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Convolutional Neural Network featuring VGG-16 Model for Glioma Classification

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Abstract—Magnetic Resonance Imaging (MRI) is a body sensing technique that can produce detailed images of the condition of organs and tissues. Specifically related to brain tumors, the resulting images can be analyzed using image detection techniques so that tumor stages can be classified automatically. Detection of brain tumors requires a high level of accuracy because it is related to the effectiveness of medical actions and patient safety. So far, the Convolutional Neural Network (CNN) or its combination with GA has given good results. For this reason, in this study, we used a similar method but with a variant of the VGG-16 architecture. VGG-16 variant adds 16 layers by modifying the dropout layer (using softmax activation) to reduce overfitting and avoid using a lot of hyper-parameters. We also experimented with using augmentation techniques to anticipate data limitations. Experiment using data The Cancer Imaging Archive (TCIA) - The Repository of Molecular Brain Neoplasia Data (REMBRANDT) contains MRI images of 130 patients with different ailments, grades, races, and ages with 520 images. The tumor type was *Glioma*, and the images were divided into grades II, III, and IV, with the composition of 226, 101, and 193 images, respectively. The data is divided by 68% and 32% for training and testing purposes. We found that VGG-16 was more effective for brain tumor image classification, with an accuracy of up to 100%.

Keywords—Classification; MRI; brain tumor; Glioma, CNN; VGG-16.

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I. INTRODUCTION

Medical image analysis and processing are instrumental in the medical field, particularly for non-invasive medicine and clinical studies. Medical imaging techniques and analysis tools enable physicians and radiologists to administer a specific diagnosis. Medical image preprocessing has emerged as one of the most important tools for identifying and diagnosing various problems. Imaging technology assists physicians in visualizing and analyzing images to detect abnormalities in internal structures. Medical image data obtained from Bio-medical devices such as Magnetic Resonance Imaging (MRI) indicates the presence or absence of a lesion along with the patient's history, serving as a critical factor in diagnosis [1].

The human brain is one of the most complex organs working and engaging with billions of cells. The emergence of brain tumors is alleged to be due to escalating uncontrolled cell division, forming an abnormal cell growth around or in the brain, further classified as benign and malignant [2]. Brain

tumor probability in the human brain remains soaring [3]. Abnormal cell growth affects the normal functionality of brain activity and destroys healthy cells [4]. The UK cancer research company reports 5,250 annual deaths due to brain-related activity [5]. In addition, World Health Organization (WHO) reports that brain tumor accounts for less than 2% of human cancers. The current WHO classification for brain tumors is strictly histopathological, limiting its clinical application. Consequently, such limitations trigger medical imaging applications for diagnosis and treatment planning, including more automated methods. The growing amount of brain MRI image data has created new opportunities for medical science in search of accurate data analysis and diagnosis [6].

Researchers have preferred magnetic resonance imaging (MRI) to diagnose and model the brain tumor progression in the detection and treatment phases. MRI is employed to examine the structures presented in the brain [7]. MRI images significantly provide a wealth of information regarding scrambled structures and abnormalities in brain tissue due to high image resolution [4], [8]. MRI images of the brain

provide the preeminent sources to detect and identify brain tumors, including the treatment process [8]. MRI scanning is widely accepted in neurology to visualize the detailed characteristics of the brain and other skull structures [9].

In recent years, wide arrays of studies in the field of medical imaging have demonstrated significant progress in the classification of brain tumors [10]. Several methods are frequently implemented to classify image data, one of which is the Convolutional Neural Network (CNN) method. Prior studies have been conducted on deep learning applications for detecting and diagnosing brain tumors [3]. Convolutional Neural Network applies the standard structure stacked by convolutional layers (optionally followed by normalization and max-pooling) added by one or more fully connected layers. This basic design variant is common in the image classification literature, generating the best results compared to MNIST, CIFAR data and most prominently on the ImageNet classification [11]. For larger datasets such as ImageNet, the current trend is to increase the number of layers [12] and layer size to solve overfitting problems [13]. Although there are concerns that max-pooling the layer might result in lower accuracy [14], a similar CNN model was successfully engaged for localization of object detection and human pose estimation [15].

Brain tumor classifications have been performed through various machine learning and imaging techniques over the years [5]. Convolutional Neural Network (CNN) is one of the deep learning methods of image classification mimicking the human brain. In its application, the CNN method has several architectural models such as inception, VGGNet, LeNet-5, AlexNet, ZFNet, and ResNet. Each of these architectural models has differences in processing various types of data images. In 2009, Zacharaki et al. [16] proposed a system to classify various levels of *glioma* in addition to the binary classification for high and low grades by utilizing SVM and KNN, depicting an accuracy rate of 85% for multi-classification and 88% for binary classification.

Prior studies applied Convolutional Neural Network (CNN) through VGG-16, a model for differential diagnosis of papillary thyroid carcinomas in cytological images, including a pilot study researched by Guan et al. [17] utilized 279 images of thyroid nodule cells. The obtained images are fragmented and divided into training data and test data. The pilot study employed both VGG-16 and Inception-V3 models, further trained and tested to obtain a comparative diagnosis. Similarly, another research was also conducted by Banerjee [18] employed a MRI dataset (Glioblastoma malignant primary brain tumors) in adults and classified as High-Grade Glioma (HGG) and Low Grade Glioma (LGG). The dataset is obtained from BraTS 2012, 2013, 2014, and 2015 competition data from The Cancer Imaging Archive (TCIA), consisting of 210 HGG cases and 75 LGG cases. Each image portrays a resolution size of 240 x 240 pixels. In addition, Banerjee's research utilizes the Convolutional Neural Network method using VGGNet and ResNet architectural models, resulting in an accuracy rate of 83.86% (VGGNet) and 84.91% (ResNet).

Specifically, this study employs the Convolutional Neural Network (CNN) method by proposing VGGNet model to classify grades II, III, and IV of glioma brain tumors. The researchers of this study selected the VGG-16 model considering its high accuracy in previous research. Therefore,

the researcher decided to use this model. Additionally, 16 layers are inserted by modifying the dropout layer (using softmax activation) to reduce overfitting. The dataset was obtained from The Cancer Imaging Archive (TCIA) with public repository access [19]. This study employed a dataset of 520 images retrieved from the website (The Repository of Molecular Brain Neoplasia Data; REMBRANDT), including MRI images of 130 patients with different ailments, grades, races, and ages [20]. Further, the image was divided into 68% train data and the remaining 32% test data and validation data. Image data in ".dcm" format is configured into ".jpg" format by using RadiAnt DICOM application to facilitate further data processing. This paper proposes a pretrained architecture using VGG16 with and without preprocessing to classify three Glioma grades.

II. MATERIALS AND METHOD

A. Dataset

This research dataset employs MRI tumor image data retrieved from The Cancer Imaging Archive [19]. The Repository of Molecular Brain Neoplasia Data (REMBRANDT) contains MRI images of 130 patients with different ailments, grades, races, and ages. The dataset was obtained from the website (The Cancer Imaging Archive (TCIA) REMBRANDT), which has ".dcm" format converted into ".jpg" using the RadiAnt DICOM application with a size of 250 x 250 pixels.

The data of this study (image data) involves 520 images from 56 patients divided into 68% train data as well as 32% test data and validation data. The images are selected from different grades of glioma (grade II, grade III and grade IV) as illustrated in Fig. 1.

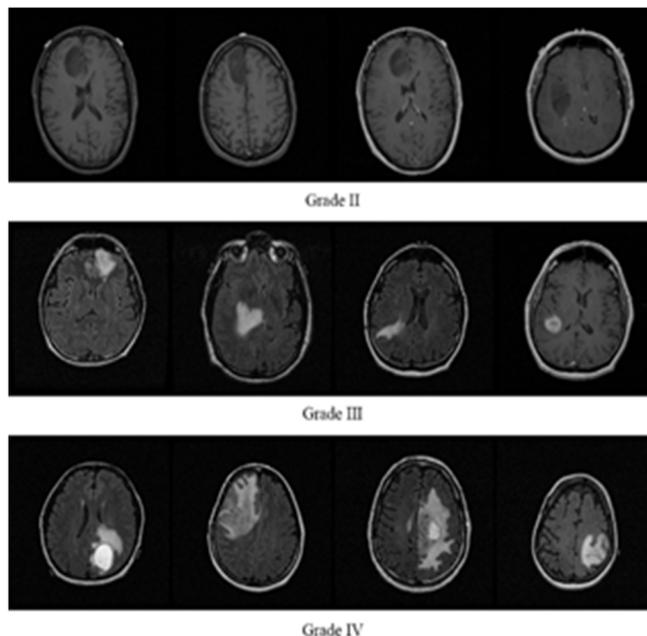


Fig. 1 Differences between grade II, grade III and grade IV

Table 1 indicates additional details about the description of the dataset. Due to limitations in data collection obtained from the internet, the researchers perform an image augmentation process to enhance the number of train data.

TABLE I
DATA DIVISION BY CLASS (GRADE II, GRADE III, AND GRADE IV)

Class Label	Number of Patients	Number of Images
Grade II	29	226
Grade III	18	101
Grade IV	19	193
Total	56	520

B. Preprocessing Data

Preprocessing was divided into more detailed task sections, including line deletion, slope estimation and correction, top and bottom line detection, alignment, and so forth [21]. Before

the data was processed, the researchers performed preprocessing techniques through image augmentation due to limited data. Image augmentation creates new data points by manipulating (rotating, resizing, and cropping) the original data. In addition, image augmentation is performed to enhance the diversity of data available for training models in deep learning without collecting new data.

The first preprocessing accomplished in this study was through image cropping. In the preprocessing process, cropped images are employed to clarify the tumor area enabling the system to recognize its class. Fig. 2 describes the tumor's image cropping process by removing the image's background area, presenting a more apparent image.

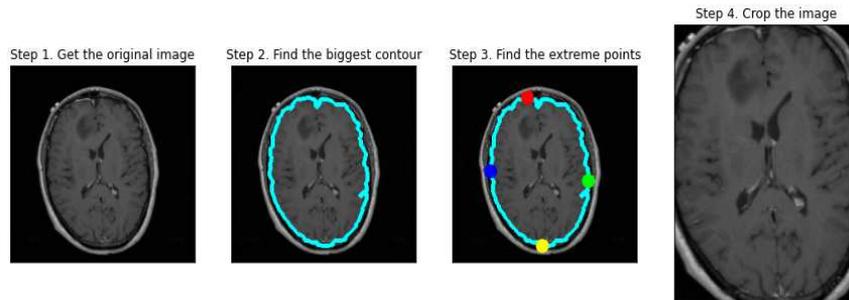


Fig. 2 Image Cropping Process

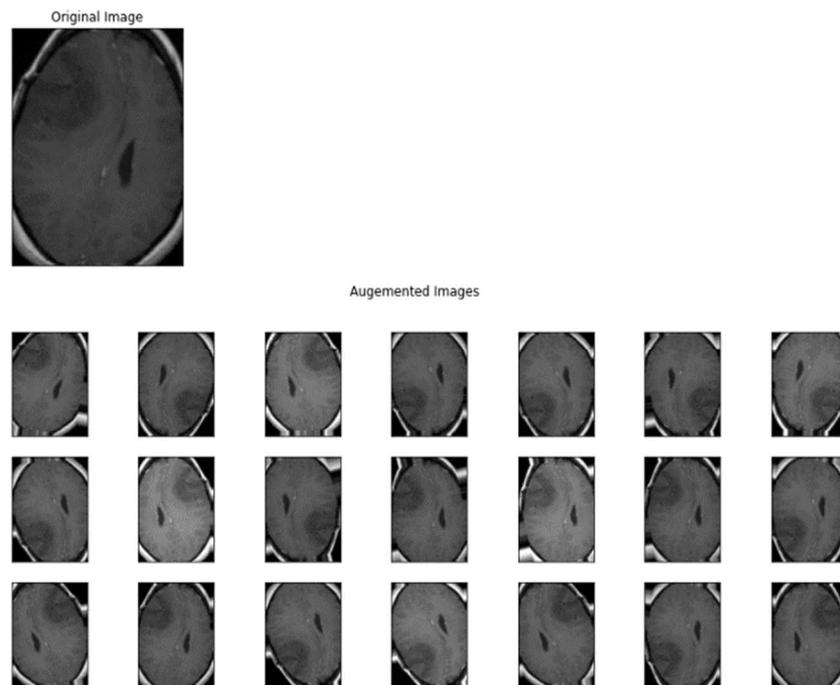


Fig. 3 Image Augmentation Process in 21x1 images

Image augmentation is performed in the second preprocessing process due to the limited amount of data collected and carried out as many as 21 x 1 images by changing the image scale and rotation, as illustrated in Fig. 3.

C. VGG-16 Model Architecture

VGG-16 is regarded as a convolutional neural network (CNN) proposed to win the ILSVR (Imagenet) competition in 2014. VGG-16 is considered one of the best vision models to

date, with the unique feature of adding 16 layers instead of having a large number of hyper-parameters, as illustrated in Fig. 4. Specifically, VGG-16 focuses on the layers with 3 x 3 filter convolutions, step 1, and padding.

With the simple concept, VGG solely uses the 3 x 3 convolutional layers and 2 x 2 pooling throughout the network of filters. The softmax classifier for output follows the two fully connected layers (each having 4096 nodes). VGG contains approximately 14 million parameters consumed in

the fully connected layer, which, however, results in more time-consuming to run this network model.

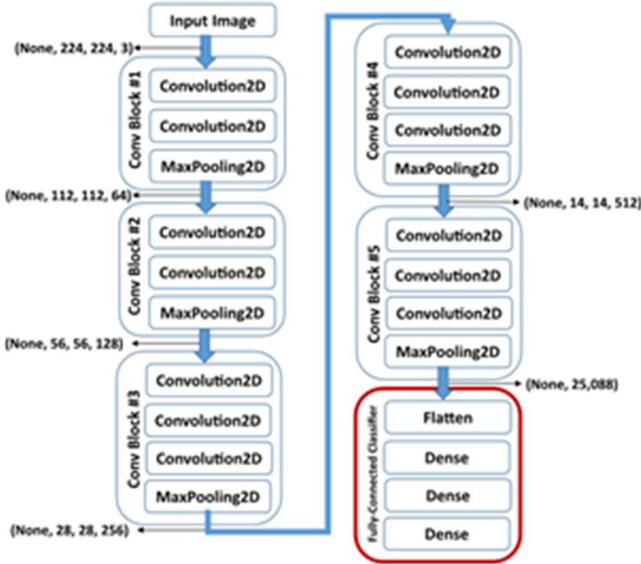


Fig. 4 VGG-16 Model Architecture

The design of the model illustrates the program to classify MRI tumor images. The VGG-16 model involves approximately 14 million parameters containing 16 convolutional layers with a very small receptive field, including 3 x 3 and five max-pooling layers with a size of 2 x 2 to perform spatial stacking, followed by three fully connected layers. In addition, the VGG-16 model is equipped with the regulation in the fully connected layer. The VGG-16 model architecture on ImageNet database is removed when fully connected prior to training as an in-depth feature generator to produce semantic vector images [22].

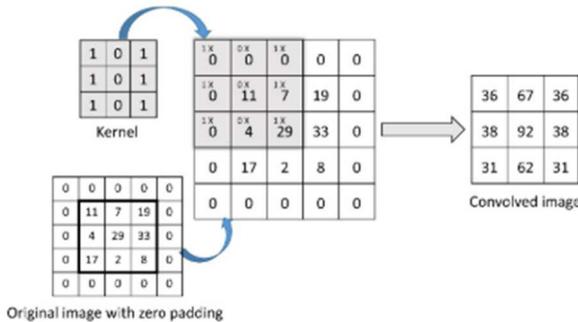


Fig. 5 An Example of a Process at the Convolutional Layer

The main process of CNN lies in the Convolution Layer, which performs a convolution operation on the previous layer's output, as described in Fig. 5. Each convoluted layer will convert each filter to the input data portion generating an activation map or 2D feature map.

Fig. 6 demonstrates the pooling layer stage after the convolutional layer. The pooling layer is a matrix measurement consisting of filters at a certain size and stride. Each shift will be determined by the number of strides in the feature map area of the pooling layer as an important step in creating a CNN model. The most common form of the pooling layer is to employ a 2 x 2 filter applied in step 2 and operated on each slice of the input. Max pooling divides the output

from the convolution layer into several small grids consuming the maximum value from the grid to compile the reduced image matrix.

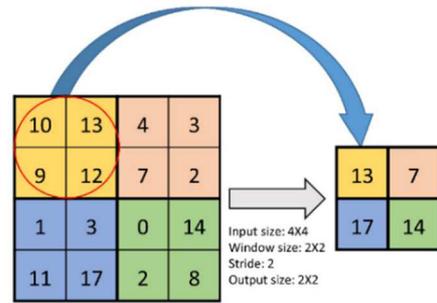


Fig. 6 The Max Pooling Process

The Fully Connected Layer stage is utilized to process and classify the data. The feature map produced at the pooling map stage will be processed through a "flatten" part, generating a vector as input at the Fully Connected Layer stage.

The dropout layer in Fig. 7 serves as a way to prevent overfitting. Overfitting is a condition in which the data used for training is at its best; therefore, the test is performed by using different testing data, which can reduce the accuracy. The dropout layer works by temporarily removing a neuron and new weight, not applied to neurons when the transmission is carried out.

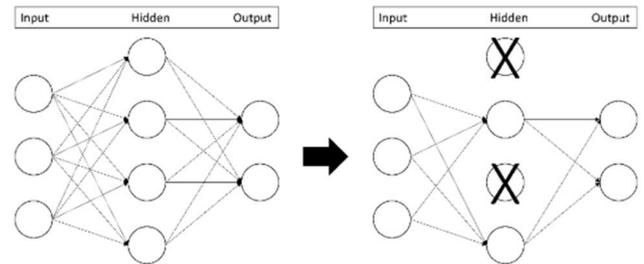


Fig. 7 A process on the Dropout Layer

III. RESULTS AND DISCUSSION

At this stage, the test is conducted twice, through testing with the data preprocessing technique and without the data preprocessing technique. Parameter changes are also activated at the dropout layer, which aims to find the best accuracy results. The MRI image dataset in this study was retrieved from The Cancer Imaging Archive (TCIA), comprising 520 images divided into train data (68%), test data, and validation data (32%). The dataset has three classes: glioma grade II, grade III, and grade IV.

The VGG-16 model is tested to locate the best accuracy value, with and without preprocessing data. The dataset used in this study has a ".jpg" format. The first process is conducted by uploading a ".jpg" dataset to Google Drive. In Google Collab, data uploads are essential for further process. The data image is resized to 224 x 224 because VGG-16 model can only process data of that size. The difference in testing lies in the use of preprocessing techniques in each test. This study specifically utilizes preprocessing techniques, including cropping and augmentation.

A. Scenario 1

In scenario 1, the dataset was obtained from The Cancer Imaging Archive (TCIA), presenting the three classes: *glioma* grade II, grade III, and grade IV. The total number of datasets comprised 520 images divided into train data (68%) as well as test data and validation data (32%). The time process was conducted 500 times by using SoftMax activation on the dropout layer, and the first test was performed without data preprocessing.

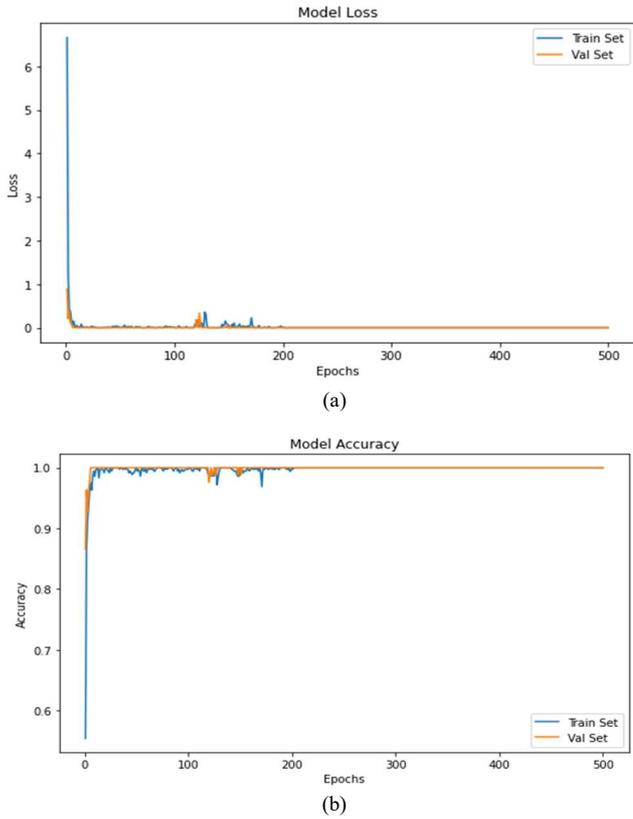


Fig. 8 Loss (a) and accuracy (b) plot without preprocessing technique

Fig. 8 illustrates the first test utilizing softmax dropout layer activation conducted 500 times without using preprocessing techniques to obtain the maximum and final accuracy of 100%. The result explains that the glioma brain tumor is appropriate to be processed using the VGG-16 model without preprocessing data. The confusion matrix details are explained in Fig. 9.

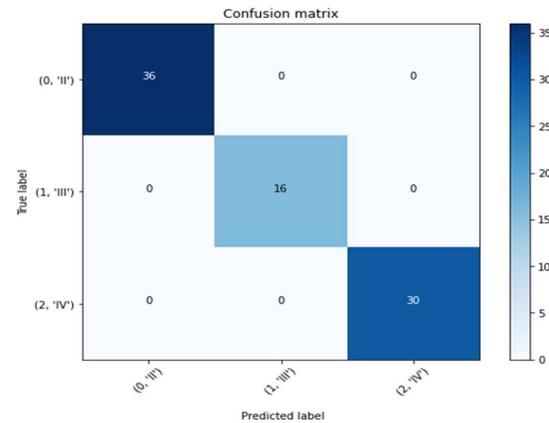


Fig. 9 Confusion matrix scenario 1

B. Scenario 2

Scenario 2 for glioma grade II, grade III, and grade IV utilized 520 image data divided into train data (68%) and test data and validation data (32%). Scenario 2 is performed 500 times using SoftMax activation and data preprocessing through image cropping and augmentation techniques. Fig. 10 illustrates that the second test (Scenario 2) applies preprocessing techniques, conducted 500 times and obtaining the final accuracy rate of 99% (high, but not optimal). The confusion matrix details are explained in Fig. 11.

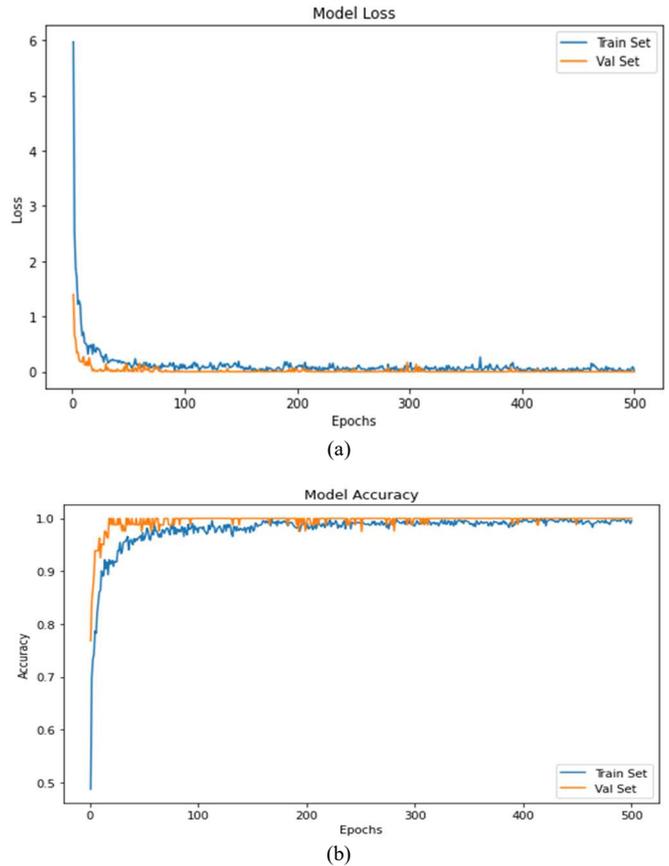


Fig. 10 Loss (a) and accuracy (b) plot with preprocessing technique

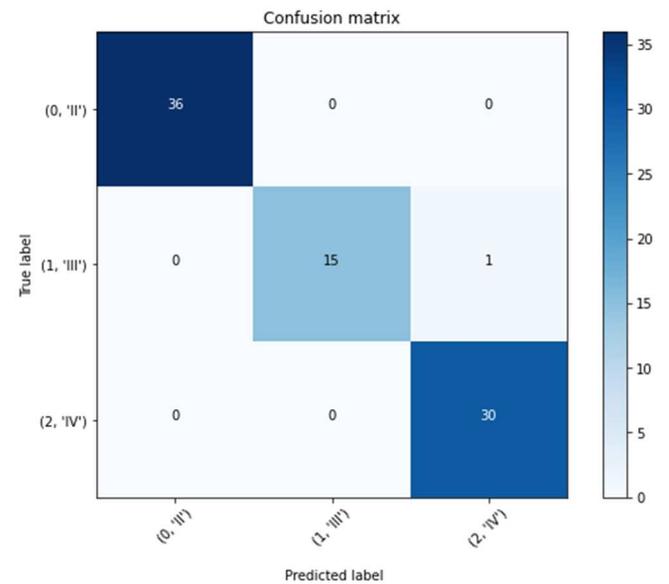


Fig. 11 Confusion matrix scenario 2

C. Evaluation

In this study, we propose a deep learning method to classify grade problems in gliomas using the glioma tumor dataset from The Cancer Imaging Archive (TCIA) REMBRANDT based on glioma tumor grade (grade II, grade III, and grade IV). Experiments with Scenario 1 (without augmentation) and Scenario 2 (with authentication) show that Scenario 1 performs better than Scenario 2 with 100% and 99% accuracy, respectively (see Table 2). This is very interesting because augmentation generally increases performance but decreases performance here. We suspect that this augmentation result is more optimistic, and it will be our future work to investigate it.

TABLE II
SCENARIO WITH AND WITHOUT PREPROCESSING

Scenario	Data	Preprocessing	Model	Accuracy
1	520	Not	VGG-16	100%
2	520	Yes	VGG-16	99%

TABLE III
COMPARISON WITH PREVIOUS RESEARCH

Model	Dataset	Accuracy	Method
Sultan et al. [5]	REMBRANDT-GLIOMA	98.7%	CNN
Anaraki et al. [23]	REMBRANDT-GLIOMA	90.0%	GA-CNN
Proposed	REMBRANDT-GLIOMA	100%	VGG-16

We compared our results with the previous studies using the same data (REMBRANDT-GLIOMA) (see Table 3). The performance of VGG-16 is convincingly better than GA-CNN by Anaraki et al. [23] and CNN by Sultan et al. [5], with margins of 10% and 1.3%, respectively. Next, we plan to investigate VGG-16 against other types of brain tumors and concurrent combinations of brain tumors.

IV. CONCLUSION

As proposed in this study, the Convolutional Neural Network (CNN) featuring VGG-16 model can produce a high accuracy rate on MRI image datasets. The data preprocessing technique was applied in the second test (scenario 2) but did not generate the maximum accuracy rate (99%). Meanwhile, the first test (scenario 1) conducted without the data preprocessing technique generated the maximum accuracy rate (100%). In sum, with or without data preprocessing techniques are proven to generate greater accuracy than those in referred studies and use other CNN model architectures.

REFERENCES

- [1] R. J. Young and E. A. Knopp, "Brain MRI: Tumor evaluation," *Journal of Magnetic Resonance Imaging*, vol. 24, no. 4, pp. 709–724, Oct. 2006, doi: 10.1002/JMRI.20704.
- [2] A. Wadhwa, A. Bhardwaj, V. V.-M. resonance imaging, and undefined 2019, "A review on brain tumor segmentation of MRI images," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0730725X19300347>.
- [3] Z. Hu et al., "Deep learning for image-based cancer detection and diagnosis— A survey," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0031320318301845>
- [4] H. Mohsen, E. El-Dahshan, ... E. E.-H.-F. C. and, and undefined 2018, "Classification using deep learning neural networks for brain tumors," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2314728817300636>.
- [5] H. Sultan, N. Salem, W. A.-A.-I. Access, and undefined 2019, "Multi-classification of brain tumor images using deep neural network," *ieeexplore.ieee.org*, Accessed: Jun. 13, 2022. [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/8723045/>.
- [6] G. Mohan, M. S.-B. S. P. and Control, and undefined 2018, "MRI based medical image analysis: Survey on brain tumor grade classification," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1746809417301398>.
- [7] J. Amin, M. Sharif, M. Yasmin, S. F.-P. R. Letters, and undefined 2020, "A distinctive approach in brain tumor detection and classification using MRI," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S016786551730404X>.
- [8] M. Mittal, L. Goyal, S. Kaur, I. Kaur, ... A. V.-A. S., and undefined 2019, "Deep learning based enhanced tumor segmentation approach for MR brain images," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1568494619301000>.
- [9] A. Tiwari, S. Srivastava, M. P.-P. R. Letters, and undefined 2020, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S016786551930340X>.
- [10] N. Gordillo, E. Montseny, P. S.-M. resonance imaging, and undefined 2013, "State of the art survey on MRI brain tumor segmentation," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0730725X13001872>.
- [11] C. Szegedy et al., "Going Deeper with Convolutions," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 07-12-June-2015, pp. 1–9, Sep. 2014, doi: 10.48550/arxiv.1409.4842.
- [12] M. Lin, Q. Chen, and S. Yan, "Network In Network," *2nd International Conference on Learning Representations, ICLR 2014 - Conference Track Proceedings*, Dec. 2013, doi: 10.48550/arxiv.1312.4400.
- [13] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov, "Improving neural networks by preventing co-adaptation of feature detectors," *arxiv.org*, Accessed: Jun. 13, 2022. [Online]. Available: <https://arxiv.org/abs/1207.0580>.
- [14] T. F. Gonzalez, "Handbook of approximation algorithms and metaheuristics," *Handbook of Approximation Algorithms and Metaheuristics* (1st ed.), Chapman and Hall/CRC. <https://doi.org/10.1201/9781420010749>.
- [15] A. Toshev, ... C. S. the I. conference on computer, and undefined 2014, "DeepPose: Human pose estimation via deep neural networks," *openaccess.thecvf.com*, Accessed: Jun. 13, 2022. [Online]. Available: http://openaccess.thecvf.com/content_cvpr_2014/html/Toshev_Deep_Pose_Human_Pose_2014_CVPR_paper.html.
- [16] E. I. Zacharaki et al., "Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme," *Magnetic Resonance in Medicine*, vol. 62, no. 6, pp. 1609–1618, 2009, doi: 10.1002/MRM.22147.
- [17] Q. Guan et al., "Deep convolutional neural network VGG-16 model for differential diagnosing of papillary thyroid carcinomas in cytological images: a pilot study," *ncbi.nlm.nih.gov*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/pmc6775529/>.
- [18] S. Banerjee, S. Member, I. Supervisor, F. Masulli, S. Member, and S. Mitra, "Brain Tumor Detection and Classification from Multi-Channel MRIs using Deep Learning and Transfer Learning".
- [19] K. Clark et al., "The cancer imaging archive (TCIA): Maintaining and operating a public information repository," *Journal of Digital Imaging*, vol. 26, no. 6, pp. 1045–1057, Dec. 2013, doi: 10.1007/S10278-013-9622-7.
- [20] "Wiki - The Cancer Imaging Archive (TCIA) Public Access - Cancer Imaging Archive Wiki." <https://wiki.cancerimagingarchive.net/> (accessed Jun. 13, 2022).

- [21] A. Rehman and T. Saba, "Neural networks for document image preprocessing: State of the art," *Artificial Intelligence Review*, vol. 42, no. 2, pp. 253–273, 2014, doi: 10.1007/S10462-012-9337-Z.
- [22] K. Gopalakrishnan, S. Khaitan, A. C.-... and building materials, and undefined 2017, "Deep convolutional neural networks with transfer learning for computer vision-based data-driven pavement distress detection," *Elsevier*, Accessed: Jun. 13, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0950061817319335>.
- [23] A. Kabir Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 1, pp. 63–74, Jan. 2019, doi: 10.1016/J.BBE.2018.10.004.