Brain Tumor Classification in MRI Images Using VGG19 with Type-2 Fuzzy Logic

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A Brain Tumors are highly dangerous illnesses that significantly reduce the life expectancy of patients. The classification of brain tumors plays a crucial role in clinical diagnosis and effective treatment. The misdiagnosis of brain tumors will result in wrong medical intercession and reduce chance of survival of patients Precisely diagnosing brain tumors is of utmost importance for devising suitable treatment plans that can effectively cure and improve the quality of life for patients afflicted with this condition. To tackle this challenge, present a framework that harnesses deep convolutional layers to automatically extract crucial and resilient features from the input data. Systems that use computers and with the help of convolutional neural networks have provided huge success stories in early detection of tumors. In our framework, utilize VGG19 model combined with fuzzy logic type-2 where used fuzzy logic type-2 that applied to enhancement the images brain where Type-2 fuzzy logic better handles uncertainty in medical images, improving the interpretability of image enhancement by managing noise and subtle differences with greater precision than Type-1 fuzzy logic for MRI images often contain ambiguous or low-contrast areas where noise, lighting conditions different and greatly improve accuracy. while used the VGG19 architecture to feature extraction and classify Tumor and non- Tumor. This approach enhances the accuracy of tumors classification, aiding in the development of targeted treatment strategies for patients. The method is trained on the Br35H dataset, resulting in a training accuracy of 0.9983 % and Train loss of 0.2118 while the validation accuracy of 0.9953 % validation loss of 0.2264. This demonstrates effective pattern learning and generalization capabilities. The model achieves outstanding accuracy, with a best accuracy for the model of 0.9983 %, While the test accuracy of the model reached of 99 %, and both of sensitivity and specificity at 0.9967 %. Additionally, the proposed method achieved F1- score of 0.9991 %.

Povzetek: Opisana je izvirna klasifikacija možganskih tumorjev z uporabo MRI slik. Predstavljen je okvir, ki združuje model VGG19 z mehko logiko tipa Uporablja se za izboljšanje kakovosti slik in boljše upravljanje negotovosti, medtem ko VGG19 arhitektura služi za ekstrakcijo značilnosti in klasifikacijo tumorjev. Ta pristop pomaga pri razvoju ciljno usmerjenih strategij zdravljenja.

1 Introduction

The brain, a complex organ within the human body, is responsible for governing the entire nervous system, comprising approximately 100 billion nerve cells [1]. Brain tumors, which can be benign or malignant, pose significant risks to overall health [2]. Malignant brain tumors grow rapidly and lack well-defined margins, making them dangerous and prone to spreading [3]. The intracranial pressure caused by a brain tumor can further accelerate its growth and potentially lead to brain damage [4]. While brain tumors are not as common as other types of cancer, they still rank as the 10th leading cause of global deaths [5]. These tumors have enduring physical and psychological effects on patients' lives, disrupting proper brain function [6].

Automatic segmentation and classification of brain tumors play a vital role in the field of medical imaging, enabling diagnostics, growth prediction, and treatment planning [7]. Traditional methods have relied on region-based tumor segmentation, but with the advancements in deep learning, classification tasks aided by artificial intelligence have gained prominence [8]. The use of AI and deep learning techniques has significantly improved medical image processing and facilitated efficient disease diagnosis, particularly for life-threatening conditions like cancer [9,10].

However, the key contributions of the paper are summarized as follows:

The proposed approach combines a fuzzy inference system is utilized in conjunction with VGG19to brain tumor classification.

Enhancement contrast of brain tumor images by using Type-2 Fuzzy Logic.

Utilizing the pretrained model of VGG16 to extract features of brain tumor images and classification.
Evaluate the trained models by computing not only overall accuracies but also Sensitivity, Specificity and F1_Score.
It Numerous studies have concentrated on employing deep learning techniques for the classification and detection of brain tumors.
Banerjee S. et al. [11] used a deep learning-based YOLO model that combines L-type fuzzy logic to detect skin cancer, where used L-type fuzzy number approximations for lesion region during feature extraction process. The experiments were conducted using two databases, ISBI 2017 and ISBI 2019, where the accuracy was 99% on ISBI 2017 dataset and 97.11% on ISIC 2019 dataset.
Naseer et al. [12] enhanced the accuracy of early brain tumor diagnosis by utilizing a Convolutional Neural Network (CNN). The proposed CNN model was trained on a benchmark dataset named BR35H, comprising brain tumor MRIs. Interestingly, the deep network model was trained using only 28% of the data and evaluated on the remaining 72% of unseen data obtained from various brain tumor MRI datasets. The results revealed an impressive average correct diagnosis rate of 98.81% for brain tumors, with a perfect accuracy of 100% achieved on two specific datasets. This study underscores the potential of CNNs in improving the accuracy of early brain tumor diagnosis.
Remzan et al. [13] developed the of sequential CNN model to classify brain tumors in magnetic resonance imaging (MRI) images and used the pre-processing steps for selecting RGB images and resizing. Custom data is created by deriving it from the Br35H dataset, the proposed approach achieves an accuracy of a good accuracy of 98,27%. This technique enables the diagnosis of brain tumors and other medical imaging-related issues with promising results.
Gómez-Guzmán et al. [14] conducted a study to automate the classification of brain tumors by comparing six pre-trained models with one generic CNN model developed specifically for this task. The objective was to determine the most suitable deep learning (DL)
parts of human beings. Image filters are employed to eliminate continuous noise present in the input images. The approach demonstrates a high accuracy of approximately 98.67% in tumor and cancerous detection, outperforming Conv-ML and hybrid approaches. Additionally, the average processing time for each image, including tumor and cancerous region detection, is approximately 9.78 seconds. This approach showcases promising results in efficient and accurate tumor detection in medical imaging.
Filatov and Yar [15] employed pretrained CNNs, particularly the Efficient Net models, for the diagnosis and classification of brain tumors. Specifically, ResNet50, EfficientNetB1, EfficientNetB7, and EfficientNetV2B1 models were employed. To address the challenges posed by small datasets and limited computational power, image augmentation and transfer learning techniques were utilized. The results indicate that Efficient Net models outperformed other models due to their advantageous properties, including width, depth, and resolution scaling. Among the models tested, EfficientNetB1 demonstrated the best performance, achieving a training accuracy of 87.67% and a validation accuracy of 89.55%. These findings highlight the effectiveness of pretrained CNNs, particularly the Efficient Net family, in accurately diagnosing and classifying brain tumors.
Pal et al. [16] utilized a transfer learning approach by employing a Convolutional Neural Network (CNN) as the model, specifically using the VGG16 architecture. The CNN was trained on a benchmark dataset called BR35H, which consists of MRIs of brain tumors. Various geometric data augmentation techniques were applied to enhance the training process. The resulting model achieved an Area Under the Curve (AUC) of 0.92, indicating a high level of efficiency in accurately classifying the images.
ÖZTÜRK and KATAR [17] utilized the pre-trained EfficientNet-B0 model to classify brain MRI images into tumorous or normal categories. The dataset was divided into 70% for training, 20% for validation, and 10% for testing. During the testing phase, the pre-trained EfficientNet-B0 model exhibited outstanding performance, achieving 99.33% accuracy, 99.33% sensitivity, and a 99.33% F1 score.
Abbood et al. [18] worked comparative study the application of deep learning models, specifically AlexNet, VGG16, GoogleNet, and RestNet50, for tumor detection in MRI scans. Applied the preprocessing on images before classification such as separating the brain area from the image, resizing the separated brain image to 240 X240 and normalizing the images. Based on accuracy, the results showed that RestNet50 is the best model with an accuracy of 95.8%. These studies collectively highlight the effectiveness of deep learning models in accurately diagnosing and classifying brain tumors.
Shen et al. [19] proposed a hierarchical integrated model based on deep learning and fuzzy logic to overcome the drawbacks of pixel-based segmentation where ResU-segNet was used for the segmentation stage and IT2PFCM for the classification stage. The method was applied to the publicly available INbreast mammography database and the accuracy was 50%, sensitivity was 50%, and specificity was 87.55%.

Table 1: Summarizing of the related works.

Authers	Dataset	Model	Accuracy	specificity	Sensitivity	F1-Score	AUC
Gehad et al. [11]	ISBI 2017, ISBI 2019	YOLO +L-type fuzzy logic	99.00 % 97.111%	-	-	-	-
Naseer et al. [12]	BR35H	Custom CNN	98.81%	-	-	-	-
Remzan et al. [13]	BR35H	Sequential CNN	98.27%	-	-	-	-
Gómez-Guzmán et al. [14]	Multiple	Generic CNN + Pre-trained Models	98.67%	-	-	-	-
Filatov & Yar [15]	Small datasets	EfficientNetB1	89.55 %	-	-	-	-
Pal et al. [16]	BR35H	VGG16	-	-	-	-	0.92%
ÖZTÜRK & KATAR [17]	BR35H	EfficientNet-B0	99.33%	99.33%	99.33%	99.33%	-
Abbood et al. [18]	BR35H	ResNet50	95.80%	-	-	-	-
Shen et al. [19]	Dataset for breast cancer	IT2PFCM	50%	87.55%	50%	-	-
Proposed Method	BR35H	VGG19 with Type-2 Fuzzy Logic	99%	0.9967%	0.9967%	0.9991%	0.9989%

2 Fuzzy logic

Uncertainty in information can lead to deficiencies or missing data, such as imprecision, incompleteness, vagueness, or unreliability. Fuzzy logic systems, specifically type-1 fuzzy sets (T1 FS), are effective in handling a significant portion of this uncertainty by representing imprecision with numerical values ranging from 0 to 1. Fuzzy image processing plays a crucial role in representing uncertain data, providing benefits such as efficient management of vagueness and ambiguity, handling imprecise data, and utilizing expert knowledge in image processing application [20].

When dealing with high degrees of uncertainty or more complex uncertainty, interval type-2 fuzzy logic systems (IT2 FS) are recommended. IT2 FS employ IT2 fuzzy sets and utilize an additional type-reduction process [21]. IT2 fuzzy sets have primary memberships represented by Footprint of Uncertainty (FOU) regions, consisting of Upper Membership Functions (UM) and Lower Membership Functions (LMF) [21]. The structure of an IT2 fuzzy logic system resembles that of a type-1 fuzzy logic system, However, with the incorporation of IT2 FS and a type-reduction process, an IT2-FS ($\tilde{X}$) is defined

with a type-2 membership function $\mu\tilde{X}\ (x,\ u)$ as in equation [22]. (1)

$$\tilde{X} = \int_{x\in D_{\tilde{X}}}^{\prime} \int_{u\in J_x}^{\prime} \frac{\mu_{\tilde{X}}(x,u)}{(x,u)} \qquad (1)$$

In the given context, the symbol $\iint$ represents the union over all admissible x and μ. The term J_x is referring to the primary membership of x, while μ_X¯ (x,u) denotes a type-1 fuzzy set referred to as the secondary set in T1-FS. For a type-2 fuzzy set X˜, the uncertainty in its primary membership is characterized by a region known as the Footprint of Uncertainty (FOU). The FOU can be described using an Upper Membership Function (UM) μ_X¯and a Lower Membership Function (LMF) μ_X¯. When the primary membership Jx is an interval set, an IT2-FS (Interval Type-2 Fuzzy Set) is constructed, where

μ_X¯(x,u)=1 for all u in the interval set Jx, which lies within the range [0,1] [23].
Fuzzy logic and metaheuristic techniques have been successfully applied in image enhancement problems, with fuzzy image processing encompassing approaches that involve understanding, representing, and processing images, segments, and features as fuzzy sets. Fuzzification and defuzzification steps enable the processing of images using fuzzy techniques, with the middle step of membership modification being particularly powerful. Fuzzy logic is a powerful tool for noise removal in image processing due to its ability to handle uncertainty. Fuzzy filters, such as the Fuzzy Filter (FF), employ gray level mapping and membership functions to enhance image contrast by assigning higher weights to gray levels close to the mean. These filters can define membership functions globally or locally for different image segments [24,25]. Fuzzy enhancement techniques in image processing utilize fuzzy set theory and fuzzy rules to determine pixel gray levels within image windows. Methods like the MF and Neighborhood Averaging filter with fuzzy values offer variations of traditional filters by incorporating fuzzy rules for pixel intensity decisions [26], thus providing effective denoising solutions. The fuzzy logic in image processing show in Figure 1 [27].

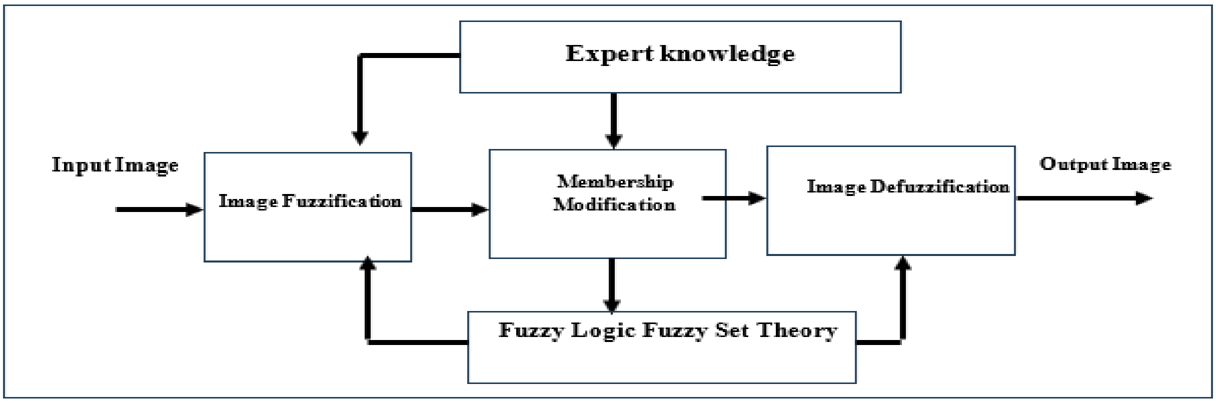


Figure 1: Fuzzy image processing

3 Materials and methods

Figure 2 illustrates the proposed method for binary tumor classification. relies upon three major steps, which include A) Dataset preprocessing, B) apply fuzzy logic on images, and C) apply the vgg19 for the classification.
In the field of medical image analysis and classification, the proposed method aims to improve the accuracy and efficiency of brain tumor classification. It consists of three main stages: pre-processing, image enhancement using fuzzy logic, and tumor classification using transfer learning with the VGG19 model.

3.1 Pre-processing

During the pre-processing stage, a dataset of 3000 images is utilized, and data augmentation techniques such as including geometric we used parameters of augmented images are scaling range of [0.9, 1.3] to improve robustness and give more diversity to the training data and to ensure that small tumor details are not lost, flipping horizontal of true rotation range 0f (10) for give accurate contrast to images and prevent distortion of important features in them. The images are also resized to a standardized size of 224x224 to ensure consistency during training and improve the VGG19 model's performance.

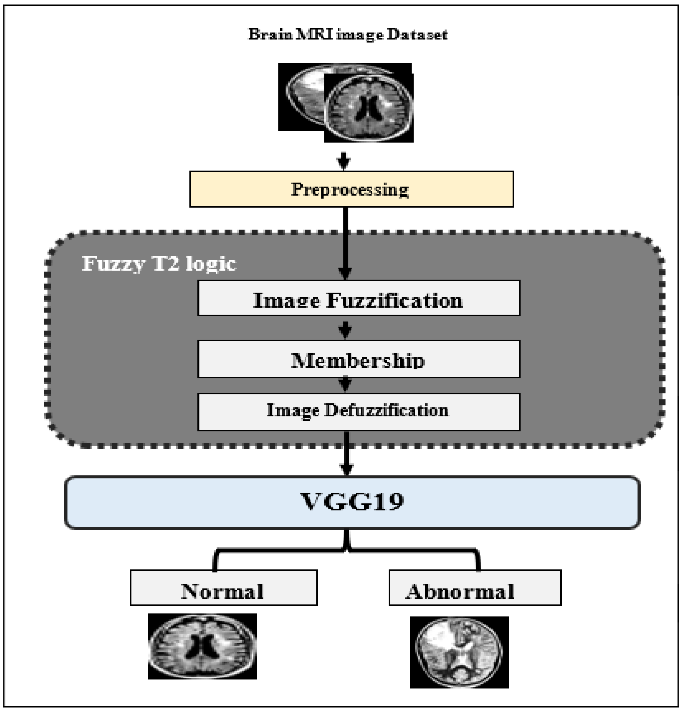


Figure 2: Proposed method.

3.2 Image enhancement using fuzzy logic

Here are the steps of the algorithm for enhancing tumor image using a Fuzzy Inference System to enhance the contrast

Algorithm Fuzzy logic enhancement
Input: A tumor image **Output: enhancement image with FIS** Step1: Read the image and store it in a variable (e.g., img) Step2: Convert the input image from grayscale to CIELAB color space and focus on the L channel. Step3: Extract the L channel from the LAB image: l = lab[:, :, 0]. Step4: Compute the average pixel intensity, denoted as the M value. Step5: Perform fuzzification: For every pixel, evaluate the degree of membership for each class using the pixel intensity and the M value. The pixel intensity varies within the range of 0 to 255. i. Create a list (x) ranging from -70 to 400. ii. Initialize an empty dictionary, FuzzyTransform. iii. Iterate over each element (i) in x and assign FuzzyTransform[i] the value of Infer(np.array([i]), M). Step6: Apply the fuzzy transform to the L channel: i. Compute unique values (u) and inverse mapping (inv) of the L channel using np.unique(l, return_inverse=True). ii. Use list comprehension to calculate the fuzzy transformed values for each unique value, based on FuzzyTransform[i], where i corresponds to the unique value. iii. Reshape the transformed values to match the shape of the original L channel: l = np.array([FuzzyTransform[i] for i in u])[inv].reshape(l.shape). Step7: Perform defuzzification: Calculate the centroid value for each pixel's output fuzzy set. The centroid value ranges from -70 to 400. Step8: Normalize the output pixel intensity, transforming it from the range [-70, 400] to the range [0, 255]. Step9: Combine the adjusted L channel with the original AB channels, and then convert the resulting image back from CIELAB to grayscale. Step10: Display the final image

By following these steps, the Fuzzy Inference System enhances the contrast of the tumor image, making it easier to visualize and analyze. Where fuzzy logic type 2 is superior to fuzzy logic type 1 because it has a greater ability to handle uncertainty caused by factors such as noise, illumination variation, and overlapping values between tumor and healthy tissue in MRI images. This additional ability makes it more accurate in representing ambiguous data and improves the process of classifying tumors more reliably.

3.3 VGG19 model

To classify brain tumors, the pre-trained VGG19 model is used for feature extraction. VGG19 is known for its accurate feature extraction capabilities and is applied to enhance the classification accuracy of brain tumors. It consists of 16 convolutional layers for feature extraction and 3 layers for image classification [28,29]. The model takes the input layer has an input size of 224 × 224 × 3 and then convolutional layers where small kernels of size 3x3 and a stride of 1 are used where these layers consist of 5 blocks where the first block consists of two convolutional layers and 64 filters followed by 2 while the second block consists of two convolutional layers and 128 filters while the third block consists of 4 convolutional layers and 256 filters while the fourth block consists of four convolutional layers as well and 512 filters while the last block also consists of four convolutional layers and 512 filters and all these convolutional cards are connected by a max pooling layer with 2x2, stride and then followed by three fully connected layers where the first two layers of the fully connected contain 4096 neurons and the last layer contains 1000 neurons [30,31]. In the proposed model we will freeze all convolutional layers and change fully connected layer to 512 neurons change the last layer and make it contain 2 neurons in the binary of brain tumor classification contributing to more precise diagnosis and treatment decisions in medical imaging applications.

4 Results

The architecture was designed utilizing the Python programming language within a software package. The implementation specifically targeted central processing units (CPUs). All experimentation was conducted on Colab, utilizing a 15G graphics processing unit (GPU). Table 1 concludes the parameters set for the proposed model.

Table 1: The hyper parameter setting.

Hyperparameter	**Setting**
Input Size	224*224
Training Splitting Ratio	Train:70%,Val:15%,Test:15%
Batch Size	64
Epoch size	20
Learning Rate	0.01
Dropout	0.5
Optimizer	Adam

The learning rate of 0.01 was chosen to balance training speed and optimal convergence. Multiple learning rates (e.g. 0.001, 0.01, 0.1) have been tested, and it has found that 0.01 achieves stable and efficient convergence during training without oscillations or divergence issues.

The dropout rate was set to 0.5 to reduce overfitting, where 50% of neurons are randomly dropped during training. This rate ensures sufficient regularization while maintaining a sufficient number of neurons to accommodate important patterns.

A batch size of 64 has chosen, as it balances computational efficiency and model performance. This size allows for more stable gradient updates and fits within the available memory constraints.

Finally, the number of epochs was set to 20, as it was found to be sufficient to achieve model convergence without overgeneralization. After this number, the model performance was observed to stabilize on the validation data without any further optimization.

4.1 Datasets

In this study, a publicly available dataset obtained from Kaggle (Br35H) was utilized to conduct the experiments. The dataset consisted of 1500 brain MRI images with tumors and an equal number of 1500 brain MRI images without tumors. Before conducting the analysis, all the images underwent skull stripping and were categorized as "yes" if they contained a tumor and "no" if they were tumor-free 1. Figure 3 illustrates the dataset, with images containing tumors labeled as "yes" and images without tumors labeled as "no." [33,34,35,36,37].

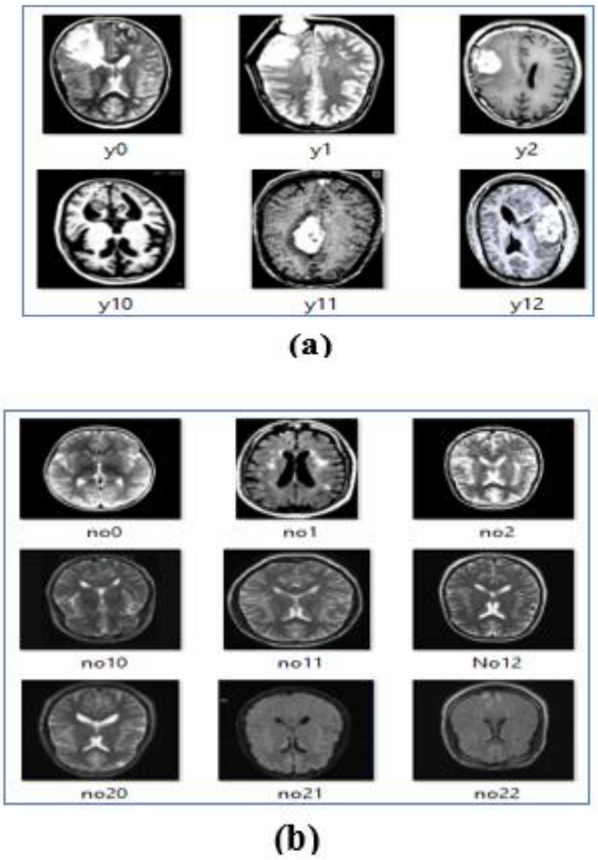


Figure 3: Sample dataset: (a) with tumor (b) without tumor

4.2 Performance evaluation

In evaluating the performance of a classification system, several statistical indices are commonly employed. These indices include Accuracy (ACC), which assesses the overall correctness of the system by considering true positives and true negatives. Sensitivity (SE), which is also known as True Positive Rate or Recall, quantifies the percentage of accurately predicted positive instances among all the actual positive instances. On the other hand, Specificity (SP) assesses the percentage of accurately predicted negative instances among all the actual negative instances. To create a comprehensive metric, the F1 Score integrates precision and recall, taking into account both the true positive rate and the false positive rate. The formulas for these metrics are as follows in equation (2-5) [21-24].

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

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

$$SP = \frac{TN}{FP + TN} \tag{4}$$

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

4.3 Implementation

As described in the previous section, the neural network was tested on the Br35H dataset. Table 2 the achieved accuracy of 0.9983%, with a validation accuracy of 0.9953%, a training loss of 0.2118, and a validation loss of 0.2264. This level of consistency was reached at the 20th epoch of training. Using an image showcases size of 224*224 and the cancerous brain database, the VGG19 model achieves an impressive validation accuracy rate of 99.83%, in this model the training time has been 22s and 152 ms. Figure 4 depicts the classification results for the binary class, showcasing the accuracy and loss values.

Table 2: Accuracy and loss of model over 20 epochs

Epochs	Train-loss	Train-acc	Val-loss	Val-acc	Best -acc
1/20	0.3409	0.9183	0.4168	0.8617	0.9983
5/20	0.2481	0.9867	0.2688	0.9717	
12/20	0.2217	0.9967	0.2425	0.9863	
20/20	0.2118	0.9983	0.2264	0.9953	

The results show the performance of a deep learning model with Type-2 Fuzzy Logic for brain tumor classification. As the model trains through 20 epochs, both the training and validation losses steadily decrease, indicating learning progress. The training accuracy increases, demonstrating the model's ability to fit the training data. The validation accuracy also improves, showing good generalization to new data. The model achieves very high validation accuracy, reaching 99.53% accuracy at the end of training.

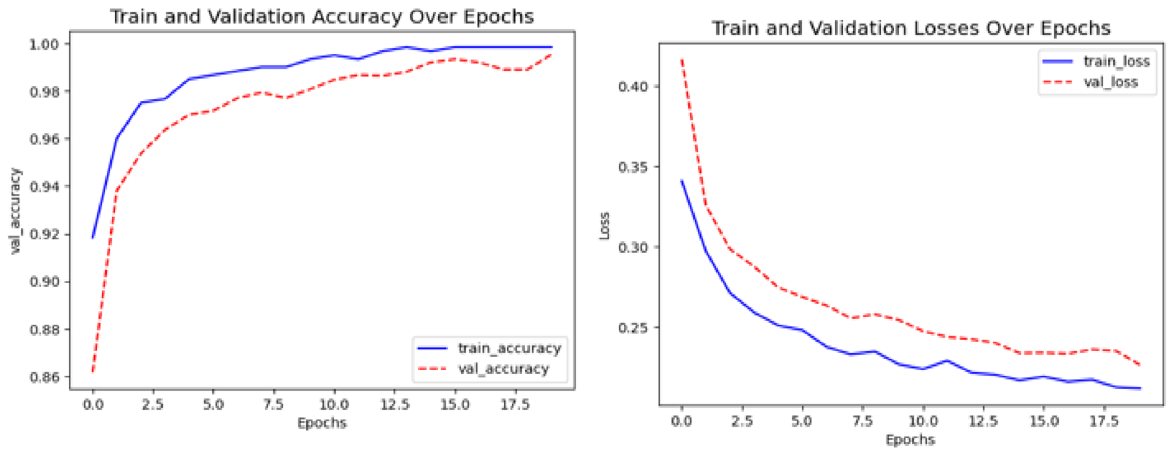


Figure 4: Training and validation over 20 epochs, (a)loss, (b) accuracy

The Table 3. presents performance evaluation of models of applying VGG19 with fuzzy logic for tumor binary classification. Overall, the findings indicate that the combination of VGG19 and fuzzy logic has proven to be effective in accurately classifying tumor images. The high accuracy, sensitivity, specificity, and F1 score demonstrate the model's ability to correctly identify tumor images while minimizing both false positives and false negatives. These results hold promising implications for medical diagnosis and treatment planning in the field of oncology. Additionally, the Figure 5. displays the confusion matrix , Figure 6. display receiver operating characteristic for this classification task. and Figure 7 showcases some feature maps from the VGG19 layers.

Table 3: Performance Evaluation of Models

Attributes	Value Range (%)
Accuracy	99%
Sensitivity	0.9967%
Specificity	0.9967%
F1_Scor	0.9991%
AUC	0.9989%

The results indicate that the model performs excellently for the given classification task. The model is capable o f accurately classifying positive and negative instan ces, particularly in the context of brain tumor cla ssification.

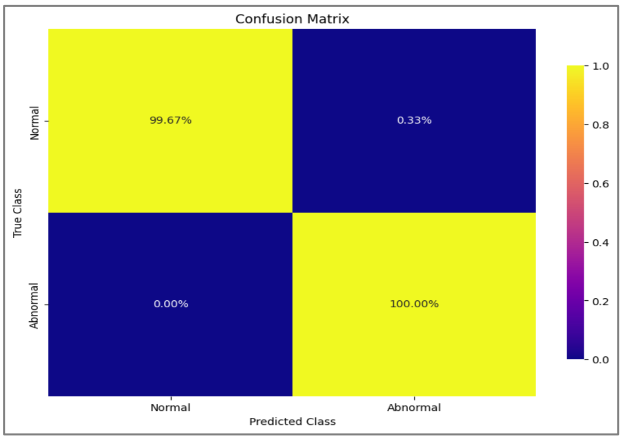


Figure 5: Confusion matrix

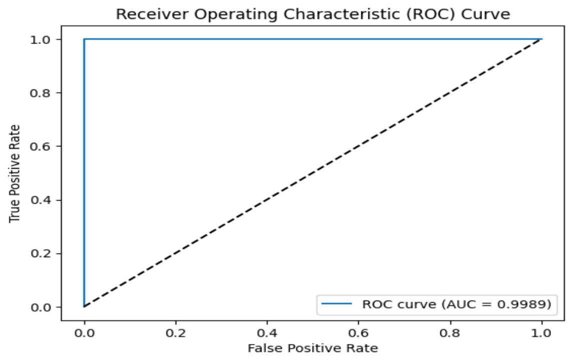
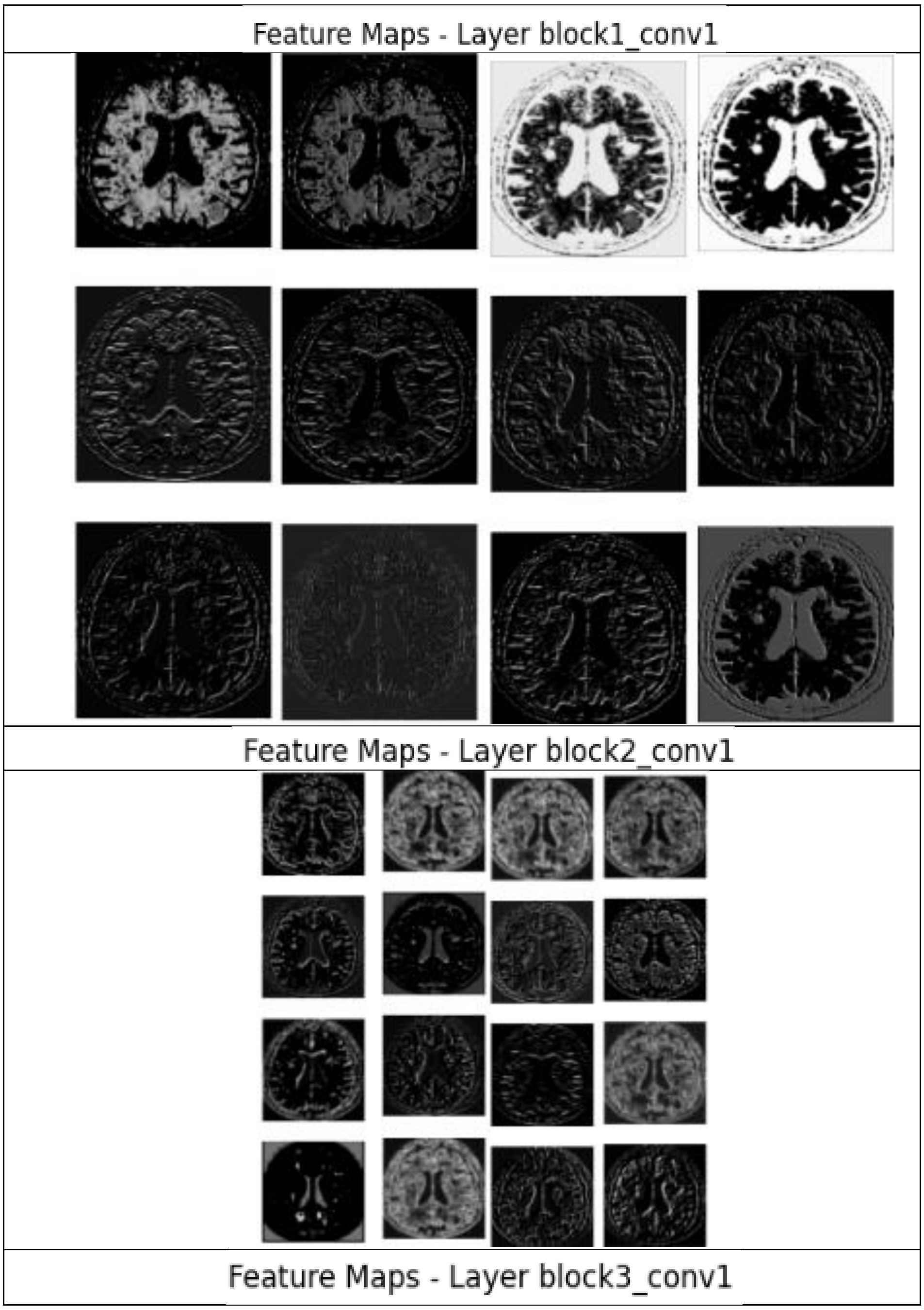


Figure 6: ROC curve



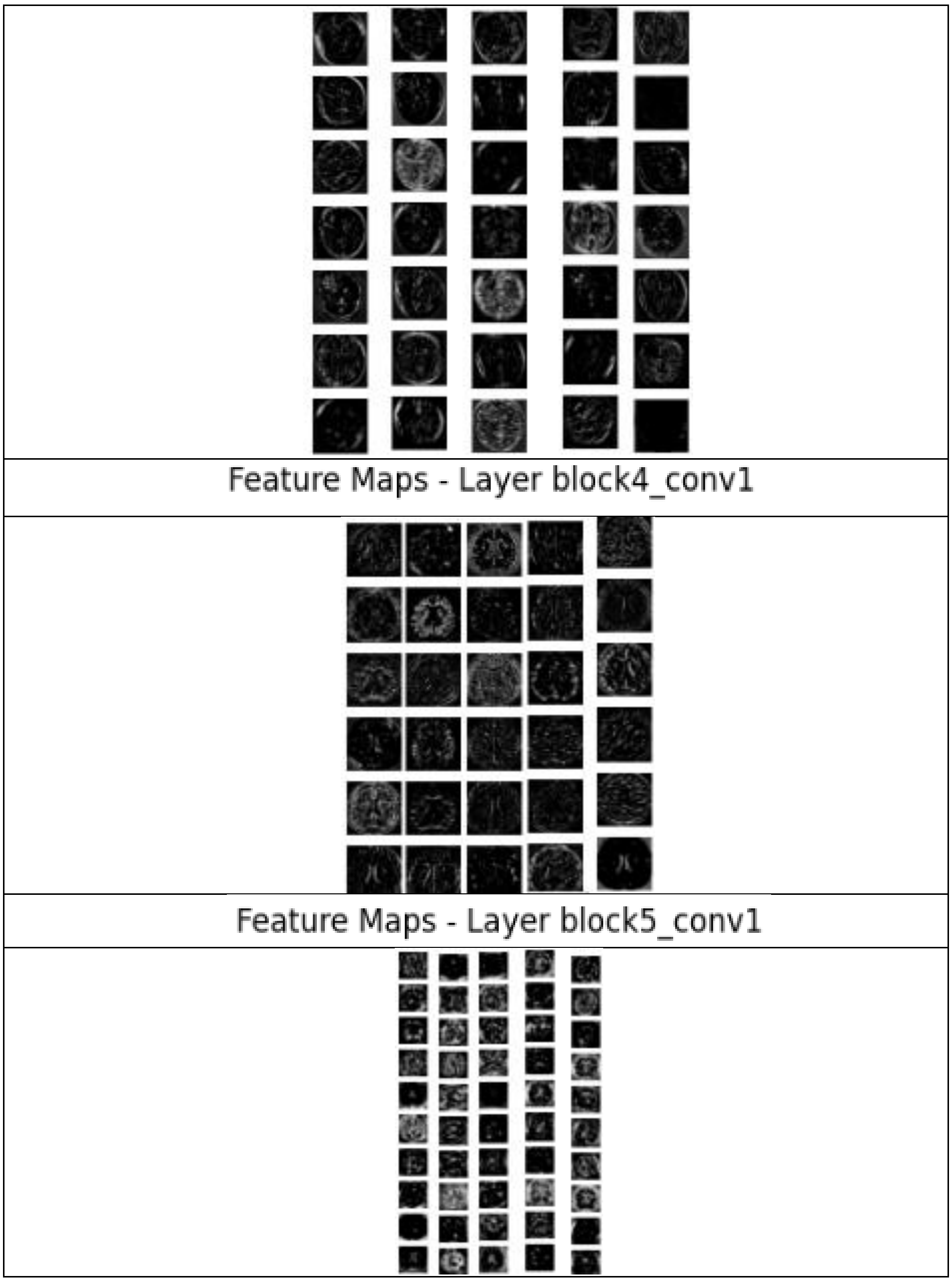


Figure 7: Some feature maps from the VGG19 layers.

5 Discussion

This study demonstrates the effectiveness of combining the VGG19 architecture with Type-2 fuzzy logic for brain tumor classification in MRI images whereType-2 fuzzy logic significantly improves image enhancement by addressing noise, low contrast, and lighting inconsistencies in MRI scans. This enhanced capability ensures better preprocessing of MRI images, enabling the model to detect and classify tumor regions more accurately. The proposed model achieved high results when applied to the Br35H database, where the model enjoyed a training accuracy of 99.83%, the validation accuracy was 99.53%, the test accuracy was 99%, the sensitivity was 99.67%, the specificity was 99.67%, while the F1 was 99.91%. With these results, we notice that the proposed model outperforms many models discussed in the related works section. The training loss is 0.2118, while the validation loss is 0.2264. This decrease in the loss indicates that it is possible to generalize the model to a larger data set and expand its application scope across unseen data.

6 Potential future directions

1. Improve the model by replacing VGG19 with more efficient structures such as swin transformer to reduce computational costs while maintaining accuracy.
2. Integrate the model with explainable artificial intelligence (XAI) techniques such as Grad-CAM or

SHAP to provide clearer visualizations of the regions that influenced classification decisions.
3. Extend the fuzzy logic framework to include decision rules that are more explainable to clinicians.
4. Integrate multimodal data such as merging MRI images with other data sources such as CT scans, genomic data, or clinical reports to improve classification accuracy and robustness.

7 Conclusion

In this paper applying VGG19 with fuzzy logic to the Br35H dataset produces highly promising results. The model consistently reduces both training and validation loss, indicating successful learning and generalization. The training accuracy improves from 0.9183 to 0.9983, demonstrating the model's increasing proficiency. Likewise, the validation accuracy notably improves from 0.8617 to 0.9953, showcasing effective pattern learning and generalization. The model obtains an exceptional best accuracy of 0.9983 on the training data, with a test accuracy of 99%, sensitivity and specificity both at 0.9967, and an F1 score of 0.9991. Overall, VGG19 with fuzzy logic proves to be a powerful approach for the Br35H dataset, accurately capturing features and delivering reliable results.

References

[1] G. A. Amran et al., “Brain Tumor Classification and Detection Using Hybrid Deep Tumor Network,” Electron., vol. 11, no. 21, pp. 1–21, 2022, doi:10.3390/electronics11213457.

[2] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, “Brain tumor classification in MRI image using convolutional neural network,” Math. Biosci. Eng., vol. 17, no. 5, pp. 6203–6216, 2020, doi: 10.3934/MBE.2020328.

[3] F. J. Díaz-Pernas, M. Martínez-Zarzuela, D. González-Ortega, and M. Antón-Rodríguez, “A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network,” Healthc., vol. 9, no. 2, 2021, doi: 10.3390/healthcare9020153.

[4] R. Vankdothu and M. A. Hameed, “Brain tumor MRI images identification and classification based on the recurrent convolutional neural network,” Measurement: Sensors, vol. 24 p. 100412, 2022, doi: 10.1016/j.measen.2022.100412.

[5] N. Saranya, D. Karthika Renuka and J. N. Kanthan, “Brain tumor classification using convolution neural network,” Journal of Physics Conference Series, vol. 1916, no. 1, pp. 012206, 2021, doi:10.1088/1742-6596/1916/1/012206

[6] M. A. Khan et al., “Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists,” Diagnostics, vol. 10, no. 8, pp. 1–19, 2020, doi: 10.3390/diagnostics10080565.

[7] A. Rehman, S. Naz, M. Razzak, F. Akram, and M. Imran, “A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning,” Circuits, Systems, and Signal Processing, vol. 39, no. 2, pp. 757–775, 2020, doi: 10.1007/s00034-019-01246-3.

[8] G. A. Amran et al., “Brain Tumor Classification and Detection Using Hybrid Deep Tumor Network,” Electron., vol. 11, no. 21, pp. 1–21, 2022, doi: 10.3390/electronics11213457.

[9] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, “Brain tumor classification in MRI image using convolutional neural network,” Math. Biosci. Eng., vol. 17, no. 5, pp. 6203–6216, 2020, doi: 10.3934/MBE.2020328.

[10] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, “A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning,” Circuits, Syst. Signal Process., vol. 39, no. 2, pp. 757–775, 2020, doi: 10.1007/s00034-019-01246-3.

[11] S. Banerjee, S. Singh, A. Chakraborty, A. Das, and R. Bag, “Melanoma Diagnosis Using Deep Learning and Fuzzy Logic,” Diagnostics, vol. 10, no. 8, 2020.

[12] A. Naseer, T. Yasir, A. Azhar, T. Shakeel, and K. Zafar, “Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI,” Int. J. Biomed. Imaging, vol. 2021, 2021, doi: 10.1155/2021/5513500.

[13] N. Remzan, K. Tahiry, and A. Farchi, “Brain tumor classification in magnetic resonance imaging images using convolutional neural network,” Int. J. Electr. Comput. Eng., vol. 12, no. 6, pp. 6664-6674, 2022, doi: 10.11591/ijece. v12i6.

[14] D. P. and D. S. T., “a Feature-Based Decision-Making Approach (Fbdma) for Tumor Detection Using Deep Learning,” Indian J. Computer. Sci. Eng., vol. 14, no. 1, pp. 63–80, 2023, doi: 10.21817/indjcse/2023/v14i1/231401068.

[15] D. Filatov and G. N. A. H. Yar, “Brain Tumor Diagnosis and Classification via Pre-Trained Convolutional Neural Networks,” pp. 0–5, 2022, [Online]. Available: http://arxiv.org/abs/2208.00768.

[16] S. S. Pal, P. Ray Mahapatra, S. Paul, and S. Dolui, “A Novel Brain Tumor Classification Model Using Machine Learning Techniques,” no. 7, pp. 87–98, 2023, doi: 10.46647/ijetms. 2023.v07i02.011.

[17] T. ÖZTÜRK and O. KATAR, “A Deep Learning Model Collaborates with an Expert Radiologist to Classify Brain Tumors from MR Images,” Turkish J. Sci. Technol., vol. 17, no. 2, pp. 203–210, 2022, doi: 10.55525/tjst.1143392.

[18] A. A. Abbood, Q. M. Shallal, and M. A. Fadhel, “Automated brain tumor classification using various deep learning models: A comparative study,” Int. J. Electr. Comput. Eng., vol. 22, no. 1. pp. 252–259, 2021, doi: 10.11591/ijeecs. v22.i1.

[19] T. Shen, J. Wang, C. Gou, and F.-Y. Wang, “Hierarchical Fused Model with Deep Learning and

Type-2 Fuzzy Learning for Breast Cancer Diagnosis," IEEE, vol. 28, no. 12, 2020.

[20] O. Castillo, M. A. Sanchez, C. I. Gonzalez, and G. E. Martinez, "Review of recent type-2 fuzzy image processing applications," Inf., vol. 8, no. 3, pp. 1–18, 2017, doi: 10.3390/info8030097.

[21] F. Orujov, R. Maskeliūnas, R. Damaševičius, and W. Wei, "Fuzzy based image edge detection algorithm for blood vessel detection in retinal images," Appl. Soft Comput. J., vol. 94, 2020, doi: 10.1016/j.asoc.2020.106452.

[22] P. K. Mishro, S. Agrawal, R. Panda, and A. Abraham, "A Novel Type-2 Fuzzy C-Means Clustering for Brain MR Image Segmentation," IEEE Trans. Cybern., vol. 51, no. 8, pp. 3901–3912, 2021, doi: 10.1109/TCYB.2020.2994235.

[23] A. Taskin and T. Kumbasar, "An open source matlab/Simulink toolbox for interval type-2 fuzzy logic systems," Proc. - 2015 IEEE Symp. Ser. Comput. Intell. SSCI 2015, pp. 1561–1568, 2015, doi: 10.1109/SSCI.2015.220.

[24] Luo, Na, et al. "Fuzzy logic and neural network-based risk assessment model for import and export enterprises: A review." Journal of Data Science and Intelligent Systems, vol. 1, no. 1, pp.2-11, 2023.

[25] Y. Yin and H. Zhi, "University Financial Management Performance Evaluation Based on Fuzzy Logic Expert System," Informatica, vol. 48, no. 13, 2024.

[26] M. Donny Devanda, Utama Nugeraha, and Ditdit, "Group Decision Support Model for Tech-Based Startup Funding Using Multistage Fuzzy Logic," Informatica, vol. 47, no. 131, 2023.

[27] M. Kabir, J. Mobin, A. Hassanat, and M. S. Rahman, "Image Contrast Enhancement using Fuzzy Technique with Parameter Determination using Metaheuristics," arXiv:2301.12682v1 pp. 1–14, 2023, [Online]. Available: http://arxiv.org/abs/2301.12682.

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

[29] B. Mohammed, A. Anouar, and benblidia Nadjia, "Grad-CAM Guided Preprocessing and Convolutional Neural Network for Efficient Mammogram Images Classification," Informatica, vol. 47, no. 129, 2023.

[30] Z. Ullah, A. Odeh, I. Khattak, and M. Al Hasan, "Enhancement of Pre-Trained Deep Learning Models to Improve Brain Tumor Classification," Informatica (Slovenia), vol. 47, no. 6. pp. 165–172, 2023, doi: 10.31449/inf. v47i6.4645.

[31] R. A. Dihin, E. N. AlShemmary, and W. A. M. Al-Jawher, "Wavelet-Attention Swin for Automatic Diabetic Retinopathy Classification," Baghdad Sci. J., vol. 21, no. 8, pp. 2741–2756, 2024, doi: 10.21123/bsj.2024.8565.

[32] R.A. Dihin, Alharan, A.F.H., Abdulameer, M.H., Ali, N.S. Evaluation the Performance of Statistical and Information-Theoretic Properties over FFT-OFDM, IICETA 2022 - 5th International Conference on Engineering Technology and its Applications, 2022, pp. 52–57

[33] S. Tammina, "Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images," Int. J. Sci. Res. Publ., vol. 9, no. 10, 2019.

[34] M. M. Zahoor and S. H. Khan, "Brain Tumor MRI Classification using a Novel Deep Residual and Regional CNN," 2022, [Online]. Available: http://arxiv.org/abs/2211.16571.

[35] J. Kang, Z. Ullah, and J. Gwak, "Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers," Sensors, vol. 21, no. 6, pp. 1–21, 2021, doi: 10.3390/s21062222.

[36] N. Salih, M. Ksantini, N. Hussein, D. B. Halima, and S. Ahmed, Deep Learning Models and Fusion Classification Technique for Accurate Diagnosis of Retinopathy of Prematurity in Preterm Newborn, Baghdad Sic. J., 2023, doi: https://doi.org/10.21123/bsj.2023.8747.

[37] M., EL ATILLAH, K. EL FAZAZY, and J. Riffi, Classification of Arabic Alphabets Using a Combination of a Convolutional Neural Network and the Morphological Gradient Method, Baghdad Sic. J., vol. 21, no. 1, 2024, doi: https://doi.org/10.21123/bsj.2023.