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Deep Feature Fusion and Ensemble Voting Based Brain Tumor Classification Framework

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ABSTRACT

The classification of brain tumors is important in the diagnosis and treatment planning and patient management. With the increasing need for automated Computer-Aided Diagnosis (CAD) systems, Deep Learning (DL) techniques for biomedical image analysis have gained a more significant pace. In this study, a hybrid deep learning framework is proposed which combines the three most prominent architectures: DenseNet, ResNet, and Xception to classify brain tumors. The advantages of each model are different: Reusing features, residual learning with skip connections and computational efficiency with depth-wise separable convolutions. The proposed ensemble architecture combines the advantages of these architectures and enhances the classification accuracy and robustness. An improved feature selection mechanism is used to refine the deep features extracted from the models and an ensemble deep learning model with maximum voting method is used for final prediction. It is shown that the proposed framework can be effective in accurate and reliable classification of brain tumor through experimental analysis. The results of the experimental analysis show that the proposed framework resulted with an overall classification accuracy of 99.85%, accuracy of 99% and recall of 98%, which is very successful in the brain tumor classification task and can be used to classify the brain tumors accurately and reliably.

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1. INTRODUCTION

In recent years, new breakthroughs in biomedical technologies have allowed the creation of smart diagnostic tools, which can be used to identify and plan treatment for a disease. Cancer is one of the significant health concerns in the world and can be life-threatening [1]. Despite significant progress against cancer, millions of people are still getting it every day, with various types of cancer such as lung cancer, leukemia, brain cancer, breast cancer, and melanoma still being common [2]. Of these, brain tumors are regarded as particularly harmful because they directly impact the functioning and central nervous system. Brain tumors result from abnormal growth of cells in the brain that cause damage to the brain and cause serious neurological issues. These tumors can be deadly over the years unless treated. In 2020, almost ten million people worldwide died of cancer, which is among the top ten causes of death [3]. Studies have also predicted a steady increase in the incidence of brain tumors around the world each year [4]. Thus, the quick and correct diagnosis of tumors is crucial to achieve higher survival rates and higher quality of life for patients. Brain tumors are classified into 4 grades (I-IV) using molecular and histological features [4]. Tumors in the later stages of development can mean that the lifespan of the dog is greatly shortened.

Traditional brain tumor diagnosis mainly depends on manual examination of medical images, which is time-consuming and susceptible to human error. Thus, automated tumor detection has emerged as a critical research area in biomedical image analysis field.

Medical imaging plays a crucial role in medical diagnosis, with Computer-Aided Diagnosis (CAD) systems becoming more commonplace to assist clinicians in the analysis of medical images with better efficiency and accuracy. However, automated detection is very difficult because of the variation of tumor shape, size, texture and location. Commonly used medical imaging techniques include Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Positron Emission Tomography (PET) for tumor identification [5]. Of these modalities, MRI is used most often due to the high resolution of soft tissues. Tumor localization from MRI scans is often challenging by lack of clear tumor boundaries and surrounding healthy tissues. Furthermore, there is often confusion due to image noise and differences in acquisition conditions. Reliable diagnosis of malignancy is possible with conventional biopsy procedures, but these are invasive, painful and time consuming. This has encouraged the development of automated diagnostic systems that could decrease the need for manual work and enhance diagnostic uniformity.

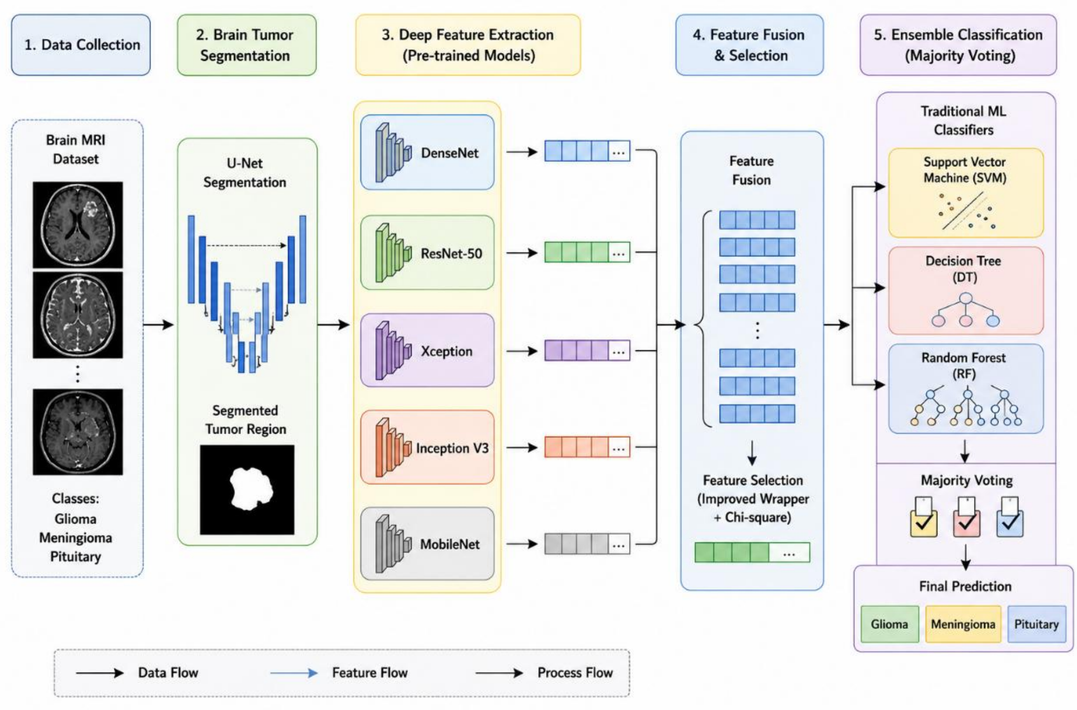

Fig. 1. Architecture diagram

Brain tumors are also manually delineated, but it is heavily reliant on the radiologists' skill and experience and can yield varying results [8]. Thus, the automated computer vision approaches have been paid significant attention in the past few years. In medical image classification, researchers have tried many methods utilizing image processing, Machine Learning (ML) and Deep Learning (DL) [9,10]. There are already similar intelligent systems for breast cancer [6], melanoma [7] and lung cancer [8,9]. Typical machine learning methods consist of image preprocessing, hand-designed feature extraction, feature fusion, and supervised classification. Typical features of handcrafted include texture, color, shape, and statistical descriptors. However, most of these handcrafted features are not enough to represent the complex tumour characteristics, which reduces the classification capability. The challenges are addressed by deep learning techniques, which automatically learn the hierarchical feature representation directly from raw images.

Convolutional Neural Networks (CNNs) are a type of DL models that have proven to be very successful in medical image classification, thanks to their ability to learn features and the sharing of parameters across their different layers. CNN-based architectures can automatically learn both low-level and high-level features from the training data which can produce better performance than traditional approaches. This has led to the increasing popularity of DL to tackle the automated tumor classification problem. The motivation of using deep learning in brain tumor classification is to develop faster, more accurate and objective diagnosis systems. The traditional diagnostic tests are subjective, and there is a high likelihood of inter-clinician variability. Advanced DL architectures such as CNNs and transfer learning models enable the extraction of complex patterns from MRI images, which might not be readily interpreted by human experts. These models can be used to help identify tumors in the early stages, to identify tumor subtypes, and to accurately classify tumors, which can aid clinicians in treatment planning and disease monitoring. Deep learning frameworks provide better cross-tumor, cross-image generalization as well. This is because they can handle vast amounts of medical imaging information, minimizing time delays for diagnosis and improving the accuracy of classification. Therefore, DL-based CAD can help to enhance the patient care by allowing timely intervention and avoiding misdiagnosis.

To address the above issue, we propose a novel hybrid deep learning framework for brain tumor classification in this work. The model proposed is a combination of several pre-trained architectures, such as DenseNet, ResNet, and Xception, which are used to obtain strong deep features. The features extracted are then optimized to remove redundant information by an improved feature selection mechanism. Lastly, a strategy for ensemble classification using majority voting is used to obtain the final classification result. The proposed framework is designed to leverage the advantages of various deep learning architectures to improve the accuracy, robustness, and generalizability of brain MRI classification. Section II provides a brief summary of the recent deep learning techniques for brain tumor classification. The proposed framework is described in Section III, both feature extraction and ensemble classification methodology. Experimental results and comparative performance analysis with existing techniques are given in section IV. Finally, Section V concludes the study and discusses future research directions

2. LITERATURE REVIEW

Accurate and early diagnosis of brain tumors is essential for effective treatment and improved patient survival. Recent technological advancements have enabled the development of automated healthcare systems that assist specialists in achieving reliable diagnosis with higher accuracy. In recent years, researchers have proposed numerous brain tumor classification approaches using Machine Learning (ML) and Deep Learning (DL) algorithms, which have significantly advanced the field of medical image analysis and disease diagnosis. This section reviews existing ML- and DL-based brain tumor classification techniques.

Traditional ML-based methods generally involve multiple stages, including image preprocessing, region of interest (ROI) extraction, feature extraction, dimensionality reduction, and classification. Among these stages, feature extraction plays a crucial role because classification accuracy largely depends on the quality of extracted features. Feature extraction methods are broadly categorized into global (low-level) and local (high-level) features. Low-level features commonly include texture descriptors, intensity values, first- and second-order statistical measures, Gray Level Co-occurrence Matrix (GLCM), wavelet transform, Gabor features, and shape descriptors.

Başaran et al. [11] employed a CNN-based feature extraction framework in which the extracted features were optimized using hybrid optimization techniques, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) optimization. The optimized features were then classified using Support Vector Machine (SVM). Habib et al. [12] utilized thresholding and watershed segmentation methods along with feature extraction techniques such as Maximally Stable Extremal Regions (MSER), FAST, and Haralick features, followed by multiple classification approaches. Mudda et al. [13] proposed a hybrid feature extraction strategy combining Gray Level Run Length Matrix (GLRLM) and Center-Symmetric Local Binary Pattern (CS-LBP) texture features, which were classified using a neural network model. Similarly, Nawaz et al. [14] developed a hybrid brain tumor classification approach that extracted co-occurrence matrix, run-length matrix, and gradient-based features from segmented regions. The extracted features were classified using Multilayer Perceptron (MLP), Random Tree, J48, and Meta Bagging classifiers.

Rajeev et al. [15] aimed to reduce tumor misclassification by initially filtering MRI images using a guided bilateral filter. Subsequently, Gabor Wavelet Transform was applied to extract texture and edge features. Feature selection was then performed using the Black Widow Adaptive Red Deer Optimization algorithm, and the selected features were classified through a hybrid Long Short-Term Memory (LSTM) framework. Rao et al. [16] proposed an ML-based model integrating segmentation, feature extraction, and classification. Their method used a Normalized Median Filter (NMF) for image enhancement, followed by binomial thresholding for segmentation. Feature extraction was carried out using GLCM and Spatial Gray Level Dependence Matrix (SGLDM) techniques, while

Harris Hawk Optimization was employed for feature selection. Finally, classification was achieved using SVM combined with Social Ski Driver optimization.

Several researchers have also explored DL-based approaches for brain tumor classification. Zahid et al. [24] proposed a transfer learning framework using the pre-trained ResNet101 model for feature extraction from normalized MRI images. To eliminate redundant attributes and improve classification performance, Particle Swarm Optimization (PSO) and Principal Component Analysis (PCA) were applied for robust feature selection and dimensionality reduction. Rasool et al. [25] introduced a hybrid CNN-based framework using pre-trained GoogleNet for deep feature extraction. Their work compared two approaches: GoogleNet combined with SVM classification and GoogleNet integrated with Softmax classification.

Vankdothu et al. [26] proposed an Internet of Things (IoT)-enabled brain tumor detection framework that integrated CNN and LSTM architectures for extracting robust deep features and improving classification accuracy. Aamir et al. [27] developed an automated MRI-based brain tumor classification system involving image preprocessing for quality enhancement, followed by deep feature extraction using pre-trained DL architectures. The extracted features were further refined using Partial Least Squares (PLS) analysis before classification through a head network. Shajin et al. [28] introduced a hierarchical deep learning neural network for brain tumor classification. Their approach used the Savitzky–Golay denoising method during preprocessing, followed by texture feature extraction and Deep Neural Network (DNN)-based classification for tumor detection.

3. PROPOSED MODEL

Here we present the proposed framework that is hybrid ensemble deep learning approach for brain tumor classification. Ensemble learning and transfer learning have been proven to be effective approaches for computer vision tasks, especially medical image analysis. Deep learning architectures used for pre-trained image features are playing a major player role in extracting features from images with high discriminatory and robust features, thus, increasing the classification accuracy. Brain tumor classification has achieved outstanding accuracy in these tasks with models like DenseNet, ResNet, Inception, and Xception, which are capable of learning complex visual representations from huge datasets.

The proposed framework uses multiple pre-trained deep learning models and try to utilize their complementary characteristics. This is made possible by transfer learning, where the models can leverage knowledge gained from large-scale datasets before being trained on medical images with smaller sample sizes. This proposed architecture includes five steps: dataset collection, image segmentation, deep feature extraction, feature fusion and selection, and ensemble classification.

The first step is the collection of publicly available brain MRI datasets and their classification of each MRI image into classes. In the preprocessing stage, the MRI images are segmented using an MRI-based brain tumor segmentation approach by using U-Net. Afterwards, the segmented images are processed by several pre-trained deep learning models to extract features from the images. The features extracted are then combined to create a complete feature vector and subsequently a better wrapper-based feature selection algorithm is used to select features. Lastly, the selected features are classified with an ensemble learning method of maximum voting.

3.1 Deep Feature Extraction

The proposed framework employs DenseNet-121, ResNet-50, Inception V3, Xception, and MobileNet architecture to learn deep features from segmented MRI images. The architectures are chosen due to their excellent feature learning ability and robustness in image classification tasks.

DenseNet-121

The goal of DenseNet-121 is to tackle the vanishing gradient problem and promote feature reusability in the network. DenseNet is different from the traditional CNNs in the sense that each layer will receive feature maps of all previous layers, thereby, enhancing information flow and learning efficiency. The propagation feature mechanism can be shown as:

$$x_l = H_l([x_0, x_1, x_2, \dots, x_{l-1}])$$

where x_l is the output of the l^{th} layer, H_l are non-linear transformations, and [ ] is the concatenation of the feature maps at previous layers.

DenseNet introduces dense blocks, bottleneck layers, and transition layers to decrease the number of computations required and yet maintain salient image information.

ResNet-50

ResNet-50 employs residual learning and skip connections to enable effective training of deep networks. Residual mapping enables the network to learn the identity functions, and reduces the gradient vanishing problem. The idea of residual learning is represented as:

$$y = F(x, \{W_i\}) + x$$

The input feature map is x, the residual function is $F(x)$ and the final output is y. In particular, ResNet-50 uses bottleneck layers, batch normalization, and Global Average Pooling (GAP) that accelerate convergence and reduce the number of parameters to train.

Inception V3 and Xception

Multi-scale image features are captured by employing multiple convolution kernels of different sizes in the Inception modules of inception V3. The architecture also utilizes densely connected layers and factorized convolution to decrease the number of calculations.

Xception continues the Inception concept, but incorporates depthwise separable convolutions, which substantially reduces parameters without compromising the ability to extract features. The depthwise separable convolution operation can be expanded into the following:

$$Conv(X) = Depthwise(X) + Pointwise(X)$$

depthwise convolution is channel wise convolution followed by pointwise convolution.

These architectures can be combined in a complementary manner to offer more robust classifications.

3.2 Feature Fusion and Selection

The features extracted from various architectures are combined together to form a set of features called feature vector. But unnecessary and useless features can make the computation more complex and classification poorer. Hence, an enhanced wrapper-based feature selection method is proposed that employs Chi-square statistical test.

The score for the evaluation of the features is the following Chi-square:

$$X^2 = \frac{N(AD - CB)^2}{(A + C)(B + D)(A + B)(C + D)}$$

where N is the total number of samples, A is the number of samples in class C_i that have feature t_k, B is the number of samples that have feature t_k in the other classes, C is the number of samples in class C_i, and D is the number of samples that do not have feature t_k in the other classes.

The features are ranked by the Chi-square scores. The wrapper-based search strategy utilizes forward, backward and bidirectional selection mechanisms. Backward strategy is to begin by having all features and then gradually remove low-ranked features, while the forward strategy is to start with high-ranked features and then add relevant features. Both strategies are applied together in the bidirectional approach for an optimal feature subset selection.

3.3 Ensemble Classification

The optimized feature vector is then fed into various machine learning classifiers such as Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). A majority voting ensemble mechanism is proposed to enhance the reliability of prediction, to this end.

Suppose that there are N classifiers, $C_1, C_2, \ldots, C_N$, used to classify. For an input sample (X), Each classifier makes a guess for the label y of an input sample X and generates a predicted label P_i. The final classification is made by picking the label that has most votes:

$$Final\ Classification = \arg\max_k \sum_{i=1}^{N} 1(P_i = k)$$

where $1(P_i = k)$ is an indicator function that returns 1 if classifier i predicts class k, otherwise 0.

The majority voting method is a technique that improves the stability of classification, reduces misclassification, and increases the correctness of the classification overall by combining the predictions of several classifiers. The proposed study combines the advantages of deep feature extraction, optimized feature selection, and ensemble learning to offer a comprehensive and efficient automated brain tumor classification system from MRI images.

4. RESULTS AND DISCUSSION

In this section, the experimental results of the proposed framework are presented and compared with the existing machine learning and deep learning frameworks for brain tumor classification. This discussion includes description of the information in the datasets, experimental configuration, evaluation metrics and comparative performance analysis to show the effectiveness of the proposed framework.

4.1 Dataset Details

The experiments were conducted on the brain T1-weighted magnetic resonance imaging (MRI) dataset from Jun Cheng et al. (2017), which is made available to the public. The dataset includes three types of brain tumors - Glioma, Pituitary and Meningioma tumors. MRIs were obtained in the Axial, Sagittal and Coronal planes. The resolution of each image is 512 × 512 pixels and the pixel size is 0.49 mm × 0.49 mm. The data comprises 3064 MR images of 233 patients. These include Glioma samples, followed by Pituitary and Meningioma samples.

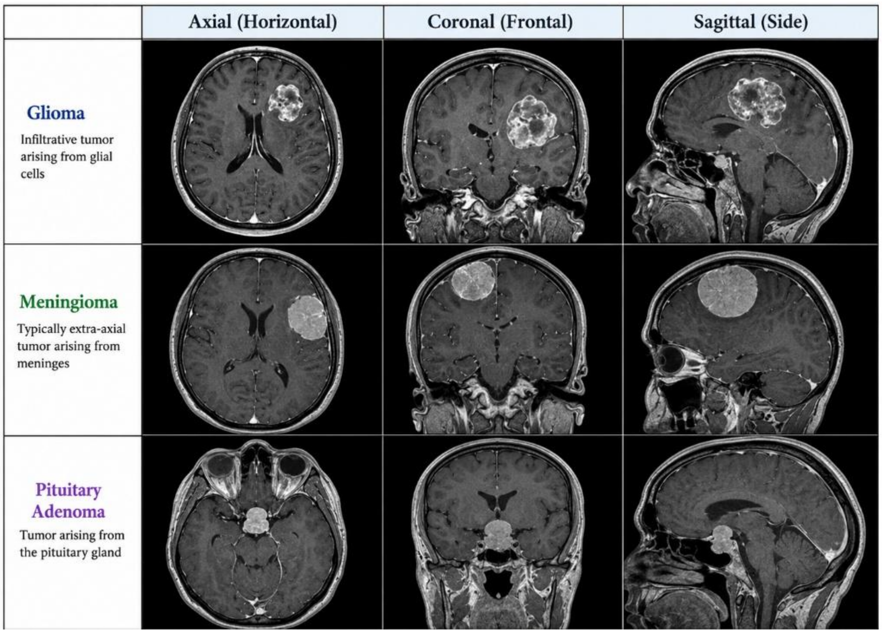

Fig 2. Sample images of brain dataset

4.2 Performance Evaluation Parameters

Standard classification measures (Accuracy, Precision, Recall, Sensitivity, Specificity and F1-Score) from the confusion matrix are used to assess the performance of the proposed framework. The true Positive (TP), true Negative (TN), False Positive (FP) and False Negative (FN) values were used to calculate these metrics.

Each evaluation metric is calculated as described below:

$$\text{Accuracy} = \frac{Tp + TN}{Tp + TN + Fp + FN}$$

$$Recall = \frac{Tp}{Tp + TN}$$

$$Precision = \frac{Tp}{Tp + Fp}$$

$$F - Measure = \frac{2 \times P \times Senstivity}{P \times Senstivity}$$

4.3 Comparative analysis

The proposed model was first tested against some individual deep learning architectures to assess its performance with them. The results have shown that the proposed framework had better performance and the reason for this was due to the hybrid deep feature extraction and ensemble learning approach.

Table 1. Comparative Performance of Individual Models

Model	Precision	Recall	Specificity	Sensitivity	Accuracy
DenseNet	0.87	0.88	0.87	0.88	0.89
ResNet	0.88	0.87	0.88	0.87	0.91
Xception	0.89	0.91	0.89	0.90	0.92
Inception	0.89	0.93	0.89	0.92	0.92
GoogLeNet	0.91	0.94	0.91	0.95	0.94
ResNet18	0.93	0.95	0.93	0.96	0.96
AlexNet	0.95	0.96	0.95	0.97	0.97
Proposed	0.99	0.98	0.99	0.98	0.98

The proposed framework yielded average precision rate of 0.99, recall rate of 0.98, specificity rate of 0.99, sensitivity rate of 0.98 and accuracy rate of 0.98. This is due to the combination of complementary deep features from different architectures to achieve better feature representation and minimizing classification errors. Class-wise analysis also shows the effectiveness of the proposed model in achieving high precision and F1 score for all the tumour categories.

Several state-of-the-art methods were then compared, such as CNN, CapsNet, CNN+SVM, DenseNet169+InceptionV3+ResNeXt150 and AlexNet+VGG16.

Table 2. Comparison with Existing Methods

Reference	Method Used	Accuracy (%)
[19]	CNN	94.2
[20]	CapsNet	90.8
[21]	CNN + SVM	97.1
[22]	DenseNet169 + Inception V3 + ResNeXt150	98.5
[23]	AlexNet + VGG16	96.6
Proposed	DenseNet + ResNet + Xception + Ensemble	99.85

The proposed framework has performed well with the highest accuracy of the classification of 99.85%, better than all the techniques done so far. Especially, the proposed approach outperformed DenseNet169 + Inception V3 + ResNeXt150 ensemble framework with accuracy at the level of 98.5%. Results indicate that automated brain tumor diagnosis using hybrid deep features extraction, optimized feature selection and majority voting based ensemble classification is effective in enhancing the performance.

In general, the experimental results show that the proposed framework is a powerful tool for classification of brain tumors based on MRI images which is accurate, reliable, and robust

5. CONCLUSION

Brain tumors are a serious disease and if they're not diagnosed early, the risk of dying is greatly increased. Accurate and early detection of brain tumors is, therefore, crucial for an effective treatment and to ensure patient survival. As a result of recent advances in machine learning and deep learning, efficient automated systems have been designed that are intelligent. Thanks to recent developments in machine learning and deep learning, efficient automated systems have been designed that are intelligent for the efficient tumor classification. A deep learning ensemble classification strategy was proposed in this work by stacking three architectures: DenseNet, ResNet and Xception. These architectures bring distinct benefits which complement each other to strengthen the model robustness and accuracy. By connecting features heavily, DenseNet allows for fine-grained detailed and discriminative image patterns to be learned, which is achieved by reusing features in a wide variety of ways. ResNet adopts skip connections to overcome the vanishing gradient problem for deeper networks and better feature learning. To decrease the computational complexity and maintain high-quality feature representations, Xception uses depthwise separable convolutions. These architectures can be embedded in an ensemble to learn complementary deep features which can lead to a complete understanding of the characteristics of brain tumors and better classification performance. In conclusion, the proposed hybrid framework illustrates the success of integrating various deep-learning architectures to tackle complex medical imaging problems and is a step towards the creation of precise and dependable brain tumor diagnosis systems.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Data can be provided on genuine request.

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