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OPTIMIZING CLEANING EFFICIENCY OF ROBOTIC VACUUM CLEANER

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1.0 ABSTRACT

An essential household chore is floor cleaning, which is often considered unpleasant, difficult, and dull. This led to the development of vacuum cleaners that could assist us with such a task.

Modern appliances are delivering convenience and reducing time spent on house chores. While vacuum cleaners have made home cleaning manageable, they are mostly noisy and bulky for everyday use.

Modern robotic vacuums deliver consistent performance and enhanced cleaning features, but continue to struggle with uneven terrain and navigation challenges.

This whitepaper will take a more in-depth look at the problem faced by the robotic vacuum cleaner (RVC) in avoiding obstacles and entanglement and how we can arrive at a solution depending on the functionalities.

2.0 INTRODUCTION

The earliest robotic vacuums did one thing passably well. They danced randomly over a smooth or flat surface, sucking up some dirt and debris until their battery charge got low and they had to return to their docks. They could more or less clean a space without the ability to understand it.

Today's robotic cleaners have made huge strides over the past few years. They are now delivering more consistent and sustained performance as well as more cleaning features, and are starting to understand their spaces in order to clean them more efficiently. Sensors plays a key role in determining the efficiency of RVC. Some of the important functionality of the sensors are,

- Step detection
- Slip detection
- Floor type detection
- Dust Detection
- Object detection
- Navigation

2.1 Pre Cleaning Challenges

RVC uses different type of sensors like infrared sensor and ultrasound sensors to detect and avoid obstacles in its path, simultaneous localization and mapping (SLAM) for navigation and path planning, bumpers to absorb the collision impact. Even with all of these it is very difficult to detect black carpets, thin carpets, small or soft objects like toys, newspapers, clothes. This forces the users to do the pre-cleaning (such as manually putting the shoes, socks and wires in order) before using the robotic vacuum cleaner, making the cleaning process a hassle.



3.0 REDUCING HUMAN INTERVENTION DUE TO WEDGING AND ENTANGLEMENT

The primary issue with traditional RVC is human assistance. The RVC should be smart enough to detect and take individual decisions “on its own” during maneuvering through the objects.

The powerful alliance of Computer Vision and Artificial Intelligence (AI) makes the traditional vacuum cleaner “smart”. Deep Learning-based methods like Object Detection, Classification, and Segmentation aids the RVC to work with sheer efficiency without affecting the cleaning performance.

So, the smart RVC perceives the environment through the mounted camera “eyes”, recognizes the obstacles, and avoids or runs over them before getting intertwined. In general, high end computing speed is required to run an AI model. But most of the RVC uses a lighter processor to save cost and power. So, it is essential to develop the light AI model without compromising the accuracy. Understanding existing object detection tools, techniques, and algorithms play a vital role in optimizing the AI model.

3.1 Object Detection

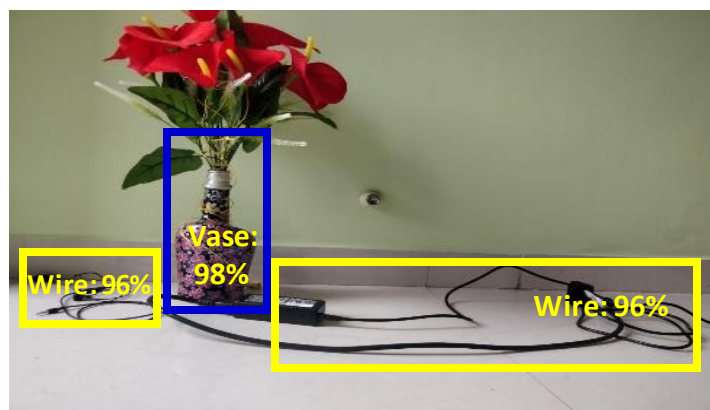


Figure 1: Object Detection

- Object Detection model classifies and localizes the objects in the image in one go. In the below image, the models predicts different instances of the objects present in the image with confidence of the object and location represented by bounding box

- Many State of the Art object detection algorithms like Single Shot Detectors (SSD), SSD-Mobile Nets (V1,V2), You Only Look Once(YOLOV1, YOLOV2, YOLOV3, YOLOV4 and its tiny versions), Region Based Convolutional Neural Network (RCNN) family (Fast R-CNN,Faster RCNN,Mask R-CNN), SqueezeDet etc. performs exceptionally well on variety of objects.
- They are trained on very huge open-source datasets like ImageNet, COCO, PASCAL-VOC, Open Images etc. Pretrained weights are available for such datasets in every implementation.
- Different open-source frameworks like Tensorflow, Pytorch, Caffe, Darknet etc. provides an ecosystem for objects detection algorithms. But such models may not be directly deployed into production

3.1.1 Challenges

To run seamlessly on any devices various factors are involved in selection of algorithm,

- Execution speed in real time
- Supporting frameworks in device-specific cases
- Model size for deployment on resource constraint devices
- Environment compatibility

3.2 Object Detection Algorithm

- Object detection pipeline involves following steps:
- Data collection and training the Deep Learning (DL) network
- Fine-tuning the network to achieve highest possible accuracy with minimum loss
- Optimizations in in terms in execution time before and after deployment of model
- Data unavailability is the major roadblock in case of training custom classes. Data collection, labelling in case of supervised learning and cleansing is laborious task. A good train dataset should have balanced and uniform data distribution

- The network (training) is responsible for learning the salient and statistical features of the objects when an image is passed through it. The layers involved in feature selection are convolutional layers, pooling layers, batch normalization layers, kernels (filters), activation functions(to add non-linearity) , up sampling and down sampling layers, route layer etc.
- During training, in forward propagation the model tries to learn the features (vectors) and stores in the form of weights when images are passed iteratively in batches. Loss is calculated using difference between the “actual” vectors and “learnt” vectors or weights.
- In Backpropagation, optimizers help in minimizing the losses by adjusting the weights using gradient descent methods
- The last layers are fully connected or convolutional layers for classification of object and regression for localizing using bounding boxes

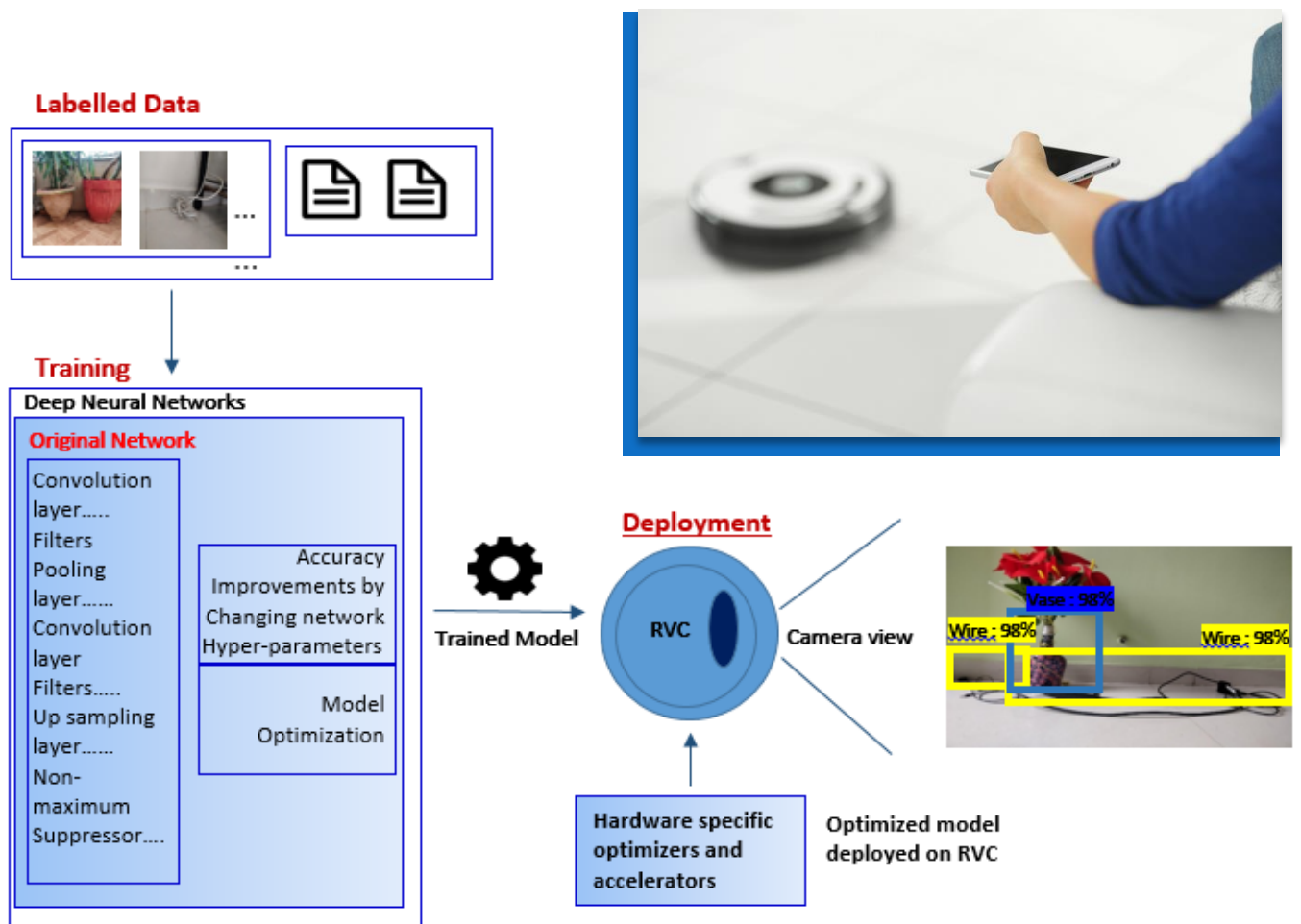


Figure 2: Overall Object Detection Pipeline

3.2.1 Challenges

- Data unavailability is the major roadblock in case of training custom classes. Data collection, labelling in case of supervised learning and cleansing is laborious task. Due to practical limitations ,resources may not be available always
- In Object detection, the performance can be less due to high number of missed and false detections, no or bad localization of objects, very low classification probability and many more reasons.
- This can be due to bad dataset, algorithm is not suitable for required use case, hyper parameters not tuned for custom data, network's incapability to learn the features, overfitting to train data etc.
- So retrospection is a crucial and time consuming process in object detection pipeline. From experimenting with multiple trails of network parameters to achieving a good dataset for training and testing, achieving good accuracy does involves a lot of experimentations



3.3 Approaches

- Data plays a pivotal role in training any object detection algorithm. A good training dataset should have:
 - Good resolution images in sufficient number with balanced classes
 - Data diversity in object orientations , variations with scales , occluded object conditions
 - Background variations ,different Lightning conditions(bright or low light)
 - Augmented data to make it more robust. Addition of noises like motion blur or Gaussian blur make it more robust in real-time environment
 - At network level, parameters tuning is important to improve accuracy
 - Deciding upon number of epochs, learning Rate (Static or Dynamic) and Early stopping ,changing network layers to improve the feature extraction capability without overfitting, use of pretrained weights for initialization
- Synthetic dataset generation methods like Generative Adversial Network (GANs), Computer Graphics(CG) etc. proves beneficial in many scenarios where data availability is difficult
- Semi-supervised Methods like Few Shot learnings, One-shot learnings with few labelled data works remarkably in data crunch conditions
- Ensemble learning are helpful for more more accurate predictions



3.4 Optimization

Deploying such intensive and high computational networks requires high-end capability GPU devices. For real time applications running such heavy network on resource-constraint device with maximum efficiency is a big challenge. So optimizations of algorithms while maintaining the accuracy constitutes the key for successful deployment.

Neural networks (NN) are developed using CUDA based frameworks usually on NVIDIA GPU for reduced training time. CUDA stands for Compute Unified Device Architecture which is a parallel computing platform and application programming interface (API) model created by NVIDIA. But CUDA enabled GPUS are only available for NVIDIA and does not support other hardwares. But these boards often support open GPU compute standard known as OpenCL

- OpenCL is used to program on heterogeneous CPU or GPU devices supported by AMD, Intel, ARM, Qualcomm Snapdragon. So conversion of all the Deep learning layers written in CUDA to OpenCL for executing the algorithm on other edge devices solves the problem from cross board execution
- Customized OpenCL kernels implementation using different math based libraries provides additional increase in speed to optimize matrix multiplications and other convolutional operations
- With hardware specific open source optimizations tools like ARM NN and ARM Compute Library the Machine learning (ML) based models can run efficiently on Arm based platforms. They provide support for frameworks like Caffe, Tensorflow and ONNX



- NNPACK is also a computational acceleration package for which supports neural network frameworks, such PyTorch, Caffe2, MXNet, tiny-dnn, Caffe, Torch, and Darknet on mutli-core GPU's.

This is an overview of basic object detection pipeline and what are the challenges in using this model. The solutions proposed makes possible seamless deployment of object detection model in RVC providing additional support in cleaning performance



4.0 IMPROVED CLEANING PERFORMANCE OVER DIFFERENT SURFACES

Today's robots might stay on course perfectly well when the route is flat, but most can be stopped in their tracks by a slight tilt in the surface, such as a transition from wood to carpet or when trying to pass over a cord or wire. They may encounter a slight incline and attempt to power over it, only to wind up drowning in a dog's water bowl or worse.

The RVC should be smart enough to decide when and where the right amount of suction power to be used and in case of wet mopping the RVC should not run on the carpet. Floor type detection is the key factor to make the decision.

4.1 Dead Band Zone

In general ultrasound sensors are used to detect the floor type, Ultrasonic technology is able to Determine the hardness of a target, based on the strength of the received echo amplitude observed by the sensor. Harder surfaces like tile reflect a stronger echo than softer surfaces like carpet, with this echo different floor type can be easily identified.



- Ultrasonic sensors can detect a variety of materials, regardless of shape, transparency, or color
- Certain objects can be more difficult to detect, like angled surfaces that direct the echo away from the sensor, or permeable targets like sponge, foam, and soft clothing. These absorb more reflected ultrasonic energy
- It can detect black carpet. But, when the sensor is too close to the source (Dead band Region) it will not detect the echoes. So, it is difficult to mount on the bottom side of the RVC. The dead band distance varies from 44mm to 305mm depends on the model

- It is not able to detect thin object lesser than 5 cm width. So it cannot detect thin obstacles like furniture legs, wires, toys

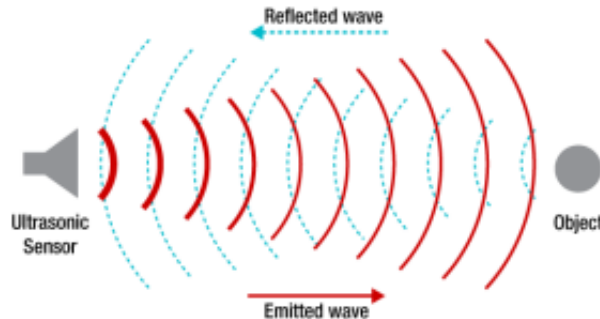
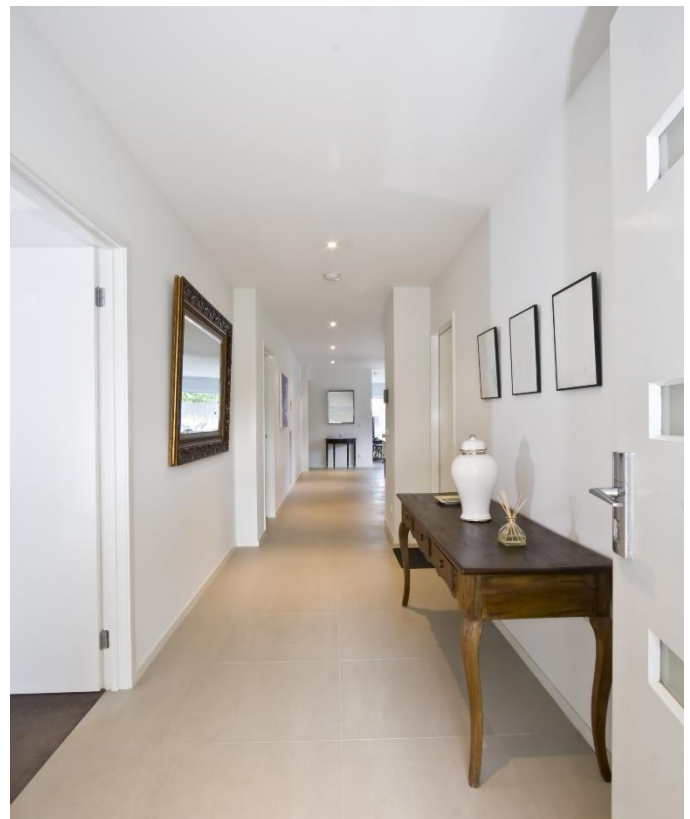


Figure 3: Working Principle of Ultrasound sensor

4.2 Non Reflecting Surfaces

Optical-based sensing technologies have a similar principle to ultrasonic technology. Instead of using sound waves, however, optical technology uses LEDs to emit light waves and detect the time-of-flight, which can then convert based on the speed of light principle. IR Laser with IR Camera also works in the same principle. The speed of light is much faster than the speed of sound, therefore optical-based sensing is faster than ultrasonic.



- It does have limitations in bright ambient lighting conditions and smoky or foggy environments, however, as these environments make it difficult for the light receptor to detect the emitted light.
- It has limitations in detecting clear materials like glass or water. Light passes through these materials
- Not possible to detect black carpet, because black color didn't reflect the light rays

- It does have limitations in bright ambient lighting conditions and smoky or foggy environments, however, as these environments make it difficult for the light receptor to detect the emitted light.
- It has limitations in detecting clear materials like glass or water. Light passes through these materials
- Not possible to detect black carpet, because black color didn't reflect the light rays

4.3 Floor Type Detection

From the above sensor study, Ultrasound sensor have limitation of dead band distance and Optical based sensor have limitation of bright ambient lighting, light ray absorption. Both these cases makes black carpet detection impossible. Today almost all the manufacturers facing this problem of black carpet detection.

So after extensive research we found, using of Optical Mouse (IC - ADNS2620) technology will the address the issue of black carpet detection. The technology uses a LED as light source which emit the light to the surface.

Then the reflected image will captured using CMOS (camera). The output of will be in the form of Pixelated image. The difference in pixelated image will indicate different floor type.

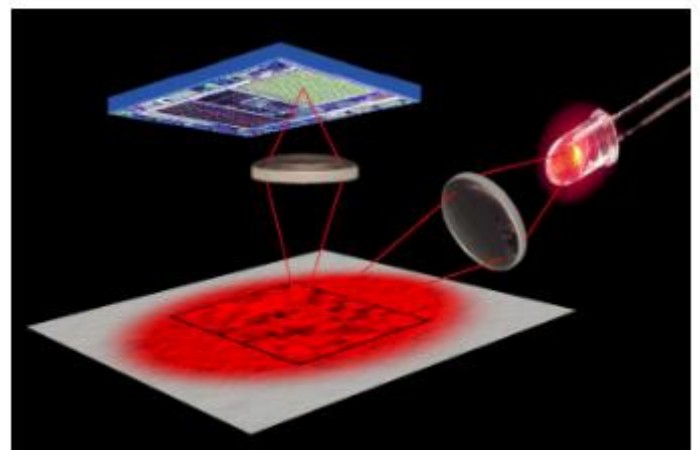
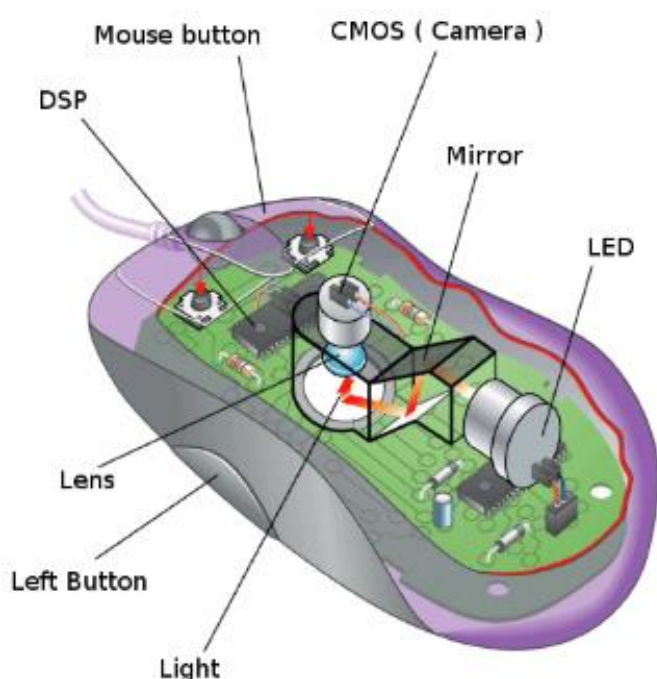


Figure 4: Working Principle of Optical Mouse

4.3.1 Pixelated Data from the CMOS (Camera)

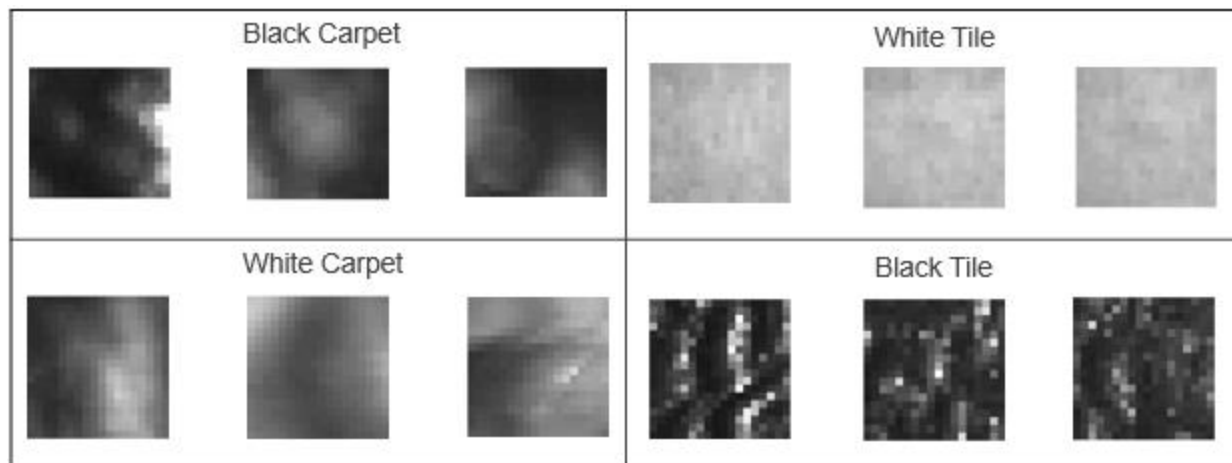


Figure 5: Pixel Data of Different Floor Type

The above pixel data collected from the mouse shows clear variation between carpet and tile floor. To improve the image quality, more LED can be added with high power camera. With the help pixel data using Digital Image Processing Technology the RVC can differentiate and identify the floor types.



5.0 CONCLUSION

This whitepaper has explained some of the critical challenges like floor type detection and issues with wedging of robotic vacuum cleaner, which is standard across most present-day RVC available in the market. The main focus is to provide an economical, innovative, and robust solution to be implemented on the next generation RVC. We saw two methods using optical sensors and machine vision-based algorithms to address these challenges.

This document can be used as a quick guide to understanding the functionality of the different sensors and black carpet detection. Also, to understand the methods of developing a light AI model that can run in low-end capability GPU without compromising the accuracy.



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ABOUT TATA ELXSI

Tata Elxsi is a design-led innovation company that blends technology, creativity, and engineering to help customers transform ideas into products and solutions aspired by the consumers. We are a part of the \$100 billion Tata group addressing the consumer products, healthcare, media & entertainment, transportation, communications, and semiconductor sectors.

Tata Elxsi has been supporting leading home appliance OEM from the past 20 years, providing them support in product management starting from consumer research, industrial design, and product engineering, including mechanical, hardware and software, prototyping, and manufacturing support. The home appliance practice also brings skills in AI and robotics, IoT, analytics, and other advanced technologies to help customers transform devices with connectivity and intelligence needed for the digital future.

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