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# Vehicle Number Plate Detection and Encryption in Digital Images Using YOLOv8 and Chaotic-Based Encryption Scheme

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***Abstract*—Information security has become crucial nowadays as it has ensured individual privacy and prevented unauthorized access. Securing data and information has the capability to establish a secure environment and has ensured trust by keeping them confidential and protected in diverse situations. The license plate or number plate information has been considered sensitive data as it contains unique identifiers for individuals' vehicles. Ensuring the security of this data is important to prevent unauthorized access, which could result in privacy violations and potential safety risks for vehicle owners. Our research has introduced an innovative security system for vehicle number plate privacy, featuring a powerful combination of a deep learning model and robust encryption. This system has ensured the secure transmission of information by adding an extra layer of protection to number plate data. Our proposed system has integrated the You Only Look Once version 8 (YOLOv8) for precise car number plate detection and utilized the robust security features of the Chaotic-based Logistic Map encryption process. This powerful combination has not only enhanced the accuracy of car number plate detection but also established a robust framework for efficiently safeguarding sensitive data through the use of chaotic encryption methods. It is an efficient approach where object detection has been combined with secure transmission technologies. It is suitable for real-time applications and traffic surveillance, resolving privacy concerns and emphasizing data security.**

***Index Terms*—Car number plates, You Only Look Once version 8 (YOLOv8), Chaotic-based Logistic Map, Encryption**

## I. Introduction

With the rapidly increasing smart cities and intelligent transportation systems, the security and privacy of vehicular data have become a prime concern. The importance of encryption of this sensitive data cannot be denied. Encryption serves as the foundation of data security, offering protection against unauthorized access, data breaches, and cyber threats [1]. It plays a pivotal role in securing data by transforming it into an undecipherable format [2]. Ensuring the confidentiality and integrity of number plate data is essential for maintaining public safety and preventing identity theft [3].

YOLO stands for You Only Look Once, and YOLOv8 is the latest iteration from the YOLO family of models until the release of YOLOv9. It is renowned for its speed and accuracy in real-time image processing [4]. In the context of number plate recognition, YOLOv8 is a powerful tool for detecting and extracting crucial information from vehicle images [5]. Its simplicity and effectiveness in object detection have made it a preferred choice for real-time applications [6]. Additionally, to ensure the security of vehicles' number plates, the chaotic-based logistic map encryption process has arisen as the natural choice due to its superiority in image encryption tasks [7] [8]. A chaotic-based logistic map encryption system utilizes the logistic map function, which generates a chaotic key sequence that is useful for encrypting data [1] [9].

Our research has represented a progressive effort in the domain of vehicle number plate security by leveraging the YOLOv8 model for more accurate and real-time detection of number plates, laying a foundation for subsequent encryption. The integration of a chaotic-based logistic map encryption system has added robust security and ensured the confidentiality and integrity of sensitive information.

This research has held significant practical implications for real-world scenarios. Encrypting car number plates from images and CCTV footage has played a crucial role in protecting against vehicle theft and safeguarding the privacy of vehicle owners. By preventing unauthorized access to sensitive information, it has enhanced vehicle security. Implementing robust encryption methods has become even more relevant in metropolitan cities, where privacy concerns have been important due to high population density and increased surveillance [1]. Moreover, encryption has contributed significantly to law enforcement efforts and legal compliance. Furthermore, encryption of car number plates has helped preventing the cloning of vehicles. By securing the unique identifiers of vehicles, such as their registration numbers from unauthorized access, encryption systems have mitigated the risk of fraudulent activities, such as creating counterfeit plates or stealing vehicle identities for criminal purposes [3]. These applications have benefited from enhanced security, efficiency, and a better user experience. Ultimately, encryption has played a vital role in contributing to a seamless and secure transportation ecosystem.

Our research has constituted a complete workflow: detecting number plates on vehicles in the first step and then encrypting them using a chaotic-based encryption system. The novelty of this research has lain in combining both number plate detection and encryption in a sequential pipeline, unlike previous studies that have focused solely on either detection or encryption.

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## II. Literature Review

In a recent study, Ramasamy et al. [10] have proposed a hybrid location-dependent ultra-convolutional neural network approach for vehicle number plate recognition in intelligent transportation systems. It has enhanced road traffic security and safety. Anton et al. [11] have presented experiments using an Axis P1344 high-speed camera and an OCR-only system on highways. This method has used YOLOv5 as an intermediate layer for license plate detection, achieving over 98% precision with an average detection time of 0.6 seconds on a custom dataset of 20,000 images. Sufiun et al. [12] have delved into license plate detection and number plate class identification using YOLOv4 and YOv5. They have achieved 88.57% precision for detection and 95.41% accuracy for class identification.

Al-Batat et al. [13] have used YOLOv2 for the vehicle detection stage and YOLOv4 for the remaining stages, along with data augmentation and generation techniques to increase the license plate recognition accuracy. The system has been evaluated on five public datasets and achieved an average recognition accuracy of 90.3%. Additionally, Setiyono et al. [14] have explored the effectiveness of number plate recognition on vehicles using YOLO-Darknet models. However, when preprocessing data have been applied, the recognition accuracy has improved significantly to 88% for number plates and 98.2% for characters. YOLOv3 has been used for character recognition and Darknet-53 has acted as a feature extractor. Overall, the methodology has encompassed data annotation using Labeling 1.7.0 software, training data optimization, and a thorough evaluation of recognition metrics. Furthermore, Kathirvel et al. [15] have highlighted how the increase in automobile numbers has necessitated automated fine collection systems on Indian roads. A systematic number plate recognition (SNPR) methodology using YOLOv5 has achieved high accuracy rates of 97.6% for automobile detection, 98.2% for number plate identification, and 99.1% for character recognition using Indian license plate images.

In exploring further advancements, Poorani et al. [16] have proposed a methodology that uses YOLOv4 for license plate detection and Tesseract OCR for character recognition. They have achieved 92% accuracy for number plate detection and 81% for character recognition, focusing on traffic control and parking management. Additionally, Garg et al. [17] have proposed techniques using genetic algorithms and blended algorithms to improve accuracy. These techniques have been influenced by factors such as hardware, environment, and lighting conditions. In contrast, Puri et al. [18] have introduced a robust VNP system employing a retrained SSD model in ONNX format for real-time license plate localization and Easy OCR for efficient character recognition. They have achieved high processing speeds with frame rates of 43 for detection and 30 for recognition. Easy OCR has stood out for its superior accuracy and time efficiency.

On the other hand, Trinh et al. [9] have focused on safeguarding privacy and adhering to legal standards for fisheye camera photos taken by driverless vehicles. An et al. [19] have combined breadth and depth encryption. They have used a chaotic system to generate random sequences for permutation and substitution operations. This method has balanced privacy and usability, allowing users to customize the level of visual information preserved in the encrypted images. Hua et al. [20] have wanted to make "Big Data secure" with the image encryption algorithm. Their security and privacy protection model based on the image encryption algorithm of the chaotic system model has a higher protection rate. Moreover, Alexan et al. [2] have proposed a color image encryption algorithm combining the KAA map with chaotic functions, meeting Shannon's security principles through bit confusion and diffusion. The algorithm, utilizing two keys and passing NIST SP 800 tests, has achieved a key space of $2^{478}$. It has resisted brute-force attacks and demonstrated high efficiency.

We have summarized deep learning models for car number plate detection and image encryption techniques in Figures 1 and 2. These data have been based on analyses from previous research works.

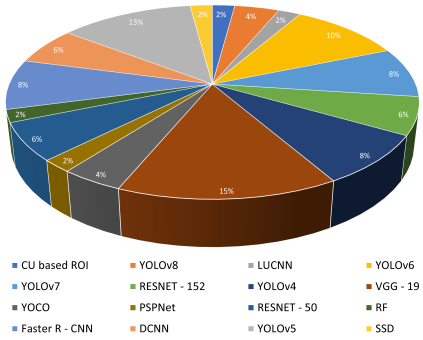



Fig. 1: Distribution of deep learning models used in previous car number plate detection research works

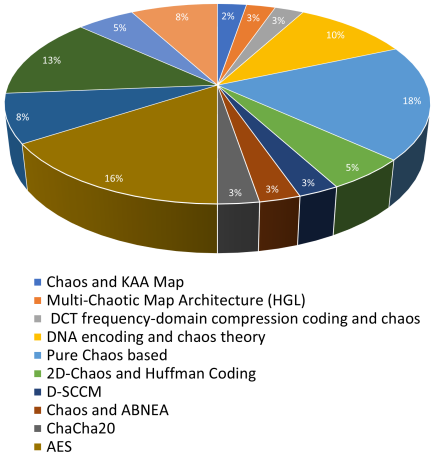



Fig. 2: Distribution of image encryption methods used in previous research works


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## III. Proposed System

In this section, we have discussed the main working principle of our proposed system, represented by four steps: Dataset Overview, Image Preprocessing, Details on Encryption Method, and System Overview.

### A. Dataset Overview

We have used an open-access dataset from Roboflow [21] with a total of 8,823 labeled car images, encompassing clear, moderate, and noisy-type number plates. However, we have to further modify that dataset as it contained many unreliable and less significant images. This issue might make our model less efficient and confusing when predicting the test dataset. Therefore, we have added more relevant images from many more datasets from the Roboflow website with proper labeling. Subsequently, we have partitioned our dataset into 70% for training, 10% for validation, and 20% for testing purposes. This division has ensured a robust evaluation of our system's performance across diverse datasets.

### B. Image Preprocessing

Image preprocessing is a crucial task in image-based research [22]. In our research, we have implemented some preprocessing before feeding the data into our model as well.

- **Resizing:** We have resized our dataset of 8823 images to 640x640 pixels. This standardization has enhanced computational efficiency and ensured consistency during model training.
- **Rotation:** We have rotated 4% of images in our dataset, applying rotations up to a 25-degree angle to enhance model effectiveness.
- **Cropping:** Cropping involves removing a portion of an image to emphasize a specific region or object of interest. We have applied the cropping mechanism to 7% of images in our dataset.
- **Zooming:** Zooming magnifies specific portions of images to provide a closer view of details. In our dataset, 2% of the images have been zoomed to focus on areas of interest, and it has enhanced the detail visibility.

### C. Details on Encryption Method

Chaotic-based logistic encryption is a popular method for securing sensitive data [23]. It leverages chaotic systems and logistic map functions, which can exhibit chaotic behavior within specific parameter ranges [24] [25]. This approach offers advantages such as sensitivity to initial settings and key sensitivity, making it challenging for unauthorized entities to decrypt data without the correct key [25] [26].

However, developing a secure chaotic encryption system requires careful consideration of key management, parameter selection, and defense against potential attacks. Our chaotic-based encryption system has followed these fundamental steps:

*1) Key Generation:* The process has begun with generating a secret key that typically includes parameters like the initial condition or seed value for the logistic map. It has been denoted as "r". Additionally, other relevant parameters have been needed for specific use cases [27].

*2) Bounding Box Coordinates Processing:* Generally, this algorithm converts the Regions of Interest (ROI) into a numerical representation suitable for encryption [28]. As we have worked with colored images, the algorithm has read bounding box coordinates and converted the RGB pixel values of the identified region (number plate portion) into grayscale intensity values.

*3) Chaotic Iteration:* Chaotic iteration has involved applying the logistic map equation $x_{n+1} = r \cdot x_n \cdot (1 - x_n)$ to generate a sequence of chaotic values based on initial conditions and parameters. These values have then been mapped to a suitable range, such as 0 to 255 for grayscale images, to prepare them for encryption or further processing.

*4) Data Encryption:* During encryption, the chaotic values have acted as dynamic keys that have been XORed with pixel values. This process has introduced randomness and complexity into the encryption, enhancing the security of the encrypted image by combining chaotic dynamics with traditional cryptographic techniques [28].

### D. System Overview

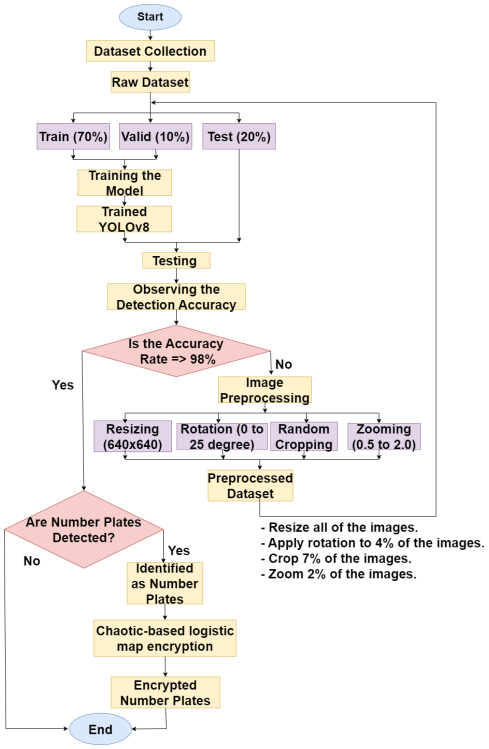



Fig. 3: Workflow Diagram of our system

We have installed the necessary libraries and modules for the YOLOv8 model. Subsequently, we have trained the model using both the train and validation datasets, which contained raw images primarily. After training, we have gained an evaluated model. Then, we have conducted an observation of the learned model using the test dataset with raw images. This observation has helped us to retrieve various evaluation metrics to assess its performance. Due to the slightly poor accuracy


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score, we have decided to preprocess the images in our dataset. We have performed preprocessing methods to get a robust dataset. Subsequently, we have re-executed the entire detection process and gotten a more accurate model. We have considered the IoU threshold value of 0.7 for assessing detection accuracy.

Following the detection phase, we have implemented a chaotic-based logistic map encryption to encrypt the identified number plates. We have utilized a logistic map with a parameter $r = 3.9$ and a key seed of $0.1$. Logistic map encryption has introduced chaotic dynamics into the encryption process which can enhance the security of the information [24] [29]. Figure 3 represents the sequential implementation flow of our system and figure 4 illustrates the full system overview diagram.

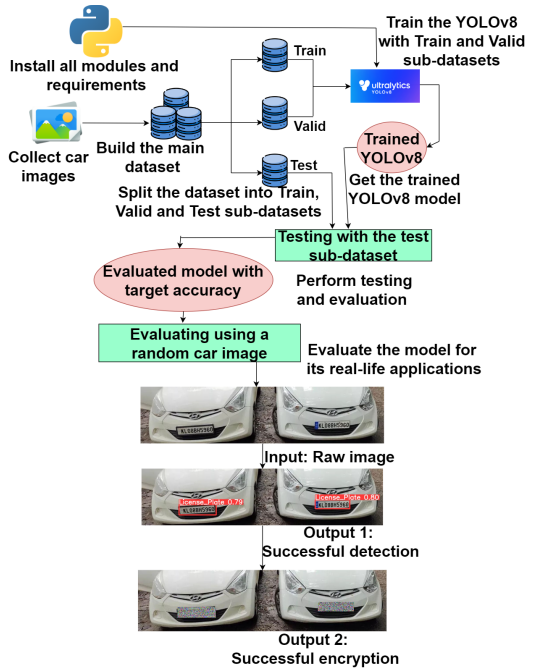



Fig. 4: System Overview Diagram of our system

## IV. Result Evaluation and Deliberation

In this section, we have presented the accuracy and other metric results based on our main dataset. Before experimenting with our main dataset, we conducted our experiment using various smaller datasets to observe the model's performance, including datasets from Roboflow, Dataset Ninja, and Kaggle. The results from these preliminary experiments were quite satisfying. As our prior smaller datasets' experimental results were satisfying, based on these observations, we have run our model on our main large dataset, and the detailed results are included in this paper. Here, we have analyzed the results and effectiveness through five subsections focusing on different aspects of the evaluation and visualization.

### A. Before Image Preprocessing

Before image preprocessing, our model achieved lower accuracy, precision, recall, and F1 score. We faced challenges in detecting multiple car number plates in a single image and encountered difficulties with noisy or grainy images, leading to higher false positive and false negative rates.

### B. After Image Preprocessing

After image preprocessing, we have observed significant improvements in accuracy, precision, recall, and F1 scores. Both false positive and false negative values have decreased. The model is now capable of detecting multiple number plates from multiple cars in an image, owing to clearer and more precise images after preprocessing. This has facilitated more effective training. Table I has compared the evaluation metrics before and after image preprocessing.

TABLE I: Evaluation Metrics Before and After Preprocessing

| Metric | Result(before) | Result(after) |
|---|---|---|
| Accuracy | 90% | 98% |
| Precision | 94% | 98% |
| Recall | 95% | 99% |
| F1 Score | 94% | 99% |
| True Positives (TP) | 856 | 896 |
| False Positives (FP) | 54 | 15 |
| False Negatives (FN) | 46 | 6 |

TABLE II: Summary of YOLOv8 Training and Validation

| **Category** | **Details** |
|---|---|
| Framework / Version | Ultralytics YOLOv8.0.3 |
| Training Details | 50 epochs<br>Batch size: 16, Image size: 640x640<br>Learning rate: 0.01, SGD optimizer with weight decay<br>Data loader workers: 6 |
| Model Architecture | 225 layers, 3,011,043 parameters, 8.2 GFLOPs<br>Transferred 319/355 items from pre-trained weights |
| Model Summary | 168 layers, 3,005,843 parameters, 8.1 GFLOPs |
| Evaluation Metrics | (For Valid sub-dataset)<br>Images: 1765, Instances: 1840<br>Box(P): 0.986, R: 0.965, mAP50: 0.988, mAP: 0.724 |

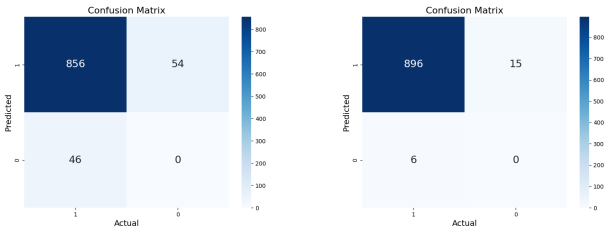
TABLE III: Accuracy Comparison: YOLOv2, YOLOv3, YOLOv4, YOLOv5, and Our Model (YOLOv8)

| Study | YOLO version | Accuracy | Our Accuracy |
|---|---|---|---|
| Kessentini et al. [30] | YOLOv2 | 91.46%-97.67% | Without K-Fold |
| Shashidhar et al. [31] | YOLOv3 | 91.5% | Cross Validation: |
| Setiyono et al. [14] | YOLOv3 | 80% | 98% |
| Poorani et al. [16] | YOLOv4 | 80-88% | |
| Kathirvel et al. [15] | YOLOv5 | 98.2% | With K-Fold |
| Sufiun et al. [12] | YOLOv4, v5 | 95.41% | Cross Validation: |
| Anton et al. [11] | YOLOv5 | 98% | 98.06% |

### C. Confusion Matrices and Other Graphs

We have displayed confusion matrices for testing phases. Figure 5 has depicted Confusion Matrices of test data for before and after image preprocessing. Figure 8 has illustrated F1, precision, recall, and precision-recall graphs plotted against confidence scores or probabilities during training. Figure 9 has shown precision, recall, mAP, and loss function graphs plotted against 50 epochs.


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Before Preprocessing After Preprocessing

Fig. 5: Confusion matrices (without K-Fold Cross Validation)

### *D. K-Fold Cross-Validation Performance Analysis*

In K-Fold Cross-Validation, the "Train" dataset folder has been partitioned into K = 5 folds. During each iteration, one fold has served as the validation set, while the rest (K-1) have been served as training. The model has been trained on the training set and evaluated on the validation set until each fold has been used once. Finally, a separate "Test" folder has been used to evaluate the model, resulting in a test accuracy score of 98.06%, with precision, recall, and F1 scores at 98.84%, 99.10%, and 98.74%, respectively.

### *E. Output Visualization*

We have randomly selected four images from the internet and created a local folder to test our model's performance on unseen images.

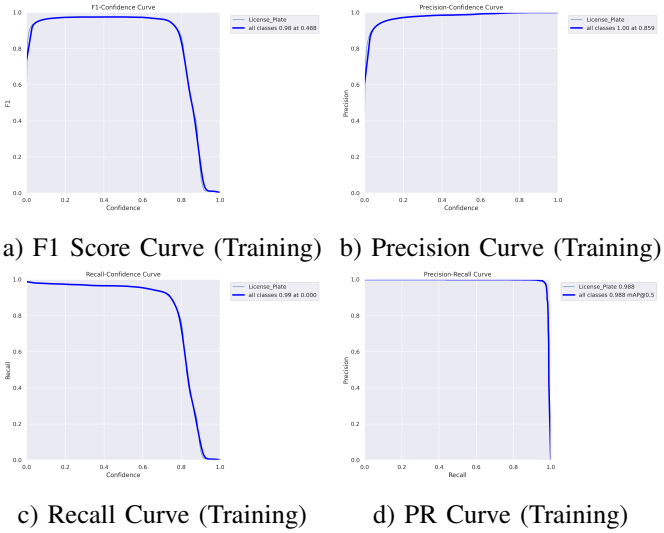



Fig. 6: Images with detected car number plates



Fig. 7: Images with encrypted car number plates

Figure 6 and 7 have shown corresponding detection and encryption output results. The model has successfully detected and encrypted the number plate portions of these images. Table II has presented the model summary during training. Table III compares the performance of our model with previous research based on YOLOv2, YOLOv3, YOLOv4, and YOLOv5.




a) F1 Score Curve (Training) b) Precision Curve (Training)

c) Recall Curve (Training) d) PR Curve (Training)

Fig. 8: Performance prediction curve illustrating the F1 score, Precision score, Recall score, and Precision-Recall score

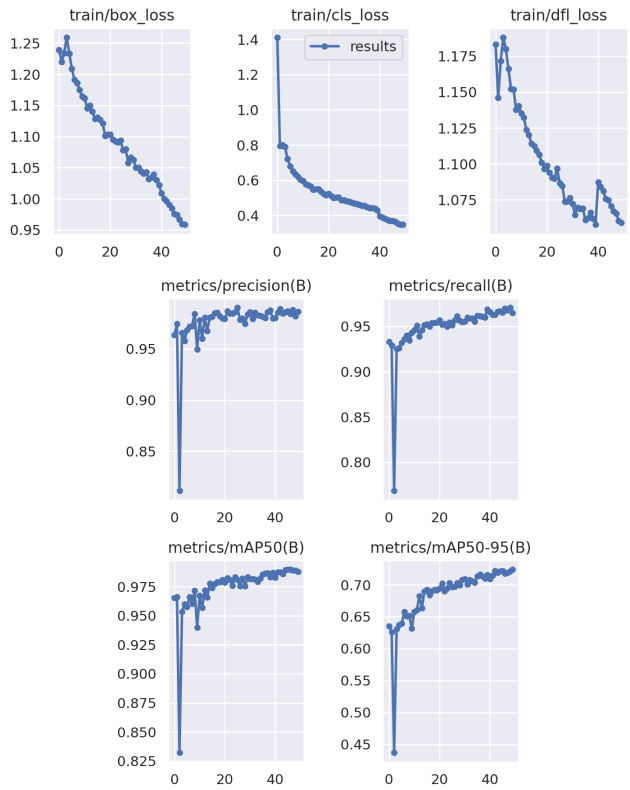



Fig. 9: Essential graphs related to loss functions, precision, recall, and mAP


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## V. Conclusion

In conclusion, our research has combined YOLOv8 with a chaotic-based encryption method to enhance vehicle number plate security, addressing the growing importance of vehicular data security in smart cities. YOLOv8 has ensured accurate object detection, while encryption has prevented unauthorized access, resulting in outstanding accuracy and real-time processing capabilities with a 98% accuracy. Our F1 score, Precision, and Recall results have been 99%, 98%, and 99%, respectively. Additionally, we have achieved a test accuracy score of 98.06% after the K-Fold Cross Validation process while the precision, recall, and F1 scores are at 98.84%, 99.1%, and 98.74%, respectively. This work has represented a significant advancement in security, technology, and transportation, contributing to the privacy, accuracy, and efficiency of vehicle number plate data. In our future work, we are willing to enhance vehicle data security by combining advanced object identification with different encryption processes, ensuring that our approach adapts easily to changes and performs well across various smart city settings.

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