



Enhanced Brain Tumor Classification: A Comprehensive Analysis of CNN Models and Vision Transformers for Improved Diagnosis

Nikhil V¹, M. Rithani²

¹ Student, and ² Faculty

Dept. of Computer Science and Engineering,

Amrita School of Computing,

Amrita Vishwa Vidyapeetham,

Chennai, India

nikhilvenkataraj@gmail.com

Abstract: To classify brain cancers from MRI images, this study evaluates the effectiveness of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs). The study emphasizes the need for correct tumor classification in neuro-oncology, which influences therapy decisions and prognosis assessments. Using a dataset of 7023 images classified as glioma, meningioma, no-tumor, and pituitary, the study investigates the historical backdrop, current methodologies, obstacles, and prospects in brain tumor classification. CNNs, known for their capacity to extract hierarchical features, and ViTs, which are adept at capturing global dependencies, are assessed for their efficacy in this task. The study stresses the significance of using advanced deep learning algorithms for precise diagnosis and treatment planning in neuro-oncology. Despite constraints such as dataset restrictions and model optimization complexities, the investigation yields excellent results, with ViTs emerging as the most accurate classifier, with an accuracy of 97.43%. Furthermore, insights from visualization approaches such as confusion matrices, training curves, and validation curves can help understand model performance dynamics and indicate areas for improvement. Future research topics include refining classification models, investigating new factors, and developing image-based classification approaches to improve patient care and healthcare delivery.

Keywords: Classification, Convolutional Neural Networks (CNN), Vision Transformers (ViTs), Brain Tumors, Neuro-Oncology, Deep Learning

1. INTRODUCTION

In the field of neuro-oncology, classification of brain tumors is a fundamental component that influences treatment choices, prognosis assessments, and research initiatives. The field of brain tumor classification has experienced a radical transformation in recent years due to the development of sophisticated imaging methods, genetic profiling, and machine learning algorithms. This study explores the historical foundations, contemporary approaches, difficulties, and prospective developments in the field of brain tumor classification, delving deeply into its complexities.

Brain tumors are classified as either benign (non-cancerous) or malignant (cancerous), which are aberrant cell growths within the brain [1]. They can arise from various structures like the meninges, glial cells, and other brain components. Among the most perilous tumors affecting both adults and children are brain tumors [2], classified by location, cell type, and malignancy. Symptoms vary based on size, location, and growth rate, including headaches, seizures, vision issues, speech difficulties, weakness, and behavioral changes. Computed tomography (CT) and Magnetic Resonance Imaging (MRI) are standard diagnostic tools for brain tumors. MRI-based deep learning aids in brain tumor classification [3], providing detailed internal visualization using magnetic fields and radio waves, crucial for diagnosing various conditions.

The application of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) architectures for brain tumor classification using MRI data has emerged as a critical area of research in recent years. Because CNNs can automatically learn discriminative features from raw pixel data, they have been widely used in medical image analysis. CNNs can identify complex patterns in MRI images and classify brain cancers accurately by using hierarchical feature extraction. They are also



resilient and scalable, which makes them ideal for processing a wide range of datasets with different degrees of complexity. It has been utilized extensively to address a variety of issues, but its image processing capabilities are particularly strong for use in health-related applications [4]. A class of deep neural networks called convolutional neural networks (CNNs) is widely applied to the analysis of visual input. They have input, output, hidden layers, and hyperparameters [5]. ViTs are particularly good at detecting global dependencies in images, which helps them to simulate long-range interactions and contextual linkages, both of which are essential for correctly classifying tumors.

Despite the notable progress achieved with CNNs and ViTs, challenges persist in brain tumor categorization. Scarcely annotated MRI datasets, class imbalances, and interpretability issues hinder the development of reliable classification models. Integrating multimodal imaging data, such as DTI, PET, and MRI, holds promise for improving the accuracy and reliability of classification algorithms in the future. The fusion of multimodal data with advanced deep learning architectures like CNNs and ViTs presents a transformative approach to brain tumor classification, with potential implications for patient care, clinical decision-making, and neuro-oncology research. This research aims to automate brain tumor classification through extensive testing and fine-tuning of deep learning models [6].

2. LITERATURE REVIEW

A comprehensive analysis of the corpus of research on the detection and categorization of brain tumors is given in the literature review for brain tumor classification. This review seeks to shed light on the current approaches, technologies, and innovations used in the classification process by examining scholarly articles, journals, and research.

Noreen et al. (2020) [2] provided with a deep learning method that uses multi-level extraction of features and concatenation to classify brain tumors. They extract characteristics and combine them to perform classification using pre-trained models such as Inception-v3 and DensNet201, obtaining great accuracies of 99.34% and 99.51%, respectively, on testing samples. This strategy performs better than current ML and deep learning techniques. The study's focus is restricted to a three-class brain tumor dataset, indicating the necessity for additional validation on more extensive and varied datasets to evaluate generalizability.

Gumaei et al. (2019) emphasize the importance of accurate brain tumor classification systems for medical diagnosis. Their proposed methodology blends mixed feature extraction techniques, such as the PCA-NGIST method and min-max normalization, with a regularized extreme learning machine. On published datasets, categorization accuracy is 94.233%. The report recommends future exploration with various approaches across biological datasets, as well as comparison analysis using other classifiers [7].

Ferdous et al. (2023) provide LCDEiT, a Linear Complexity Data-Efficient Image Transformer for brain tumor classification with MRI data. It uses a teacher-student strategy and an external attention mechanism to overcome biases and dependency issues in deep learning models, enabling quick training with less data. Evaluation on benchmark datasets shows high accuracy (98.11% for Figshare, 93.69% for BraTS-21), outperforming current methods. LCDEiT has potential in improving medical imaging diagnostics, particularly in resource-constrained environments. Future study could focus on dataset balancing and increasing experimental databases to improve performance [8].

Atha and Chaki (2023) introduce SSBTCNet, a semi-supervised brain tumor classification network based on MRI images. Combining supervised classification networks with an unsupervised



autoencoder (AE) improves classification performance. Using semi-supervised learning, both the classifier and the AE learn latent features at the same time, with a fuzzy logic-based method helping instance generation. Evaluation across datasets reveals superiority to existing approaches. The study stresses the efficacy of unsupervised learning in boosting classification accuracy, particularly with insufficient labeled data. Future study should include validation using larger datasets, investigating alternative designs, and addressing issues such as tumor localization and efficacy upgrades [1].

The literature review on brain tumor classification identifies research gaps, particularly in the use of CNNs and cutting-edge algorithms such as ViTs, as well as the need for enhanced datasets. While CNNs have proven effective, other models such as ViTs provide great opportunities for improving classification accuracy. However, existing datasets frequently lack diversity and quantity, reducing the robustness of these models. To solve these constraints, future research should focus on refining CNN and ViTs structures as well as collecting larger and more representative datasets.

3. PROPOSED METHODOLOGY

3.1 Visualization of Dataset:

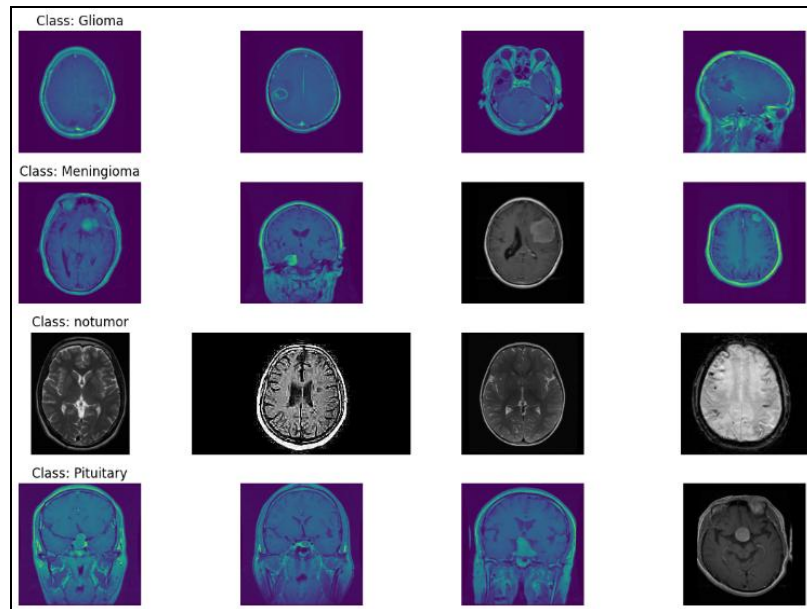


Figure 1: Images belonging to different classes (Augmented and Normal Images)

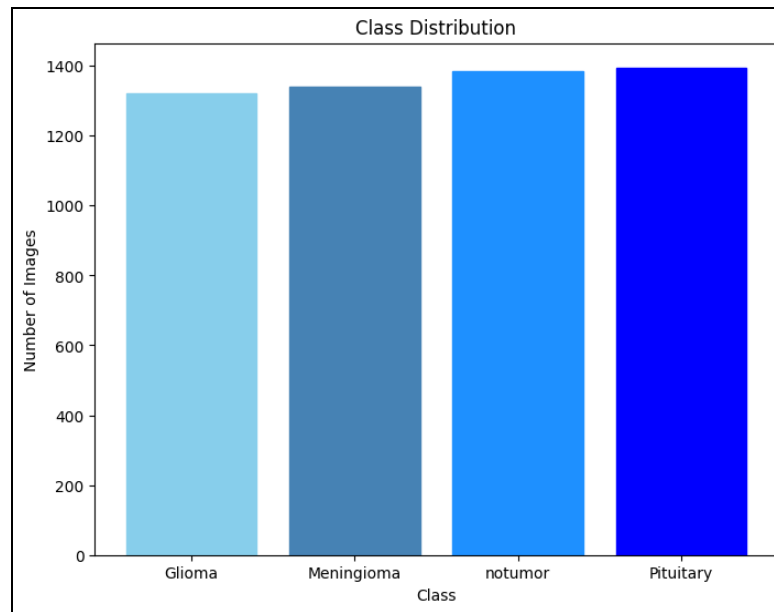


Figure 2: Different class distribution

3.2 Data Collection and Processing:

7023 photos were utilized in the dataset for this study, which was divided into training and testing sets. The training set consists of 5712 images and the testing set consists of 1311 images. Glioma, Meningioma, No-Tumor, and Pituitary are the four unique classes into which the images are categorized. These groups denote both the lack of tumors and various forms of brain tumors. The training set is used to help the model learn patterns, features, and relationships within the dataset. The testing set is used to assess the model's performance in forecasting previously unobserved data. The images are in .jpg format and can be pre-processed.

The image quality in medical photography is frequently affected by unanticipated circumstances such as noise and brightness [9]. So, the following techniques are applied to generalize the images, which improves the network's capacity to acquire information and extrapolate from the data set [10].

- **Data Loading and Resizing: Rescaling:** This process sets the image's pixel values to a normal range of 0 to 1. Normalization is essential because it helps to standardize the input data, which facilitates effective learning and convergence of the neural network.
- **Scaling the Data:** Pixel values normally range from 0 to 255 (for 8-bit images), where 0 represents black and 255 represents white. This makes scaling crucial. You may effectively scale all pixel values down to the range of 0 to 1 by dividing them by 255. By guaranteeing that the input data has a constant scale, the normalization process can aid in enhancing the neural network's convergence during training.
- **Data Augmentation:** To successfully increase the heterogeneity of the training dataset, random transformations are conducted to the training images. This code snippet outlines a Keras layer-based data augmentation pipeline [11].

3.3 Model Architecture:



Convolutional Neural Networks (CNN): CNNs are a subset of deep neural networks that are mostly employed in image processing. They are effective instruments for segmentation, classification, and picture recognition, among other tasks. CNNs are built with the ability to identify feature spatial hierarchies automatically and adaptably from the input images. They are designed to take the raw pixel data and use it to learn structural patterns and characteristics automatically and adaptively.

- i. **Convolutional Layers:** The convolutional layer is the first essential part of CNNs. These layers extract features like edges, textures, and forms from input images by applying learnable filters, often known as kernels. Every filter creates a feature map that emphasizes pertinent spatial patterns by convolving across the input image.
- ii. **Pooling Layers:** Pooling layers, which come after convolutional layers, are frequently used to down sample feature maps while keeping the most crucial data. By choosing the largest value from each input subregion, max pooling, for example, lowers the spatial dimensions of the data and strengthens the network's resistance to changes in the input images.
- iii. **Flattening:** Before being sent to fully connected layers, the feature maps are transformed into a 1D vector. The geographic data is transformed in this way so that it can be used in layers of a standard neural network.
- iv. **Fully Connected Layers:** Each of the neurons in each layer above and below is linked to all the other neurons in the network in a fully connected neural network. These layers enable the network to discover complex relationships between the collected features and the target labels.
- v. **Activation Functions:** Activation functions allow the model to develop and represent complex mappings between the inputs and outputs by injecting non-linearity across the network.
- vi. **Model Compilation:** The model must be compiled using the proper loss functions, optimizers, and evaluation metrics after the architecture has been defined.

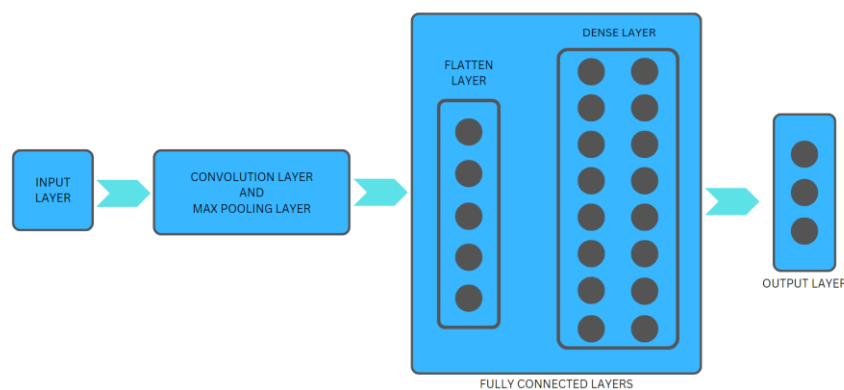


Figure 3: Architecture Diagram of CNN

Vision Transformers: A novel type of neural networks called Vision Transformers (ViTs) was developed to manage computer vision problems. ViTs do not use any convolutional layers; instead, they only rely on self-attention processes, in contrast to conventional CNN's which have long dominated computer vision architecture. The architecture and related group of networks define the



global reliance in the input sequence data using the Self-attention mechanism. Compared to its earlier version, Long Short-Term Memory (LSTM) Transformer, which is based on Self-attention, may demonstrate great scalability, model capacity, and data parallel processing [12].

- i. **Self-Attention Mechanism:** Originally included in the Transformer framework for tasks involving natural language processing, the self-attention mechanism forms the basis of Vision Transformers. The self-attention feature enables the model to assess the relative significance of distinct input components when analyzing a particular aspect. Self-attention is employed in Vision Transformers to record inter-image patch global dependencies.
- ii. **Image patching** involves creating smaller, fixed-size patches from the input image. Every patch, which is usually 16 by 16 pixels, is handled like a token, much like words in jobs involving natural language processing. After that, these
- iii. patches are linearly embedded into vectors with lower dimensions.
- iv. **Positional Encoding:** Positional encodings have been added into the patch embeddings since Vision Transformers lack CNNs' inherent understanding of spatial relationships. The spatial location of every patch in the image is disclosed by positional encodings.
- v. **Transformer Encoder:** The positional encodings and patch embeddings are sent to a Transformer encoder. Following multiple layers of self-attention processes, feed-forward neural networks (FFNs) make up the encoder. Each layer aggregates data from many patches, enabling the model to improve its comprehension of the visual features.
- vi. **Classification Head:** A fixed-size representation of the complete image is produced by normally pooling the output of the last Transformer encoder layer over all patches. To forecast the image's class labels, this representation is subsequently input into a classification head, such as a fully connected layer or a layer with SoftMax.

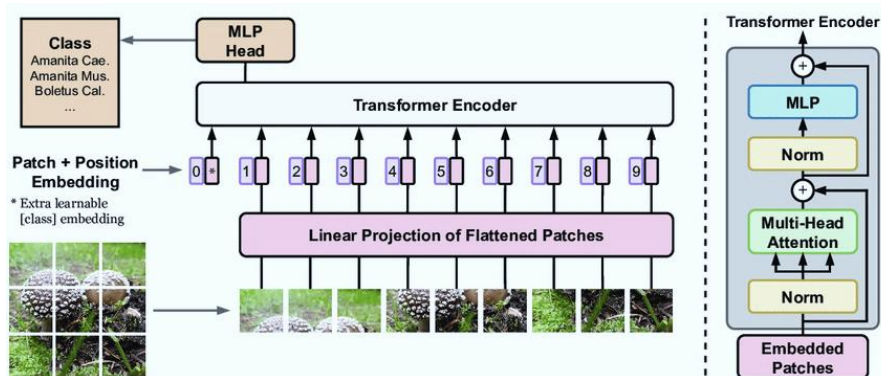


Figure 4: Architecture diagram of Vision Transformers [13]

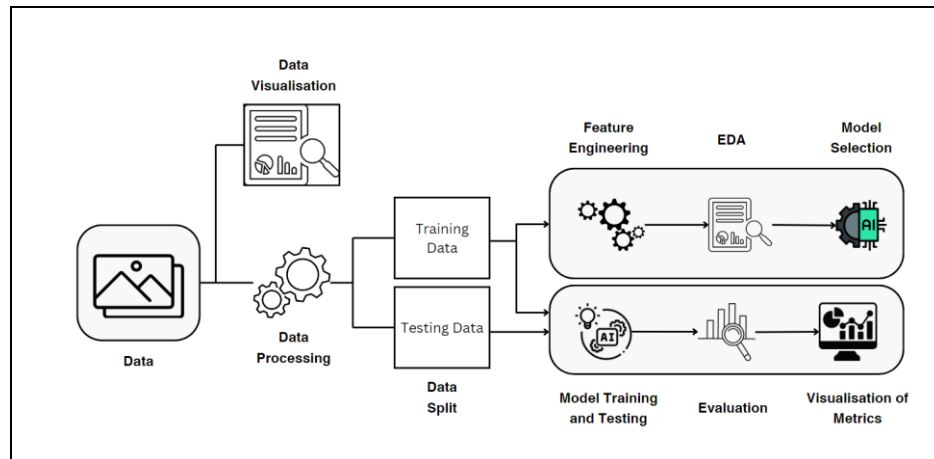


Figure 5: Model Architecture

3.4 Model Training:

The training technique used a hybrid approach, combining classic Convolutional Neural Networks (CNN) with Vision Transformers (ViTs) to enable thorough model learning. For CNN, two optimizers were used: Adam and RMSProp with ReLU and Tanh functions, both with fixed learning rate schedules. Dropout regularization was used to reduce overfitting, as well as weight decay to help stabilize training. With a small batch size, CNN experienced 10 epochs of training, while the ViTs, which was launched later, underwent 5 epochs. To guarantee an accurate and trustworthy forecast, the data was separated divided into sets for training and testing [14]. An 80-20 split of the dataset was made into train and test categories.

4. RESULTS

In this study, Convolutional Neural Networks (CNN) and Vision Transformers (ViT) were the two models utilized to categorize photos of brain tumors. We performed a comparative analysis of different machine learning algorithms [15]. Both models were trained and tested with brain tumor images. The findings show that deep learning is excellent for classifying brain tumors. The CNN models were optimized using popular algorithms like Adam and RMSProp, which played a significant role in altering network parameters to minimize the loss function and improve prediction performance. Different activation functions were investigated for CNN architecture to add non-linearity to the model, which is essential for capturing intricate patterns and features in the brain tumor images. To make this procedure easier, activation functions known as Rectified Linear Unit (ReLU), Leaky ReLU, and Hyperbolic Tangent (tanh) were used. We evaluate our approach using commonly used metrics: recall, F1-score, accuracy, and precision [16].

1. Recall: This statistic evaluates how well the model separates all relevant instances of brain cancer from all real cases of brain tumors.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

2. F1 Score: The precision and recall harmonic means are represented by the F1-score. It provides information about the overall accuracy of the model by striking a balance between recall and precision.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

3. Accuracy: This metric calculates the proportion of all images that correctly diagnose brain tumors.



$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Predictions}$$

4. Precision: The ratio of actual positive predictions to all positive predictions the model makes is known as precision. It illustrates how the model can prevent misunderstanding images of non-tumors for pictures of tumors.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

The obtained results are given in the tabulated form below:

Model	Activation	Accuracy	Precision	Score	Recall
ResNet	ReLU	96%	95%	0.93	96%
ResNet	LU	96%	95%	0.59	96%
ResNet	Leaky ReLU	96%	95%	0.62	95%
MSProp	ReLU	96%	95%	0.7	96%
MSProp	LU	96%	95%	0.6	96%

Table 1: Performance Metrics for CNN

Model	Accuracy	Loss
ViTs	97.43%	0.0017

Table 2: Performance Metrics for Vision Transformer

When comparing the performance of Convolutional Neural Networks (CNN) and Vision Transformers (ViTs) in categorizing brain tumor images, the Transformer model clearly beats the CNN models in terms of accuracy. Specifically, the Transformer model obtained a remarkable accuracy of 97.43%, exceeding the greatest accuracy attained by any CNN model, which was 96%. This suggests that the Transformer model is superior at accurately categorizing brain tumor images. Furthermore, the Transformer model attained this impressive accuracy with a loss of 0.0017, demonstrating its usefulness in this task. According to the data provided, the Transformer model is the most accurate classifier for brain tumor picture categorization.

Beyond just measuring accuracy, an analysis of the training, validation, and confusion curves offers further information into the model's performance. The confusion matrix shows true positives, false positives, true negatives, and false negatives, indicating the model's categorization strengths and limitations. Furthermore, the training and validation curves show the model's learning progress over epochs, suggesting training stability and potential overfitting/underfitting. These visualizations provide useful insights into the models' performance dynamics, which contribute to their improvement for accurate brain tumor picture classification.

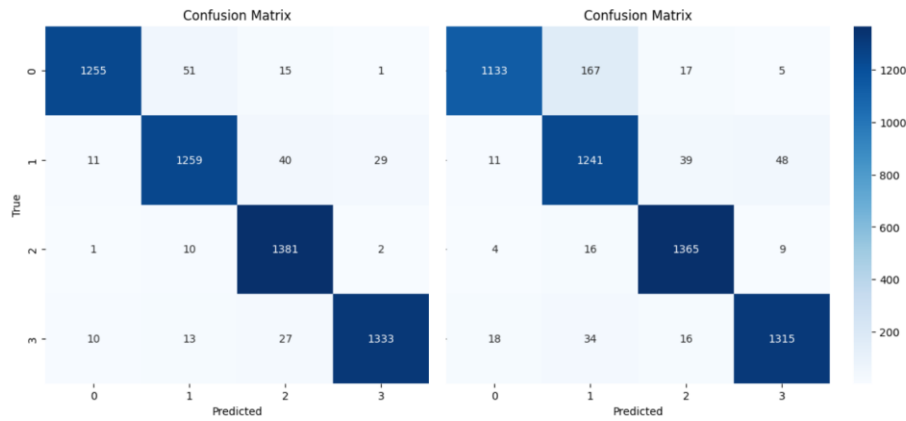


Figure 6: Confusion Matrix for Adam using Tanh and ReLU function

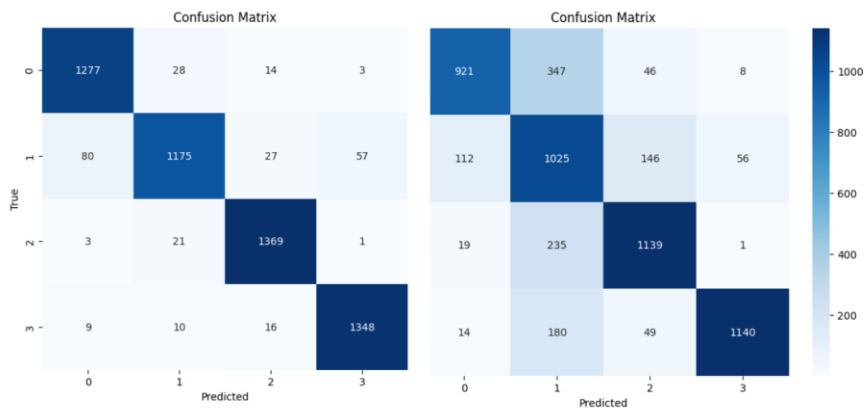


Figure 7: Confusion Matrix for RMSProp using ReLU and Tanh function

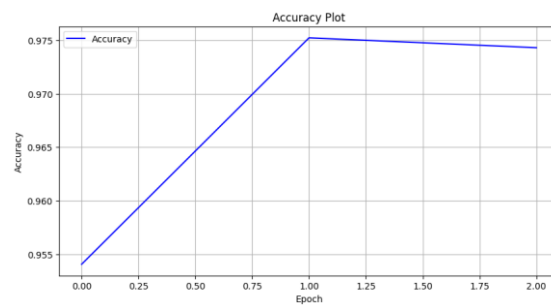


Figure 8: Accuracy vs Epoch plot

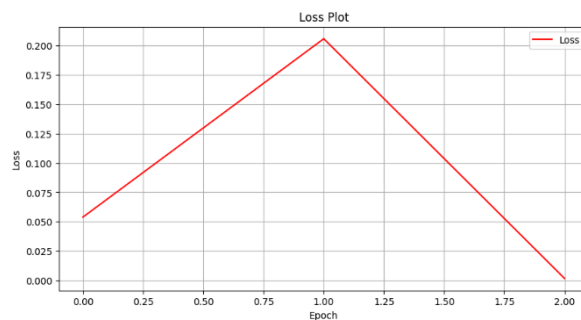




Figure 9: Loss vs Epoch plot

5. CONCLUSION

This work concludes by demonstrating how well deep learning techniques—in particular, Convolutional Neural Networks (CNN) and Vision Transformers (ViTs)—classify brain cancers from medical photos. It underscores the significance of CNN in automated medical image segmentation, as evidenced by its state-of-the-art results [17]. The optimization process in CNN models was facilitated by employing popular algorithms like Adam and RMSProp, which aided in adjusting network parameters to minimize loss and enhance predictive performance. Various activation functions, including Rectified Linear Unit (ReLU), Leaky ReLU, and Hyperbolic Tangent (tanh), were explored. Despite the inherent challenges in interpreting and managing medical image datasets [18], the findings emphasize the importance of leveraging advanced machine learning techniques for precise diagnosis and treatment planning. Further analysis was performed through visualization of training and validation curves, as well as confusion matrices, providing insights into model performance and potential areas for improvement.

The application of the model may be limited by the dataset's depiction of brain tumor images. Analytics can be used to analyze and decide on different other data [19] regarding brain tumor. This emphasizes the pivotal role of high-quality and comprehensive datasets in training effective classification models [20]. Furthermore, the choice of activation functions and optimization methodologies may have varying effects on model performance, depending on the dataset and task specifications. As a result, more validation on various datasets is required to ensure the stability and effectiveness of our suggested technique.

Moving forward, future research can capitalize on this approach to develop a robust tumor classification model applicable to a wide range of medical images [21]. Given that imaging-based testing forms the cornerstone of diagnostic procedures in clinical settings for genuine medical conditions [22], further exploration of the suggested model with additional parameters is warranted [23]. Moreover, there is ample scope for expansion and refinement of image-based classification methodologies, urging future studies to continue advancing in this domain [24]. In addition to having performance, the offered solution needs to be economically sound [25]. These advancements have implications for improving patient outcomes and the provision of healthcare. This work contributes to the subject by investigating different CNN models, Transformers, and Ensemble models [26].

6. REFERENCES

- [1] Z. Atha and J. Chaki, "SSBTCNet: Semi-Supervised Brain Tumor Classification Network," in *IEEE Access*, vol. 11, pp. 141485-141499, 2023, doi: 10.1109/ACCESS.2023.3343126.
- [2] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran and M. Shoaib, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor," in *IEEE Access*, vol. 8, pp. 55135-55144, 2020, doi: 10.1109/ACCESS.2020.2978629.
- [3] K. Neamah et al., "Brain Tumor Classification and Detection Based DL Models: A Systematic Review," in *IEEE Access*, vol. 12, pp. 2517-2542, 2024, doi: 10.1109/ACCESS.2023.3347545.
- [4] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi and J. Si, "Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images," in *IEEE Access*, vol. 10, pp. 34716-34730, 2022, doi: 10.1109/ACCESS.2022.3153306.
- [5] S. Solanki, U. P. Singh, S. S. Chouhan and S. Jain, "Brain Tumor Detection and Classification Using Intelligence



Techniques: An Overview," in IEEE Access, vol. 11, pp. 12870-12886, 2023, doi: 10.1109/ACCESS.2023.3242666.

[6] H. A. Shah, F. Saeed, S. Yun, J. -H. Park, A. Paul and J. -M. Kang, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet," in IEEE Access, vol. 10, pp. 65426-65438, 2022, doi: 10.1109/ACCESS.2022.3184113.

[7] A. Gumaei, M. M. Hassan, M. R. Hassan, A. Alelaiwi and G. Fortino, "A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification," in IEEE Access, vol. 7, pp. 36266-36273, 2019, doi: 10.1109/ACCESS.2019.2904145

[8] G. J. Ferdous, K. A. Sathi, M. A. Hossain, M. M. Hoque and M. A. A. Dewan, "LCDEiT: A Linear Complexity Data-Efficient Image Transformer for MRI Brain Tumor Classification," in IEEE Access, vol. 11, pp. 20337-20350, 2023, doi: 10.1109/ACCESS.2023.3244228

[9] M. Ranjith Kumar, G. V. K. Kumar, V. Nikhil, R. Ishwariya and V. Govindan, "A Robust Convolutional Neural Network Approach for Classifying Skin Cancer," 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI), Raipur, India, 2023, pp. 1-6, doi: 10.1109/ICAIIHI57871.2023.10489085.

[10] M. R. Kumar, R. Mani, P. Revathi, S. Sabarinathan and V. Govindan, "A Robust and Fast Symmetric Text Encryption Algorithm Based on Fermat's Two Squares Theorem," 2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India, 2023, pp. 1-5.

[11] R. Kamalraj, S. Neelakandan, M. Ranjith Kumar, V. Chandra Shekhar Rao, Rohit Anand, Harinder Singh, "Interpretable filter based convolutional neural network (IF-CNN) for glucose prediction and classification using PD-SS algorithm," Measurement, vol. 183:109804, 2021.

[12] K. T. Chitty-Venkata, M. Emani, V. Vishwanath and A. K. Somani, "Neural Architecture Search for Transformers: A Survey," in IEEE Access, vol. 10, pp. 108374-108412, 2022, doi: 10.1109/ACCESS.2022.3212767.

[13] Picek, Lukas & Sulc, Milan & Matas, Jiri & Heilmann-Clausen, Jacob & Jeppesen, Thomas & Lind, Emil. (2022). Automatic Fungi Recognition: Deep Learning Meets Mycology. Sensors. 22. 633. 10.3390/s22020633.

[14] S. Singh, D. Chaudhary, B. Yogiraj, R. N. Prajapathi and S. Rana, "Adam Optimization of Burger's Equation Using Physics-Informed Neural Networks," 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), Gharuan, India, 2023, pp. 129-133

[15] S. M. Kuriakose, P. Basa Pati and T. Singh, "Prediction of Diabetes Using Machine Learning: Analysis of 70,000 Clinical Database Patient Record," 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2022, pp. 1-5, doi: 10.1109/ICCCNT54827.2022.9984264.

[16] A. Mishra, R. Jha and V. Bhattacharjee, "SSCLNet: A Self-Supervised Contrastive Loss-Based Pre-Trained Network for Brain MRI Classification," in IEEE Access, vol. 11, pp. 6673-6681, 2023, doi: 10.1109/ACCESS.2023.3237542.

[17] G. Wang et al., "Interactive Medical Image Segmentation Using Deep Learning With Image-Specific Fine Tuning," in IEEE Transactions on Medical Imaging, vol. 37, no. 7, pp. 1562-1573, July 2018, doi: 10.1109/TMI.2018.2791721.

[18] P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen and P. Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network," in IEEE Access, vol. 7, pp. 46278-46287, 2019, doi: 10.1109/ACCESS.2019.2902252.

[19] Rithani M., R. Prasanna Kumar & Srinath Doss, "A review on big data based on deep neural network approaches," Artificial Intelligence Review (2023). DOI: <https://doi.org/10.1007/s10462-023-10512-5>

[20] V. Nikhil, S. A. Sahaaya Arul Mary, B. Natarajan, A. Bajulunisha, R. S. Anuradha and K. Venkatraman, "Revolutionizing Influenza A Detection in Humans: Unleashing the Power of XGBoost Classification," 2024 IEEE International Conference for Women in Innovation, Technology & Entrepreneurship (ICWITE), Bangalore, India, 2024,



pp. 229-234, doi: 10.1109/ICWITE59797.2024.10503406.

[21] A. M. Hasan, H. A. Jalab, F. Meziane, H. Kahtan and A. S. Al-Ahmad, "Combining Deep and Handcrafted Image Features for MRI Brain Scan Classification," in *IEEE Access*, vol. 7, pp. 79959-79967, 2019, doi: 10.1109/ACCESS.2019.2922691.

[22] H. A. Hafeez et al., "A CNN-Model to Classify Low-Grade and High-Grade Glioma From MRI Images," in *IEEE Access*, vol. 11, pp. 46283-46296, 2023, doi: 10.1109/ACCESS.2023.3273487.

[23] M. Assam, H. Kanwal, U. Farooq, S. K. Shah, A. Mehmood and G. S. Choi, "An Efficient Classification of MRI Brain Images," in *IEEE Access*, vol. 9, pp. 33313-33322, 2021, doi: 10.1109/ACCESS.2021.3061487.

[24] N. S. Amer and S. B. Belhaouari, "EEG Signal Processing for Medical Diagnosis, Healthcare, and Monitoring: A Comprehensive Review," in *IEEE Access*, vol. 11, pp. 143116-143142, 2023, doi: 10.1109/ACCESS.2023.3341419.

[25] M. S. P. Rahul and M. Rajesh, "Image processing based Automatic Plant Disease Detection and Stem Cutting Robot," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2020, pp. 889-894, doi: 10.1109/ICSSIT48917.2020.9214257.

[26] S. S et al., "Generalized Deep-learning Models to Classify Allen Telescope Data," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10306700.