https://doi.org/10.31436/ijpcc.v10i2.455

Brain Tumour Classification Using Vanilla Convolutional Neural Networks

Md Najmul Huda, Akeem Olowolayemo*, Ayesha Dupe Adeleye, Amin Nur Rashid, Abrar Habib Haque
Department of Computer Science, Kulliyyah of Information & Communication Technology, International Islamic University, Malaysia

*Corresponding author: akeem@iium.edu.my
(Received: 20th February2024; Accepted: 8th June 2024; Published on-line: 30th July 2024)

Abstract— Brain tumours are a common and dangerous type of malignant tumour that, if not detected early enough, can cut short a patient's life. The segmentation and classification of brain tumours using solely traditional medical image processing is a difficult and time-consuming task. Various imaging modalities, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound image, are frequently utilized to assess brain, lung, liver, breast, prostate and other tumours. MRI images are specifically utilised in these analyses to detect brain tumours. As a result, developing approaches for detecting, recognizing, and classifying the conditions based on image analysis becomes essential. A comprehensive and automatic classification system is important to saving human lives. The geographical and anatomical heterogeneity of brain tumours makes automatic categorization challenging. This study proposes an automated method for detecting brain tumours using Convolutional Neural Networks (CNNs) classification, with the primary goal of developing a deep learning model that is capable of accurately identifying and classifying images as either having a brain tumour or not. In this paper, we provide a classification model for brain tumours based on a Deep Convolutional Neural Network with a vanilla neural network technique. The proposed method's performance on a publicly available dataset of 3000 Brain MRI Images yielded superior results, with accuracy and F1 score of 98.00 percent and 98.00 percent, respectively. This study shows that the proposed vanilla-CNN model can be used to make it easier for brain tumours to be automatically classified.

Keywords— Brain tumour, CNN, Classification, Deep learning, MRI, Vanilla-CNN.

I. Introduction

The brain is one of the most sensitive organs in human body, controlling the body's main functions and traits. According to the most recent data from the World Health Organization (WHO), brain tumours are one of the most common types of cancer that kill people around the world. Brain tumours may be malignant or benign. Gravity within the skull might hasten the growth of a brain tumour. In the worst-case scenario, it can induce brain damage, which can be deadly. Cancer of the brain and nerve system is the tenth highest cause of mortality in both men and women. This year, primary brain and CNS tumours are expected to kill 18,280 adults in the United States (10,710 men and 7,570 women) and in 2020, an estimated 251,329 persons worldwide are expected to die from primary brain and CNS cancers [1]. A malignant tumour is dangerous and can lead to death. Based on their characteristics, the WHO divides brain tumours into grade 1 and 2 tumours, which are low-grade tumours also known as benign tumours, and grade 3 and 4 tumours, which are high-grade tumours also known as malignant tumours [2].

Several techniques are used to diagnose a brain tumour, including CT scans and EEGs, but the most effective and extensively used method is magnetic resource imaging (MRI). Radio waves and strong magnetic fields are used in MRI to make images of the organs inside of the body. MRI delivers more comprehensive information about interior organs than CT or EEG scans, consequently it is more effective. It has been shown that there is no universal system for detecting and segmenting brain tumours independent of their location, shape, or intensity [3]. Recent research has presented several algorithms for the feature extraction and categorization of brain cancers. The grey-level co-occurrence matrix (GLCM) [4],[5] is a popular tool for extracting low-level characteristics. Conventional brain tumour classification approaches typically include region-based tumour segmentation before feature extraction and classification, which has outstanding performance for both 2D and 3D medical imaging [6],[7]. We proposed developing a deep learning model for classifying MRI images containing brain tumours into "Tumour" or "Non-tumour" in this research. We also look at how well the proposed model works in terms of accuracy and high F1-score.

II. Related Work

Classifying brain tumours into subtypes is a challenging research problem. Recent work on automated medical diagnosis improves performances because of the arrival of deep learning concepts. Deep learning techniques have

https://doi.org/10.31436/ijpcc.v10i2.455

been broadly used in medical image analysis for cancer diseases and cancer diagnosis [1]. Zuo et al. [2] developed a deep learning algorithm for human skin detection, which is a part of dermatology diagnostics. Charron et al. [3] used a deep convolutional neural network (CNN) to monitor brain metastases. More recently, a particular class of deep learning, known as deep transfer learning, has dominated the studies on visual categorization, object recognition, and image classification problems [4]. Transfer learning allows using a pre-trained CNN model, which was developed for another related application to be utilised for another classification problem set. Transfer learning has shown its potential in CAD of medical problems also. Zhou et al.[5] used a pre-trained InceptionV3 model for differentiating benign and malignant renal tumours on CT images. Deniz et al. [6] proposed a classifier for breast cancer on histopathologic images. The authors used a pre-trained VGG-16 model and a fine-tuned AlexNet for extracting features, which were then classified using a support vector machine (SVM). Hussein et al. [7] introduced a learning model for lung tumour characterization and pancreatic tumour characterization. The learning model was based on knowledge transfer and had a 3D CNN architecture. The accuracy measures reported in the transfer learning-based algorithms were superior to those obtained using handcrafted algorithms. Specifically, transfer learning has gathered attention in applications related to neuro-oncology. Studies were conducted to extract deep features from brain MRI images using pre-trained networks [8], [9]. The studies showed the capability of transfer learning to work with smaller datasets. Yang et al. [10] used AlexNet and GoogLeNet in their research work on the grading of glioma from MRI images. Regarding the performance measures observed, GoogleNet proved superior to AlexNet for the task. Talo et al. [11] achieved remarkable classification performance with deep transfer learning in their work on brain abnormality classification. The authors used ResNet-34, and the experiments included training of modified dense layers, training with data augmentation, and fine-tuning of a transfer learning model. The experimental results concluded that a deep transfer learned model could be adapted to medical image classification with minimum pre-processing. Jain et al. [12] used a pre-trained VGG-16 network to diagnose Alzheimer's disease from MRI. Transfer learning was applied to content-based image retrieval (CBIR) for brain tumours [13]. The evaluation was performed on a publicly available dataset and obtained promising results.

The digital image processing community has developed several segmentation methods, many of them ad hoc. The four most common methods are 1.) amplitude thresholding; 2.) texture segmentation; 3.) template matching and 4.) region-growing segmentation. These types of procedures are used for dividing the brain images into three categories: (a) Pixel-based, (b) Region or Texture Based (c) Structural based. Based on the region obtained, the required information is extracted. Different researchers proposed different methods and algorithms for detecting brain tumours, stroke, and other abnormalities in the human brain using MRI.

A. Brain Tumour Classification in Medical Imaging

A brain tumour is one of the most complex disorders that occurs when the brain cells begin to grow uncontrollably. The most crucial issue before starting treatment is detecting and classifying tumours from brain magnetic resonance imaging (MRI) scans. For ages, researchers have worked hard to develop the best approach for real-life medical image recognition with greater precision. The current manual approach is inconvenient, time-consuming, and human error-prone. These flaws emphasize the significance of establishing a fully automated deep learning-based brain tumour classification approach. The task of brain tumour classification in medical imaging has been a prominent area of research due to its critical implications for diagnosis and treatment planning. Early efforts primarily relied on traditional image processing techniques and manual feature extraction. Studies such as [13] demonstrated the effectiveness of these methods but were limited by their dependence on handcrafted features and the challenges posed by the complex and diverse nature of brain tumour images.

B. Deep Learning in Medical Image Analysis

In recent years, the advent of deep learning has revolutionized medical image analysis. Convolutional Neural Networks (CNNs) have shown remarkable success in various tasks, including image classification, segmentation, and detection. Researchers have applied CNNs to brain tumour classification with notable achievements. For instance, the study in [14] proposed a deep learning model that outperformed traditional methods by automatically learning hierarchical features from MRI images.

Recent research shows that the deep learning methods perform well on image classification tasks and provide better accuracy than machine learning methods. Deep learning is that subset of machine learning which do not require manual feature extraction, which is an added advantage to such techniques. Paul et.al had developed a generalized method for brain tumour classification using fully connected neural networks that achieved an accuracy of 91.43% [8]. Brats-2013 is the benchmark dataset used by most of the researchers. Later, various CNN-based methods for classification of brain tumour were proposed. In one such method, three types of tumours: Meningioma, Glioma, and Pituitary tumours were classified, which yielded the classification accuracy of 97.3% [9]. In another work, the CNN based approach tried on three different datasets and after data augmentation using Deep CNN, it yielded 95.23% for Meningioma, 95.43% for Glioma, and 98.43% accuracy for Pituitary tumour [15].

C. *MRI-Based Brain Tumour Classification*

Several studies have specifically focused on utilizing Magnetic Resonance Imaging (MRI) for brain tumour classification. [16] explored the use of advanced MRI sequences, such as diffusion-weighted imaging, in conjunction with deep learning to improve classification accuracy. In recent years, an enormous number of approaches to brain tumour classification on MRI brain images have been proposed based on deep transfer learning models. CNN was realized as the first real-world application in 1998 to observe handwritten digits. Also [17] developed a hybrid model based on CNN for classifying the tumour type in the brain. The study in [16] proposed an automated brain tumour detection mechanism applying CNN with transfer learning models on the MRI brain image dataset. The effect of MRI image data preprocessing steps analysed by authors improves the classification accuracy in predicting brain tumour disease. Researchers focused on developing a new CNN-based model to classify the three forms of tumours that existed in brain MRI images. The study in [16] investigated presenting a CNN pretrained model with image segmentation techniques. The authors in [18] suggested a VGG-16 pretrained CNN model for the classification of multigrade brain tumours. ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), a visual database project, was launched by ImageNet in 2010. This challenge provides a platform for many researchers to analyse the performance of proposed methodologies developed on the given image dataset and obtain a higher classification accuracy rate. Equally, the study in [15] proposed CNN architecture AlexNet to achieve good results on various tasks based on visual recognition. Meanwhile, [13] investigated the fusion of multiple MRI modalities for a comprehensive understanding of tumour characteristics.

D. *Vanilla Convolutional Neural Networks*

While sophisticated architectures like U-Net and ResNet have been widely employed in medical image analysis, the use of vanilla CNNs for brain tumour classification has gained considerable attention. Vanilla CNNs, with their simpler structures, offer advantages in terms of interpretability and computational efficiency. The study in [19] demonstrated the efficacy of a vanilla CNN in brain tumour classification, paving the way for exploring less complex architectures. Vanilla neural networks are termed as an extension to linear regression supervised algorithm. Vanilla neural networks are similar to other linear regression and just differ in their hidden layers which plays a major role as all the extra computations in vanilla neural networks work in the hidden layer. The hidden layer, denoted with H, has three "neurons" (H0, H1, H2) and any number of neurons can be added in hidden layers. With hidden layer, backpropagation algorithm can be used in Vanilla neural network [19].

E. *Challenges and Future Directions*

Despite the progress made in brain tumour classification, challenges such as limited annotated datasets, class imbalance, and interpretability persist. Recently, researchers have focused their attention to automating the feature extraction process and standardizing the networks by exploring the scope of CNNs and Transfer Learning in the field. All these techniques extract features of individual images in an automated fashion, but they lack the ability to learn the image level relationships or the pixel-to-pixel relationships. This creates a scope for adding a novel step in feature extraction, that is to explore pixel-pixel relationships. The motivation and objective of this research is to devise a mechanism to account for the pixel-based relationships and to create a relation-aware representation for Brain tumour classification. Relation aware representation uses the relationships amongst the data points as a knowledge base for effective learning of the model. Future research should address these challenges and explore novel techniques, potentially integrating domain knowledge and multi-modal information to further improve the accuracy and robustness of the classification models.

III. PROPOSED METHODOLOGY

CNN has recently been popular in a variety of medical image processing applications, particularly in the classification and segmentation of MRI brain tumours. In this paper, a new CNN model is proposed for classifying brain tumours.

In this study, we developed a basic CNN model and used it to extract augmented MRI image data of 512 x 512 input size with RGB Colour channels and a batch size of 64. The important feature is pulled out by using four convolutional layers. 4 x 4 filters are used in each convolutional layer and 4 x 4 are used in the pooling layers. A modest number of filters are utilised to detect edges, corners, and lines. Then, a max-pooling layer was applied to the image in order to produce the most comprehensive summary possible. Finally, we used a 256-neuron fully connected dense layer with a SoftMax output layer to compute the probability score for each class and classify the final decision labels as Yes or No, depending on whether the input MRI image contains cancer or not. The layout of our suggested CNN architecture is shown in Figure (1).

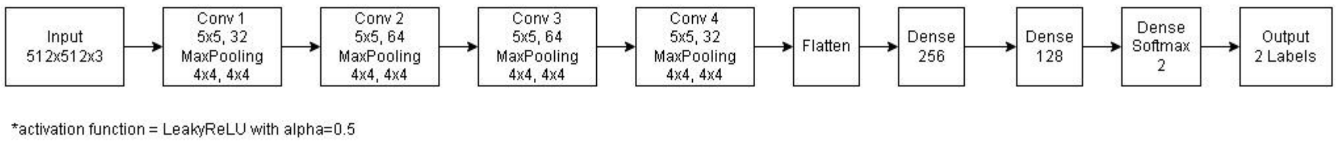

Fig. 1 The proposed Convolutional Neural Network Architecture.

A. *Convolution Layer*

This layer is the most significant and core component of the CNN model, and it is also where the name "Convolution Neural Network" comes from. A CNN's fundamental design consists of many convolutional layers, pooling layers, and fully connected layers [8]. The convolution layer's job is to figure out which of the existing layer's features correspond to the various kinds of local connections.

B. *Non-linearity Layer*

The non-linearity layer represents the second layer of the model. CNN is made better at fitting by adding the nonlinear factor. Activation functions such as Sigmoid, ReLU, leaky ReLU, and ELU are used to do this. To evaluate the CNN's classification performance and learning speed, the leaky ReLU function was chosen as the activation function. The expression is (Equation 1), where x is the input value.

$$f(x) = \begin{cases} 0.01x \ for \ x < 0 \\ x \ for \ x \geq 0 \end{cases} \quad (1)$$

C. *Pooling Layer*

The pooling layer is responsible for combining related features in order to reduce the precision of feature maps [9]. The dimension of feature maps is lowered in the suggested model by using the MaxPooling operation, which is simple to use and produces the best results.

D. *Fully Connected Layer (FC)*

The fully connected layer (FC) works with a flattened input, which means that each input is coupled to every neuron. At the network's end, the FC layer is used. The goal of this layer is to flatten the output of the preceding layer because the features must be one-dimensional (1D) data before training with the classifier. The output is fixed as the number of classes used when it is used as the last layer [10].

E. *Optimization*

In deep neural networks, we use a variety of optimization techniques to minimize the loss by modifying parameters such as weights and learning rates. In this experiment, the 'adam' optimizer proposed by Diederik Kingma [11] is utilised. The stochastic gradient descent principle is used in the learning process to provide a strategy for stochastic optimization. Because it can handle sparse gradients on noisy situations, the 'Adam' optimizer, which stands for adaptive moment estimation, was chosen.

F. *Performance Measure*

F1-score accuracy was employed in this study. The F1-score considers both recall and precision. Recall and accuracy are averaged together to get an F1-score. If the dataset has a good balance of recall (R) and precision (P), the F1-score is the best. The formulas for determining these performance measures are shown in Equations 2 through 5:

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F1\ Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (5)$$

where TP stands for True Positive, TN stands for True Negative, FP stands for False Positive, and FN is for False Negative. These characteristics are calculated using the confusion matrix, which contains information on the incorrect and correct classification of images across all categories.

G. *Image Data*

Publicly available dataset is imported from Kaggle website [12]. It consists of 3000 images, 1500 of which are MRIs of the brain that have tumours and 1500 of which do not contain tumours.

https://doi.org/10.31436/ijpcc.v10i2.455

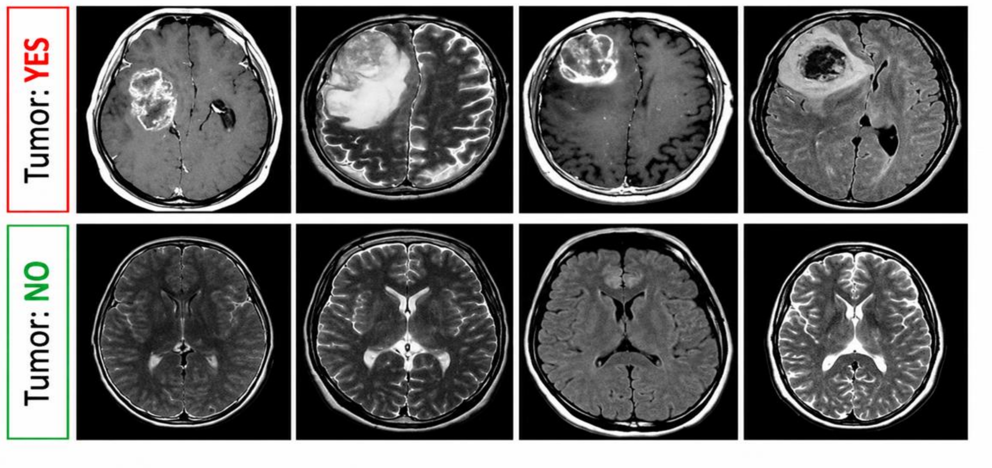

Fig. 2 Dataset examples[20].

IV. Results and Discussion

MRI scans of tumours and non-tumours are included in our dataset. We divided our data into three categories: training, validation, and testing. There are 80% images for training, 10% for validation, and 10% for testing to determine the accuracy of our model. With a batch size of 64, we trained the models for 25 epochs. Our proposed model demonstrated a 98 percent accuracy rate on both our Training and Validation on our datasets.

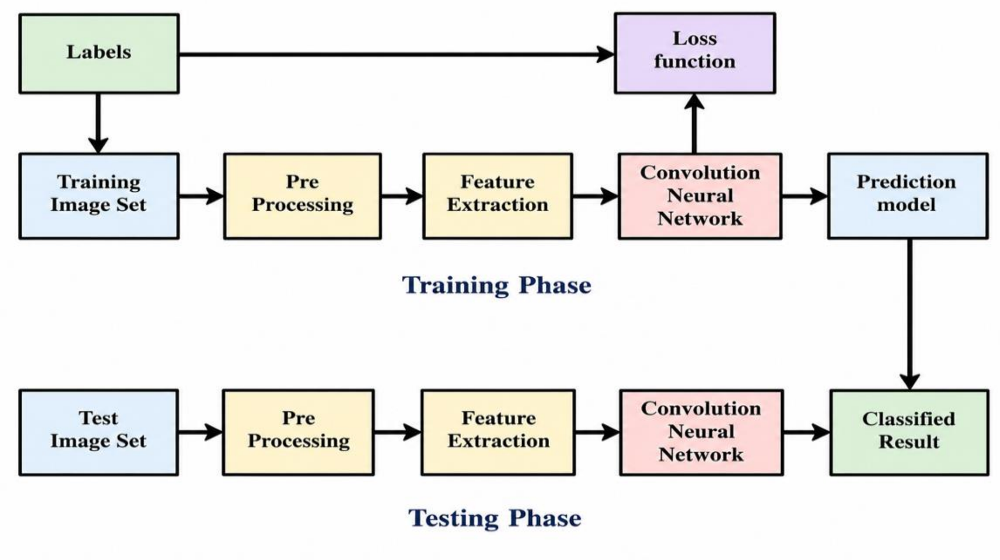

Fig. 3 Block diagram for brain tumour classification using CNN.

Figure 4 shows the Model Accuracy and Model Loss of the proposed Model. The time of computation and complexity is low, and an accuracy is high.

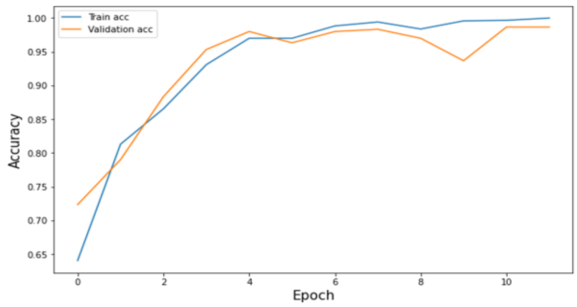

Fig. 4 Model Accuracy.

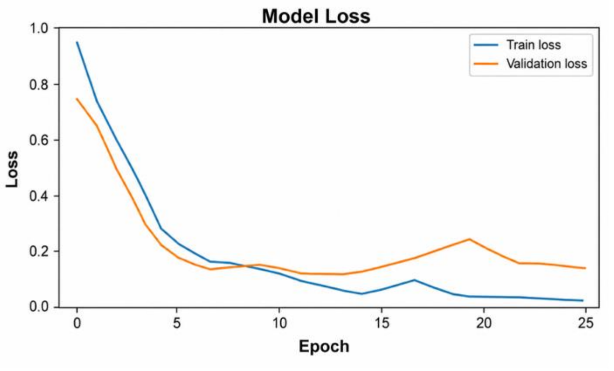

Fig. 5 Model Loss.

We evaluated our model on unseen testing data. As shown in Fig. 5, True Positive and True Negative show the correct way to classify, with TP showing abnormal brain images as positive and TN showing normal brain images as positive. False Positive and False Negative, on the other hand, show the incorrect way to classify, with FP showing normal brain images as positive tumours and FN showing abnormal brain images as negative tumours.

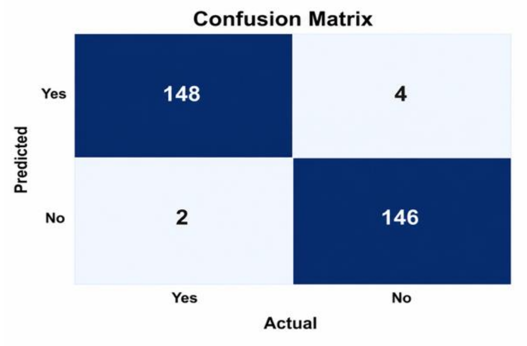

Fig. 6 Model Loss.

The algorithm is slightly better at predicting true negatives than true positives, according to the confusion matrix.

Classes	Precision	Recall	F1 Score	Support
Yes (Tumorous)	**0.99**	**0.97**	**0.98**	**150**
No (Non-Tumorous)	**0.97**	**0.99**	**0.98**	**150**

Fig. 7 Classification report.

All it is more crucial for a classifier to classify abnormalities than a normal case from a medical standpoint. Both tumourous and non-tumourous labels in this report had the same precision, recall, and F1-score classification metric values. This demonstrates that the model is functioning effectively while maintaining a high level of accuracy.

V. Conclusions

In this research, we employed the Vanilla CNN model to classify MRI brain tumours. Our model makes use of many layers of varying sizes as well as the SoftMax classifier. The proposed technique's experimental investigation is based on publicly available datasets, as previously mentioned. The architecture's training and validation accuracy achieved a remarkable 98.00 percent performance. This high accuracy underscores the superior performance of the proposed technique based on the Vanilla CNN model. It is hoped that utilizing this technique may aid in the early detection of brain tumours before they cause physical complications such as paralysis, other impairments, or death.

Future studies in this work would focus utilizing images from other modalities and improving deep network topologies by incorporating a multi-channel classifier that significantly increases classification performance. We equally hope to include different classifications of tumors rather than just tumour or no-tumour identification

Acknowledgment

The authors hereby acknowledge the review support offered by the IJPCC reviewers who took their time to study the manuscript and find it acceptable for publishing.

Conflict of Interest

The authors declare that there is no conflict of interest

References

[1] American Society of Clinical Oncology, "Brain tumor: Statistics," Cancer.Net. Accessed: Jun. 19, 2022. [Online]. Available: https://www.cancer.net/cancer-types/brain-tumor/statistics

[2] National Health Service (NHS), "Brain tumours." Accessed: Jun. 19,2022. [Online]. Available: https://www.nhs.uk/conditions/brain-tumours/

[3] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, and T. R. Mengko, "Brain tumor classification using convolutional neural network," *IFMBE Proc*, vol. 68, no. 1, pp. 183–189, 2019, doi: 10.1007/978-981-10-9035-6_33.

[4] Q. T. Ostrom *et al.*, "American Brain Tumor Association Adolescent and Young Adult Primary Brain and Central Nervous System Tumors Diagnosed in the United States in 2008-2012," *Neuro Oncol*, vol. 18, pp. i1–i50, 2015, doi: 10.1093/neuonc/nov297.

[5] N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation," *Magn Reson Imaging*, vol. 31, no. 8, pp. 1426–1438, 2013, doi: 10.1016/j.mri.2013.05.002.

[6] L. C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder-decoder with atrous separable convolution for semantic image segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and*

Lecture Notes in Bioinformatics), vol. 11211 LNCS, pp. 833–851, 2018, doi: 10.1007/978-3-030-01234-2_49.

[7] F. Milletari, N. Navab, and S. A. Ahmadi, "V-Net: Fully convolutional neural networks for volumetric medical image segmentation," *Proceedings - 2016 4th International Conference on 3D Vision, 3DV 2016*, pp. 565–571, 2016, doi: 10.1109/3DV.2016.79.

[8] I. A. El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. S. Ahmad, "Differential deep convolutional neural network model for brain tumor classification," *Brain Sci*, vol. 11, no. 3, 2021, doi: 10.3390/brainsci11030352.

[9] J. Yang, F. Xie, H. Fan, Z. Jiang, and J. Liu, "Classification for dermoscopy images using convolutional neural networks based on region average pooling," *IEEE Access*, vol. 6, pp. 65130–65138, 2018, doi: 10.1109/ACCESS.2018.2877587.

[10] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for Brain Tumor Classification," *Neural Process Lett*, vol. 53, no. 1, pp. 671–700, 2021, doi: 10.1007/s11063-020-10398-2.

[11] D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, pp. 1–15, 2015.

[12] A. Hamada, "Br35H: Brain tumor detection 2020," Kaggle, 2020. [Online dataset]. Available: https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection

[13] T. Rahman and M. S. Islam, "MRI Brain Tumor Classification Using Deep Convolutional Neural Network," in *2022 International Conference on Innovations in Science, Engineering and Technology, ICISET 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 451–456. doi: 10.1109/ICISET54810.2022.9775817.

[14] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, "Brain tumor classification in MRI image using convolutional neural network," *Mathematical Biosciences and Engineering*, vol. 17, no. 5, pp. 6203–6216, 2020, doi: 10.3934/MBE.2020328.

[15] S. Arora and M. Sharma, "Deep Learning for Brain Tumor Classification from MRI Images," in *Proceedings of the IEEE International Conference Image Information Processing*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 409–412. doi: 10.1109/ICIIP53038.2021.9702609.

[16] C. Srinivas *et al.*, "Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images," *J Healthc Eng*, vol. 2022, 2022, doi: 10.1155/2022/3264367.

[17] S. Divya, A. Ali, N. Ibrahim, and L. Padma Suresh, "Automated Models for the Classification of Magnetic Resonance Brain Tumour Images," in *ICAC 2023 - 28th International Conference on Automation and Computing*, Institute of Electrical and Electronics Engineers Inc., 2023. doi: 10.1109/ICAC57885.2023.10275235.

[18] M. Aamir *et al.*, "A deep learning approach for brain tumor classification using MRI images," *Computers and Electrical Engineering*, vol. 101, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108105.

[19] M. Ravinder *et al.*, "Enhanced brain tumor classification using graph convolutional neural network architecture," *Sci Rep*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-41407-8.

[20] Md. A. B. Siddique, S. Sakib, M. M. R. Khan, A. K. Tanzeem, M. Chowdhury, and N. Yasmin, "Deep Convolutional Neural Networks (CNN) based Brain Tumor Detection in Brain MRI Images," in *Proceedings - 5th International Conference on Smart Systems and Inventive Technology, ICSSIT 2023*, 2023, pp. 976–979. doi: 10.1109/ICSSIT55814.2023.10060968.