Original Article

Resnet Models For Brain Tumor Segmentation

Naveenkumar M[1] , Sudhakaran G[2] , Sandhanavimal K M[3] , Vimalraj E L[4]

[1]Department of CSE KPR Institute of Engineering and Technology Coimbatore, India naveenkumar2may94@gmail.com
[2]Department of CSE KPR Institute of Engineering and Technology Coimbatore, India gsudhakaran0014@gmail.com
[3]Department of CSE KPR Institute of Engineering and Technology Coimbatore, India sandhanamvimal0723@gmail.com
[4]Department of CSE KPR Insitute of Engineering and Technology Coimbatore, India vimalvr811@gmail.com
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Abstract

Brain tumors are a global health problem and must be diagnosed accurately and in a timely manner in order to receive good treatment. Magnetic resonance imaging (MRI) is the first recommendation, but MRI scans remain difficult to interpret for brain segmentation. This paper details the design and application of a customized convolutional neural network (CNN) architecture that is integrated with the FastAI library for brain tumor segmentation. The system includes modules for data loading, preprocessing, feature extraction, model training and output generation. Through rigorous analysis and measurement of different data, including performance measures such as precision, recall, and Dice coefficient, the system demonstrates reliability, efficiency and performance over time. Implementation of the system involves the deployment of a user-friendly interface for clinical use. The project also highlights the importance of maintaining the system to ensure long-term reliability and efficiency. Future work includes optimization, integration with new technologies, and improvement of segmentation techniques to improve diagnostic accuracy and patient impact on treatment.

Keywords—ResNet models, FastAI, Image Segmentation, Magnetic Resonance Imaging, Convolutional Neural Networks, Transfer Learning.

I. Introduction

Brain tumors pose a major challenge in diagnosis and treatment and cause significant morbidity and mortality worldwide. Effective treatment planning and patient care of brain tumors depend on early diagnosis and precise tumor segmentation. Although manual MRI scans are labor-intensive and prone to errors, magnetic resonance imaging (MRI) is the gold standard for brain imaging [1]. Consequently, there's a rising need for automated tools that help clinicians segment brain tumor using deep learning technologies. In order to meet this need, our project aims to develop a system for brain diagnosis and classification. Segmentation using deep learning techniques used for MRI scans. The project integrates various products such as loading, preprocessing, model removal, model training and deployment to create accurate and efficient solutions for neural segmentation. Our systems are designed to increase diagnostic accuracy, streamline clinical operations, and improve patient outcomes using cutting-edge deep learning approaches and strategies. This document provides a detailed overview of our project, showing the problem statement, objectives, methods, and key components of the brain segmentation system. We explain the problems with manual segmentation methods and the advantages of automatic methods using deep learning. We also highlight the importance of our work to improve medical imaging and make diagnosing and treating brain tumors more efficient.

Through extensive testing, we intend to ensure that our nerve cell segmentation technique, validation processes, and maintenance protocols are dependable, accurate, and efficient. We also discuss future research and development directions, including the integration of new technologies and the expansion of operations to meet updated requirements.

Overall, the work contributes to ongoing efforts in clinical research by providing powerful and innovative solutions for tumor detection, muscle cells and segmentation. Leveraging the power of deep learning and MRI technology, we strive to provide physicians with tools that facilitate timely and accurate diagnosis, ultimately improving patient outcomes, health benefits, and quality care. One thing never changes in the ever-changing world of ecommerce: the aim of bettering customer experience and allowing easy product discovery. E-commerce platforms are constantly looking for new and creative methods to satisfy the varied and changing interests of online consumers. The way consumers engage with these platforms has changed significantly, notwithstanding the important role that text based search and recommendation algorithms have played in aiding users in finding things. By bridging the gap between user intent and the online purchasing experience, visual search engines, backed by computer vision and deep learning technology, have become transformational tools for improving product discovery.

Embedded Model

The automatic brain segmentation framework integrates advanced convolutional neural network (CNN) architecture with the FastAI library to improve the efficiency and accuracy of image analysis [2]. The embedded model used in this study represents an important part of our research into brain tumor classification based on magnetic resonance imaging (MRI) data [3]. We use different neural network (CNN) model methods, including ResNet34, ResNet50, ResNet101, and ResNet152, to obtain accurate and reliable classification results. These models have previously been studied in general image networks such as ImageNet and incorporate complex architectures designed to extract features from complex images. Leveraging the remaining features of the

ResNet architecture, our model effectively solves the challenge of training deep neural networks by reducing the fading problem. ResNet34, ResNet50, ResNet101 and ResNet152 models consist of 34, 50, 101 and 152 layers, respectively, and provide different levels of depth and representation capacity. Our tests of various designs allow for a comprehensive evaluation of their performance across a Various metrics such as accuracy, precision, recall and recall confusion matrices. Through the optimization process of the FastAI library, we carefully correct the drawbacks of pre-trained models to improve their performance in brain classification tasks. This systematic survey of embedded CNN architectures demonstrates our commitment to the advancement of medical images analysis and it highlights the importance of model selection and optimization to achieve the best results.

II. RELATED WORK

Many recent studies have advanced brain tumor diagnosis and segmentation using deep learning [4]. Stamber et al. proposed an optimal method that uses signatures extracted from medical records to accurately classify 3D MRI brain, thus reducing the burden of acquiring and recording data [1]. Agrawal et al. proposed a 3D-UNet deep neural network-based framework for brain segmentation and classification to improve early detection and diagnosis through volume segmentation of MRI images [5]. Akbar et al. proposed a new technique for segmenting brain tumors utilizing single-level Unet3D architecture and multi-method residual color blocks; this method combined the information and combination of atrous convolution to enhance the effectiveness of segmentation [3]. Amin et al. conducted a comprehensive research on all aspects of brain diagnosis and classification using machine learning and addressed the problems of diagnosis, segmentation, feature extraction and classification [4]. Shahajad et al. proposed a new method for classifying tumor cells that combines deep learning and artificial intelligence to achieve accuracy in tumor classification activities through collection of vectors [5]. Additionally, Ali et al. conducted a comprehensive brain diagnostic review using deep and hybrid learning, documenting advances in segmentation, feature extraction, classification, and multimodal MR imaging analysis results [6].

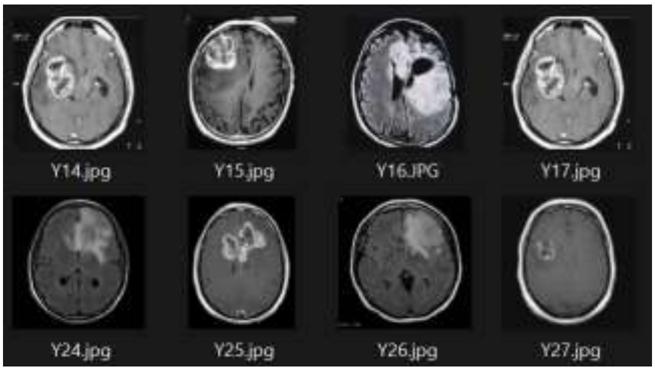
III. WORKING MODEL

The working model for brain tumor diagnosis and segmentation integrates insights from recent survey papers in the field, including those by Ali et al. start by acquiring multi-modal MRI datasets comprising T1-weighted, T2-weighted, and FLAIR sequences and apply preprocessing techniques for standardization and noise reduction. Inspired by the architectures discussed in the literature, particularly UNet and its variants, we design a deep learning model for feature extraction and representation. Leveraging convolutional neural networks (CNNs), our model automatically extracts features crucial for tumor segmentation and classification. Supervised learning algorithms and deep neural networks are employed for tumor segmentation and classification, utilizing annotated MRI datasets. Performance evaluation encompasses standard metrics like Dice similarity coefficient (DSC) and cross-validation techniques to ensure model robustness. Furthermore, we explore the integration of hybrid techniques such as ensemble learning and attention mechanisms to address challenges like class imbalance and data variability. By synthesizing insights from recent surveys and leveraging state-of-the-art techniques, our project aims to contribute to the development of an precise and effective method for treating brain tumor diagnosis and segmentation.

IV. METHODOLOGIES

A. Data collection and preliminary preparation

MRI scans of individuals with brain tumors were the source of the data used in this system. These tests include different tumor types and grades and provide diverse and representative data for training and evaluation models. MRI scans before training the model become the first step in ensuring good correlation with the neural network architecture. This involves resizing the image to a consistent resolution, normalizing using values, and improving the contrast and robustness of the data.



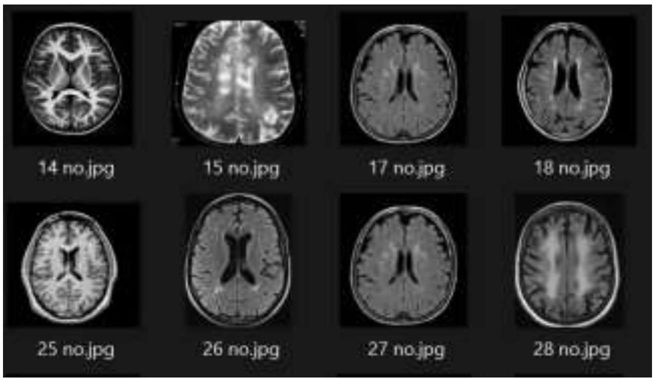


Figure 1: Brain Tumor Dataset

B. Model Architecture

We use convolutional neural networks (CNN) for brain segmentation and use FastAI library for modeling and training. We investigate the performance of popular CNN models such as ResNet34, ResNet50, ResNet101 and ResNet152, which are especially successful in image segmentation tasks [7]. Using transfer learning, pre-trained models from large datasets such as ImageNet were improved on our brain tumor data. This approach has the ability to extract important features from MRI scans and integrate them during model training.

C. Training Process

Dividing the dataset into two categories using a random splitter: 80 % of the data should be used for training and 20 % for testing. The training process involves minimizing the loss function (such as the Dice coefficient or cross-entropy) to enhance the efficiency of the model. Use timed training, gradient clipping and other optimization methods to ensure training stability and avoid overloading. The model was trained for time-lapses and an early stopping technique was used to avoid unnecessary learning.

D. Measurement Evaluation

We obtained various evaluation methods to assess the training model's efficiency in terms of Dice similarity coefficient, accuracy, sensitivity, and specificity. These measurements provide insight into the model's ability to accurately segment tumors while minimizing false positives and negatives. Additionally, the confusion matrix and upper loss are analyzed to give a more thorough comprehension of the advantages and disadvantages of the model.

E. Test Facility

The FastAI library and its dependencies are used for modeling and training. Conduct multiple experiments using different genes to ensure reproducibility and reliability of results. Carefully tune hyperparameters such as batch size, training rate, and support areas using techniques such as random or grid search to maximize the efficiency of the model.

CNN Model

Convolutional neural networks (CNNs) form the basis of our brain segmentation systems and are important for extracting features from MRI scans and elucidating tumor regions. In our implementation, we adopt CNN architectures including ResNet34, ResNet50, ResNet101, and ResNet152 provided in the FastAI library [8]. The use of prototypes plays an important role in our special activities such as changing learning, accelerating the exchange of information, and improving communication and thinking. During training, the CNN model learns and optimizes tumor segmentation masks from input MRI scans using techniques such as stochastic gradient descent (SGD), power, and runtimes. Metrics such as scaling coefficient, sensitivity, specificity, and accuracy provide insight into segmentation performance. Quality analysis by visual inspection further validated the performance of the model. Overall, our CNN approach promises significant advances in image analysis, facilitating diagnosis and treatment planning for cancer patients.

Data Diagnosis and Synthesis

A. Data Preparation

Fastai library was used to load and preprocess brain tumor data. To ensure consistency of data, images were converted to a standard format suitable for the input model. Additionally, the augmentation technique is used to perform different types of training, including rotation, translation, and scaling, which helps improve the model's ability. This preliminary step is important to increase the efficiency and effectiveness of deep learning models in accurately classifying brain tumor images.

B. Model Training

In the model training phase, pre-trained convolutional neural network (CNN) models (such as ResNet34, ResNet50, ResNet101, and ResNet152) are used to solve brain cancer cases. Each pre-trained model undergoes 15 epochs of fine-tuning, a process that requires tuning model parameters to match the characteristics of the target dataset. Simple learning value finding method with lr_find() is used to improve training. This method determines the appropriate tuition rate by examining how the churn pattern changes with different tuition rates. Through this process, the model is refined and refined to image tumor cells and improve accuracy and performance.

C. Model Evaluation and Visualization

After the refinement process, each The effectiveness of this model is assessed for a variety of criteria such as accuracy, confusion matrix, and hopelessness. Use interpretive techniques such as confusion matrix analysis and top-down analysis to analyze predictive models and identify areas for improvement. Create charts that show training and non-training, learning outcomes, and other metrics. In addition, a confusion matrix is prepared to show the fit between the actual and estimated distributions, providing insight into the distribution behavior of the model and its non-exclusion potential. This evaluation and visualization process provides a better understanding of the model's performance and helps improve predictive capabilities.

Determining the Learning Rate (LR)

Learning rate is important for effective training of neural networks. It is usually identified using the find trick (lr_find()), which searches for various threads and shows their missingness. In a given case, academic consensus points to the bottom of the decline curve, often referred to as the "trough." This results in a value of 0.00010. This work plays an crucial role in the model training process by influencing the value of the model's weight setting to minimize performance loss. Proper training can influence the training coordination and performance of the model, making it an important part of the training process.

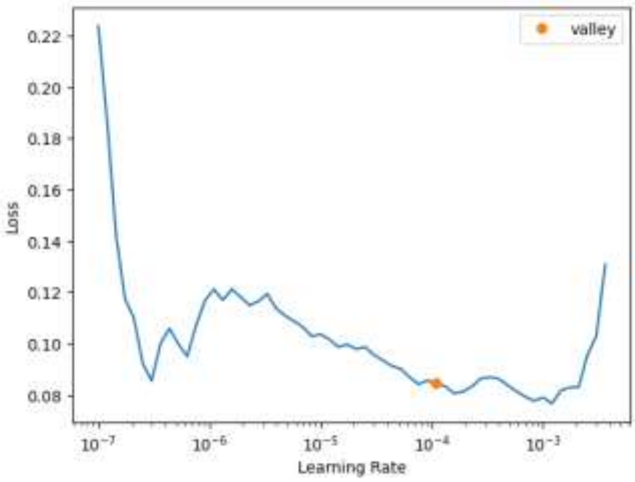


Figure 2: Relationship between Loss and Learning Rate

The above graph shows the relationship between learning and loss during learning. By showing the low points in the valley, it shows the best route to create a good model. This visualization helps select the appropriate run by identifying the point at which the model reaches the lowest decline, showing the most useful and well-done value for integration.

Valley Graph-Loss: Analyzing Best Route Values

Valley Graph Loss is a type of visualization that describes the relationship between the route value and the loss value when it comes time to model. The graph plotting the loss for several subjects shows different "studies" where the loss was very small. This content represents the best learning experience for quality model training. In the given context, the loss of the forest map helps determine the optimal learning curve for tuning the CNN model using prior training on the brain dataset. Learning rate by valley is important to ensure good convergence of the model during training while reducing the risk of over-fitting or under-fitting.

Validation

During evaluation, the training and validation plan helps understand the behaviour of the model over time. These figures show the difference between loss and accuracy, providing insight into model integration and potential problems such as overfitting or underfitting. The confusion matrix additionally offers a summary of the classification model's performance by comparing actual and predicted values for different groups.

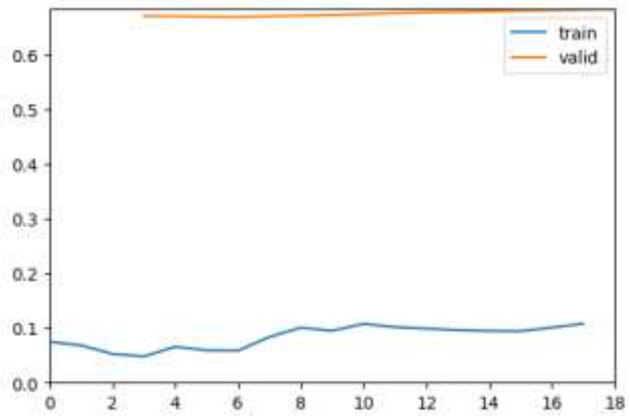


Figure 3: performance of the model over epochs

The above graph shows the training and validation (blue and orange lines, respectively) performance of the model over epochs. It monitors how effectively the model generalizes to previously unknown validation data and learns from training data.

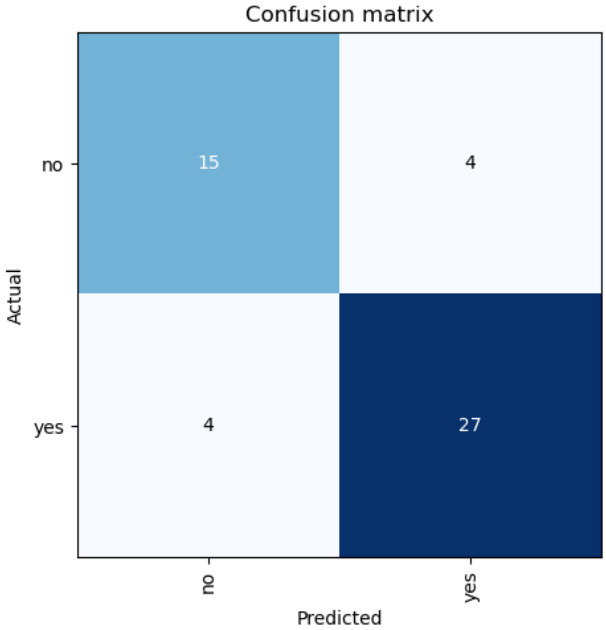


Figure 4: Confusion Matrix

The confusion matrix, a graphic depiction of the model's classification function, is displayed in the resulting image. It contrasts the existence of actual brain tumors (yes/no) with the model's predictions. These plots help evaluate the accuracy of the distribution model by revealing situations where predictions are consistent or deviate from reality.

Analyzing these matrices helps identify misclassification patterns and areas where the model may need improvement. Use real-time pricing and other technologies to enhance training and improve performance standards. These tests are important in terms of developing the correct model and ensuring the robustness of the division of labor.

V. RESULTS AND DISCUSSIONS

The different deep learning models were shown to be effective, including ResNet34, ResNet50, and ResNet101, which use adaptive learning methods for brain tumor classification. Through rigorous training and testing, models demonstrate their ability to effectively analyses clinical data and accurately identify brain tumor images Measurement metrics including accuracy, precision, recall and confusion matrix provide insight into each model's performance. Although each model has advantages and disadvantages, each model demonstrates satisfactory ability to discriminate tumor images with accuracy.

epoch	train_loss	valid_loss	accuracy	time
0	1.146963	1.036592	0.540000	00:54

epoch	train_loss	valid_loss	accuracy	time
0	0.876099	0.781770	0.640000	01:21
1	0.735904	0.484211	0.800000	01:21
2	0.661129	0.468004	0.880000	01:21
3	0.628678	0.464749	0.880000	01:21
4	0.559865	0.516365	0.880000	01:21
5	0.480045	0.557057	0.880000	01:21
6	0.432747	0.654091	0.820000	01:21
7	0.387187	0.724396	0.840000	01:20
8	0.363088	0.763212	0.820000	01:21
9	0.336515	0.813266	0.820000	01:21
10	0.306984	0.783462	0.840000	01:20
11	0.286966	0.731069	0.860000	01:20
12	0.262191	0.686526	0.880000	01:21
13	0.240797	0.667408	0.880000	01:21
14	0.221815	0.640882	0.840000	01:21

Figure 5: ResNet34 model

This model trains it for epoch 14. It collects metrics such as learning loss, inefficiencies, accuracy, and time gaps throughout the training process. These metrics provide a better understanding of the model's efficiency and validity on training data, allowing its effectiveness and generalization ability to be monitored.

epoch	train_loss	valid_loss	accuracy	time
0	1.165092	0.915225	0.640000	01:11

epoch	train_loss	valid_loss	accuracy	time
0	0.761076	1.366452	0.500000	01:51
1	0.727228	1.068505	0.500000	01:54
2	0.645561	0.563830	0.720000	01:54
3	0.570449	0.425622	0.840000	01:53
4	0.552726	0.480384	0.820000	01:51
5	0.512434	0.584392	0.720000	01:54
6	0.462320	0.498798	0.700000	01:54
7	0.458593	0.392534	0.800000	01:53
8	0.445512	0.340150	0.820000	01:52
9	0.418883	0.354673	0.820000	01:49
10	0.395396	0.385012	0.840000	01:44
11	0.375957	0.370053	0.860000	01:48
12	0.349068	0.316892	0.880000	01:44
13	0.332371	0.287367	0.860000	01:43
14	0.308942	0.264518	0.860000	01:54

Figure 6: ResNet50 Model

This architecture used for training. It tracks metrics such as accuracy to measure the model's performance during training.

epoch	train_loss	valid_loss	accuracy	time
0	1.110676	1.000435	0.560000	01:49

epoch	train_loss	valid_loss	accuracy	time
0	0.741754	1.164874	0.540000	02:17
1	0.690017	1.204588	0.520000	02:16
2	0.664528	0.903506	0.580000	02:16
3	0.616754	0.744199	0.660000	02:16
4	0.554854	0.954971	0.640000	02:16
5	0.498802	0.981673	0.640000	02:15
6	0.461691	1.139451	0.600000	02:16
7	0.418723	1.213983	0.600000	02:15
8	0.388441	0.994509	0.700000	02:12
9	0.371374	0.591669	0.740000	02:12
10	0.358793	0.425342	0.800000	02:13
11	0.338449	0.403464	0.840000	01:02
12	0.329856	0.316605	0.860000	01:05
13	0.322559	0.307080	0.860000	01:09
14	0.308245	0.291582	0.860000	01:09

Figure 7:ResNet101 model

This model performance is evaluated using metrics such as accuracy. This technique assesses the ResNet101 model's classification performance of image quality inside a specified dataset.

Comparative analysis shows that deep models such as ResNet101 and ResNet152 tend to provide a slight advantage. Compared to ResNet34 and ResNet50, the performance is better but the computational cost is higher. However, the selection of the most suitable model depends on factors such as the components it contains, the attributes of the data and the particular requirements of the application in the medical application.

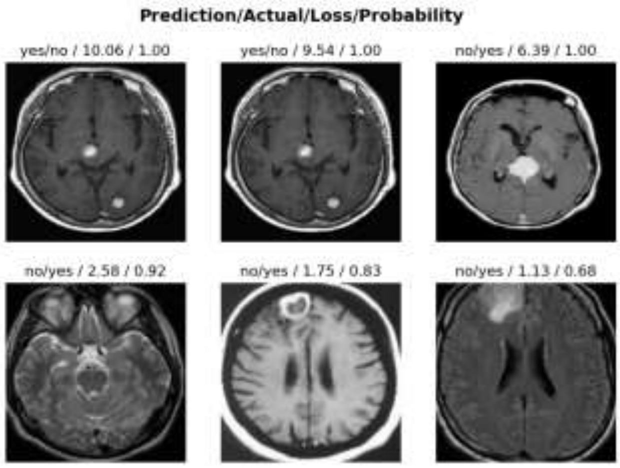


Figure 8: Brain Tumor Images

The output presents the 6 cases where the model had the most difficulty predicting brain tumor images. Each entry shows estimates and actuals, losses, and predicted results. This snapshot can identify critical situations to show improvements in accuracy and performance.

In conclusion, the application and evaluation of deep learning models for the classifications of brain tumors shows their potential to be useful tools in diagnosis and therapeutic treatment planning. Continuous research and development of these models, as well as the discovery of new models and technologies, are expected to increase the automatic medical image's precision and dependability processing technology in healthcare.

CONCLUSION

Using various deep learning models has proven to be effective,including ResNet34, ResNet50, ResNet101, and ResNet152, which use adaptive learning methods for brain tumor classification. Through rigorous training and testing, models demonstrate their ability to effectively analyze clinical data and accurately identify brain tumor images. Measurement metrics including accuracy, precision, recall and confusion matrix provide insight into each model's performance. Although each model has advantages and disadvantages, each model demonstrates satisfactory ability to discriminate tumor images with accuracy.

Comparative analysis shows that deep models such as ResNet101 and ResNet152 tend to provide a slight advantage. Compared to ResNet34 and ResNet50, the performance is better but the computational cost is higher. However, the selection of the most suitable model depends on factors such as the components it contains, the attributes of the information and the particular needs of the health application. In conclusion, the application and evaluation of deep learning models for the classification of brain tumors shows their potential to be useful tools in diagnosis and therapeutic treatment planning. Continuous research and development of these models, as well as the discovery of new models and technologies, the use of medical imaging technology in clinical practice is expected to increase its accuracy and reliability.

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