brain tumors are pivotal tasks, and Computer-Aided Diagnosis (CAD) emerges as an invaluable tool in their medical practice [12]. Three distinct types of brain tumors, meningioma, pituitary, and glioma, present unique challenges, and precise and timely analysis is paramount for effective treatment. The treatment choice hinges on factors like the pathological type, the tumor’s stage at the examination time, and its grade [13].

While many methods of brain tumor classification have traditionally focused on segmentation, an equally essential but often overlooked aspect lies in feature extraction and classification. Therefore, current research is pursuing deep learning techniques to bolster classification tasks. Recent studies have shown the efficacy of deep learning in enhancing the performance of computer-aided medical diagnosis, not only in brain tumor cancer but also in critical diseases like lung cancer detection and the analysis of breast cancer images [14].

Deep learning has eliminated manual feature engineering, making it suitable for medical image analysis. Transfer learning has addressed data limitations, improving model performance. Several studies showcased the effectiveness of deep learning in achieving high accuracy for brain tumor classification, often surpassing previous methods [15]. This highlights the potential for deep learning to enhance brain tumor diagnostics, contributing to better patient care and clinical practices [16].

II. LITERATURE REVIEW

Our literature review of approximately 40 research papers reveals a predominant use of both traditional and deep learning methods in brain tumor detection as seen in Fig. 1, there is a notable trend towards deep learning approaches due to their enhanced feature extraction capabilities and classification accuracy.

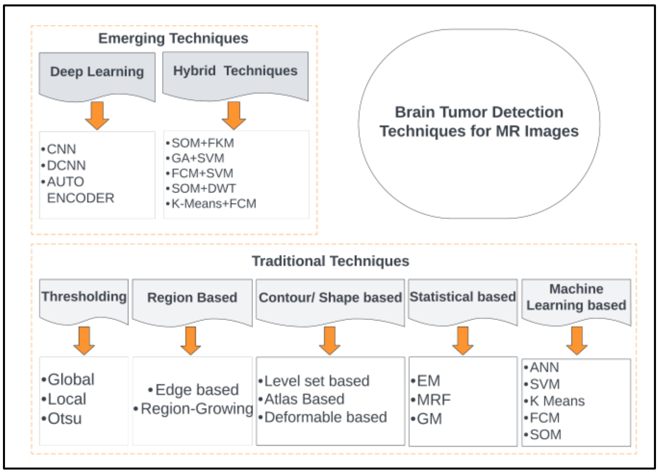


Fig. 1. Brain Tumor Detection Techniques for MR Images

In our research, we employ deep learning models in conjunction with other methodologies to classify and detect brain tumors from MR images, aiming to achieve higher precision and robustness in medical imaging applications.

Numerous Studies have explored U-Net architecture, a successful convolutional neural network for image segmentation, which is applied here to detect brain tumors in 3D MRI. The workflow involves pre-processing MRI scans, extracting features using U-Net, segmenting the tumor region, and evaluating performance. An impressive test accuracy of 99.4% was achieved [17].

Several studies explore CNNs for brain tumor detection. This work utilizes a 23-layer CNN and a fine-tuned VGG16 architecture on two datasets: Figshare (3064 scans) and Harvard Medical (152 slices). The models achieved high accuracy (97.8% and 100%) on both datasets, demonstrating the potential of CNNs for brain tumor classification [18].

“Brain Tumor Segmentation Based on a New Threshold Approach" introduces an innovative methodology for automating brain tumor segmentation from MRI images. Through robust preprocessing techniques like median filtering and histogram equalization, the algorithm ensures standardized intensity values and noise removal. Comprehensive feature extraction, including intensity, texture, and shape features, enriches the algorithm's ability to differentiate tumor from healthy tissue. The novel thresholding algorithm capitalizes on bimodal intensity distributions, accurately delineating tumor boundaries. Post-processing with morphological operations further refines segmentation results [19].

Another paper based on Proposed hybrid CNN-SVM approach for brain tumor analysis in MRI scans. Their method achieves high accuracy (98.49% detection, 99.2% classification) on an independent test set. It leverages CNNs for tumor segmentation and SVMs for classifying benign or malignant tumors after thresholding the segmented region. This combination offers strengths from both techniques, potentially making it suitable for a Computer-Aided Diagnosis (CAD) system for brain tumors. Further exploration of the specific CNN-SVM architecture and comparisons with existing methods would strengthen the review of this approach [20].

III. MATERIAL AND METHODS

A. Dataset Used For Research:

The survey's primary focus is tumor detection, but one potential drawback is the restricted access to medical data for research because of security restrictions. Table I presents a list of data sources comprising different MRI images obtained from different scanning techniques based on the publications this study analyzed. Table I illustrates the predominance of various data sources, mostly private datasets and the Brain Tumor Segmentation (BraTS) dataset.

TABLE I. DATASETS OF BRAIN TUMORS:

Name	Description	Web Link
BRATS	Contains BRATS 2018, 2019, 2020, 2021 datasets	http://braintumorsegmentation.org/
TCGA-LGG	MRI scans: Around 500 T1-weighted and T2-weighted MRI	https://www.cbioportal.org/
Figshare	Specific data of images vary	https://figshare.com/
Harvard Medical Dataset	A smaller dataset than others, but has well-defined classes	https://dataverse.harvard.edu/
BrainWeb Dataset:	32 T1weighted, 32 T2weighted, 32 FLAIR, and 32 DTI volumes.	https://brainweb.bic.mni.mcgill.ca/
OASIS	Structural MRI from 416 subjects	https://www.oasis-brains.org

This study employs a comprehensive combined dataset derived from three primary sources: Figshare, SARTAJ, and Br35H. The dataset comprises 7023 MRI scans of the human brain, categorized into four distinct groups: pituitary, glioma, meningioma, and no tumor. Notably, the Br35H dataset exclusively contains images labeled as "no tumor."

During our investigation, we identified mislabeled images within the glioma category of the SARTAJ dataset, a discovery supported by findings from other researchers and evidenced by the inconsistent performance of models trained on this dataset. Consequently, this issue was addressed by replacing the mislabeled glioma images with those obtained from the Figshare repository.

The Figshare dataset includes 3064 T1-weighted contrast MRI slices acquired from 233 patients diagnosed with brain tumors between 2005 and 2010, sourced from General Hospital, Tianjin Medical University, and Nanfang Hospital in China. Notably, these images offer comprehensive views, encompassing axial, coronal, and sagittal perspectives. From this extensive pool, we selected 926 images of Glioma Tumor from Figshare Dataset to enhance our combined dataset, by allocating 100 images for testing and retaining 826 for training. This can be seen in Table II.

TABLE II. COMBINED DATASET UTILIZED IN THIS STUDY:

Primary Combined Dataset Utilized in this Study		
Tumors	***Training***	***Testing***
Pituitary tumor	1457	300
Glioma tumor	1321	300
Meningioma tumor	1339	306
No tumor	1595	405
Category Total:	5712	1311
Total:	**7023**	

B. *Pre-Processing:*

Gaussian Filter: In our efforts to enhance image quality for seamless integration with deep learning models, we implemented a systematic preprocessing approach. Initially, we applied a Gaussian filter to the original dataset to reduce noise and enhance visual clarity. This foundational step set the stage for subsequent improvements, aiming to provide a clear basis for model comprehension.

Otsu Thresholding: Otsu's method is an image segmentation technique that transforms image into a binary image using thresholding. This non-linear process classifies pixels into either the foreground or background, creating a bimodal histogram.

The method uses statistical principles to identify the ideal threshold range. It works by minimizing the weighted sum of variances within the foreground and background classes, thereby determining the best threshold. This optimal threshold divides the image into two classes, ensuring the combined variance is minimized.

CLAHE: Following the Otsu Thresholding, we applied Contrast-Limited Adaptive Histogram Equalization (CLAHE) to enhance image contrast and accentuate details, promoting overall clarity. Through CLAHE, we aimed to amplify important features within each image, ensuring key details were retained and highlighted.

Subsequently, we resized the images to align with the unique input requirements of each deep learning model utilized, including Inception V3, GoogLeNet, and Vgg-19. This tailored resizing ensured optimal compatibility across a diverse range of model architectures, facilitating seamless integration and maximizing performance. The entire procedure can be seen in Fig. 2.

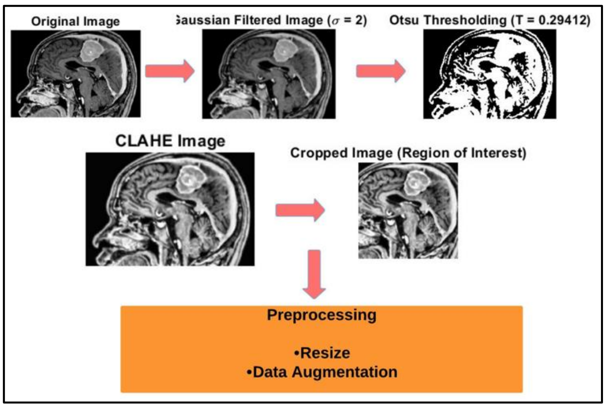


Fig. 2. Image Processing Workflow

Moreover, our preprocessing pipeline included rigorous dataset partitioning into three distinct groups: 80% for training, 10% for validation, and 10% for testing. This meticulous division facilitated robust model development and evaluation, ensuring thorough training and assessment under stringent standards.

C. *Proposed Architecture:*

Convolutional Neural Network:

CNNs are structured to automatically learn hierarchical patterns and features directly from raw input data, making them particularly effective in tasks where spatial relationships are important, such as image processing.

The convolutional layers in CNNs apply filters to input data, extracting features at different spatial hierarchies. These features are then down sampled and combined through pooling layers, which help reduce the computational burden and extract the most relevant information. CNNs generally comprise two primary elements:

1. ***Feature Extraction:*** This module includes a series of stacked layers that use convolutional layers to identify detailed features from input images. Additionally, pooling layers are used to decrease spatial dimensions.

2. ***Classification Module:*** The classification section integrates fully connected (FC) layers to interpret learned features and produce predictions, ensuring accurate image classification. This modular design empowers CNNs to effectively capture intricate image patterns and make well-informed classifications.

Transfer Learning:

Transfer learning, is a technique in machine learning, that allows us to repurpose a model trained for one task to tackle a related but different task. This is done by adjusting the pre-trained model's weights for the new task, serving as the foundation for a new model. The concept hinges on the idea that a model can reuse features learned from a large dataset in this case a dataset that has a total of 7023 MRI Scans, this not only saves time but also the resources used compared to starting a new.

Transfer learning has found success in various fields like image recognition, natural language processing, and speech recognition. By leveraging pre-trained models, it achieves cutting-edge performance even with limited training data. Its applications span diverse areas of deep learning, including image classification, object detection, and tumor identification. In our study, we utilized three transfer learning models, all operating with varying input sizes according to the pre-trained model, ensuring adaptability across our analyses.

Decision Level Fusion:

Recent research has shown that combining multiple classification techniques enhances classification accuracy, thereby boosting performance. However, this fusion process is computationally intensive, which poses a challenge, especially when quick performance evaluation of brain tumors is the primary goal. Fig. 3 illustrates the proposed fusion technique visually.

The classification scores are merged into a unified final score using a research-backed method known as score-level fusion, which enhances the accuracy of class determination. Decision-level fusion, a technique used to consolidate classification decisions from multiple feature vectors and classifiers into a single decision, can be employed to finalize conclusions effectively. The outcomes of the three models' decisions may be incorporated into a single vector. The features of three DL models (Inception v3, GoogLeNet, Vgg19) were integrated to achieve fusion at the decision level.

Many of the challenges encountered in machine learning have been addressed through fusion modeling, which enhances overall performance by integrating the predictive abilities of multiple models into a single one. The fusion process involves incorporating various training datasets or methods and integrating the predicted outcomes from each base model to provide a unified predictive capability.

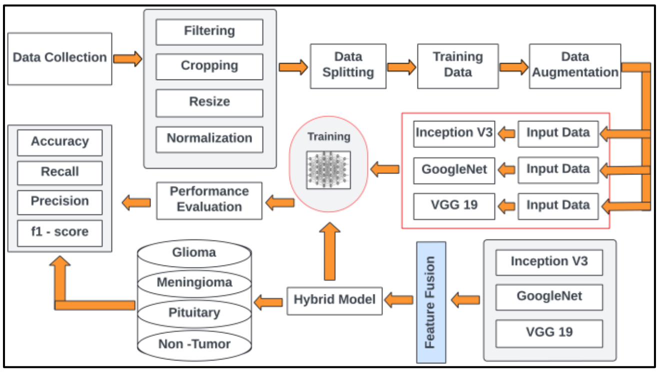


Fig. 3. Illustration of the training procedures for Inception V3, GoogLeNet, and VGG-19 alongside the suggested fusion.

D. Performance Evaluation Metrics:

The assessment of the networks' efficacy in detecting and classifying brain tumors involved the computation of several performance metrics given in equations (1) through (5).

TABLE III. ASSESSMENT METRICS FOR PERFORMANCE EVALUATION:

Metrics Used	Equation	
Accuracy	$ACC = \frac{TP + TN}{TP + TN + FP + FN}$	(1)
F1- Score	$F1 = \frac{2TP}{2TP + FP + FN}$	(2)
Sensitivity or Recall	$SE = \frac{TP}{TP + FN}$	(3)
Specificity	$SP = \frac{TN}{TN + FP}$	(4)
Precision	$Pr = \frac{TP}{TP + FP}$	(5)
Over here, terms such as **TP, TN, FP** and **FN** are the true positive, negatives, false positive and false negatives		

IV. EXPERIMENTAL RESULTS

Hyperparameters: The experiments were conducted using the MATLAB V23 Deep Network Designer Framework on a Windows operating system running on a 3.2 GHz Intel Core i5 processor with 16 GB of RAM and a 12GB GPU. Training was carried out over 30 epochs with a validation iteration frequency set at 50 and a learning rate of 0.01.

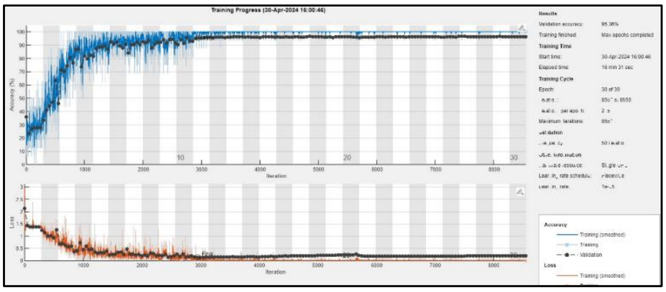
To validate the effectiveness of the proposed simultaneous Deep CNN architecture for brain tumor identification and categorization. The dataset was systematically organized into four distinct folders, encompassing diverse categories such as pituitary tumor, meningioma tumor, glioma tumor, and normal brain images. In total, the combined dataset comprised 7023 images, with 5712 images allocated for training the model, while the remaining 1311 images were reserved for testing the model's performance.

The robustness of our Proposed model was clearly evident, affirming its adeptness in accurately discerning and categorizing various brain tumor cases. Detailed results of our model's performance are presented in Table IV.

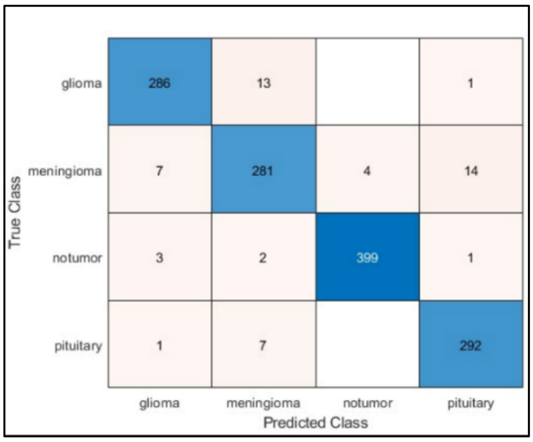
TABLE IV. CLASSIFICATION RESULTS:

No	Model Name	Validation Accuracy	Testing Accuracy	Number of layers
1	Inception V3	98.25 %`	98.47%	48
2	Google Net	95.36%	95.95%	22
3	Vgg-19	91.24%	90.08%	19

GoogLeNet: also known as Inception-v1, is a convolutional neural network (CNN) architecture developed by researchers at Google. The GoogLeNet architecture with 22 layers to construct a highly reliable model for Brain Tumor detection. The key innovation of GoogLeNet is its deep and complex architecture that aims to achieve high performance while being computationally efficient.



(a) Training Plot: GoogLeNet model achieved 95.36% validation accuracy on the brain tumor dataset.

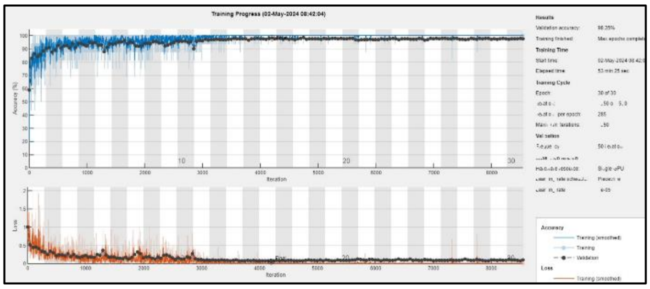


(b) Confusion Matrix: 1,258 correctly classified images

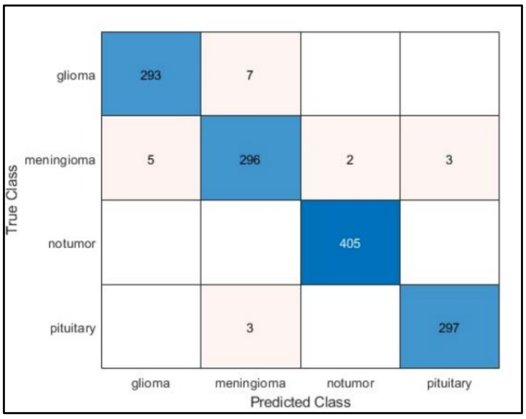
Fig. 4. GoogLeNet, (a) Training Plot (b) Confusion Matrix

Google Net architecture incorporates a comprehensive network of 22 layers. The diagonal of the confusion matrix shows the number of correctly predicted examples. The model correctly predicted 286 glioma tumors, 281 meningioma tumors, 399 no tumors, and 292 pituitary tumors. The off-diagonal elements of the confusion matrix show the number of incorrectly predicted examples. The model got a lower accuracy of 95.36% on the validation data. This can be seen in Fig. 4.

INSEPTION_V3: Inception-v3, also known simply as Inception 3, is a deep convolutional neural network architecture. It is a successor to the original Inception model (Inception-v1 or GoogLeNet) and builds upon its design principles while incorporating various improvements. Inception-v3 is known for its depth, efficiency, and performance in various computer vision tasks, including image classification, object detection, and image segmentation. It has been widely used and serves as a foundation for further advancements in deep learning architectures.



(a) Training Plot: Inception_V3 model achieved 98.25% validation accuracy with 30 epochs.

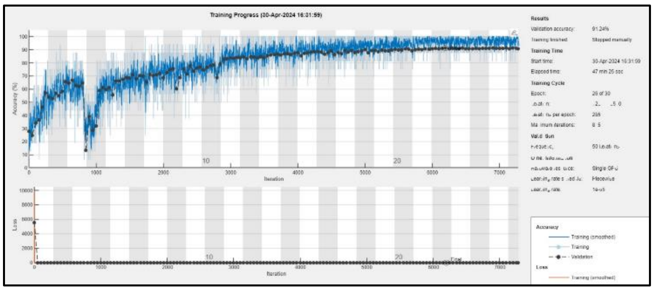


(b) Confusion Matrix: 1,291 correctly classified images

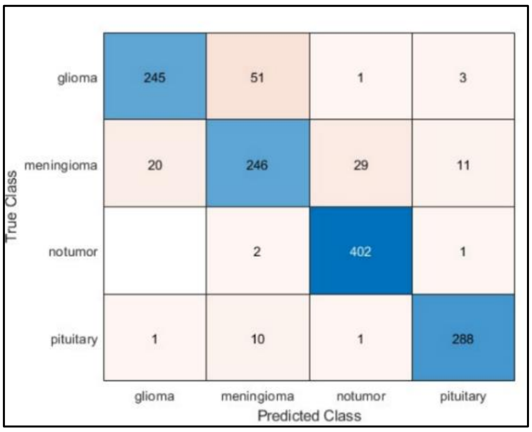
Fig. 5. Inception-V3, (a) Training plot (b) Confusion Matrix

The model correctly predicted 293 glioma tumors, 296 meningioma tumors, 405 no tumors, and 297 pituitary tumors. The model showcased its high proficiency by achieving an impressive validation accuracy of 98.25%, signifying its exceptional capability in accurately categorizing various brain tumor cases. This can be seen in Fig. 5.

VGG-19: VGG19 has a simple and uniform architecture, with small 3x3 convolutional filters and max pooling layers. This simplicity makes it easy to understand and implement. Due to its popularity and effectiveness, pre-trained VGG19 models are readily available and widely used for transfer learning. By leveraging the features learned by VGG19 on a large dataset like ImageNet, one can adapt the model to perform well on smaller, domain-specific datasets with minimal training data.



(a) Training Plot: The fine-tuned GoogLeNet model achieved 95.36% validation accuracy on the brain tumor dataset.



(b) Confusion Matrix: 1,181 correctly classified images

Fig. 6. VGG-19, (a) Training Plot (b) Confusion Matrix.

The model correctly predicted 245 glioma tumors, 246 meningioma tumors, 288 Pituitary tumors, and 402 no tumors. The off-diagonal elements of the confusion matrix show the number of incorrectly predicted examples. This can be seen in Fig. 6.

TABLE V. EVALUATION METRICS RESULS:

No:	Model Name:	F1-score:	Precision:	Recall (Sensitivity):
1	Inception V3	98%	96%	97%
2	Google Net	97%	95%	99%
3	VGG - 19	99.2%	96%	98%

V. CONCLUSION

In light of the potentially severe impact of brain tumors, early detection emerges as a critical imperative. Through the integration of diverse deep learning models, notably Inception V3, GoogLeNet, and Vgg-19, alongside innovative techniques like fusion and classification, the study has significantly enhanced the accuracy and efficiency of brain tumor identification. Notably, the Inception V3 model achieved a remarkable validation accuracy of 98.25%, underscoring the strides made in diagnostic precision.

However, the study is not without its limitations. Restricted access to medical data hampers dataset comprehensiveness and diversity, potentially impeding the generalizability of findings. Dependency on pre-trained models like Inception V3, GoogLeNet, and VGG-19 may restrict exploration of novel, potentially more effective architectures, risking oversight of unique tumor features. Moreover, the identification of mislabelled images within the glioma category of the SARTAJ dataset highlights dataset inaccuracies, posing challenges to model performance.

Looking towards future advancements, collaboration with medical institutions offers the promise of enriching access to diverse datasets, thereby enhancing model robustness. Simultaneously, the development of custom deep learning architectures tailored for brain tumor classification holds potential for precision improvement. Integrating multimodal data sources alongside MRI scans can further bolster diagnostic accuracy and reliability. Continuous learning frameworks ensure model adaptability by incorporating new data, aligning seamlessly with evolving medical knowledge.

In sum, these collective efforts aim to propel brain tumor detection capabilities to new heights, ultimately fostering enhanced patient care and outcomes. Through collaborative data access, exploration of diverse model architectures, and a commitment to dataset integrity, reliable brain tumor classification systems can be advanced, offering hope and support to patients and clinicians alike.

REFERENCES

[1] Tseng, Cheng-Jui, and Changjiang Tang. "An Optimized XGBoost Technique for Accurate Brain Tumour Detection Using Feature Selection and Image Segmentation." Healthcare Analytics, vol. 4, Elsevier BV, Dec. 2023, p. 100217, doi:10.1016/j.health.2023.100217.

[2] Anaya-Isaza, Andrés, et al. "Optimizing MRI-based Brain Tumour Classification and Detection Using AI: A Comparative Analysis of Neural Networks, Transfer Learning, Data Augmentation, and the Cross-transformer Network." European Journal of Radiology Open, vol. 10, Elsevier BV, Jan. 2023, p. 100484, doi:10.1016/j.ejro.2023.100484.

[3] Rahman, Takowa, and Md. Saiful Islam. "MRI Brain Tumour Detection and Classification Using Parallel Deep Convolutional Neural Networks." Measurement: Sensors, vol. 26, Elsevier BV, Apr. 2023, p. 100694, doi:10.1016/j.measen.2023.100694.

[4] Sangui, Smarta, et al. "3D MRI Segmentation Using U-Net Architecture for the Detection of Brain Tumour." Procedia Computer Science, vol. 218, Elsevier BV, Jan. 2023, pp. 542–53, doi:10.1016/j.procs.2023.01.036.

[5] Islam, Khairul, et al. "Brain Tumour Detection in MR Image Using Superpixels, Principal Component Analysis and Template Based K-means Clustering Algorithm." Machine Learning With Applications, vol. 5, Elsevier BV, Sept. 2021, p. 100044, doi:10.1016/j.mlwa.2021.100044.

[6] Khan, Md. Saikat Islam, et al. "Accurate Brain Tumour Detection Using Deep Convolutional Neural Network." Computational and Structural Biotechnology Journal, vol. 20, Elsevier BV, Jan. 2022, pp. 4733–45, doi:10.1016/j.csbj.2022.08.039.

[7] "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumour." IEEE Journals & Magazine | IEEE Xplore, 2020, ieeexplore.ieee.org/document/9025004.

[8] "A YOLOv3 Deep Neural Network Model to Detect Brain Tumour in Portable Electromagnetic Imaging System." IEEE Journals & Magazine | IEEE Xplore, 2021, ieeexplore.ieee.org/document/9446998.

[9] "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumour Detection on MRI Images." IEEE Journals & Magazine | IEEE Xplore, 2021, ieeexplore.ieee.org/document/9515947.

[10] "Data Augmentation and Transfer Learning for Brain Tumour Detection in Magnetic Resonance Imaging." IEEE Journals & Magazine | IEEE Xplore, 2022, ieeexplore.ieee.org/document/9720964.

[11] "Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network." IEEE Journals & Magazine | IEEE Xplore, 2022, ieeexplore.ieee.org/document/9718069.

[12] Majib, M. S., Rahman, M. M., Sazzad, T. M. S., Khan, N. I., & Dey, S. K. (2021b). VGG-SCNET: A VGG Net-Based deep learning framework for brain tumour detection on MRI images. IEEE Access, 9, 116942–116952. https://doi.org/10.1109/access.2021.3105874

[13] "Brain Tumour Classification Using Fine-Tuned GoogLeNet Features and Machine Learning Algorithms: IoMT Enabled CAD System." IEEE Journals & Magazine | IEEE Xplore, 1 Mar. 2022, ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9501999

[14] Jian, Muwei, et al. "Tumour Detection in MRI Brain Images Based on Saliency Computational Modeling." IFAC-PapersOnLine, vol. 53, no. 5, Elsevier BV, Jan. 2020, pp. 43–46, doi:10.1016/j.ifacol.2021.04.123.

[15] Solanki, Shubhangi, et al. "Brain Tumour Detection and Classification Using Intelligence Techniques: An Overview." IEEE Access, vol. 11, Institute of Electrical and Electronics Engineers, Jan. 2023, pp. 12870–86, doi:10.1109/access.2023.3242666.

[16] Raghavendra, U., et al. "Brain Tumour Detection and Screening Using Artificial Intelligence Techniques: Current Trends and Future Perspectives." Computers in Biology and Medicine, vol. 163, Elsevier BV, Sept. 2023, p. 107063, doi:10.1016/j.compbiomed.2023.107063.

[17] Roy, Sunita, et al. "Brain Tumour Segmentation Using S-Net and SA-Net." IEEE Access, vol. 11, Institute of Electrical and Electronics Engineers, Jan. 2023, pp. 28658–79, doi:10.1109/access.2023.3257722.

[18] Khan, Md Saikat Islam, et al. "Accurate Brain Tumor Detection Using Deep Convolutional Neural Network." Computational and Structural Biotechnology Journal, U.S. National Library of Medicine, 27 Aug. 2022, www.ncbi.nlm.nih.gov/pmc/articles/PMC9468505/. Accessed 12 June 2024.

[19] Ourselin, Sébastien, et al. Springer, Information Processing in Medical Imaging: 24th International Conference, IPMI 2015, Sabhal Mor Ostaig, Isle of Skye, UK, June 28-July 3, 2015, Proceedings, 2015.

[20] Author links open overlay panelM.O. Khairandish a, et al. "A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images." IRBM, Elsevier Masson, 11 June 2021