

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage: www.joiv.org/index.php/joiv



BY SA

Brain Tumor Identification Based on VGG-16 Architecture and CLAHE Method

Suci Aulia^{a,*}, Dadi Rahmat^b

^a Applied Sciences Department, Telkom University, Bandung, Indonesia ^b School of Electrical Engineering and Informatics, Bandung Institute of Technology, Bandung, Indonesia Corresponding author: *suciaulia@telkomuniversity.ac.id

Abstract—Magnetic Resonance Imaging (MRI) in diagnosing brain cancers is widespread. Because of the variety of angles and clarity of anatomy, it is commonly employed. If a brain tumor is malignant or secondary, it is a high risk, leading to death. These tumors have an increased predisposition for spreading from one place to another. In detecting brain abnormality form such as a tumor, from a magnetic resonance scan, expertise and human involvement are required. Previous, the image segmentation of brain tumors is widely developed in this field. Suppose we could somehow use an automatic brain tumor detection technology to identify the presence of a tumor in the brain without requiring human intervention. In that case, it will give us a leg up in the treatment process. This research proposed two stages to identify the brain tumor in MRI; the first stage was the image enhancement process using Clip Limit Adaptive Histogram Equalization (CLAHE) to segment the brain MRI. The second one was classifying the brain tumor on MRI using Visual Geometry Group-16 Layer (VGG-16). The CLAHE was used in some instances, there were CLAHE applied in FLAIR image on green color, and CLAHE applied in Red, Green, Blue (RGB) color space. The experimental result showed the highest performance with accuracy, precision, recall, respectively 90.37%, 90.22%, 87.61%. The CLAHE method in RGB Channel and the VGG-16 model have reliably on predicted oligodendroglioma classes in RGB enhancement with precision 91.08% and recall 95.97%.

Keywords- Brain Tumor; Magnetic Resonance Imaging; CLAHE; VGG-16; deep learning.

Manuscript received 8 Jan. 2022; revised 15 Feb. 2022; accepted 2 Mar. 2022. Date of publication 31 Mar. 2022. International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.

I. INTRODUCTION

Brain abnormalities must be recognized early to give prevention and treatment. As a condition, anomalies in the brain must be detected for a practitioner to make precise and effective decisions [1]. If a person is suspected of having any abnormalities, they will be subjected to a series of testing. There are a variety of imaging techniques tests available for brain scannings, such as Single Photon Emission Computed Tomography (SPECT), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and other imaging techniques. MRIs are considered for brain tumor identification because of their capacity and ability to produce detailed images [2]. It is a noninvasive, radiation-free test. It is also the safest imaging method [3]. Because the MRI has a meager contrast ratio [4], we need to enhance the MRI to improve the contrast. Thus, this research proposed an experiment to enhance the MRI contrast before entering the brain tumor identification.

Contrast enhancement is a common preprocessing technique used in image processing and computer vision to improve the performance of downstream operations. Contrast limited adaptive histogram equalization (CLAHE) is a common choice for dealing with 3D images obtained in observational and scientific settings among the available ways based on nonlinear histogram transformations [5]. CLAHE was popular because of its computational efficiency. It conducts local image contrast changes with low noise amplification. In previous studies, CLAHE has succeeded in improving the quality of the scleral area on eye images [6], provides better visualization of fluorescence microscopy images [5], underwater images [7], Optical Character Recognition (OCR) images [8], fingerprint images [9], fundus retina Images [10], and also to increase the light intensity of facial images in the face recognition research [11].

According to prior related works, the image enhancement process, such as increasing the contrast ratio, plays a crucial role in biomedical imaging diagnoses, notably for detecting brain tumors on MRI. Thus, in this research, we used the CLAHE for the image enhancement process on the MRI before entering the brain tumor identification. Afterimage enhancement process to improve the data quality using the CLAHE method and then continued into classification. We propose the CNN-based deep learning architecture Visual Geometry Group-16 Layer (VGG-16) to classify the brain tumor-based histological types on the Magnetic Resonance Imaging Datasets because its performance achieved high performance as return advance accuracy [12-14].

II. MATERIALS AND METHOD

A. Proposed Method

We present a model VGG-16 classifier with CLAHE to identify tumor-based histological type by imaging. This study has taken specific steps to gain highly accurate performance, seen in Fig. 1.



Fig. 1 Proposed method

This research used brain imaging from MRI to identify the histological tumor classes. Each histological types have unique extraction features from dataset images. The model VGG-16 performs a computational classifier to calculate these features' weight and return predicted tumor classes based on histological types. Adaptive threshold using clip limit by CLAHE gives contrast enhancement in the image dataset. It has well-known for improving the image quality for classification performance. CLAHE limited the number of pixel values elevation to derive a preferred histogram.

Several images from the dataset have been removed, causing the missing value in label target and visibility of tumor segmentation. Besides proposing this study to identify the histological type of tumor in brain imaging, to avoid that issue, the data was used mainly with the presence of tumor in a total of 1373 sliced images. The data was split for training, validation, and testing with 60%, 20%, and 20%, respectively, as seen in Fig. 2.



Fig. 2 Visualization data proportion

The VGG-16 is a supervised machine learning, and it is essential to process the training data to identify the testing data. The data validation is used in the middle of training data and testing data to optimize excellent testing performance.

B. Brain Tumor

The brain tumor is an abnormal segment that develops from parts of the brain and its meninges. It originates when cancer spreads excessively, forming an abnormal cluster of cells around or inside the brain [15]. The brain tumor has variations, and there are some called astrocytoma, oligoastrocytoma, and oligodendroglioma. They have named a cell type that occurs tumor and are included in Grade II or lower-grade glioma. This tumor tends to aggressive behavior over time in a slow-growing tumor.

C. Brain Magnetic Resonance Imaging (MRI) Datasets

Magnetic Resonance Imaging (MRI) is non-invasive medical equipment for observing the organ inside the human body. MRI is superior to contrasting soft tissue and is popularly used for brain visualization. It performs magnetic resonance of 0.0064-1.5 tesla to the captured image of crosssection anatomy [16]. MRI can capture images in axial, sagittal, and coronal planes. The modality delivers information from MRI to assist clinicians in diagnoses [17]. The downloaded dataset was from the Kaggle repository [18] that contains The Cancer Imaging Archive (TCIA) with The Cancer Genome Atlas (TCGA) patients. It has 7858 images, including the masking images from 110 patients. The image in the dataset had three dimensions channel: pre-contrast sequence, FLAIR sequence, and post-contrast sequence. Each track represents Red, Green, and Blue stacked in RGB color space shown in Fig. 3.



Fig. 3 Brain magnetic resonance imaging (MRI) datasets

D. Clip Limit Adaptive Histogram Equalization (CLAHE)

Histogram expresses the image illumination by the cumulative pixel intensity distribution [19]. Histograms are very efficient in terms of calculating complexity. This procedure will produce satisfactory results if the low and high points are correctly recognized and the suitable threshold is set [20]. The image appears brighter with higher pixel values. It is darker, with lower pixel values dominating [7]. The equalization gives signal amplification to each cumulative distribution to make contrast enhancement in TCGG brain image.

Furthermore, the clip limit justifies the excess values amplification that reduces noise for a relevant result. Image enhancement with CLAHE applied with certain steps [21][22]:

- Split image size into MxN subregion with M = N.
- Calculate the histogram of each subregion.
- Find the probability of histogram values.
- Set a clip limit n_T to the histogram values h_k use (1).

$$\mathbf{h}_{\mathbf{k}} = \begin{cases} n_T & \text{if } \mathbf{p}_{\mathbf{x}}(\mathbf{k}) \ge n_T \\ \mathbf{p}_{\mathbf{x}}(\mathbf{k}) & \text{else} \end{cases} \quad \mathbf{k} = 1, 2, \dots, \mathbf{L} - 1 \quad (1)$$

Value p_x represents the probability of the pixel intensity, k is the pixel intensity, and L is the maximum pixel-level intensity value.

• Sum all the probability by Cumulative Distribution Function (CDF) C(i) use (2).

$$C(i) = \sum_{k=0}^{i} h_k \quad 0 \le i \le L - 1$$
 (2)

The C(i) is denoted as the cumulative distribution function of *i* grayscale levels.

• Apply histogram equalization transformation *h*(*u*) use (3).

$$h(u) = \left[\frac{C(i) - C_{min}}{1 - C_{min}} * (L - 1)\right]$$
(3)

The h(u) described histogram equalization function of u grayscale intensities, then C_{min} as the minimum value of the cumulative distribution.

Distribute clipped C_k pixel values to all histogram bins use (6).

$$n_{\mu} = \frac{MN - \sum_{k=0}^{i} h_k}{L} \tag{4}$$

$$h_{k} = \begin{cases} n_{T} & \text{if } p_{x}(k) + n_{\mu} \ge n_{T} \\ p_{x}(k) + n_{\mu} & \text{else} \end{cases}$$
(5)

$$C_k = \frac{1}{MN} \sum_{k=0}^{i} h_k \tag{6}$$

The n_{μ} is a clipped region original histogram level, h_k is the normalized clipped histogram, and C_k represents the cumulative histogram value.

E. Visual Geometry Group-16 Layer (VGG-16)

Visual Geometry Group-16 Layer (VGG-16) is deep learning with neural network architecture based on convolutional layers [23]. It has been widely used for the classification model. VGG has two fully connected layers followed by a softmax activation function for the output layer [24]. All these layers have different weights, and each layer forms this many networks architecture. The VGG-16 architecture is shown in Fig. 4. Furthermore, detail of the output shapes of each layer is presented in Table 1.

VGG-16 has applied the convolutional network to scaling down input shape in advance to learn over the input summary as a classification model. Rectified linear unit (ReLu) is a component in convolution network to solve functional hidden layer for learning model. A fully connected layer tends to identify the convolutional output to perform classification. The output layer used softmax activation for multiclass classification.

 TABLE I

 Detail shape of VGG-16 architecture

| Layer (type) | Output Shape |
|----------------------------|-----------------------|
| input (Input Layer) | [(None, 224, 224, 3)] |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) |
| block2_pool (MaxPooling2D) | (None, 56, 64, 128) |
| block3_conv1 (Conv2D) | (None, 56, 64, 256) |
| block3_conv2 (Conv2D) | (None, 56, 64, 256) |
| block3 conv3 (Conv2D) | (None, 56, 64, 256) |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) |
| block4 conv1 (Conv2D) | (None, 28, 28, 512) |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) |
| block4 conv3 (Conv2D) | (None, 28, 28, 512) |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) |
| block5 conv1 (Conv2D) | (None, 14, 14, 512) |
| block5 conv2 (Conv2D) | (None, 14, 14, 512) |
| block5 conv3 (Conv2D) | (None, 14, 14, 512) |
| block5 pool (MaxPooling2D) | (None, 7, 7, 512) |
| flatten (Flatten) | (None, 25088) |
| Dense_1 (Dense) | (None, 4096) |
| Dense_2 (Dense) | (None, 4096) |
| output (Dense) | (None, 1000) |



Fig. 4 VGG-16 architecture

F. The Performance Evaluation

To measure the performance evaluation for histological tumor classification using the VGG-16 model was based on a confusion matrix to calculate accuracy, precision, and recall. A confusion matrix is a statistical method used to compare the predicted and actual values. The True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values are generated from the confusion matrix were used to determine model performance. The True indicates that the model correctly identified the actual values. In contrast, the False condition means the model failed to predict the actual values accurately, then Positive and negative show the prediction and non-prediction classes [25]. The evaluation parameters are calculated with mathematical operations, as shown in (7-9).

$$Accuracy = \frac{TP + FP}{TP + TN + FP + FN}$$
(7)

$$Precision = \frac{TP}{TP + FP}$$
(8)

$$\operatorname{Recall} = \frac{TP}{TP + FN} \tag{9}$$

III. RESULTS AND DISCUSSION

This study performed the brain MRI segmentation from the TCIA dataset using image enhancement with CLAHE to gain better classification results. The FLAIR sequence is more sensitive to the tumor segment than others since the second channel that affects the tumor is highlighted with green color in the brain image. The images are previously split into three-channel colors, Red, Green, and Blue, respectively, as seen in Fig. 5. The original image dataset in Fig. 3 has low contrast. The input image for the VGG-16 model requires an acceptable image



Fig. 5 Result of dataset images on each RGB channel.

quality to give higher performance. The Lower contrast gives less reflection of the brain tumor; it makes an uncertainty distribution pixels value for featuring object in the image. Histogram equalization with clip limit threshold enhances contrast in brain image that can be seen in Fig 6.

The input shape for this model uses a custom input layer with input shape $256 \times 256 \times 3$ of image dimension. The model extracts $8 \times 8 \times 512$ features with a total of 32768 values. The output layer from this model used three classes with softmax activation function for classifying the lower-grade glioma tumor in brain MRI datasets. The proposed model VGG-16 in this paper is constructed in Fig. 7 and model detail in Table 2.



Fig. 6 The differences of after processed used CLAHE on the dataset. (a) original image, (b) CLAHE in FLAIR channel, (c) CLAHE in RGB channel



Fig. 7 Design of proposed model VGG-16

TABLE II DETAIL SHAPE OF PROPOSED MODEL

| Layer (type) | Output Shape | |
|---------------------------------------|-----------------------|--|
| input (Input Layer) | [(None, 256, 256, 3)] | |
| block1_conv1 (Conv2D) | (None, 256, 256, 64) | |
| block1_conv2 (Conv2D) | (None, 256, 256, 64) | |
| block1_pool (MaxPooling2D) | (None, 128, 128, 64) | |
| block2_conv1 (Conv2D) | (None, 128, 128, 128) | |
| block2_conv2 (Conv2D) | (None, 128, 128, 128) | |
| <pre>block2_pool (MaxPooling2D)</pre> | (None, 64, 64, 128) | |
| block3_conv1 (Conv2D) | (None, 64, 64, 256) | |
| block3_conv2 (Conv2D) | (None, 64, 64, 256) | |
| block3_conv3 (Conv2D) | (None, 64, 64, 256) | |
| <pre>block3_pool (MaxPooling2D)</pre> | (None, 32, 32, 256) | |
| block4_conv1 (Conv2D) | (None, 32, 32, 512) | |
| block4_conv2 (Conv2D) | (None, 32, 32, 512) | |
| block4_conv3 (Conv2D) | (None, 32, 32, 512) | |
| block4_pool (MaxPooling2D) | (None, 16, 16, 512) | |
| block5_conv1 (Conv2D) | (None, 16, 16, 512) | |
| block5_conv2 (Conv2D) | (None, 16, 16, 512) | |
| block5_conv3 (Conv2D) | (None, 16, 16, 512) | |
| <pre>block5_pool (MaxPooling2D)</pre> | (None, 8, 8, 512) | |
| flatten (Flatten) | (None, 32768) | |
| dense (Dense) | (None, 512) | |
| output (Dense) | (None, 3) | |

We used clip limit to gain pixel intensity to highlight the tumor area in this experiment. The result showed a higher classification performance with the proposed method, as shown in Table 3.

| TABLE |
|----------------------------|
| FESTING PERFORMANCE |

| No | Method | Acc | Prec | Rec |
|----|---------------------------|--------|--------|--------|
| 1 | Original | 84.07% | 84.37% | 80.06% |
| 2 | CLAHE in FLAIR Channel | 84.81% | 81.96% | 85.83% |
| 3 | CLAHE in RGB Channels | 90.37% | 90.22% | 87.61% |

The second experiment results in the FLAIR image conducted more contrast in the tumor segment. The FLAIR enhancement with CLAHE is located in layer two in the RGB image, and it gives the result greener visually. It also increases the tumor signals concentration. The result did not provide excellent performance since it still segments the nontumor. The confusion matrix gives all the VGG-16 testing results, as shown in Fig. 8.

The last experiment was image enhancement used CLAHE in all RGB layers. The result showed the highest performance considering the two experimental before it has used 270 images data which achieved accuracy, precision, and recall, respectively 90.37%, 90.22%, and 87.61%. It increases the accuracy rate by 6.30% from the original TCGA brain MRI segmentation research. Meanwhile, the identification result of each class gives variances precision and recall performance. It defines the model excellently on a particular histological tumor prediction class. The performance of each class is shown in Fig. 9.



Class I: Astrocytoma Class II: Oligoastrocytoma Class III: Oligodendroglioma

Fig. 8 Classification results (a) original, (b) FLAIR enhancement, (c) RGB channel enhancement



Astrocytoma Oligoastrocytoma Oligodendroglioma

Fig. 9 Performance results based on confusion matrix for each class

The VGG-16 model for histological tumor classes prediction has different performances for each class. This model has better precision in predicting astrocytoma after contrast enhancement in the RGB channel with the CLAHE method. However, it returns low recall, which means it has more False Positive results. False Positive return misdiagnosis that makes the model prediction unreliable.

IV. CONCLUSION

This paper performs the classification of a histological brain tumor in lower-grade gliomas. We used the VGG-16 model to identify the brain tumor in the MRI dataset. In this research, we used the Clip Limit Adaptive Histogram Equalization (CLAHE) for the image enhancement process on the MRI dataset before entering the brain tumor identification using VGG-16. The experimental performance return achieves better accuracy from the original dataset and FLAIR enhancement. The highest score from the VGG-16 model by RGB enhancement with CLAHE gives an accuracy, precision, recall, respectively 90.37%, 90.22%, 87.61%. The oligodendroglioma in advance with CLAHE image enhancement on RGB channel was more reliably, and other classes can return precision 91.08% and recall 95.97%.

REFERENCES

- I. Wahlang, P. Sharma, S. Sanyal, G. Saha, and A. K. Maji, "Deep learning techniques for classification of brain MRI," Int. J. Intell. Syst. Technol. Appl., vol. 19, no. 6, pp. 571–588, 2020, doi: 10.1504/IJISTA.2020.112441.
- [2] H. W. Goo and Y.-S. Ra, "Advanced MRI for Pediatric Brain Tumors with Emphasis on Clinical Benefits," Korean J. Radiol., vol. 18, no. 1, p. 194, 2017, doi: 10.3348/kjr.2017.18.1.194.
- [3] N. H. Apriantoro and Christianni, "Analisis Perbedaan Citra MRI Brain pada Sekuent1se dan T1flair," Sinergi, vol. 19, no. 3, pp. 206– 210, 2015.
- [4] H. Kaur and J. Rani, "MRI brain image enhancement using Histogram Equalization techniques," in 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Mar. 2016, no. 1, pp. 770–773, doi: 10.1109/WiSPNET.2016.7566237.
- [5] V. Stimper, S. Bauer, R. Ernstorfer, B. Scholkopf, and R. P. Xian, "Multidimensional Contrast Limited Adaptive Histogram Equalization," IEEE Access, vol. 7, pp. 165437–165447, 2019, doi: 10.1109/ACCESS.2019.2952899.

- [6] M. S. Maheshan, B. S. Harish, and N. Nagadarshan, "On the use of Image Enhancement Technique towards Robust Sclera Segmentation," Procedia Comput. Sci., vol. 143, pp. 466–473, 2018, doi: 10.1016/j.procs.2018.10.419.
- [7] J. Ma, X. Fan, S. X. Yang, X. Zhang, and X. Zhu, "Contrast Limited Adaptive Histogram Equalization-Based Fusion in YIQ and HSI Color Spaces for Underwater Image Enhancement," Int. J. Pattern Recognit. Artif. Intell., vol. 32, no. 07, p. 1854018, Jul. 2018, doi: 10.1142/S0218001418540186.
- [8] H. K. Buddha, J. S. Meka, and P. Choppala, "OCR Image Enhancement & Implementation by using CLAHE algorithm," Mukt Shabd J., vol. IX, no. IV April, pp. 3595–3599, 2020.
- [9] M. Sepasian, W. Balachandran, and C. Mares, "Image Enhancement for Fingerprint Minutiae-Based Algorithms Using CLAHE, Standard Deviation Analysis and Sliding Neighborhood," Lect. Notes Eng. Comput. Sci., vol. 2173, no. 1, pp. 1199–1203, 2008.
- [10] Erwin, R. P. Sari, G. R. Utami, and A. N. Harison, "Enhancement Citra Fundus Retina Menggunakan CLAHE dan Wiener Filter," in Prosiding Annual Research Seminar 2018 Computer Science and ICT ISBN, 2018, vol. 4, no. 1, pp. 978–979.
- [11] P. Musa, F. Al Rafi, and M. Lamsani, "A Review: Contrast-Limited Adaptive Histogram Equalization (CLAHE) methods to help the application of face recognition," in 2018 Third International Conference on Informatics and Computing (ICIC), Oct. 2018, no. October, pp. 1–6, doi: 10.1109/IAC.2018.8780492.
- [12] A. Elnakib, H. M. Amer, and F. E. Z. Abou-Chadi, "Early lung cancer detection using deep learning optimization," Int. J. online Biomed. Eng., vol. 16, no. 6, pp. 82–94, 2020, doi: 10.3991/ijoe.v16i06.13657.
- [13] D. Bendarkar, P. Somase, P. Rebari, R. Paturkar, and A. Khan, "Web Based Recognition and Translation of American Sign Language with CNN and RNN," Int. J. online Biomed. Eng., vol. 17, no. 1, pp. 34– 50, 2021, doi: 10.3991/ijoe.v17i01.18585.
- [14] B. R. Nanditha, A. G. Kiran, H. S. Chandrashekar, M. S. Dinesh, and S. Murali, "An Ensemble Deep Neural Network Approach for Oral Cancer Screening," Int. J. online Biomed. Eng., vol. 17, no. 2, pp. 121– 134, 2021, doi: 10.3991/ijoe.v17i02.19207.
- [15] Mohsen H., El-Dahsan E. A., El-Horbaty E. M., and M. Salem A. "Classification using deep learning neural networks for brain tumors," Future Computing and Informatics Journal, vol. 3, pp. 68-71, 2018.
- [16] W. S. Prakoso, I. Soesanti, and S. Wibirama, "Enhancement methods of brain MRI images: A Review," 2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE), 2020.
- [17] T. Kaur and T. K. Gandhi, "Automated Brain Image Classification based on VGG-16 and transfer learning," 2019 International Conference on Information Technology (ICIT), 2019.
- [18] M. Buda, E. A. AlBadawy, A. Saha, and M. A. Mazurowski, "Deep radiogenomics of lower-grade gliomas: Convolutional neural

networks predict tumor genomic subtypes using mr images," Radiology: Artificial Intelligence, vol. 2, no. 1, 2020.

- [19] S. M. Pizer, R. E. Johnston, J. P. Ericksen, B. C. Yankaskas, and K. E. Muller, "Contrast-limited adaptive histogram equalization: speed and effectiveness," in [1990] Proceedings of the First Conference on Visualization in Biomedical Computing, 1990, pp. 337–345, doi: 10.1109/VBC.1990.109340.
- [20] R. M. Yanni, N. E.-K. El-Ghitany, K. Amer, A. Riad, and H. El-Bakry, "A new model for image segmentation based on Deep Learning," International Journal of Online and Biomedical Engineering (iJOE), vol. 17, no. 07, p. 28, 2021.
- [21] S. Saifullah, "Analisis Perbandingan HE dan CLAHE pada Image Enhancement dalam Proses Segmenasi Citra untuk Deteksi Fertilitas Telur," J. Nas. Pendidik. Tek. Inform., vol. 9, no. 1, p. 134, Apr. 2020, doi: 10.23887/janapati.v9i1.23013.
- [22] J. Joseph, J. Sivaraman, R. Periyasamy, and V. R. Simi, "An objective method to identify optimum clip-limit and histogram specification of contrast limited adaptive histogram equalization for MR images," Biocybernetics and Biomedical Engineering, vol. 37, no. 3, pp. 489– 497, 2017.
- [23] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: 10.1109/TPAMI.2016.2577031.
- [24] R. Girshick, "Fast R-CNN," in 2015 IEEE International Conference on Computer Vision (ICCV), Dec. 2015, vol. 2015 Inter, pp. 1440– 1448, doi: 10.1109/ICCV.2015.169.
- [25] A. Samreen, A. M. Taha, Y. V. Reddy, and S. P, "Brain tumor detection by using Convolution Neural Network," International Journal of Online and Biomedical Engineering (iJOE), vol. 16, no. 13, p. 58, 2020.