Comparative Analysis of CNNs and Vision Transformer Models for Brain Tumor Detection

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Abstract: Brain tumors are irregular cell mixtures existing within the brain or central spinal canal. They could be cancerous or benign. The likelihood of the best possible prognosis and therapy increases with the speed and accuracy of detection. This work provides a method for detecting brain tumors that combines the capabilities of vision transformers and CNNs. In contrast to other studies that primarily relied on standalone CNN or ViT architectures, our method uniquely integrates these models with a Support Vector Machine classifier for the improvement of accuracy and robustness in medical image classification. While the ViT makes it possible to combine CNN and ViT to improve the accuracy of medical imaging of the disease, the CNN extracts hierarchical features. In-depth analyses of benchmark datasets pertaining to imaging modalities and clinical perspectives were conducted. According to the experimental findings, ViT and EfficientNet identified tumors with an accuracy of 98%, while the greatest reported accuracy of 98.3% was obtained when ViT was combined with an SVM classifier. Our findings suggest that our method may improve brain tumor detection methods.

1 INTRODUCTION

The abnormal growth of cells inside the brain or Central Spinal Canal is the first indication of a brain tumor. They fall into two categories: malignant-invasive and benign-non-invasive. Benign tumors are less aggressive because they do not contain cancer cells, and they tend to have very well-defined periphery patterns. Generally, they are amenable to surgical interventions. Even benign tumors can potentially wreak havoc on a patient's health by compressing sensitive sites or interfering with the circulation of the cerebrospinal fluid. Whereas malignant tumors are composed of cancer cells, their ability to invade local tumors and easily spread to adjacent tissues renders them potentially deadly. Radiation therapy, chemotherapy, and surgical intervention may be provided as treatment options.

Extremely large computational efforts are often required by this process-altering image encoders into pixel sequences for their scrutiny. In response, Parmar et al. (2018) considered self-attention in local patches only around the query pixels while avoiding the cost of global computations over the full image.

Meanwhile, for medical imaging, especially in brain tumor detection and identification, there is no little tribulation, heavily influencing treatment plans and patient outcomes. Recent developments in deep learning have fueled potential unlocks in the evaluation of medical images, though tumor diagnosis-based medical image analysis remains to date, still an area earning its mark in practical applications. CNNs have shown promise in feature extraction and classification in many applications, including medical imaging. In parallel, Vision Transformers (ViTs) appeared and became popular

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because of their capability to extract distant associations from image data, which affords a unique interpretation methodology.

Medical imaging experts continue to have serious challenges in the identification and diagnosis of brain tumors, which accordingly has a profound impact on treatment and patient outcomes. Deep learning techniques have come recently with a whole different ball game in medical image processing, allowing pathways towards accuracy and efficiency in tumor diagnosis that have never been encountered. These provide effective tools for feature extraction and classification in different medical imaging fields using CNNs. Concurrently, Vision Transformers (ViTs) are mushrooming into popularity for excelling at extracting distant associations from image data; hence, offering a potentially new abstraction of image interpretation.

Especially, this paper aims to do complete and thorough and full measure-in-dependent study on the CNN and Vision Transformers for cerebral tumor detection in medical images. Such systems regain their respective advantages by using each of the architectures' strengths for a more resilient tumor detection system and more accurate local-based statistics. With the proposed method, we intend to utilize all possible local and global information in the medical images concurrently to deliver more detailed and accurate tumor structure analyses.

In this work, we carry out comprehensive studies on standard brain tumor picture datasets, comparing our hybrid approach's efficacy to both standalone Vision Trans-former models and traditional CNN-based techniques.

Our results show the potential for CNN (EfficientNet B0) and Vision Transformer fusion technique to improve the diagnostic accuracy and simplify the clinical decision-making process, as evidence by the usefulness of both methods in brain tumor detection. We speculated about the effects this work could have on future medical imaging research and presented suggestions for improving techniques for brain tumor detection.

Contributions

This paper makes the following contributions:

- Provide a hybrid approach for brain tumor detection that combines EfficientNet and Vision Transformers (ViT) with SVM.
- A thorough comparison of CNN, solo ViT, and our suggested hybrid model.
- Reach cutting-edge outcomes on MRI datasets with an accuracy of 98.3%.

2 RELATED WORKS

The search for precise detection methodologies for cerebral tumors has sparked significant research efforts in recent years. Numerous approaches have been investigated to address this vital need in the field of health. Conventional diagnostic modalities such as magnetic resonance imaging (MRI) and computed tomodensitometry (CT scans) have historically been the primary tools used to identify brain tumors. Their effectiveness in early detection and precise delineation of terrorist borders, however, remains a challenge.

To identify and comprehend these cerebral tumors, specialized ondelettes and sup-port systems have been used in conjunction with MRI. The precise and automated classification of brain IRM pictures holds significant value in medical research and interpretation. Uncontrolled cell division that results in aberrant cell clusters inside or outside the brain is the cause of brain tumors. These aberrant cell clusters harm healthy cells and interfere with regular brain function. The objective was to distinguish between brain tissue that was unaffected by tumors and brain tissue that had tumors, whether benign or malignant. Gurbină et al. (2019)

CNN applied to MRI images has been shown to be beneficial in many recent studies for the classification of brain-related illnesses. Yuan et al. (2018).

Researchers and medical professionals can locate the area of the brain afflicted by a tumor by using MRI, an imaging method that shows the anatomy and structure of the human brain. Sakhthidasan et al. (2021)

Abd-Ellah et al. (2019) have presented an enhanced method for detecting brain tumors in order to identify malignant tumors. Due to the low contrast of mous tissues, lesion detection is a challenging task that requires the use of adaptive clustering k-means to obtain a better segmentation method in order to improve prediction accuracy.

A thorough review of well-known deep learning models that are applied to various types of brain tumor investigation by Waqas et al. (2020).

Amarapur et al. (2019) discussed both traditional automatic learning methods and deep learning techniques for the validation of cerebral tumors. With the aid of deep learning approaches, they were able to identify, segment, and classify brain tumors effectively using three different algorithms, leading to improved performance.

A high-level System Cancer Diagnosis by coalescing the four Level-I taxonomy components

"DIV" Data, Image Segmentation processing and VIEW is proposed by Laukamp et al. (2019). Level-I taxonomy DIV evaluation consists of acceptance Rate and Completion Rate by DL convoluiton neural networks.

Archana et al. (2023) performed a comparative study of several optimizers used in convolutional neural networks (CNNs) to detect brain tumors from medical photos. The study examined how well the Adam and SGD optimizers performed when applied with the AlexNet and Le-Net CNN architectures. The study's findings, which were based on a dataset of 1547 images, showed that the AlexNet architecture and Adam optimizer outperformed LeNet and SGD to obtain an average accuracy of 94.76%.

The use of deep neural networks and machine learning methods for the early diagnosis of brain tumors using MRI data was investigated by Wani et al. (2023). A variety of CNN architectures, including AlexNet, GoogleNet, VGG-19, a bespoke model, and a collection of machine learning models, were used in the study. Significant emphasis was made on data gathering, preprocessing, and classification procedures in order to address class imbalance and data heterogeneity. The group of models that attained the maximum accuracy of 90.625% suggests that combining deep and conventional machine learning techniques has bright futures.

Rajinikanth et al. (2022) applied various pooling techniques with the pre-trained VGG16 and VGG19 convolutional neural networks (CNNs) to identify glioma and glioblastoma brain tumors from magnetic resonance imaging (MRI) images. Employing the ADAM Optimizer, the work has examined the classification performances of the SoftMax, Decision Tree (DT), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM) classifiers on 2000 images acquired from The Cancer Imaging Archive (TCIA). The results showed that DT based on average-pooling and VGG16 managed to gain maximum classification accuracy, which was 96.08%.

Recent developments in Vision Transformers (ViT) have shown that they may effectively extract features from images by utilizing self-attention techniques, outperforming conventional convolutional neural networks. Zhang et al. (2O22)

In this section, we look closely at a few recently published, more successful techniques (See Table 1).

Table 1: Research on the detection of brain tumors.

Authors	Techniques	Dataset	Accuracy
Archana et al. (2023)	CNN, AlexNet, LeNet	1547 images of Brain Tumor Dataset	94.76%.
Wani et al. (2023)	AlexNet, GoogleNet, VGG-19,	Brain tumor Dataset MRI scans.	90.625%
Rajinikanth et al. (2022)	VGG16 VGG19 SVM, KNN	MRI images	96.08%
K. Laukamp et al. (2019)	Deep learning Model	Data View (DIV)	95,08%

Our study produced impressive results that outperformed previous methods. Through the automation and optimization of the diagnostic procedure, this research has a significant potential to improve early brain tumor detection, which could improve patient care and quality of life. Our findings advance the state of the art in the categorization of cerebral tumors and demonstrate the effectiveness of transfer learning in the analysis of medical images.

3 METHODOLOGIES

This section describes the process of developing our experiments to improve the accuracy of brain tumor detection. The first step is to collect data. The second stage involves data pre-processing, such as data augmentation techniques. The last step is to predict the outcome, where the ViT and EfficientNet B0 models are applied.

3.1 Gathering Data

The tomodensitometry (CT) and magnetic resonance imaging (MRI) are two of the many biomedical imaging techniques that are vital for the detection of brain tumors. The MRI, which is especially well-known for its high resolution and detailed information, provides better viewpoints. Table 2 displays the MRI dataset from the well-known Kaggle website, which had 3264 images categorized into three groups.

Table 2 provides a clear overview of the training and test data distribution across classes, now including percentages to highlight data balance or imbalance for glioma, meningioma, and pituitary categories.

Table 2: Contents of a collection for brain MRI scans.

Data Label

Class	Train set (%)	Test set (%)
Glioma	40%	42%
Meningioma	35%	33%
Pituitary	25%	25%

3.2 Pre-Processing

Our brain tumor MRI dataset underwent a number of pre-processing procedures to guarantee data consistency and quality. In order to improve model understanding and prediction accuracy, these steps included resizing images to a standard dimension, normalizing the data to improve model convergence, and using augmentation techniques to diversify the dataset and represent different tumor classes, such as glioma, meningioma, pituitary (See Figure 1).

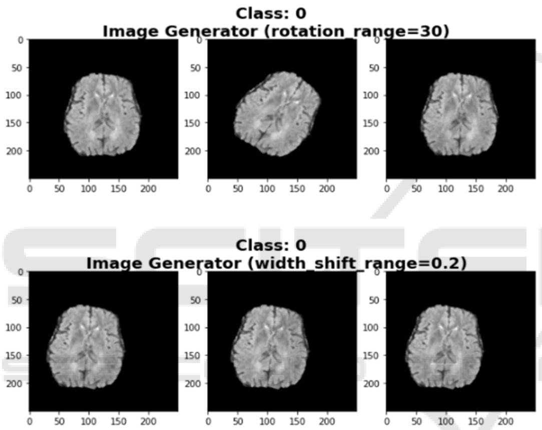

Figure 1: Using the MRI brain tumor data augmentation technique.

Table 3: Augmentation techniques used.

Technique	Parameters	Objective
Rotation	[-30°, +30°]	Introduce angle variations
Translation	[-0.2, +0.2]	Simulate horizontal/vertical shifting
Scaling	[0.8, 1.2]	Represent different tumor sizes
Horizontal/vertical flip	Random	Reduce directional bias
Luminosity/ Contrast	[0.5, 1.5]	Simulate different lighting conditions

The data augmentation methods used to increase model generalization and resilience in brain tumor detection tasks are shown in Table 3.

3.3 Proposed Architectures

3.3.1 Vision Transformer (ViT)

Vision Transformer model debuted at the 2021 International Conference on Learning Representations (ICLR) in the paper "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale." ViTs adapt transformer topologies from natural language processing (NLP) to convert input images into patches resembling word tokens.

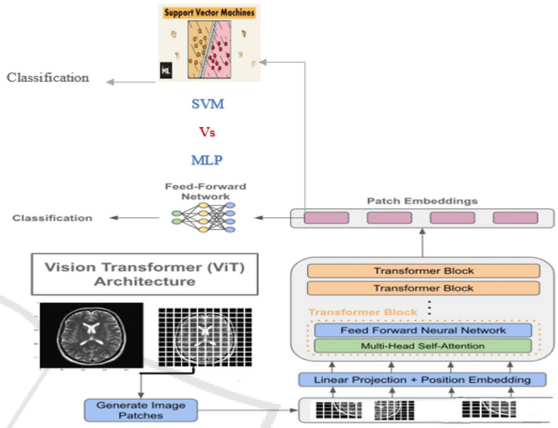

Figure 2: Vision Transformers (ViT) architecture.

Brain tumor images are converted into "patches" for examination. The raw image is divided into small sections prior to applying the "patches," which are then processed by the ViT model to produce insightful representations. This transformation process, ViT can effectively identify and categorize aspects of brain tumors as well as other relevant components in the medical image.

For classification, the standard ViT employs a Feed-Forward Network (FFN) (See Figure 2). In our approach, we replaced the FFN classifier with a Support Vector Machine (SVM) to leverage its proven performance in the medical field. Yang et al. (2018)

The Support Vector Machine (SVM) classifier is utilized for brain cancer detection due to its ability to handle high-dimensional data and create a robust decision boundary between different classes (See Figure 3). Rajinikanth et al. (2022)

By finding the optimal hyperplane that maximizes the margin be-tween tumor and non-tumor samples, the SVM can accurately classify new, unseen images as either containing a brain tumor or not. Its effectiveness in medical applications, including cancer detection, stems from its ability to minimize classification errors and enhance predictive accuracy. Garcia et al. (2020)

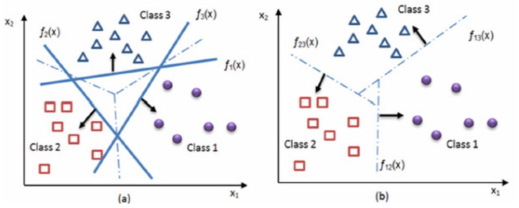

Figure 3: SVM approaches; (a) one-versus-all method, (b) one-versus-one method. **Tan et al. (2023)**.

3.3.2 EfficientNet B0

A convolutional neural network (CNN) with limited processing and memory capacity, EfficientNet B0 is intended for deep learning applications. Due to the simultaneous optimization of the CNN models' depth, width, and resolution, it has a lightweight but robust architecture (See Figure 4).

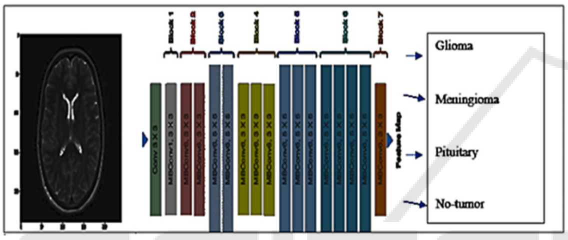

Figure 4: Efficient Net B0 architecture.

With the release of EfficientNetV2, model performance and training speed were enhanced, making it especially appropriate for computationally demanding jobs like medical imaging. Zhang et al. (2023)

4 EXPERIMENTS AND RESULTS

This section describes the data collection process; the images of cerebral tumors serve as the basis for the data used in this work. Effective categorization results are achieved when a broad and diverse data set is used. We will describe and discuss the experimental configurations in the following. The obtained results are then presented and contrasted with the suggested systems.

We investigate the potent capabilities of CNN and Vision Transformers (ViT) architectures to solve the challenging task of picture classification on the cerebral tumor data game. Conventional convolutional neural networks (CNNs) have been the architecture of choice for image-related tasks, but vision-related tasks (ViTs) introduce auto-attention mechanisms inspired by the Transformer architecture, which was originally designed for natural language processing.

Furthermore, in order to actually carry out the study, a phase of analysis and discussion of the experiment's parameters is required (See Table 4).

Table 4: Parameters of EfficientNet B0 Model.

Total parameters	4,054,695
Trainable parameters	4,012,672
Non-trainable parameters	42,023

In this work, we combined a Support Vector Machine (SVM) for classification with Vision Transformers (ViT) as the foundation for feature extraction. The following are specifics of the SVM configuration that was used:

- **Kernel Function:** Because **radial basis function (RBF)** can handle nonlinear feature spaces, that's the kernel we used.

Kernel Parameters for RBF:

- **Sigma:** The value of sigma, also called gamma, is fixed at 0.01. The influence of a single training point is controlled by this parameter.
- **Coefficient:** A second parameter was set to 0.5. For some RBF kernel implementations, it is commonly referred to as coef0. The impact of the linear term in the polynomial and sigmoid kernels is adjusted by this coefficient.

4.1 Dataset

An accurate dataset is essential for using CNNs to classify brain tumors into Glioma, Meningioma, and Pituitary categories. Our dataset, sourced from medical facilities, includes three distinct labels for tumor classification:

- Glioma: classification for brain tumors with gliomas as its defining feature.
- Meningioma: The categorization of brain tumors classified as meningiomas
- Pituitary: Brain tumors associated with the pituitary gland.

The gathered dataset is split into two sub-sets: the first represents the 80% training portion and the second, the 20% test portion. There are three classes of images for each of the two image portions, and each class corresponds to a distinct label for brain tumor classification (See Figure 5).

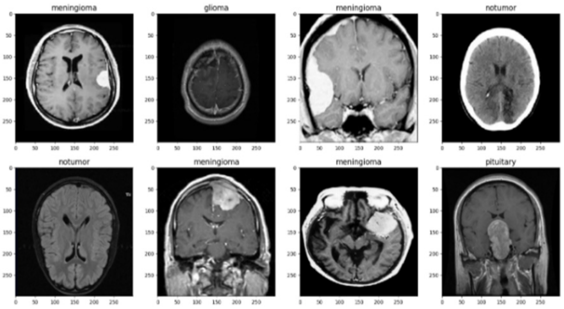

Figure 5: Samples of brain tumor labels.

4.2 Results and Discussion

One of the most widely used systems, the Convolutional Neural Network (CNN) model, is used to classify brain tumors into the Glioma, Meningioma, and Pituitary classes. The performance of the CNN convolutional neural network, the EfficientNet B0, and the Vision Transformers (ViT) architectures are the main subjects of the experimental investigation. The following figures (6 and 7) provide a summary of our suggested system's performance.

4.2.1 Vision Transformers ViT

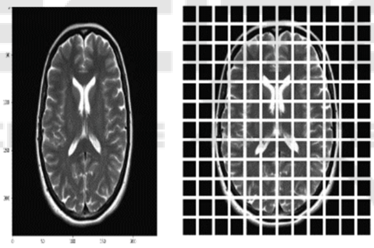

Figure 6: Sample of Brain tumor image applying ViT.

Figure 6 illustrates a brain tumor MRI image processed by the Vision Transformer (ViT), dividing the image into grid-like patches for feature extraction and classification.

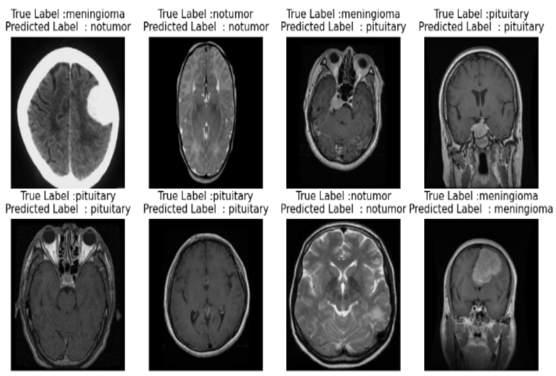

Figure 7: Performance of ViT approach.

The standard ViT shows equable scores of 98% in measures of precision, recall, F1 score, and accuracy, demonstrating reliable classification. Using ViT and SVM, we get an enhanced precision of 98.39% and an accuracy of 98.3%; this means reduced false positives, while recall drops slightly to 98.03%. The F1 slightly increases to 98.2% signifying an overall improvement.

These metrics indicate that ViT can achieve very good brain tumor detection by accurately distinguishing tumor images from the rest of the medical images. (See Table 5)

Table 5: Classification report of our proposed method (ViT).

Methods/ Metrics	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Standard ViT	98%	98%	98%	98%
ViT with SVM	98,39%	98,03%	98,2%	98,3%

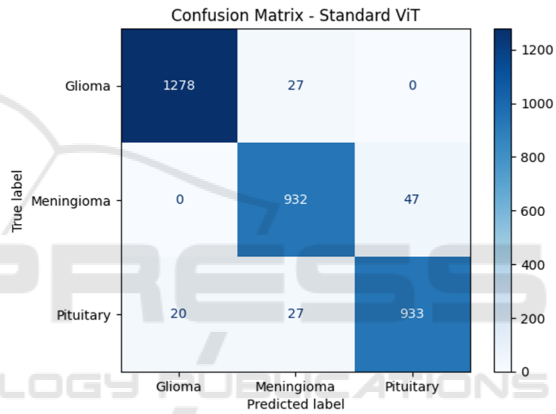

Figure 8: Confusion matrices using ViT.

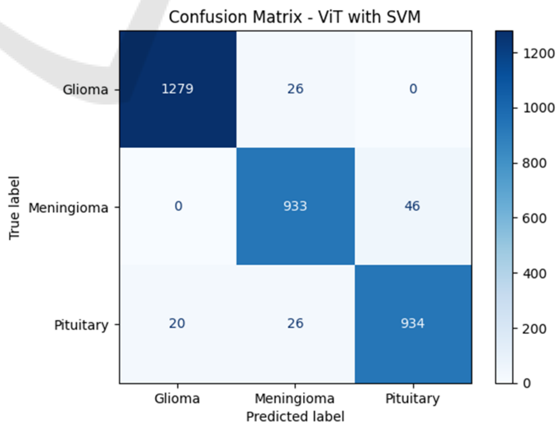

Figure 9: Confusion matrices using ViT combined with SVM.

Figures 8 and 9 presents the confusion matrices generated for the image brain tumor detection task using ViT and ViT combined with SVM.

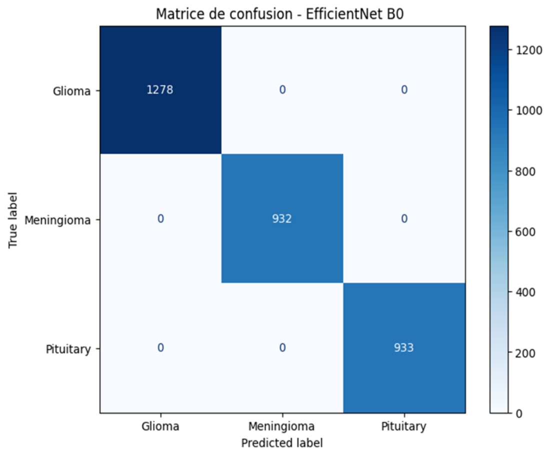

Figure 10: Confusion matrix of the proposed methods (Efficient Net B0).

For the Standard ViT model, with perfect balance between them. It predicts the majority of cases correctly, and only makes minor errors, especially in the Gliomas class because of its small number of false negatives. On the whole, the model is performing well, with only the slightest hit to certain classes.

All three metrics indicate extremely high precision and recall (98%).

On the other hand, the ViT with SVM slightly improves overall precision (98.39%) against the Standard ViT according to incorrect predictions of a small number of false negatives identified with the Glioma class. In some classes, the performance on Meningioma was a little compromised; however, this model establishes a more balanced mechanism across the classes, with an overall increase due to lesser errors expected, thus proving this is an efficient and a more reliable model to perform tumor detection.

4.2.2 Efficient Net B0

To evaluate a brain tumor detection model's efficacy, its ability to classify gliomas, meningiomas, and pituitary tumors is assessed. EfficientNet B0's confusion matrix (Figure 9) shows true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Metrics like precision, recall, and specificity are computed to measure its performance.

Plotting the metrics for the 98% accurate Efficient Net B0 architecture would undoubtedly shed light on the model's performance throughout evaluation and training. Loss and additional measures like validation accuracy, validation loss, and confusion matrix are frequently presented alongside accuracy (See Figure 11).

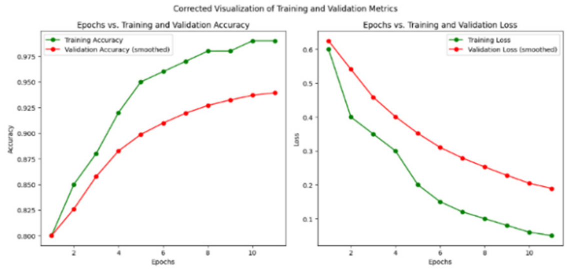

Figure 11: Accuracy vs Epoch and Loss vs Epoch Graph (Efficient Net B0).

Table 6: Classification report of our proposed methods (Efficient Net B0).

	Precision	Recall	F1-score	Support
Glioma	0.98	0.96	0.97	93
Meningioma	0.98	1.0	0.98	51
Pituitary	0.98	0.98	0.98	96
Accuracy			0.98	327
Macro avg	0.98	0.98	0.98	327
Weighted avg	0.98	0.98	0.98	327

The effectiveness of a brain tumor detection model is assessed in this work. Accompanying the support values for every class are f1-score, recall, and precision metrics. The model's promise for brain tumor diagnosis is demonstrated by its high precision, recall, for all classes, as well as its overall accuracy of 98% (see Table 6). The CNN and ViT hybrid strategy make use of complementary strengths. Likewise, SVMs continue to be reliable classifiers for tasks involving medical imaging. He et al. (2022)

Table 7: Performance Comparison using Brain tumor Dataset.

Authors	**Architecture**	**Accuracy**
Our Proposed	Vision Transformer ViT	98%
	ViT with SVM	**98.3%**
	EfficientNet B0	98%
Wani et al. (2023)	CNN, AlexNet, LeNet	94.76%
Rajinikanth et al. (2022)	AlexNet, GoogleNet, VGG-19	90.62%
Zhang et al. (2022)	VGG16, VGG19, SVM, KNN	96.08%
Pang et al. (2023)	Deep Learning Model	95.08%

Table 7 compares various brain tumor detection methods. Our models (EfficientNet, ViT, and SVM) achieved a maximum accuracy of 98.3%, outperforming previous methods like VGG19, AlexNet, GoogleNet, and KNN. This demonstrates the effectiveness of our lightweight and efficient architectures, such as Net B0 and ViT, in achieving promising results for early tumor diagnosis with high accuracy.

4 CONCLUSIONS

Our investigation into EfficientNet and Vision Transformer methods yielded a notable 98.3% accuracy for brain tumor identification. By combining Vision Transformer, SVM, and EfficientNet, we developed a reliable MRI-based detection system. Future work could explore Faster R-CNN integration to improve the speed and accuracy of tumor diagnosis, potentially enhancing patient outcomes and advancing brain tumor detection.

REFERENCES

N. Parmar, A. Vaswani, J. Uszkoreit, L. Kaiser, N. Shazeer, A. Ku, and D. Tran. (2018).Image transformer, International conference on machine learning. PMLR, pp. 4055–4064

M. Gurbină, M. Lascu and D. Lascu. (2019).Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines, 42nd International Conference on Telecommunications and Signal Processing (TSP).

Yuan, Lin, et al.(2018).multi-center brain imaging classification using a novel 3D CNN approach, IEEE Access 6 , 49925-49934

K.Sakthidasan, A S Poyyamozhi, Shaik Siddiq Ali, and Y.Jennifer. (2021).Automated Brain Tumor Detection Model Using Modified Intrinsic Extrema Pattern based Machine Learning Classifier Fourth International Conference on Electrical, Computer and Communication Technologies.

M. K. Abd-Ellah, A. I. Awad, A. A. Khalaf, and H. F. Hamed. (2019). A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned, Magnetic resonance imaging, vol. 61, pp. 300-318.

M. Waqas Nadeem, Mohammed A. Al Ghamdi, Muzammil Hussain, Muhammad Adnan Khan, Khalid Masood Khan, Sultan H. Almotiri and Suhail Ashfaq Butt.(2020). Brain Tumor Analysis Empowered with Deep Learning: A Review, Taxonomy, and Future Challenges Brain Sci.

B. Amarapur.(2019).Cognition-based MRI brain tumor segmentation technique using modified level set method, Cognition, Technology & Work, vol. 21, pp. 357-369.

K. R. Laukamp, F. Thiele, G. Shakirin, D. Zopfs, A. Faymonville, M. Timmer, et al.(2019). Fully automated detection and segmentation of meningiomas using deep learning on routine multiparametric MRI, European radiology, vol. 29, pp. 124-132.

B. Archana, M. Karthigha, and D. Suresh Lavanya. (2023). Comparative Analysis of Optimisers Used in CNN for Brain Tumor Detection, Institute of Electrical and Electronics Engineers (IEEE).

S. Wani, S. Ahuja, and A. Kumar.(2023).Application of Deep Neural Networks and Machine Learning algorithms for diagnosis of Brain tumour, in Proceedings of International Conference on Computational Intelligence and Sustainable Engineering Solution, Institute of Electrical and Electronics Engineers Inc. pp. 106–111.

V. Rajinikanth, S. Kadry, R. Damasevicius, R. A. Sujitha, G. Balaji, and M. A. Mohammed. (2022).Detection in Brain MRI using Pre-trained Deep-Learning Scheme, the 3rd International Conference on Intelligent Computing, Instrumentation and Control Technologies: Computational Intelligence for Smart Systems, ICICICT

He, K., Zhang, X., Ren, S., & Sun, J. (2022). Synergizing Convolutional and Transformer Models for Vision Tasks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(8), 4257-4268.

Yang, Z. R. (2018). Biological applications of support vector machines. Briefings in bioinformatics, 5(4), 328-338.

Jraba, S., Elleuch, M., Ltifi, H., & Kherallah, M. (2023). Alzheimer Disease Classification Using Deep CNN Methods Based on Transfer Learning and Data Augmentation. International Journal of Computer Information Systems and Industrial Management Applications, 1-10..

Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing, 408, 189-2

Tan, M., Pang, R., & Le, Q. V. (2023). EfficientNetV2: Smaller models and faster training. International Conference on Machine Learning (ICML), 10023-10033.