Improving Brain Tumor Detection Efficiency with Convolutional Neural Network

Abstract—**An aberrant cell growth in the brain is called a brain tumor. These growths may be malignant (cancerous) or benign (non-cancerous). Benign tumors are generally slower-growing and less likely to invade nearby tissues, while malignant tumors can grow more rapidly and may spread to other parts of the brain or the body. Delay in the detection of a brain tumor may result in the tumor growing larger and potentially becoming more challenging to treat. Hence, early detection and treatment of a brain tumor are crucial for treatment options, preventing further damage, improved prognosis, and for preventing complications. This paper aims to improve the performance of brain tumor detection using Convolution Neural Network (CNN) with accuracy 98%. Transfer Learning technique is applied on CNN after taking a pre-trained model on a large dataset and fine-tuning it.**

Index Terms— **Convolutional Neural Network, Brain Tumor, Deep Learning, Transfer Learning, Image Segmentation.**

I. INTRODUCTION

A mass or growth of aberrant brain cells is called a brain tumor. Malignant (cancerous) or benign (non-cancerous) tumors are the two types of tumors. A brain tumor's location, size, and growth rate can all affect its symptoms. Headaches, seizures, vision changes, issues with balance or coordination, nausea, and behavioral or personality changes are common symptoms.

Tumor of the brain is a life-threatening disease that affects the brain. It is critical to detect the tumor at an early stage in order to save lives. Medical images are employed in one of the strategies for detecting brain tumors. Brain tumor diagnosis, in particular, necessitates a high level of precision, as even little errors might result in consequences. Brain tumor disclosure is still a difficult task in medical image processing.

To detect the tumor, the image of the brain is complicated. Several sounds, as well as latency, have an impact on image accuracy. A doctor can perform various tests, such as imaging studies including Magnetic Resonance Image (MRI) or Computed Tomography (CT) scans, to diagnose the presence of a brain tumor and determine the appropriate course of action, which may involve surgery, radiation therapy, chemotherapy, or a combination of these treatments.

If not detected early enough, a brain tumor is a very frequent and destructive malignant tumor condition that results in a shorter life. After a tumor has been detected, it is vital to classify it in order to develop an efficient treatment plan.

The effects of a delay in the detection of a brain tumor can vary depending on the type, size, and location of the tumor. In general, early detection and treatment of a brain tumor are crucial for several reasons. Early detection allows for a wider range of treatment options. Depending on the type and stage of the tumor, treatment may involve surgery, radiation therapy, chemotherapy, or a combination of these approaches. The effectiveness of these treatments can be significantly higher when the tumor is detected early. Brain tumors can exert pressure on surrounding tissues and structures, causing neurological symptoms and impairing brain function. Early detection and intervention can help prevent further damage to the brain and reduce the severity of symptoms. Early diagnosis often leads to a better prognosis. Malignant brain tumors, in particular, can be aggressive, and early treatment may improve the chances of successful intervention and long-term survival. Timely treatment can improve the overall quality of life for individuals with brain tumors. It can help manage symptoms, reduce pain, and enhance the patient's well-being. Some brain tumors can cause complications such as increased intracranial pressure, seizures, or neurological deficits. Early detection and treatment can help prevent or manage these complications. Delay in the detection of a brain tumor may result in the tumor growing larger and potentially becoming more challenging to treat. Additionally, the progression of the tumor could lead to more severe symptoms and increased risks of complications.

In this paper, to detect brain tumors, deep learning is being employed. The use of deep learning techniques has shown a reduction in error in human early disease diagnosis.

II. RELATED WORKS

The brain is a critical component of the human body. This is due to the fact that the brain serves as a power source for all members of the human body, including hand gestures, foot motions, eyeballs, and other critical organs. If there is interference in the brain, such as the presence of a tumor, brain activity may be impeded. Tumors are improperly and uncontrollably growing cells, whereas brain tumors are abnormally growing cells in or around the brain [1]. Benign tumors and malignant tumors are the two forms of brain tumors.

Detection of brain tumor using different branches of Artificial Intelligence (AI) has been done by many researchers. Several Machine Learning (ML) and Deep Learning (DL) models were applied in the previous works. In [2], Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) are applied by the authors to detect brain tumor.

In [3], multilayer perception was used to detect brain tumor. The feature extraction algorithm used 3-level Discrete Wavelet Transform (DWT) with 152 features. On 2015 BraTS image with multimodal properties, the classification was applied. The achieved accuracy was 96.38%. The authors used Wavelet transformation for brain tumor classification in [4]. Basically, Gabor wavelet transform and linear binary pattern feature were applied to identify brain tumor. Their accuracy was 96%. DWT, Haar Wavelet Tranform (HWT) and Symlet Wavelet Transform (SWT) along with Support Vector Machine (SVM) were applied in [5]. With the combination of the three wavelets with 50 coefficients the obtained accuracy was 98% for 60 MR images.

A genetic algorithm with 13 features is used in [6]. As the classifier, the SVM was used and provided 98.30% accuracy. K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree(DT), Naive Bayes (NB), Logistic Regression (LR), and Random Forest (RF) are used in [7] for detecting brain tumor. The highest accuracy is achieved with RF as 91.04%. A feature extraction technique was applied in [8] to identify brain tumor with an accuracy of 95%. A Gray-Level Co-occurrence Matrix (GLCM) is used in [9] for feature extraction combined with DWT and the accuracy is 98.91% by deploying SVM.

In [10] and [11], genetic algorithm, GLCM, and DWT are used. The achieved highest accuracy is 88% and 82.70% respectively. A CNN model is used in [12] for feature extraction with 253 images. Different classifiers (SVM, KNN, NB, and RF) are applied to identify brain tumor with highest accuracy 98.50% in case of SVM and KNN. For feature extraction GLCM, GLRL, and DWT are used in [13]. Using the SVM, KNN, and RF classifiers the highest accuracy is 97% with RF. Discrete Cosine Transform is used in [14] for feature extraction and using SVM and KNN the achieved accuracy is 96.8% and 91.75% respectively.

GLCM and DWT are also used in [15] for feature extraction. By using the SVM classifier for 210 images, the highest accuracy is 98.65%. Multiple deep neural networks and SVM are used in [16] and the achieved accuracy is 98.98% for a dataset of 3064 images. A high performance method for brain tumor detection is published in [17] with 2683 images and achieved accuracy is 99.84%.

A combination of Deep Learning and DWT is used in [18] for the detection of brain tumor. The authors achieved highest accuracy of 96.96%. A CNN model is used in [19] based on Fuzzy C-Means, and SVM and DNN are used as the classifiers with highest accuracy 97.4%. For the classification of glioma brain tumor, a modified CNN is used in [20] and the achieved accuracy is 91.15%. Another CNN model (pre-trained VGG19) is used in [21] for brain tumor classification and the result shows am accuracy 87.39% before augmentation and 90.66% after augmentation.

III. METHODOLOGY

This paper applies Convolutional Neural Network (CNN) as the classifier to detect brain tumor. The data are collected form the brain tumor dataset (BraTS) available in Kaggle website. EfficientNetB0 transfer learning is applied that uses the weights from the large dataset.

Magnetic Resonance Image (MRI) can detect even the tiniest abnormalities in the human body, such as those in the brain. Hence, a model is trained to recognize these minute anomalies in MRIs and accurately predict the existence of a tumor. CNN is applied for executing the purpose successfully. As the results indicate, CNN is one of the most successful techniques for this problem statement. A highly dependent and robust model is constructed to handle this challenge utilizing picture preprocessing and transfer learning with EfficientNetB0. Keras, Tensorflow, python, matplotlib, Numpy, Pandas, Scikitlearn are applied for the model development.

A. Data Collection, Preparation, & Image Processing

The Brain Tumor Classification MRI dataset (BraTS) is used in the experiments of this research. The BraTs focues on evaluating brain tumor segmentation in multimodal MRI scans. In the dataset, total

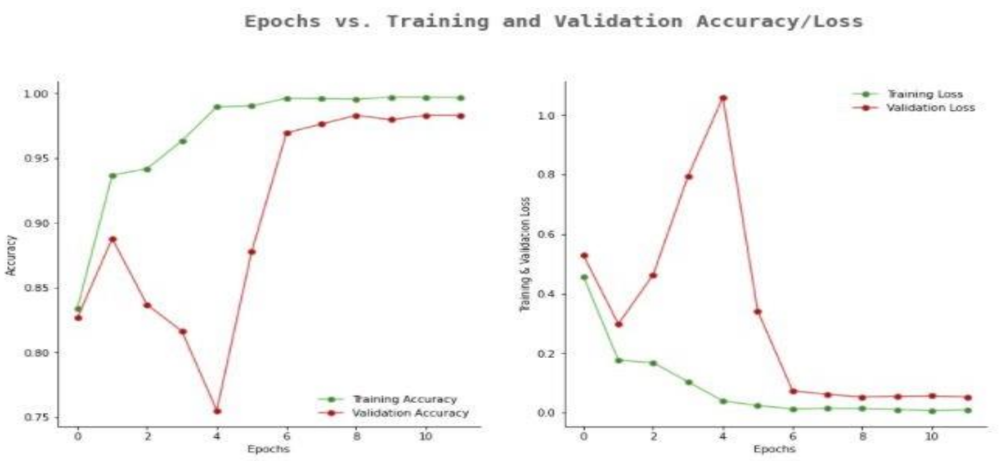

Fig. 1: Epochs vs. Training and Validation Accuracy/Loss

number of images is 4480 (2880 images are used for training and validations). For each category of brain tumor, 520 images are used for training and 200 images are used for validation. The final trained model is tested with 800 unknown images.

In order to prepare the data, transfer learning model using the weights from the large dataset is used. Images are leveled as ‘glioma_tumor’, ‘no_tumor’, ‘meningioma_tumor’, and ‘pituitary_tumor’.

The Open Source Computer Vision Library (cv2) and Python Library (tqdm) are used by dividing the dataset into 64% for training and 18% for testing. One hot encoding is performed on the labels after converting into numerical values.

B. Transfer Learning an Fine Tuning

CNN takes longer period in order to deal with very large datasets. In order to avoid this problem, the model weights are reused from pre-trained models produced for image recognition. For this purpose, EfficientNetB0 model is applied that uses the weights from the large dataset.

The model was then fine-tuned using Call back functions. Callbacks can aid in the faster resolution of errors and the development of better models. TensorBoard, ModelCheckpoint, and ReduceLROnPlateau callback functions are used. The graph in Fig. 1 shows the outcome after tuning the model.

C. Model Prediction and Evaluation

Since each row of the prediction array has four values for the relevant labels, the argmax() function is used. The argmax() function returns the indices of the maximum values along a specified axis.

Out of the four potential possibilities, the largest value in each row reflects the projected output. Using argmax(), it was possible to determine the index that corresponds to the projected outcome.

Fig. 2 shows the output for four possible images where “0” represents ‘glioma_tumor’, “1” represents ‘no_tumor’, “2” represents ‘meningioma_tumor’, and “3” represents ‘pituitary_tumor’. The heatmap of the confusion matrix is shown in Fig. 3.

	precision	recall	f1-score	support
0	0.99	0.95	0.97	93
1	0.96	1.00	0.98	51
2	0.97	0.99	0.98	96
3	1.00	1.00	1.00	87
accuracy			0.98	327
macro avg	0.98	0.98	0.98	327
weighted avg	0.98	0.98	0.98	327

Fig. 2: Model Evaluation for Four Possible Images

IV. RESULTS AND ANALYSIS

This section presents and describes the findings of the proposed brain tumor identification system using CNN. Basically, the CNN model in this paper focuses on classifying the images into four categories: ‘glioma_tumor’, ‘no_tumor’, ‘meningioma_tumor’, and ‘pituitary_tumor’. As mentioned earlier the BraTS dataset is used in the experiments where 60% of the data are used to train the model, 14% are used for testing, and the remaining 26% are used for validation.

Fig. 2 shows the graphical representation of the proposed model's brain tumor identification using MRI throughout training and validation. The model's training and validation outcomes scored 98% and 95%, respectively. The model's data loss indicates that the model has less data loss.

There are 4480 images in the dataset obtained from the Kaggle website. The images are divided into three categories: training, validation, and testing (unseen images). Each brain tumor type has 520 images, whereas the training group has 2880 images. Each brain tumor type has 200 images in the validation group, for a total of 800 images. The testing group contains 800 images, with 200 images for each form of brain tumor. The brain tumor images are scaled to 256 by 256 pixels.

The four sets of predicted and actual values are analyzed in order to evaluate the effectiveness of the proposed framework.

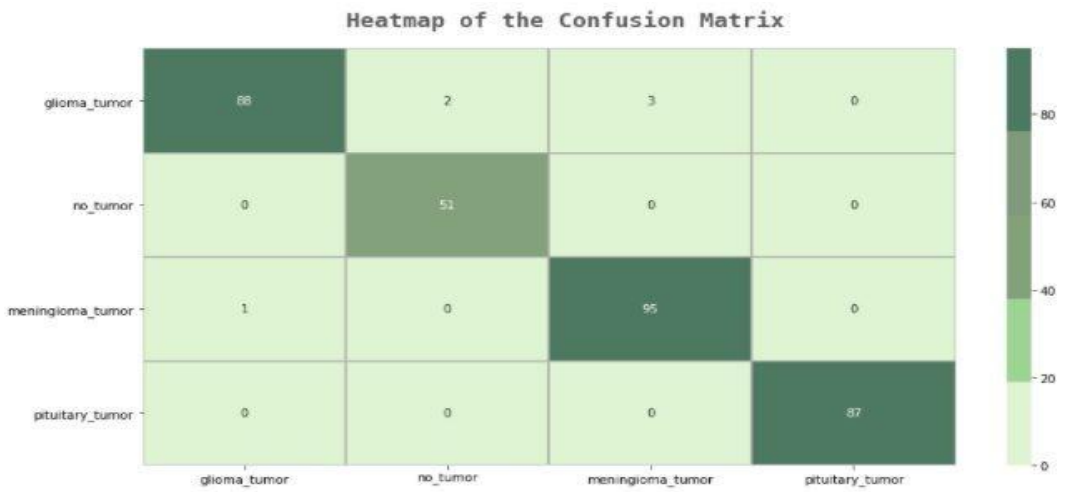

Fig. 3: Heatmap of the Confusion Matric

False Positive (FP), True Negative (TN), False Positive (TP), and False Negative (FN) are the values. When the system correctly identifies positive cases, the TP is represented, and when it correctly identifies negative cases, the TN is represented. Similar to this, FP happens when the system predicts a negative case incorrectly as positive, and FN happens when it predicts a positive case incorrectly as negative. Furthermore, Equations 1 through 4 define accuracy, precision, recall, and F1-score, respectively.

Accuracy is regarded as one of the key metrics for assessing the performance of machine learning algorithms and models [23]. Equation 1 shows accuracy as the total number of correctly identified brain tumor images from the dataset, expressed as a percentage.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Table I: Accuracy, precision, recall, and F1 score of CNN

Model	Accuracy	Precision	Recall	F1-Score
CNN	98%	98%	98%	0.98

The accuracy of positive identifications among all the instances predicted as positive is the precision metric [23]. Equation 2 defines precision as having the capacity to accurately detect and categorize real matched brain tumor images (True Positives) while reducing False Positives. In tumor identification, accuracy and precision can be very important, especially in this study on brain tumor classification using CNN.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

The capacity of the model to accurately recognize and extract

Table II: Comparative study with other existing methods for identifying brain tumor

References	Feature Extraction Method	Classifier	Accuracy
Latif et al. [3]	3-level DWT	DWT	96.38
Amin et. al [5]	Wavelet Transform	Gabor and LBP	96%
Mishra et. al [5]	Wavelet Transform	HWT, SWT, and SVM	98%
Dewan et al. [7]	Genetic Algorithm	RF	91.04%
Hamid et al. [8]	GLCM	SVM	95%
Ansari et al. [9]	GLCM and DWT	SVM	98.91% [200 images]
Li et al. [10]	Gabor transform, texture, and DWT	SVM	88%
Alves et al. [11]	Genetic algorithm, GLCM, GLRL, and DWT	SVM	82.70%
Kang et al. [12]	CNN	SVM	98.50%
Jena et al. [13]	Genetic algorithm, GLCM, GLRL, and DWT	NB	97%
Nanmaran et al. [14]	Discrete Cosine Transform	SVM	96.8%
Susanto et al. [15]	GLCM and DWT	SVM	98.65% [210 images]
Amir et al. [16]	Multiple Deep Neural Network	SVM	98.98% [3064 images]
Trong et al. [17]	Complex Network	RF	99.84% [2683 images]
Proposed Model	CNN	CNN	98% [4480 images]

all pertinent positive case instances from the dataset is known as recall [23]. Another name for recall is sensitivity. Equation 3 presents recall. In this study, a high recall score means that the model performs exceptionally well at detecting the real matched tumor images while reducing the number of cases in which true matches are missed (False Negatives).

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

The F1-score offers a thorough measurement for both false positives and false negatives and is described as a balanced evaluation of a model's performance [23]. Equation 4 presents the F1-score. A high F1-score in this paper indicates that the model maintains an ideal balance between recall of relevant instances and the accuracy of positive brain tumor identification.

$$F1 - Score \frac{2 \times Precision \times \ Recall}{Precision+Recall} \tag{4}$$

With an accuracy of 98%, the presented CNN model performs remarkably well, as Table I demonstrates. It also has good recall (98%), precision (98%), and F1-Score (0.98) in addition to accuracy. According to these results, CNN was able to effectively extract pertinent features and patterns from the input images, which enabled precise classification with a low rate of false positives and negatives.

The findings of this study are contrasted with other approaches to image classification for brain tumors in Table II. It is evident that the suggested CNN performs better at correctly identifying brain tumors than the majority of the earlier models. Accuracy is higher in [9, 15, 16, 17] than the CNN classifier presented in this paper. However, in those cases, the size of the dataset is lower than the size of the dataset used in this research. In [9], only 200 images are used; in [15], 210 images; in [16], 3064 images; and in [17], 2683 images are used. In the CNN model used in this paper, the number of images is 4480 which is quite higher than the size of the data of other existing works.

V. CONCLUSIONS

If not detected early enough, a brain tumor is a very frequent and destructive malignant tumor condition that results in a shorter life. After a tumor has been detected, it is vital to classify it in order to develop an efficient treatment plan. To detect brain tumors, deep learning is being employed in this paper. The use of deep learning techniques has shown a reduction in error in human early disease diagnosis. Using CNN the achieved accuracy is 98%, and the result is remarkable in terms of precision, recall, and F1-score.

The CNN model presented in this paper shows improved performance than the existing techniques (considering a larger dataset) in terms of accuracy in identifying brain tumor. Thus this paper will progress neural network research and have practical uses in many applications like medical sciences, and pharmaceutical companies. The model presented in this paper can provide timely treatment through early detection of the tumor which can improve the overall quality of life for individuals with brain tumors. It can help manage symptoms, reduce pain, and enhance the patient's well-being.

However, image quality can have an impact on the accuracy of the algorithms for brain tumor classification. The overall effectiveness of the classification approaches can be improved, and this type of research could be advanced with more investigations and multiple datasets.

REFERENCES

[1] P. Kleihues, WK Cavenee , Pathology & genetics of tumors of the nervous system., World Health Organization classification of tumors. Lyon, France: IARC Press., 2000

[2] M. Gurbină, M. Lascu, D. Lascu, "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), 2019, pp. 505–508.

[3] G. Latif, D. N. F. A. Iskandar, J. M. Alghazo, and N. Mohammad, "Enhanced MR Image Classification Using Hybrid Statistical and Wavelets Features," in IEEE Access, vol. 7, pp. 9634-9644, 2019, doi: 10.1109/ACCESS.2018.2888488.

[4] J. Amin, M. Sharif, M. Raza, T. Saba, M. A. Anjum, "Brain tumor detection using statistical and machine learning method," Computer Methods and Programs in Biomedicine, vol. 177, pp. 69–79, 2019, doi: 10.1016/j.cmpb.2019.05.015

[5] S. K. Mishra and V. H. Deepthi, "RETRACTED ARTICLE: Brain image classification by the combination of different wavelet transforms and support vector machine classification," Journal of Ambient Intelligence and Humanized Computing, vol. 12, pp. 6741–6749, 2021, doi: 10.1007/s12652-020-02299-y

[6] A. Sarkar, M. Maniruzzaman, M. S. Ahsan, M. Ahmad, M. I. Kadir, S. T. Islam, "Identification and classification of brain tumor from MRI with feature extraction by support vector machine," in 2020 International Conference for Emerging Technology (INCET), pp. 1–4, IEEE, 2020

[7] J. Dewan, S. Thepade, P. Deshmukh, S. Deshmukh, P. Katpale, K. Gandole (2023). Brain Tumor Type Identification from MR Images using Texture Features and Machine Learning Techniques. 10.21203/rs.3.rs-2581651/v1.

[8] M. A. A. Hamid and N. A. Khan, "Investigation and classification of MRI brain tumors using feature extraction technique," Journal of Medical and Biological Engineering, vol. 40, no. 2, pp. 307–317, 2020.

[9] M. A. Ansari, R. Mehrotra, R. Agrawal. "Detection and classification of brain tumor in MRI images using wavelet transform and support vector machine" Journal of Interdisciplinary Mathematics, vol. 23, no. 5, pp. 955–966, 2020.

[10] M. Li, H. Wang, Z. Shang, Z. Yang, Y. Zhang, H. Wan. "Ependymoma and pilocytic astrocytoma: differentiation using radiomics approach based on machine learning," Journal of Clinical Neuroscience, vol. 78, pp. 175–180, 2020.

[11] A. F. F. Alves, R. J., D. A. Miranda. "Inflammatory lesions and brain tumors: is it possible to differentiate them based on texture features in magnetic resonance imaging?" Journal of Venomous Animals and Toxins including Tropical Diseases, vol. 26, Article ID e20200011, 2020.

[12] J. Kang, Z. Ullah, J. Gwak, "MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers," Sensors, vol. 21, no. 6, Article ID 2222, 2021.

[13] B. Jena, G. K. Nayak, S. Saxena, "An empirical study of different machine learning techniques for brain tumor classification and subsequent segmentation using hybrid texture feature," Machine Vision and Applications, vol. 33, no. 1, 2022

[14] R. Nanmaran, S. Srimathi, G. Yamuna. "Investigating the role of image fusion in brain tumor classification models based on machine learning algorithm for personalized medicine," Computational and

Mathematical Methods in Medicine, vol. 2022, Article ID 7137524, 13 pages, 2022

[15] A. Susanto, C. A. Sari, H. Rahmalan, M. A. S. Doheir, “Support vector machine based discrete wavelet transform for magnetic resonance imaging brain tumor classification,” TELKOMNIKA (Telecommunication Computing Electronics and Control), vol. 21, no. 3, Article ID 592, 2023

[16] M. Aamir, Z. Rahman, W. Ahmed Abro, U. Aslam Bhatti, Z. Ahmed Dayo, M. Ishfaq, “Brain tumor classification utilizing deep features derived from high-quality regions in MRI images” Biomedical Signal Processing and Control, vol. 85, Article ID 104988, 2023

[17] T. Trong, N. Hinh, L. Dang. (2023). High-Performance Method for Brain Tumor Feature Extraction in MRI Using Complex Network. Applied Bionics and Biomechanics. 2023. 1-13. 10.1155/2023/8843488.

[18] H. Mohsen, A. E. El-Dahshan, E. M. El-Horbaty, A. M. Salem (2018). Classification using deep learning neural networks for brain tumors. Future Computing and Informatics Journal, 3(2), 68-71.

[19] J. Seetha,, S. S. Raja. (2018). Brain Tumor Classification Using Convolutional Neural Networks. Biomedical & Pharmacology Journal, 11(7), 1457-1461.

[20] S. Khawaldeh, U. Pervaiz A. Rafiq, R.S. Alkhawaldeh (2017). Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks. Applied Sciences, 8(1), 48-60.

[21] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, SW Baik. (2019). Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of computational science, 30(1), 174-82/

[22] Brain Tumor Classification MRI dataset. Kaggle. Date: 29/12/2023 https://www.kaggle.com/dschettler8845/brats-2021-task1

[23] R. Yacouby, D. Axman. (2020, November). Probabilistic extension of precision, recall, and f1 score for more thorough evaluation of classification models. In *Proceedings of the first workshop on evaluation and comparison of NLP systems* (pp. 79-91).