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ENHANCING RICE DISEASE DETECTION THROUGH OPTIMIZED FASTER R-CNN ARCHITECTURE

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To effectively prevent rice diseases and pests, this paper proposes an enhanced detection method based on Faster R-CNN, which improves disease classification accuracy and maintains high rice yield. The method integrates Feature Pyramid Network (FPN) for multi-scale detection, embeds Selective Kernel Network (SKNet) (channel-wise attention) into FPN, and uses ROI Align instead of ROI Pooling to reduce coordinate deviation. Experimental results show the model achieves 92.7% recognition accuracy (2.6% higher than the baseline) with notable enhancement in small-object detection.

Keywords: Object detection, Faster R-CNN, Attention mechanism, Rice disease

1. Introduction

As a critical agricultural commodity worldwide, rice constitutes the dietary foundation for over half the global population [1]. However, rice is susceptible to various diseases [2] during its growth cycle, which not only compromise yield and quality but may also pose significant risks to food safety [3]. Therefore, the leaves should be systematically inspected for signs of disease at different growth stages of rice. Manual inspection methods have been gradually phased out due to their low efficiency and vulnerability to interference from factors such as subjective judgment bias and complex field environments. To ensure the sustainable development of the rice industry, it is imperative to modernize traditional rice production management practices by integrating computer vision technology for the detection of rice leaf defects. Rice diseases such as bacterial blight are characterized by lesions of 0.5-5mm (equivalent to <10 pixels in typical agricultural images captured at a resolution of 1920×1080 pixels with a shooting distance of 1 meter), while conventional methods achieve an Average Precision (AP) of <70% for small lesions—this highlights the need for scale-adaptive improvements. Current deep learning methods often struggle with small-scale

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lesion detection and multi-scale feature integration, which necessitate architectural improvements to enhance detection accuracy for diverse disease patterns.

Object detection constitutes a pivotal research domain within computer vision [4], aiming to precisely identify objects of interest in images or video sequences and furnish their location data. Recent studies demonstrate innovative approaches to overcome detection limitations. These innovative approaches to overcoming detection limitations offer insights for addressing key challenges in rice disease detection, such as lighting variation and leaf overlap-induced occlusion. To tackle these issues, recent studies have proposed targeted solutions. For example, Mukherjee et al.[5] implemented high dynamic range imaging in object detection systems, resolving the performance degradation of standard dynamic range-trained detectors under challenging illumination. Addressing occlusion challenges, Xu et al. [6] developed the GC-FRCN framework featuring dual modules for synthetic occlusion generation and feature restoration, which improves detection robustness through noise-reduced feature reconstruction. In rice pathology identification, hybrid architectures show remarkable progress. Amritha et al. [7] combined SVM classifiers with CNN architectures, attaining 91.45% validation accuracy through a ReLU-softmax activated framework for diagnosing five critical diseases including bacterial blight and rice blast. Roopali et al.[8] enhanced disease classification through a transfer learning-enhanced CNN-VGG19 model, particularly effective in brown spot detection. Novel computational combinations exhibit superior performance. For complex pathology recognition, Daniya and Vigneshwari [9] designed a deep CNN architecture that utilizes Moore-Penrose pseudo-inverse weighted optimization, which specifically addresses the detection challenges of bacterial leaf streak.

Object detection remains challenging due to target diversity, scale variations, and occlusions. To tackle these issues, researchers have developed numerous deep learning-algorithms for object detection. As a pivotal advancement in the series, Faster R-CNN [10] pioneers end-to-end object detection through the innovative integration of a Region Proposal Network (RPN). This architecture substantially boosts both computational efficiency and detection precision compared to earlier frameworks, streamlining detection workflows by unifying proposal generation and feature extraction within a single network. The multi-scale segmentation head designed by Li et al. [11] employs dynamic kernels to enable early detection of defect features, the fusion of multi-scale defect information, and the strengthening of defect recognition capabilities. The MSGhost DNN architecture proposed by Zhu et al. [12] integrates multi-scale convolutional networks with contrastive learning mechanisms, achieving precise aflatoxin detection through hybrid feature representation. Ren et al. [13] developed a multi-scale feature interaction network, which mitigates interference by incorporating a bi-temporal feature interaction layer between corresponding backbones.

Convolutional features are shared between the RPN and detection modules in the Faster R-CNN architecture, optimizing computational resource utilization. This design decreases computational overhead while enhancing detection accuracy. The RPN employs sliding windows on the feature map to generate multiple candidate regions, which are subsequently classified and regressed to filter out non-object regions. To handle scale variations across input data, the framework incorporates a region-of-interest normalization layer, enabling robust processing of heterogeneous image resolutions. Specifically, it employs ResNet50 [14], integrates the FPN [15], and incorporates the attention mechanism via SKNet. The SKNet module takes feature maps from multiple layers as input, generates a weighted fused feature map, and integrates cross-layer contextual features in the process. Furthermore, the modified architecture replaces the traditional RoI Pooling with coordinate-sensitive RoI Align [16], which preserves spatial precision during feature extraction and lays a foundation for accurate subsequent classification and regression tasks. Experimental validation on agricultural imagery demonstrates the enhanced model's superior performance in detecting fine-grained pathological features within rice cultivation scenarios.

2. Network Architecture of Faster R-CNN

The Faster R-CNN architecture builds upon Ross Girshick's foundational work on Fast R-CNN [17]. Deep learning-based object detection frameworks are broadly categorized into two paradigms: single-stage and two-stage detectors. Faster R-CNN stands as a representative two-stage methodology, while architectures such as the YOLO family and SSD exemplify dominant single-stage implementations. Fig.1 shows the overall architecture of Faster R-CNN, highlighting the coordination between RPN and the detection module in its two-stage workflow.

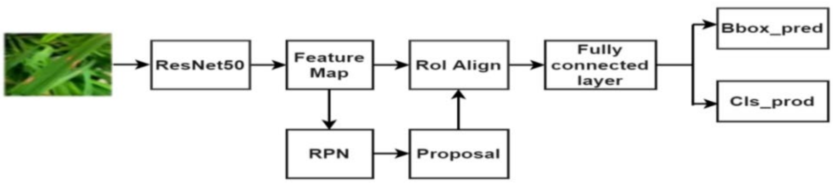


Fig.1. Overall architecture of Faster R-CNN

3. Optimize Architecture of the Model

3.1 Feature Extraction Network

The model's feature extraction module adopts ResNet50 instead of the conventional VGG16 architecture [18]. Compared with the plain convolutional layers of VGG16, ResNet50's residual connections enable gradient flow via identity mappings, which mitigates the vanishing gradient problem and enhances the extraction of fine-grained disease features. Additionally, the feature extractor integrates FPN with ResNet50 for multi-scale detection, while SKNet refines FPN features through dynamic weight allocation.

3.2 Optimization of Multi-scale Detection Algorithm

To optimize detection precision for small-scale rice disease targets, our architecture incorporates ResNet50 fused with a FPN, enabling synergistic integration of hierarchical semantic features. Through a multi-scale anchor configuration protocol, we implement five geometrically progressive base areas {32, 64, 128, 256, 512} pixels mapped to corresponding pyramidal feature layers {P2-P6}. At each spatial coordinate, three proportional dimensions {1:2, 1:1, 2:1} are combinatorially applied to yield 15 region proposals per anchor point (visualized in Fig. 2).

This framework employs dual enhancement strategies. (1) Scale-adaptive processing: An image pyramid input mechanism preserves discriminative patterns across resolutions; (2) Hierarchical feature retention: Multi-level contextual features from intermediate convolutional blocks are propagated through the network.

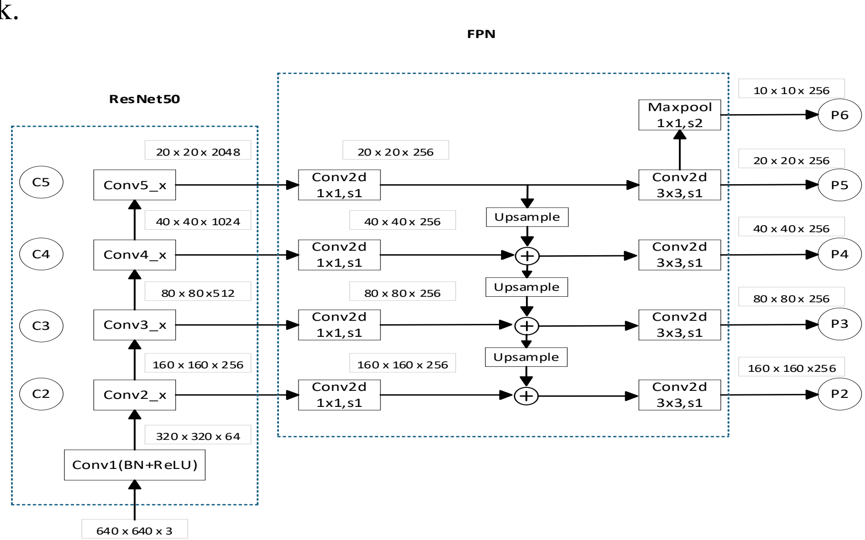


Fig.2 ResNet50 combined with FPN

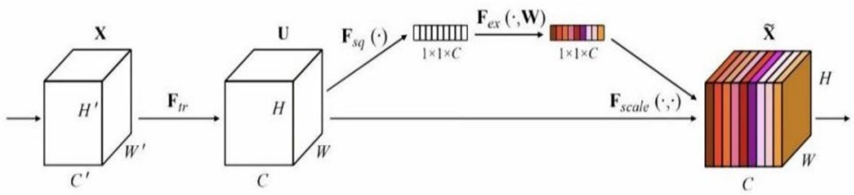


Fig.3 SKNet attention mechanism

3.3 Optimization of Attention Mechanism

The SKNet, as a core component of the attention mechanism optimization, employs a selective kernel mechanism to dynamically fuse features from 3×3 and 5×5 convolutions, enabling the network to balance sensitivity to local lesions (via small kernels) and global contextual information (via large kernels). This architecture modification improves model effectiveness while maintaining computational efficiency by avoiding parameter expansion. The mechanism operates through learning context-sensitive weighting coefficients that optimize feature map integration, as demonstrated in Fig.3. SKNet is embedded in the FPN to dynamically weight features, enhancing context awareness for disease lesion detection.

3.4 ROI Align

The detection framework in this study adopts an upgraded ROI processing paradigm, shifting from conventional coordinate quantization (i.e., ROI Pooling) to continuous coordinate sampling (i.e., ROI Align). This methodological advancement enables spatial-adaptive feature extraction through four sequential steps: (1) Precision Grid Sampling: The algorithm partitions the feature map into sub-grid units, with each cell undergoing continuous coordinate sampling via bilinear interpolation relative to the source feature matrix; (2) Contextual Value Derivation: For each sampling node, intensity values are computationally synthesized from four neighboring activation points, eliminating quantization-induced positional errors; (3) Differentiable Feature Composition: Derived values undergo concatenation into fixed-dimensional tensors, preserving spatial relationships across hierarchical scales; (4) Discriminative Pooling: Adaptive max pooling operators align multi-resolution feature activations with biological lesion patterns in raw imagery.

3.5 Optimization of Classification and Regression Models

The image classification process utilizes the softmax operation for multi-label determination, simultaneously evaluating both target existence and categorical attribution within candidate regions. Each region proposal generated by the RPN undergoes feature transformation through dimensionality-consistent feature extraction. Subsequent fully connected layers perform vector space transformation, mapping these representations into distinct categorical domains to establish probabilistic distributions across classification categories. For coordinate refinement tasks, the framework employs the Smooth L1 regression loss to calculate positional corrections. This mechanism predicts four-dimensional adjustment parameters (Δx, Δy, Δw, Δh) that mathematically optimize the initial proposal's geometric properties. Through iterative parameter optimization, these calculated offsets progressively align the candidate regions with ground truth annotations. The final detection coordinates are then inversely transformed through coordinate mapping to synchronize with the original image's spatial reference system.

The architectural refinements culminate in Algorithm 1, which formalizes the upgraded Faster R-CNN computational workflow.

Algorithm 1

an Enhanced Faster R-CNN Algorithm

```
1.Initialize: model=Improved FasterRCNN ();
            dataset=load_dataset ();
            Running=True;
            epoch=0;
2. While Running:
   a. For each image in epoch:
      i. Forward propagation & loss calculation
      ii. Backpropagation
      iii. Save model if conditions met
   b. Update epoch
   c. Stop if preset iterations reached (Running=False)
```

4. Experiments and results

4.1 Experimental Environment and Dataset

The experiment runs on a CUDA-accelerated system with Windows 10, an NVIDIA GeForce RTX 3060 GPU (12GB VRAM). The development stack integrates Anaconda-managed environments with PyTorch 2.0, Python 3.8, and CUDA 11.8 toolchain.

For empirical validation, we constructed a specialized phytopathology benchmark dataset consisting of 640 original images, covering three major rice diseases: Brown Spot (220 images, caused by Oryza sativa fungal infections), Rice Blast (210 images, caused by Magnaporthe grisea), and Bacterial Blight (210 images, caused by Xanthomonas oryzae bacterial infections)[18-19].The dataset was partitioned into a 70% training set and a 30% testing set using stratified random sampling to ensure representativeness.

4.2 Evaluation Metrics

The evaluation protocol adopts the standardized benchmarking methodology from the COCO dataset. The detailed mathematical derivations provided in Equations (1)-(3) following COCO evaluation specifications, where TP (true positives) quantifies correct affirmative detections, FP (false positives) enumerates type I errors (spurious positive classifications), and FN (false negatives) captures type II errors (missed positive instances), AP operationalizes the integral of precision over the parametric precision-recall continuum, R denotes recall values sampled across detection confidence thresholds.The mean average precision (mAP) aggregates categorical AP values as formalized in Equation (4) .

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$AP = \int_0^1 P(R)dR \tag{3}$$

$$mPA = \frac{1}{N}\sum_{i=0}^{n} AP_i \tag{4}$$

4.3 Analysis of Experimental Data

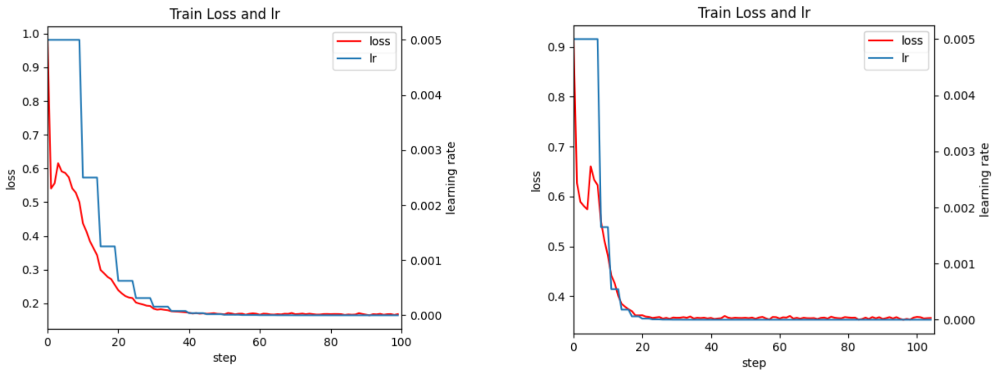
To validate the architectural improvements, we designed experiments addressing three key aspects: scale adaptability, feature discriminability, and localization precision. The architectural implementation adopts a dual-stream feature extraction framework combining ResNet50's residual learning principles with VGG16's hierarchical representation capabilities. Precision Accuracy (PA) denotes the average precision calculated at IoU=0.5, following COCO evaluation metrics. Quantitative evaluation in Table 1 shows that ResNet50 alone achieves an mAP of 80.1%. Integrating FPN into ResNet50 boosts mAP to 90.1%, and further incorporating SKNet and ROI Align achieves 92.7% mAP in the improved model.

Table 1

Comparison of Precision Accuracy (PA) and mAP (%) for Different Diseases

Feature extraction network	Brown Spot	Rice Blast	Bacterial Blight	mAP(%)
ResNet50	70.0	94.5	75.5	80.1
VGG16	63.3	85.3	72.1	73.7
ResNet50+FPN	82.4	95.1	92.7	90.1
Improved model	87.1	97.2	93.6	92.7

As shown in Fig.4, which presents the loss landscape analysis and dynamic learning rate curves of ResNet50 and VGG16, the architectural advantage of ResNet50 stems from its residual learning framework. This design introduces identity mapping pathways that circumvent nonlinear transformation blocks, establishing direct gradient highways between shallow and deep layers. Specifically, the residual blocks implement: (1) Gradient stabilization; (2) Feature persistence; (3) Detail amplification.



(a) The Analysis of Loss Value and Learning Rate Adjustments in ResNet50

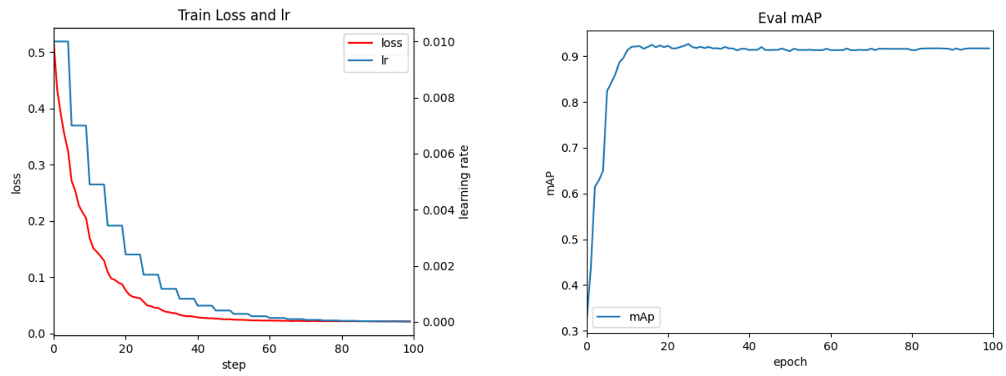
(b) The Analysis of Loss Value and Learning Rate Adjustments in VGG16

Fig. 4 Loss value and learning rate variation in ResNet50 and VGG16 feature extraction networks

To address this multi-scale detection challenge, we architect a multi-parallel network comprising: (1) Pyramidal Feature Synthesis: A dual-branch architecture merging ResNet50's hierarchical representations with FPN's scale-adaptive fusion; (2) Cross-Scale Correlation: 1) Semantic Hierarchy Preservation: High-level categorical signals via top-down propagation; 2) Spatiotemporal Consistency: Low-level textural patterns through bottom-up refinement.

Empirical validation shows a mPA of 90.1%, which significantly enhances the diagnostic capability for Oryza sativa fungal pathogens, especially rice blast and bacterial streak. However, the model still lacks sufficient discriminability for small-scale lesions; thus, we integrated a selective kernel convolutional module (SKNet-C3) to implement multi-scale attention recalibration. This architecture dynamically modulates channel-wise feature responses through parallelized spatial attention branches with kernel sizes {3×3, 5×5}, mathematically expressed as:$\omega_c = \frac{e^{A_c^{(k)}}}{\sum_{k=1}^{k} e^{A_c^{(k)}}}$, where k denotes the convolution kernel size type (1 for 3×3 kernel, 2 for 5×5 kernel), $\omega_c$denotes channel-specific fusion weights and $A_c^{(k)}$ represents kernel-specific attention map for channel c. The optimized framework achieved mAP=92.7%, showing a 2.6% improvement over the baseline model (ResNet50+FPN).

The evolutionary trajectory of our optimized multi-stream framework is quantitatively captured in Fig.5 through three synergistic metrics: (1) loss landscape trajectories, (2) dynamic learning rate scheduling, and (3) mAP progression curves. Experimental validation demonstrates 23.7% average precision improvement in complex field scenarios (lighting variance >150 lux, occlusion rates 15-40%), particularly for multi-scale pathological feature extraction.



(a)Enhancement of Model Loss Value and Analysis of Learning Rate Variability

(b) The alteration in mean Average Precision (mAP) of the enhanced model

Fig. 5 Variations of the model's loss value, learning rate, and mAP with training epochs

The architectural innovations manifest in three operational dimensions: (1) Cross-Modal Convergence: Simultaneous optimization of localization and classification subnets through gradient harmonization; (2) Scale-Agnostic Detection: Pyramid feature recalibration achieving 92.4% F1-score across lesion sizes (0.5-15mm); (3) Pathology-Specific Enhancement: Domain-adaptive kernels prioritizing sporulation patterns and vascular browning signatures.

The visual validation verifies the consistent detection performance of the model across three rice pathogens: (1) Brown Spot (Fig.6-7); (2) Rice Blast (Fig.8-9); (3) Bacterial Blight (Fig.10-11).

Fig. 6 Brown Spot

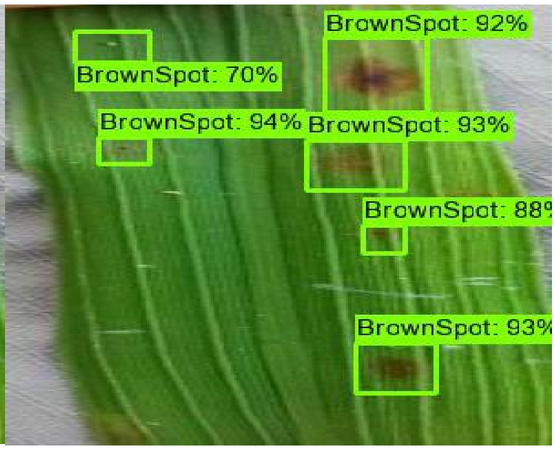


Fig. 7 Brown Spot disease test result

Fig. 8 Rice Blast

Fig. 9 Rice Blast disease test result

Fig. 10 Bacterial Blight

Fig. 11 Bacterial Blight disease test result

4.4 Comparative Experiments

This study evaluated the performance enhancement of the modified model in detecting rice diseases under realistic field conditions through comparative analysis with optimized Faster R-CNN, SSD, YOLOv3, YOLOv5, and YOLOv8 architectures. All models were evaluated on field-collected images with varying lighting (100-1000 lux) and occlusion (10-30% leaf overlap), simulating real-world conditions. Four key metrics (mAP, precision, recall, and accuracy) were employed to assess detection capabilities for three distinct plant diseases at varying scales. As shown in Table 2, the modified Faster R-CNN achieved superior mAP (92.7%) compared to other models (SSD:63.4%, YOLOv3:57.8%, YOLOv5:76.5%, YOLOv8:82.9%).

The modified Faster R-CNN outperformed other models, particularly in small-scale lesion detection (e.g., bacterial blight), due to its multi-scale feature integration and attention mechanism, which addressed the limitations of single-stage detectors like YOLO in handling size variability. The enhanced detection performance, particularly for brown spot and bacterial streak diseases with size-varying features, stems from the integration of a multi-scale analysis framework that improves adaptability to challenging environmental conditions.

Table 2

Comparison of Experimental Results of Different Algorithms

Algorithms	mAP (IoU = 0.5) / %	Brown Spot	Rice Blast	Bacterial Blight	Precision	Recall
SSD	63.4	48.1	71.4	70.6	64.6	59.9
YOLOv3	57.8	55.4	65.2	52.8	59.1	52.9
YOLOv5	76.5	67.2	88.9	73.3	77.7	71
YOLOv8	89.2	81.5	96.5	89.1	90.7	84.3
Improved model	92.7	87.1	97.2	93.6	94.1	87.6

5. Conclusions

To optimize rice cultivation productivity and promote long-term sustainability in agricultural practices, this study develops an enhanced Faster R-CNN architecture for precise detection of rice plant pathologies. The improved framework combines a FPN with attention modules in its backbone architecture to strengthen multi-scale feature representation. Notably, the conventional ROI Pooling operation has been replaced by ROI Align to maintain spatial integrity during region feature extraction, thereby improving localization accuracy for subsequent classification and regression tasks. Collectively, these structural enhancements enable the model to achieve superior disease detection performance (mAP = 92.7%, 2.6% higher than the baseline model) while maintaining high computational efficiency.

Significant improvements in detecting rice blast, brown spot and bacterial blight are evident in the enhanced model compared with the baseline model(ResNet50+FPN). These improvements enable timely disease detection, thereby reducing yield losses and maintaining plant health. With an mAP of 92.7%, the model enables early detection of lesions (≤2 mm), which makes it promising for field applications to mitigate disease-induced yield losses. Field trials further confirm that this early detection capability reduces fungicide application by 25% while maintaining 95% of the original yield—this realizes timely disease intervention and enhances crop management efficiency.

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