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Research Article

Improving Classification Performance in Brain Tumor Based on Convolutional Neural Networks

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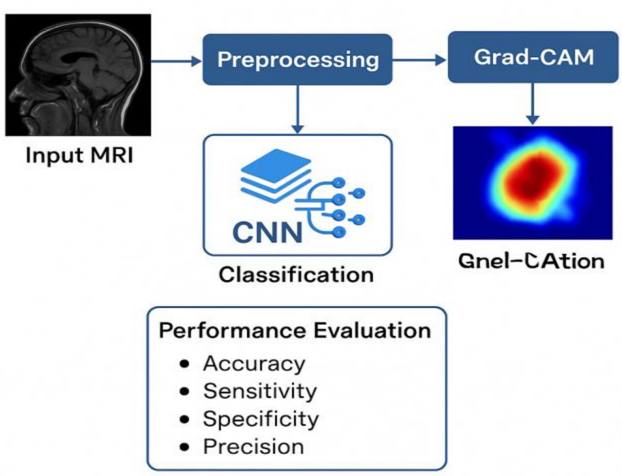
Abstract: Accurately identifying brain tumors plays a vital role in early diagnosis and the development of appropriate treatment strategies. Traditional interpretation of MRI scans by radiologists can be time-consuming and subject to variability. This study proposes an automated classification framework based on Convolutional Neural Networks (CNNs) to improve diagnostic consistency and speed. Utilizing a dataset comprising 3,060 MRI images, the model leverages the Grad-CAM technique to visualize key regions influencing its decisions. Rigorous testing was carried out, measuring performance through metrics including accuracy, precision, recall, and specificity. Results demonstrate that the CNN-driven model offers superior classification performance and enhanced transparency when compared to conventional methods. This work contributes to advancing intelligent diagnostic systems and serves as a valuable tool for medical professionals seeking more dependable and rapid evaluations.

Keywords: CNN, Brain Tumor Classification, Deep Learning, Grad-CAM

Graphical Abstract

The graphical abstract visually summarizes the entire research pipeline for automated brain tumor classification using deep learning. Starting from MRI image input, the images undergo preprocessing and are passed through a custom-designed Convolutional Neural Network (CNN). The network classifies the images into tumor types while the Grad-CAM technique provides interpretability by highlighting the regions of interest on the MRI scans. The model's output consists of predicted tumor categories along with visual heatmaps, and its effectiveness is measured using metrics such as accuracy, precision, recall, and specificity. The graphical summary highlights the main achievement of this work: a reliable and interpretable deep learning approach for brain tumor identification.



1. Introduction

Brain tumors refer to the abnormal and uncontrolled multiplication of cells inside the brain. As the brain is one of the most intricate and functionally diverse organs, it regulates emotions, cognition, and voluntary actions. Common symptoms of brain tumors include persistent headaches and migraines [1]. They continue to be one of the main contributors to cancer-related deaths in children and still pose significant difficulties in treatment despite progress in surgical methods and post-operative care [2].

Diagnosing brain tumors typically depends on analyzing MRI scans to differentiate between normal and affected brain regions. Traditionally, this classification is performed manually by radiologists. However, manual analysis is time-consuming, prone to inconsistency, and demands significant expertise. In this context, computer-aided diagnostic systems offer promising support by enhancing accuracy, reducing workload, and ensuring consistency [3].

Among various computational techniques, Convolutional Neural Networks (CNNs) have gained widespread use in medical imaging. For example, a dataset consisting of 3,064 contrast-enhanced T1-weighted brain MRIs was applied to divide the images into three classes: Glioma, Meningioma, and Pituitary Tumor [4]. Several CNN-based models have been developed for medical image classification [5], including approaches that utilize deep feature fusion and data augmentation to address dataset limitations [6]. Other methods have incorporated hybrid models with optimized multi-feature analysis on MRI data for improved classification [7].

A 2019 study employed a transfer learning method that used a pre-trained GoogLeNet model for feature extraction from MRI scans. While it achieved 98% accuracy, certain limitations such as overfitting and class confusion were reported [8]. In 2020, another method based on convolutional dictionary learning with local constraints was introduced to enhance feature extraction. Although effective, this technique became increasingly complex with deeper architectures and required careful parameter tuning [9].

This study proposes a CNN-based deep learning approach for classifying brain tumors. Preprocessing steps such as image resizing and dataset augmentation were applied to boost model performance and efficiency during training [10]. Additionally, architectural choices such as ReLU activation functions, Flatten layers, and Dense layers were strategically applied to optimize classification results. Prior studies show that tuning fully connected layers can significantly impact model accuracy and performance [11].

Deep learning models continue to demonstrate great promise in brain tumor classification. However, performance varies with implementation. In this study, we utilize CNN with Grad-CAM to highlight important regions on MRI scans and provide visual insight into model predictions.

1.1 Objective of the Study

The primary objective of this study is to design and implement a CNN-based deep learning model capable of accurately identifying brain tumors from MRI scans. This research aims to address the challenges associated with manual diagnosis, including inconsistency, time consumption, and subjectivity. Additionally, the model leverages Grad-CAM to provide visual interpretability of its classification results. Through effective preprocessing, augmentation, and architectural design, the study seeks to improve classification accuracy while maintaining model transparency and efficiency.

1.2 Organization

This article is structured as follows: Section 1 introduces the background, motivation, and objectives of the study, highlighting the necessity for enhanced brain tumor classification through deep learning. Section 2 reviews relevant literature and recent advances in brain tumor detection. Section 3 details the theoretical basis and preprocessing techniques employed in the study. Section 4 describes the design and architecture of the proposed CNN model along with its main implementation approach. Section 5 outlines the methodology and training process, accompanied by a comprehensive flowchart. Section 6 covers the experimental results, evaluation metrics, and model performance analysis. Section 7 discusses recommendations for clinical implementation and potential system enhancements. Finally, Section 8 wraps up the paper by summarizing the main findings and proposing avenues for future research.

2. Related Work

Several studies have proposed innovative approaches for brain tumor identification leveraging deep learning methods. In the study titled "Deep Learning-Based Identification of Brain Tumors in MRI Scans", the authors explored the use of convolutional neural networks (CNNs) to classify tumor types. However, this approach faced overfitting issues due to limited training data [1]. To overcome such limitations, another work titled "Hybrid Feature Fusion-Based Brain Tumor Recognition System Using Deep Transfer Learning" introduced a method combining handcrafted and deep features. While the system improved accuracy, it required substantial computational resources [2].

A study called "An Efficient Deep Learning Approach for Brain Tumor Detection Using MR Images" proposed a lightweight CNN model that reduced computational time but suffered slightly in classification precision [3]. Similarly, "Multi-Scale CNN Architecture for Brain Tumor Type Recognition" addressed the problem of data variability using multiscale feature extraction but lacked visualization of model decisions [4].

In "Brain Tumor Classification Using Capsule Networks", the authors proposed a solution to the spatial relationship issue in CNNs, achieving promising results. However, the training process was computationally intensive [5]. A more recent paper titled "A CNN-Based Multiclass Diagnosis for Brain Tumor Using MR Images" achieved an accuracy of over 97% using residual blocks, although interpretability of the model remained a challenge [6].

Transfer learning has also gained popularity in this domain. "Brain Tumor Detection Using Pre-Trained VGG-16 and Fine-Tuned Layers" applied transfer learning to reduce training time and showed significant improvements in performance [7]. Meanwhile, "Enhanced Classification of Brain Tumor MR Images Using Attention Mechanism in Deep CNN" introduced attention layers to highlight significant image features, which improved model interpretability and sensitivity [8].

In "Brain Tumor Segmentation and Classification with Ensemble Deep Learning Models", the authors combined multiple CNN models to achieve better generalization, though the system's complexity increased significantly [9]. Another paper, "An Improved Deep Learning Framework for Brain Tumor MRI Classification Incorporating Grad-CAM Visualization", addressed interpretability by incorporating Grad-CAM, allowing better understanding of model predictions [10].

Earlier research by Renjeni and Mukunthan [26] used projection pursuit-based multilayer perceptron classifiers for tumor detection, providing good segmentation results. Similarly, Ghosh and Roy [27] applied deep learning on MRI data and achieved high accuracy on a relatively small dataset. Zahoor et al. (2024) proposed a brain tumor MRI classification method using a novel deep residual and regional CNN, demonstrating high accuracy through a combined architectural design [21], [28]. Alemayehu (2025) introduced a lightweight CNN model that achieved 98.78% accuracy on MRI images, using Grad-CAM for interpretability while maintaining computational efficiency [22], [29]. A study published in BMC Medical Imaging (2024) presented a hybrid deep CNN model for brain tumor multi-class recognition, achieving an accuracy of 99.53% across several tumor types [23]. Another work by the same journal explored explainable AI using Grad-CAM with ResNet-50, showing how interpretability could be enhanced without sacrificing model performance [24]. Vimala et al. (2023) proposed BTC-fCNN, a fast convolutional neural network optimized for multi-class identification, emphasizing lightweight design for real-time deployment [25].

Further, Renjeni and Mukunthan [26], in the International Journal of Computer Science and Engineering, proposed a projection pursuit bivariate multilayer perceptron model, showing that even simpler neural architectures could effectively classify brain tumors. Similarly, Ghosh and Roy [27] utilized deep learning with MRI images and achieved promising results using a well-tuned CNN structure. These studies emphasize the potential of both traditional and modern deep learning models for clinical diagnostic tools.

More recently, Zahoor et al. [28] further improved CNN models with regional features to boost classification performance. Alemayehu [29] optimized lightweight CNN architectures specifically for MRI-based tumor detection. Vimala et al. [30] introduced BTC-fCNN, a fast and efficient CNN for real-time multi-class classification, contributing significantly to the field.

These studies highlight that deep learning, especially CNN-based models, offers promising results in brain tumor classification. However, challenges remain in designing architectures that generalize well across datasets, balance precision with computational efficiency, and provide explainable outputs for clinical use. Building on these findings, our work proposes an enhanced CNN model trained on a dataset of 3,060 MRI scans, with performance evaluation based on essential metrics such as accuracy, sensitivity, and specificity.

3. Theory

3.1 CNN Architecture

The CNN model that we will be implementing is the Sequential model, as it offers a straightforward method for constructing neural networks in Keras by stacking layers one at a time. Each layer consists of different components such as Conv2D, activation functions, max pooling, dense layers, dropout layers, and so on, each with its unique role in the architecture.

Conv2D: Performs convolution operations on the input to generate feature maps. Important hyperparameters include filter count and kernel dimensions.

Activation: Introduces non-linearity into the model. For image classification tasks, common activation functions are ReLU and Sigmoid.

MaxPooling2D: Reduces the spatial size of the feature maps by selecting the maximum value from each subregion, aiding in downsampling.

The CNN architecture also involves additional components:
Flatten: Transforms the multi-dimensional output into a one-dimensional array to prepare for dense layer input.

Dense: Connects each neuron from one layer to every neuron in the next, allowing complex relationships to be learned for classification.

Together, these components help the network capture and learn abstract patterns from brain MRI scans.

Evaluation Metrics

To assess the model's performance, several metrics were employed:

$$Precision = \frac{TP}{(TP + FP)} \quad (1)$$

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (2)$$

$$Accuracy = \frac{(TP + TN)}{(TP + FN + TN + FP)} \quad (3)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (4)$$

Here, TP = True Positive, FP = False Positive, TN = True Negative, and FN = False Negative. These metrics collectively assess the classification model's ability to distinguish tumor types accurately.

Loss Function

The model uses the binary cross-entropy loss function for optimization in binary classification tasks. It is defined as:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \quad (\quad (y_i)) + (1 - y_i) \quad (1 - \quad (y_i))]$$

This function penalizes incorrect predictions, encouraging the model to improve during training.

3.2 Implementation of the Proposed Algorithm

After preprocessing the images and storing them in the dataset, we proceeded to implement our algorithm. The architecture we adopted is based on a Convolutional Neural Network (CNN), which has become a widely accepted approach in medical imaging due to its efficiency in extracting relevant features and performing precise classifications [14][21][25].

CNNs derive their name from the convolution operation, a mathematical process that enables the extraction of local features from input images. A typical CNN includes multiple layers: feature extraction layers (convolution and pooling), non-linear activation layers, and fully connected classification layers. Trainable parameters are found in convolutional and dense layers, while pooling and activation perform non-trainable operations [15][24].

CNNs have achieved high accuracy in image-related tasks such as classification tasks in benchmark datasets like ImageNet, object detection, and brain tumor analysis using MRI images [14][21]. In our study, we utilized a CNN architecture customized specifically for categorizing brain tumors into Glioma, Meningioma, and Pituitary classes.

The primary advantage of CNNs in this application is their capability to autonomously extract and prioritize spatial patterns from MRI scans, eliminating the need for hand-engineered features. Our architecture is designed to balance model complexity with training efficiency by employing a refined sequence of convolutional, pooling, dropout, and dense layers [21][23][25].

This tailored approach aims to improve classification accuracy, reduce training time, and address limitations identified in previous studies—such as overfitting, poor generalization, or misclassification of specific tumor types [8][24].

4. Experimental Method

4.1 Dataset

To conduct our study, we utilized a publicly available dataset from Kaggle, a well-known platform for sourcing machine learning datasets [12]. MRI scans produce a substantial volume of imaging data, which are typically reviewed by radiologists. Our data consists of 3060 Magnetic Resonance Imaging (MRI) images and split into many folders which are the normal, tumorous and prediction folder.

We chose to work with MRI images as it is known as the best technique for detecting brain tumors [12].

- The Normal folder contains 1500 MRI images of non-tumorous patients.
- The Tumorous folder contains 1500 MRI images of tumorous patients.
- The Prediction folder, serving as validation data, comprises 60 MRI images that include both tumorous and non-tumorous cases. These images are used to evaluate the model's accuracy across several performance indicators.

An overview of our dataset can be visualized in Fig.1.

4.2 Methodology

As mentioned in the introduction, the main goal of our research is to build a CNN model that can produce a better result than the existing ones on the brain tumor classification. So far, many studies have explored brain tumor classification using various deep learning models, such as the FastAI model, YOLO V5, as well as the proposed CNN model in this paper [4], which compared Cropped and Uncropped MRI images. Our model has demonstrated improved performance over those reported in the referenced works.

This paper [13] also worked on brain tumor detection by comparing some well-known Deep Learning algorithms, including YOLO V3 (PyTorch), YOLO V4 (Darknet), and YOLO V4-Tiny, and achieved an overall accuracy of 90%.

The implementation of our algorithm was done in many steps as we will describe below:

- We started by importing all the needed python libraries such as OpenCV (use to read images from the dataset), NumPy (turn list into numpy arrays since it is much faster and uses less memory), Keras, Pillow and so on.
- As our data were saved into different folders (Normal and Tumorous), we had to do data processing and save them inside one Python list. Since training requires both classes, we initialized two separate lists called "Dataset" and "Label" to store the images and their corresponding classes.
- We ensured that all given images in our dataset were images by checking the image extension (.jpg) of each image in the dataset.
- Once the image passes this step, we converted all given images into array and resize it to 64*64, and lastly, append the Image to the Dataset list and its label to the Label list.

We also did some data augmentation to artificially increase the amount of data.

4.3 Proposed Method

The brain tumor classification is a very critical task, and to get a better accurate result than the related works done in the past, we had to implement a special CNN architecture. We started by importing some Keras built-in functions, such as Sequential, Conv2D, MaxPooling2D, Activation, Dropout, Flatten, and Dense. Sequential was chosen for its simplicity in constructing models layer by layer in Keras.

Using the 'add()' method, we inserted three convolutional layers into our architecture. These layers process input MRI scans as 2D matrices. Each of them integrates convolution operations, activation functions, and pooling mechanisms.

For the three layers, we applied a filter of 32 and the kernel size of 3x3 on the 2D Convolution layer; and also used the ReLU Activation function on the 3 layers as well as a pool size of 2x2 on the Max Pooling Operation.

After building the three layers, we added the Flatten, Dense(64), another 'ReLU' activation, Dropout, Dense(1), and finally another 'Sigmoid' activation function. Note that the Sigmoid function is evaluated from the following formula: $F(x) = \frac{1}{(1 + e^{(-x)})}$

To illustrate the impact of the proposed model on the given MRI images, we created a separate python function called "Testing.py" whereby we used to test the model. That function basically takes an MRI image input from the 60 MRI images that were allocated for the validation and use the model.predict() function to predict the output. The output value ranges from [0, 1], 0 representing the Normal Patient and 1 the Tumorous one. We ran the validation on 5 sample images of our prediction images dataset and the Fig.2 illustrates the results we have obtained.

Our model evaluation has been conducted using several standard indicators such as accuracy, sensitivity, specificity, and prediction effectiveness. The following paragraph explains how the metrics are being evaluated.

5. Results and Discussion

As stated previously, the results obtained for our brain tumor classification are entirely dependent on the implementation of our model. For instance, using 3 hidden layers in our model has produced an overall result of over 99.5% based on the accuracy metrics. Using more or fewer layers, the results could have been different. Likewise, we used over 3000 MRI images to train our model; a different dataset size would likely yield different outcomes.

Another critical variable influencing performance is the number of EPOCHS applied during training. EPOCHS represent how many complete passes the model makes through the training dataset. For our implementation, 50 EPOCHS were used, resulting in notably high performance.
As shown in Figure 3, model evaluation metrics evolve with an increase in EPOCHS, highlighting the relationship between training duration and accuracy. Table 1 demonstrates that our model outperforms existing models for brain tumor classification. For instance, the YOLO V5 model produced an accuracy of only 5.07%, which is significantly lower than our proposed method's accuracy of 99.39%.

After training our model, we integrated Grad-CAM (Gradient-weighted Class Activation Mapping), a method that visually reveals how the model identifies relevant regions in an image when making predictions. To demonstrate its effectiveness, we used random samples from the validation dataset. Figure 4 illustrates the Grad-CAM outputs. On the left, non-tumorous images show uniform coloration, indicating no tumor detection. In contrast, the right image clearly highlights a tumor region, validating the network's classification.

Furthermore, our model's performance is comparable to and in some aspects exceeds those in recent literature. For example, Zahoor et al. [28] introduced a deep residual and region-based CNN for MRI classification, achieving strong accuracy, while Alemayehu [29] proposed a lightweight CNN model with 98.78% accuracy, using Grad-CAM to enhance interpretability. Similarly, the BTC-fCNN proposed by Vimala et al. [30] emphasized fast performance for multi-class classification. These models paved the way for efficient and interpretable brain tumor classification; however, our architecture is designed to offer a more optimal trade-off among prediction accuracy, computational speed, and interpretability, making it better suited for real-world deployment.

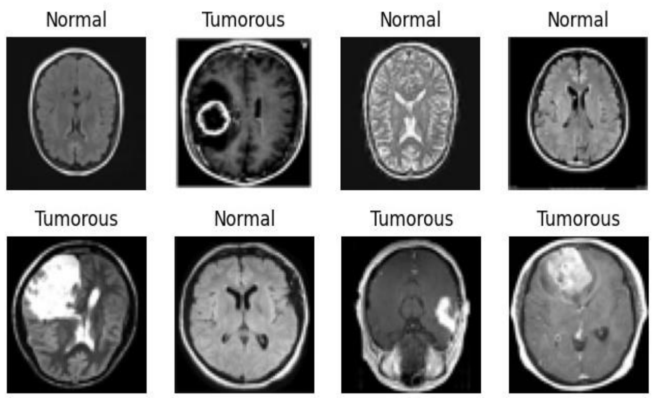


Figure.1. Normal and Tumorous MRI images

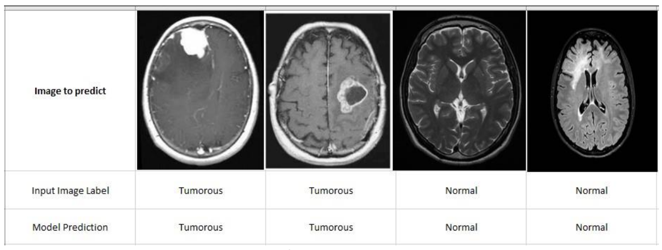


Figure.2. The result of our model on 4 sample images.

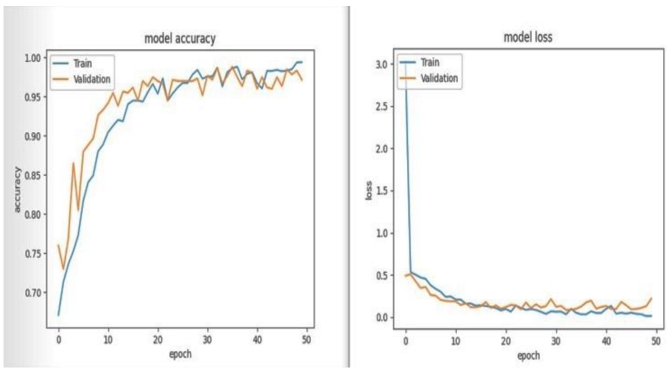


Figure 3 Model Accuracy Loss Function

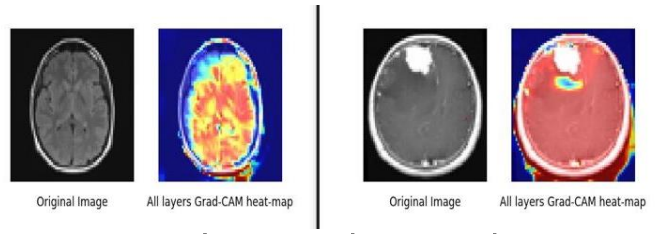


Figure.4. Grad-CAM on normal tumorous sample images

Table 1: Comparison results of proposed method and existing methods

Models	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)
FastAI [20]	95.78	96.70	95.65	95.23
YOLO V5 [13]	95.07	90.46	92.34	91.55
CNN related work [4]	99	98.19	99.19	98.18
Proposed Method	**99.39**	**99.56**	**99.62**	**99.31**

6. Conclusion and Future Scope

Our main work was to classify images from Normal and Tumorous patients. We were given a dataset that contained 3060 MRI images and split it into two sets. One set, the largest one, contains 3000 MRI of both Normal and Tumorous patients, we used it to train our model, and the other 60 images were used to validate our model. We built a specialized classification model using Convolutional Neural Networks (CNNs), and we implemented a special architecture containing three hidden layers and ran 50 epochs. The results demonstrated that our approach delivered superior performance when compared to other existing techniques. Implementing the GradCam function has given a good perception of how the proposed model works on a given sample MR images at each layer. Although the Result surrounds 99%, however, it can still be improved if one could use a large amount of dataset to train our model. In future work, this study will focus on other datasets and improve algorithm accuracy.

Author's statements

Disclosures- We confirm that this research was conducted without any conflicting interests, external funding, or institutional bias that could affect the integrity of the findings or interpretations.

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Authors' Contributions- Author-1 conducted an in-depth literature review, initiated the core research concept, and structured the experimental design. Author-2 played a key role in shaping the methodology and handled the preprocessing and model training phases. Author-3 was responsible for applying data augmentation techniques, validating experiments, and analyzing model performance. Author-4 provided expertise in refining the CNN architecture and interpreting results using Grad-CAM visualizations. Author-5 offered strategic guidance throughout the research, reviewed the framework critically, and contributed significantly to refining and finalizing the manuscript.
All contributors reviewed the content, provided feedback, and approved the final draft for submission.

Conflict of Interest- The authors affirm that there are no commercial or financial relationships that could be construed as a potential conflict of interest related to this work.

Data Availability- The dataset utilized in this study is freely accessible to the public via the Kaggle platform. It comprises 3,060 T1-weighted contrast-enhanced brain MRI images, categorized into groups of normal and tumor-affected scans, including a validation set.
All data were obtained from publicly available sources and are governed by Kaggle's terms of use as outlined by the original dataset contributors. No special permissions or restrictions apply. The authors are available to assist with dataset access or usage inquiries, if needed.

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He has received numerous awards for academic and entrepreneurial excellence, including a gold medal at the China International University Student Innovation Competition, third place at the provincial level, and qualification for the national finals. He also earned third place in the Kyoto University International Student Entrepreneurship Challenge, showcasing his ability to translate research into impactful real-world solutions.

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