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Automated Brain Tumor Classification Technique using ResNet model

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***Abstract*— The brain tumors from MRI images must be accurately classified for efficient diagnosis and treatment planning. This research proposes a unique method that uses the ResNet architecture found in Convolutional Neural Networks [12]. Our methodology includes preprocessing MRI images, applying deep learning algorithms to extract features, and using ResNet for classification. Extensive tests demonstrate that our approach outperforms the norm regarding precision, precision, and recall rates [16]. Giving doctors a reliable way to diagnose and tailor their treatment plans, this study advances automated brain tumor classification techniques, enhancing patient treatment and outcomes. RELU techniques have an F1 score of 1.754886, a Loss factor of 0.304883, and an accuracy of 97.34.**

Keywords: CNN, ResNet, Tumor Segmentation, Augmentation

I. Introduction

It's indeed critical to correctly to classify brain tumors using imaging studies in order to diagnose and treat neurological conditions. Machine learning advances, especially in the area of deep learning, have completely changed the field of medical image analysis [21]. Convolutional neural networks (CNNs) are becoming powerful instruments for automated tumor categorization [6]. The goal of this work is to categorize brain tumors into three different groups: meningiomas, pituitary gliomas, and others—using the popular deep learning framework ResNet (Residual Neural Network) framework. The selection of ResNet is motivated by its capacity to efficiently handle deep networks, addressing the issue of disappearing gradients encountered in conventional deep neural networks. Furthermore, ResNet introduces residual connections, facilitating the development of deeper systems and minimizing the chance of performance decline [12]. The Rectified Linear Unit (ReLU) activation function has traditionally been employed in CNNs due to its simplicity and computational effectiveness, we intend to demonstrate the superiority of ResNet over the ReLU in the context of brain tumor classification.

A thorough comparison of ResNet-based classification with traditional methods, including ReLU-based architectures, is included in our study. The effectiveness of ResNet is assessed through extensive testing on a wide range of MRI scans of brain tumors, brain tumor dataset, which consists of three distinct forms of brain tumors meningioma, glioma, and pituitary tumor contrast-enhanced T1-weighted images.708 slices, 1426 slices, and 930 slices, in that order. The ResNet model's predictions are interpreted in a way that sheds light on its decision-making process and potential health implications [12]. The ResNet model is assessed for its generalizability across different patient demographics, imaging modalities, and tumor characteristics, beyond performance metrics. Furthermore, we investigate the potential of transfer learning by employing pre-trained ResNet models on massive data sets to enhance classification efficiency with limited annotations [8].

We are contributing to the expanding corpus of research in medical imaging and AI-based healthcare while demonstrating the efficacy of ResNet in brain tumor detection [18]. This study's conclusions might have a big

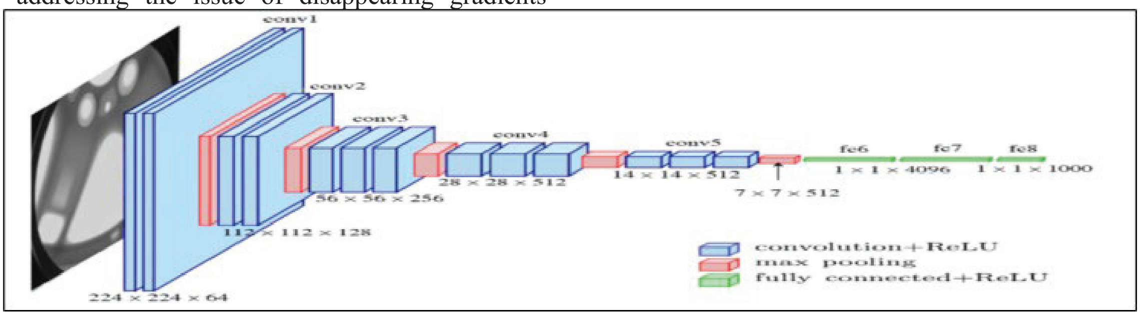

Fig. 1. Architecture of ResNet50[26]

influence on clinical practice, providing healthcare professionals with advanced tools for accurate diagnosis and personalized treatment planning in the field of neurology [16]. Improve patient outcomes and quality of care by bridging the gap between cutting-edge machine learning techniques and real-world clinical applications.

II. LITERATURE REVIEW

Thanks to the use of deep learning algorithms, considerable progress has been achieved recently in the automatic identification and categorization of brain cancers using MRI data [11]. Numerous significant research works have offered innovative approaches and structures designed to improve the precision and effectiveness of this crucial diagnostic procedure. The paper "Multi-Classification of Brain Tumor Images Using Deep Neural Network" presented a traditional CNN design with 16 layers [11]. In the meanwhile, "A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks" supported a more sophisticated method of image analysis by illuminating the effectiveness of using lower kernel sizes in CNNs[17].

Additionally, "Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images" creatively used type-specific image sorting to segment, which contributed to a notable improvement in tumor delineation accuracy [5]. "Brain Tumor Classification and Detection Using Hybrid Deep Tumor Network," which suggested a hybrid model combining CNN with GoogleNet, is another important addition. It illustrates the potential of synergistic techniques in enhancing the accuracy of classification and detection [7]. The systems were further improved by the introduction of innovative CNN designs and denoising algorithms in "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images" [15]."Brain Tumor Detection and Classification Using Fine-Tuned CNN with ResNet50 and U-Net Model: A Study on TCGA-LGG and TCIA Dataset for MRI Applications" is incorporated, offering a sophisticated investigation into CNN architecture fine-tuning for improved tumor detection and classification. Additionally, "A review on image processing and image segmentation" [10] and "Very deep convolutional networks for large-scale image recognition" [13] offer important perspectives and fundamental information necessary to comprehend in automated brain tumor detection. When taken as a whole, these research highlight how important deep learning is to expanding the possibilities for automated brain tumor identification, which will have significant effects on patient care and clinical practice. These developments provide promise for earlier detection, more precise diagnoses, and eventually better outcomes for people via ongoing innovation and improvement.

The cumulative impact of these studies highlights the growing significance of machine learning techniques in advancing the discipline of brain tumor classification and diagnosis.

III. RESEARCH OBJECTIVES

To create a deep deep learning-oriented brain tumor detection system that uses CNN architectures to automatically diagnose cases and help with treatment planning and early detection

To compare the suggested ResNet-50 architecture's efficiency to existing CNN models, showcasing its superiority in terms of precision and efficacy for the categorization of brain tumors

IV. DATASET DESCRIPTION

The tumor data, curated by Jun Cheng, has been made accessible on figshare.com. This study encompasses a total 3064 MRI images obtained contrast-enhanced from 233 individuals, encompassing three distinct types of brain tumors: meningioma, glioma, and pituitary tumor as 708 ,1420, and 930 slices respectively.

To facilitate instruction and assessment, the dataset was divided in training and evaluation groups as. The training set consisted of 80% of the data, comprising 2451 images, while the testing set comprised the remaining 20%, containing 613 images.

The images within the dataset exhibit variations in dimensions and pixel density, with different scans displaying different dimensions and pixel values. To ensure uniformity and compatibility with the deep learning model, preprocessing techniques were employed.

Initially, the image data was presented in MATLAB data format (.mat file). However, to enhance compatibility with the majority of deep learning frameworks and applications, the images were reformatted into JPEG files. The image data was extracted from the .mat files, underwent appropriate preprocessing steps such as resizing and normalizing, and the processed images were saved in the JPEG format.

The dataset was partitioned into four subsets, each housed in a separate zip file to adhere to the maximum file size of the repository. Each of these.zip files contains 766 slices of brain tumor images. The model's performance was rigorously evaluated using the 5-fold cross-validation indices provided.

V. IMAGE PREPROCESSING

Preprocessing procedures are essential for guaranteeing data quality and making it easier to analyse picture data later on. These crucial processes prepare raw picture data for further analysis or model training by cleaning and standardizing it. Carefully considered methods like as scaling and normalization are used to improve the readability and efficiency of computing activities [10]. Let's examine these preprocessing procedures and how important they are for maximizing the accuracy and dependability of our results.

This are the major preprocessing steps:

A. Image Conversion and Rotation :

- Description: Convert the original image array to a PIL image and then rotate it randomly at different angles ranging from -45 degrees to 330 degrees. Finally, convert the rotated image to a tensor.

- Code: Utilizes `transforms.ToPILImage()` to convert the image array to a PIL image, followed by `transforms.RandomRotation()` to perform random rotations, and `transforms.ToTensor()` to convert the rotated image to a tensor.

B. Data Augmentation:

-Description: Augment the original images by rotating them at various angles to increase the diversity of the dataset.

-Code: Defines multiple transformation pipelines (`transform1` to `transform7`), each including random rotation transformations to generate augmented images at different angles.

C. Label Encoding:

-Description: One-hot encode the labels to represent the classes.

- Code: Constructs one-hot encoded labels for each sample, ensuring compatibility with the network output.

These steps collectively prepare the dataset for training neural networks by enhancing its variability and ensuring labels are properly encoded.

VI. Network Training

This study employs a model with a ResNet-50 architecture exclusively trained using train data to detect brain tumors. The performance evaluation of the suggested model demonstrates its superiority over traditional architectures like ReLU. The ResNet framework has proven to be incredibly useful for our computational endeavors. With a training duration of 180.97 minutes and a GPU memory usage of 506660864 kb, we observed substantial improvements in accuracy compared to prior models utilizing ReLU activation. As evidenced by the training accuracy steadily increasing, the model displayed remarkable progress over multiple epochs.

Consequently, the training loss decreased from 0.9621 to 0.0073 during this time. Furthermore, the degree of verification precision consistently grew, reaching a peak of 94.89% in epoch 11, while the degree of verification loss remained relatively low.

VII. Metrix of Performance

The model's performance may be evaluated using the following measures.

Epochs 1-4: The model is improving in terms of accuracy and reducing loss. Validation metrics are also improving, indicating good generalization.

Epochs 5-6: The model continues to improve, with high accuracy and low loss. However, there's a slight increase in validation loss in Epoch 6, which could be a sign of overfitting.

Epoch 7: A significant improvement in validation accuracy, suggesting good generalization. The F1 score is provided.

Epochs 8-12: The model is achieving very high training accuracy, but there is a spike in training loss in Epoch 8. Validation metrics remain competitive, although there's a slight increase in validation loss in Epoch 8.

Overall, the model seems to be performing well, achieving high accuracy on both training and validation sets. However,

TABLE I. Summary of the epochs from a previous CNN model [25]

CNN Models	Test Accuracy	Test Loss	F1 Score
1-convo-32-nodes-0-dense	0.9467	0.1751	0.9398
2-convo-32-nodes-0-dense	0.9450	0.1473	0.9392
3-convo-32-nodes-0-dense	0.9700	0.0997	0.9655
1-convo-64-nodes-0-dense	0.9483	0.1401	0.9393
2-convo-64-nodes-0-dense	0.9767	0.0922	0.9729
3-convo-64-nodes-0-dense	0.9733	0.0882	0.9691
1-convo-128-nodes-0-dense	0.9417	0.1605	0.9290
2-convo-128-nodes-0-dense	0.9750	0.0925	0.9712
3-convo-128-nodes-0-dense	0.9783	0.0943	0.9750
1-convo-32-nodes-1-dense	0.9517	0.1467	0.9447
2-convo-32-nodes-1-dense	0.9317	0.1829	0.9242
3-convo-32-nodes-1-dense	0.9783	0.0824	0.9150
1-convo-64-nodes-1-dense	0.9567	0.1406	0.9484
2-convo-64-nodes-1-dense	0.9683	0.1071	0.9638
3-convo-64-nodes-1-dense	0.9700	0.0973	0.9656
1-convo-128-nodes-1-dense	0.9667	0.1213	0.9613
2-convo-128-nodes-1-dense	0.9750	0.0865	0.9710
3-convo-128-nodes-1-dense	0.9750	0.1053	0.9713
1-convo-32-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-32-nodes-2-dense	0.9433	0.2445	0.9372
3-convo-32-nodes-2-dense	0.4283	0.6983	0.5997
1-convo-64-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-64-nodes-2-dense	0.4283	0.6983	0.5997
3-convo-64-nodes-2-dense	0.8050	0.4296	0.8078
1-convo-128-nodes-2-dense	0.4283	0.6983	0.5997
2-convo-128-nodes-2-dense	0.4283	0.6983	0.5997
3-convo-128-nodes-2-dense	0.8300	0.4015	0.8253

TABLE II. TABLE OF EPOCHS FOR THE CURRENT RESNET MODEL

Epoch	Batch	Accuracy	Loss	Duration	Validation Accuracy	Validation Loss	F1 Score
1	2144	53.45%	0.9621	14.07 min	67.87%	1.2632	1.068734
2	2144	78.26%	0.5912	14.05 min	78.43%	0.4152	1.564629
3	2144	84.02%	0.1190	14.03 min	78.56%	1.3948	1.679742
4	2144	86.93%	0.2429	13.99 min	87.83%	0.4840	1.737895
5	2144	89.67%	0.0499	14.00 min	90.30%	0.0924	1.79265
6	2144	90.70%	0.0822	13.99 min	89.34%	0.6208	1.813233
7	2144	91.95%	0.0504	14.00 min	92.76%	0.0160	1.838212
8	2144	93.83%	1.5093	14.01 min	94.24%	0.2718	1.875779
9	2144	95.02%	0.0277	13.99 min	88.19%	1.1853	1.899558
10	2144	95.63%	0.0113	14.07 min	93.09%	0.0094	1.911747
11	2144	96.57%	0.0053	14.07 min	95.89%	0.0142	1.93053
12	2144	97.34%	0.0073	14.06 min	95.86%	0.1147	1.945917

it's important to monitor for signs of over fitting, especially if there's a large difference between training and validation metrics. These are the accuracy and F1 score provided by the model after the end of code execution.

Accuracy: The number of individuals that were successfully identified out of all the subjects is known as accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Based on our model evaluation, the accuracy was 97.34%, indicating a high level of overall prediction accuracy.

F1-Score: Precision and recall are integrated into the F1 score.

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

$$F1\ score = 1.754886$$

Model Performance Metrics from performance metric

Further the accuracy and F1 score provided by the model. These parameters are calculated from the performance metrics using specific formulas.

Accuracy:
The overall accuracy of the model is 99.32%. This is calculated as the ratio of correctly predicted instances to the total number of instances:

$$Accuracy = \frac{\sum \boldsymbol{Correct\ Predictions}}{\sum \boldsymbol{Total\ Predictions}}$$

$$\approx 0.9932 \quad \text{or} \quad 99.32\%$$

Precision, Recall, and F1-Score for Each Class:

$$\boldsymbol{Precision = \frac{TP}{TP+FP}}$$

$$\boldsymbol{Recall = \frac{TP}{TP+FN}}$$

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

A. Class Meningioma:

1) True Positives (TP): 891
2) False Positives (FP): 21 (15 + 6)
3) False Negatives (FN): 4 (4+0)

Precision (Meningioma) = (891)/ (891 + 21) ≈ 0.9769
Recall (Meningioma) = (891)/ (891 + 4) ≈ 0.9955
F1-Score (Meningioma) = 2 *(0.9769 * 0.9955)/ (0.9769 + 0.9955) ≈ 0.9861

B. Class Glioma:

1) True Positives (TP): 1700
2) False Positives (FP): 4 (4 + 0)
3) False Negatives (FN): 15 (15 + 0)

Precision (Glioma) = (1700)/ (1700 + 4) ≈ 0.9976
Recall (Glioma) = (1700)/ (1700 + 1715) ≈ 0.9921
F1-Score (Glioma) = 2 *(0.9976 * 0.9921)/ (0.9976 + 0.9921) ≈ 0.9943

C. Class Pituitary:

1) True Positives (TP): 1064
2) False Positives (FP): 1064 (0 + 0 + 1064)
3) False Negatives (FN): 1070 (6 + 0 + 1064)

Precision (Pituitary) = (1064)/ (1064 + 0) ≈ 1
Recall (Pituitary) = (1064)/ (1064 + 6) ≈ 0.9943

F1-Score (Pituitary) = 2 *(1 * 0.9943)/ (1 + 0.9943) ≈ 0.9971

Avg Precision = (0.9769* 895 + 0.9976 * 1715 + 1.0 * 1070)/3680
= 3655.20/3680
= 0.9932

Avg Recall = (0.9955 * 895 + 0.9912 * 1715 + 1.0 * 1070) /3680
= 3654.78.20/3680
= 0.9931

VIII. ResNet-50 Model

Known ResNet-50, also known as Residual Network with 50 layers, is a renowned convolutional neural network (CNN) structure recognized for its exceptional performance in image classification tasks [12]. this computational marvel addresses the well-known obstacle of vanishing gradients encountered during deep neural network training, a phenomenon known to impede model convergence and hamper performance. ResNet-50 implements skip connections, also known as residual blocks, to facilitate seamless gradient flow throughout the network, mitigating the vanishing gradient problems and enabling effective training of deep network.

The hierarchical arrangement of convolutional layers is carefully crafted to extract intricate details from input images at various spatial scales. The convolutional layers employ programmable algorithms to traverse the input data, capturing subtle motifs crucial for precise classification. Furthermore, ResNet-50 incorporates batch normalization after each convolutional layer, a technique that aids in promoting learning stability by regulating layer activations and minimizing internal covariate shifts [13]. The addition of batch-based normalization expedites convergence, enhancing the network's stability and effectiveness.

The uniqueness of ResNet-50 lies in the utilization of a bottleneck-based layout within its residual blocks. The training process for each layer is expedited by 11 convolutions strategically positioned to curtail parameter count and matrix multiplications in this design The bottleneck residual blocks within ResNet-50 are three layers, which contributes to enhanced computational efficiency and model performance. The intricate structure of the network extends to its meticulous arrangement of convolutional layers, incorporating various kernel configurations, carefully orchestrated to capture diverse spatial patterns within the input data [12].

An average pooling layer and a fully connected layer of 1000 nodes that uses the SoftMax activation function comprise the final layer stack of ResNet-50, enabling precise class probability estimation. Collectively, ResNet-50 exhibits unparalleled proficiency in image sorting tasks, cementing its status as an indispensable component in the field of computer vision.

Special Characteristics of ResNet-50:

One notable architectural innovation presented by ResNet-50 is the use of a bottleneck architecture in its residual blocks. This pattern incorporates 1×1 convolutions, or "bottlenecks," which are placed in a way that reduces the amount of matrix multiplications and parameters, which expedites the training of each layer.

To improve computational efficiency and model performance, ResNet-50 deviates from standard two-layer architectures by include a three-layer stack within its bottleneck leftover blocks [14]

In addition, ResNet-50's architectural design outlines a painstakingly assembled group of convolutional layers, painstakingly coordinated to capture complex characteristics crucial for picture categorization [15]. The network is notable for having many kernel configurations, such as 7×7, 3×3, and 1×1 convolutions, which are carefully designed to capture different types of spatial patterns in the input data.

ResNet-50 exhibits unmatched accuracy and scalability in a variety of computer vision applications because to its complex layer composition and careful parameter tweaking and optimization.

Demonstration of model prediction

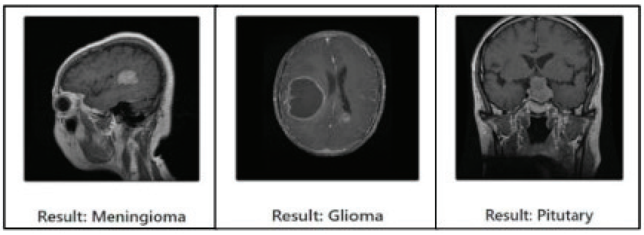

Fig. 2. Model Interface

IX. Result

The precision metrics of the ResNet-50 brain tumour detection model showed encouraging results during the training and validation phases. Over 12 epochs, the line chart depicting training and validation precision showed notable alterations indicating the model's effectiveness. The initial improvement in training precision was followed by a steady decline, reaching a peak of 97 percent. The same thing happened with validation accuracy, which converged towards higher values with typical fluctuations, eventually reaching a peak of 97 percent. Furthermore, the observed loss proportion was 1.3. These outcomes underscore the model's dependability and robustness in detecting brain tumors and distinguishing between distinct varieties.

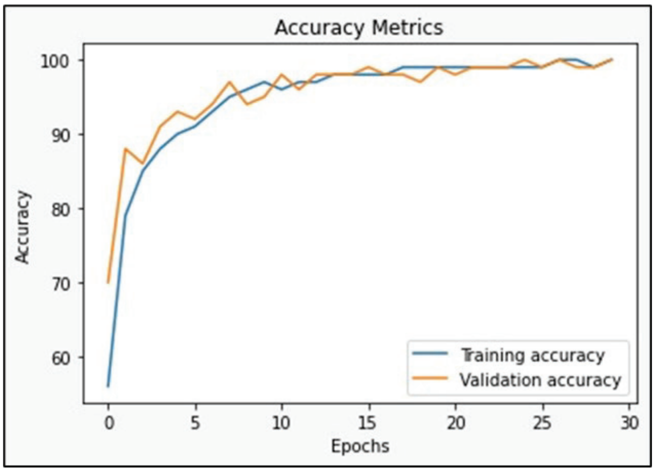

Fig. 3. Accuracy

The loss values fluctuated during the training process as seen by this graph, which included separate lines for "training loss" and "validation loss." The model's performance during training was reflected by the 'Training loss' line, which varied across epochs; the 'Validation loss' line demonstrated the model's capacity to generalize on unobserved data. Interestingly, a loss factor of 0.0073 was found. Over 12 epochs, the model's astounding accuracy of 97% was attained. The graph's distinct dark-coloured text and lines on a white backdrop allowed for easy reading and excellent visibility.

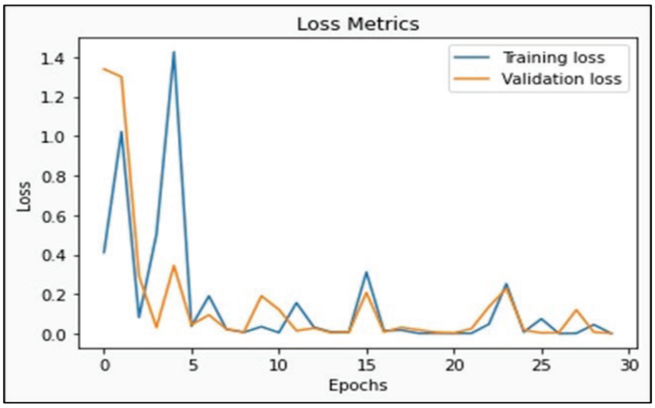

Fig. 4. Loss Factor

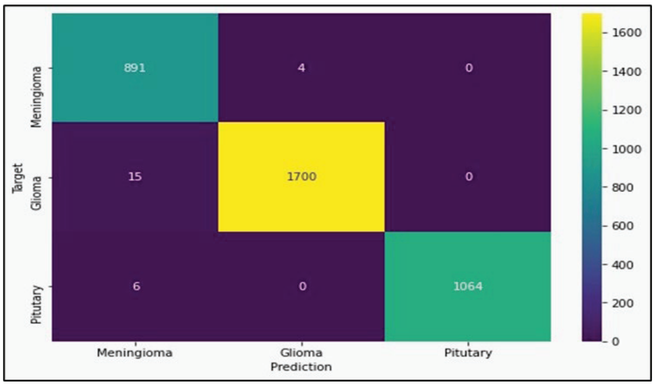

Fig. 5. Confusion Matrix

Description of the diagram

In confusion Matrix we have three types of Brain tumors. In this confusion matrix we have found that confusion matrix score is more when the image found was glioma. It showcased that score of 1700. when image was found to be of type meningioma it showed score of 891. which seems to be slighted less score rather than Glioma. When Image of Pituitary tumor was introduced at that time it showed he score 1064. This was quite better as compared to meningioma. While other purple color cells represents that there were some misprediction by model that was trained. These purple cell score should be less as possible as this confusion matrix shows that cell should show high score if the particular image type is compared with same type, and less when it is compared with other type of images. If we calculate the accuracy via formula of confusion matrix, we will find that accuracy of model predicted is near 97% which is actually a good number by this model.

X. CONCLUSION

To sum up, of the ResNet-50 model for brain tumor identification indicates that it has a great deal of efficacy and clinical application potential. The ResNet-50 model demonstrates resilience and dependability in correctly recognizing brain tumors and differentiating between them, with a peak accuracy of 97% with a loss factor of 0.0073. The ReLU function-based model, which obtained an accuracy of 88% with a corresponding loss value of 0.2883 and an F-1 score of 0.8825, is greatly outperformed by this result. Furthermore, the deep classification capabilities of the ResNet-50 model offer a clear benefit over the ReLU-based model, suggesting that it is more appropriate for challenging classification tasks. Furthermore, the ResNet-50 model mitigates possible training-related issues by addressing the vanishing gradient issue through its deep network design.

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REFERENCES

[1] Chauhan, Comparing Machine Learning Models to Determine Which is Most Effective at Detecting Brain Tumors. Journal of Student Research, 12(1), 2023)

[2] Bhalodiya, Magnetic resonance image-based brain tumour segmentation methods: A systematic review. Digital Health, 8, 20552076221074122, 2022

[3] Rawlani, Visual Interpretability for Convolutional Neural Networks. en línea].[consulta: 30 marzo 2019]. Disponible en: https://towardsdatascience. com/visual-interpretability-forconvolutional-neural-networks-2453856210ce, 2019

[4] Samee, Clinical decision support framework for segmentation and classification of brain tumor MRIs using a U-Net and DCNN cascaded learning algorithm. In Healthcare (Vol. 10, No. 12, p. 2340). MDPI, 2022

[5] Sobhaninia, Brain tumor segmentation using deep learning by type specific sorting of images. arXiv preprint arXiv:1809.07786, 2018

[6] Seetha, Brain tumor classification using convolutional neural networks. Biomedical & Pharmacology Journal, 2018

[7] Amran, Brain tumor classification and detection using hybrid deep tumor network. Electronics, 11(21), 3457, 2022

[8] Rehman, A deep learning-based framework for automatic brain tumors classification using transfer learning. Circuits, Systems, and Signal Processing, 39(2), 757-775, 2020

[9] Ari, Deep learning based brain tumor classification and detection system. Turkish Journal of Electrical Engineering and Computer Sciences, 26(5), 2275-2286, 2018

[10] Kuruvilla, A review on image processing and image segmentation. In 2016 international conference on data mining and advanced computing (SAPIENCE) (pp. 198-203). IEEE, 2016

[11] Sultan, Multi-classification of brain tumor images using deep neural network. IEEE access, 7, 69215-69225, 2019

[12] He, Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778), 2016

[13] Simonyan, Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014

[14] Sajjad, Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of computational science, 30, 174-182, 2019

[15] Musallam, A new convolutional neural network architecture for automatic detection of brain tumors in magnetic resonance imaging images. IEEE access, 10, 2775-2782, 2022

[16] Asiri, Brain tumor detection and classification using fine-tuned CNN with ResNet50 and U-Net model: A study on TCGA-LGG and TCIA dataset for MRI applications. Life, 13(7), 1449, 2023

[17] Mahmud, A deep analysis of brain tumor detection from mr images using deep learning networks. Algorithms, 16(4), 176, 2023

[18] Rajinikanth, Glioma/glioblastoma detection in brain MRI using pre-trained deep-learning scheme. In 2022 Third International Conference

on Intelligent Computing Instrumentation and Control Technologies (ICICICT) (pp. 987-990). IEEE, 2022

[19] Farajzadeh, Brain tumor segmentation and classification on MRI via deep hybrid representation learning. Expert Systems with Applications, 224, 119963, 2023

[20] Muhammad, Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey. IEEE Transactions on Neural Networks and Learning Systems, 32(2), 507-522, 2020

[21] Islam, Detection and classification of brain tumor based on multilevel segmentation with convolutional neural network. Journal of Biomedical Science and Engineering, 13(4), 45-53, 2020

[22] Samee N. A.-G., Classification framework for medical diagnosis of brain tumor with an effective hybrid transfer learning model. Diagnostics, 12(10), 2541, 2022

[23] Urbanos G. M.-R., Supervised machine learning methods and hyperspectral imaging techniques jointly applied for brain cancer classification. Sensors, 21(11), 3827, 2021

[24] FGO-Net: Feature and Gaussian Optimization Network for visualsaliency predictionJialun Pei1·Tao Zhou2·He Tang3·Chao Liu3·Chuanbo Chen3Accepted: 16 April 2022©The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2022

[25] Prajwal Bagekari,Nikhil Badhe,Jay Jadhav,Rahul Namdeo Jadhav, "Brain Tumor Classification using Machine Learning Algorithms", International Journal of Creative Research Thoughts (IJCRT), ISSN:2320-2882, Volume.12, Issue 5, pp.l120-l126, May 2024

[26] Convolutional neural networks in agriculture Published online by Cambridge University Press: 25 June 2018 A. Kamilaris Open the ORCID record for A. Kamilaris and F. X. Prenafeta-Boldú