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Research Article

# A Contactless Palmprint Imaging System Design Using MediaPipe Hands

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## Abstract

Palmprint has been widely used in biometric systems because of its durability and reliability. To avoid recognition performance degradation, dynamic region of interest extraction is a critical step for these systems. In this study, a low-cost contactless palmprint imaging system has been designed and a dynamic region of interest extraction method has been applied to palmprints using the MediaPipe Hands framework. Since the need for hygienic touchless systems has been realized in the post-COVID-19 pandemic world, a low-cost imaging system has been proposed to capture the user's hand at a distance without touching any platform. The region of interest of the user's palmprints in a real-time video stream has been extracted dynamically. This study creates a paradigm for future studies on palmprint imaging. With conducted experiments, the potential of MediaPipe Hands in terms of speed and accuracy on mobile palmprint imaging applications has been realized on Raspberry Pi 4. This work demonstrates that the employed hardware and proposed hand-tracking algorithm are suitable for designing low-cost contactless palmprint imaging systems in non-controlled ambient light conditions. For recognition purposes, a database will be released soon.

*Keywords:* Contactless biometrics, Imaging system, MediaPipe Hands, Palmprint, Region of interest.

## 1. Introduction

Hand-based biometric traits such as fingerprint, finger vein, palm vein, and palmprint have received much attention in recent years. Owing to the low-cost and user-friendly structure of image-capturing platforms, these biometric features have been deemed promising and popular [1]. Among these traits, palmprint provides extra advantages. Palmprint requires neither high-resolution images nor complex imaging platform designs. Palmprint patterns can be observed despite the low-image resolution [2]. For real-time mobile applications, low palmprint image resolution provides a small storage need and short computation time [3]. Moreover, a palmprint is robust against spoofing attacks since a user can hardly ever leaves palmprint information unintentionally on touched platforms compared to a fingerprint [4]. With extracted palmprint information by a determined area of palm as a region of interest (ROI) for feature extraction, biometric systems ensure minimum biometric information loss and maximum recognition accuracy at the same time. However, it is not easy to extract palmprint ROI dynamically due to the varying orientation of the hand on the imaging platform and variations in the user's hand size [3].

Dynamic extraction of the region that contains biometric information accurately is a key preprocessing step to increase recognition performance [5]. Evaluation of the extracted ROI rather than the whole acquired image provides shorter processing time and lower memory usage. Researchers have proposed various solutions for ROI localization in the literature. As the main steps of ROI localization, hand boundary detection, and palm region extraction on the detected hand can be listed [5]. There are roughly 3 hand boundary detection methods used for palmprint images: predefined window-based methods, mask-based methods, and threshold-based methods. These methods achieve considerable performance despite possessing some drawbacks. Predefined window-based methods do not possess an adaptive structure not to be affected by changes in the user's hand size and variations in hand orientation [6]. Mask-based methods are vulnerable to background noise while detecting hand boundaries [6]. Lastly, threshold-based methods are severely affected by unevenly distributed illumination of the imaging environment [7]. All these methods are commonly in use for the extraction of ROI of existing publicly available palmprint datasets. However, none of these methods can detect the hand boundary perfectly. To overcome these drawbacks and provide adaptive solutions to ROI extraction, some ROI extraction methods have been proposed in the literature.

Li et al. [8] utilized a maximum inscribed circle. Rather than a rectangle-based positioning, they used a circle-based segmentation approach. They maximized the extracted ROI by increasing the radius of the extracted region from the center of the palm to the contour of the palm. Poon et al. [9] used the finger web between the index finger and middle finger and the finger web between the middle finger and ring finger to extract ROI dynamically. They utilized one of these 2 webs as an axis on which the maximum square region is centered. They proposed using elliptical half-rings to avoid rotational errors on extracted ROI images. Wang et al. [10] extracted the contour of the hand with a Sobel filter. They calculated the distance between the midpoint of the wrist and each point of the contour to find corresponding valleys in the distance profile while extracting ROI. Thus, they tried to ensure a hand-size invariant solution for a robust ROI extraction. Lin et al. [11] showed the effectiveness and usability of ROI extraction methods on palmprint and palm vein images. By utilizing preprocessing operations before extracting ROI with maximum inscribed circle and centroid methods, they presented a robust extraction for palm vein and palmprint. Jaswal et al. [12] proposed a novel ROI extraction method using Bresenham's line algorithm. They extracted ROI by drawing a square with the longest possible side using the base points at the finger bottoms. They evaluated the performance of the proposed method on 3 different databases. Yan et al. [13] presented a robust solution for palm ROI extraction using a video stream. The imaging system located the position of the palm using a different color space in grabbed video frames dynamically. Kocakulak and Acır [14] proposed using Google's MediaPipe Hands framework for finding reference points on images of the IIT Delhi Touchless Palmprint Database. They used MediaPipe Hands for dynamic ROI extraction and avoided the cumbersome structure of conventional hand boundary detection methods. They reduced the required time for ROI extraction on this dataset considerably with the help of the lightweight structure of MediaPipe Hands while having accurate and adaptive results.

Based on the review of existing ROI extraction methods, MediaPipe Hands, which is a machine learning-based hand tracking framework and is commonly used for gesture recognition and hand-based augmented reality applications, has been utilized to extract ROI dynamically. Since quicker and more hygienic solutions are expected from touchless systems with more degrees of freedom for the placement of the hand, the proposed imaging system on Raspberry Pi with a web camera has been utilized in this framework. Despite varying illumination and hand rotation on the imaging platform, MediaPipe localizes the hand and finds the reference points on the user's hand for dynamic ROI extraction consistently owing to being well-trained with annotated images [15]. This framework provides a novel solution that has 2 hidden models working together. The first model detects the palm side on a full-hand image, and the second model finds the coordinates of 21 reference points on the detected palm.

The rest of this paper is organized as follows: Section 2 presents existing palmprint datasets and contactless palmprint acquisition devices in the literature. Section 3 introduces the proposed contactless palmprint acquisition system and describes the utilized ROI extraction method in detail. Section 4 presents the conducted experiments for this extraction method on the designed device. Lastly, Section 5 concludes this paper with an outlook on future works.

## 2. Related Works

### 2.1. Databases

With the recent studies on palmprint imaging technology, the number of publicly available datasets has increased. In Table 1, some publicly available palmprint databases are listed. In near future, a publicly available palmprint database will be released using the proposed design in this study. The number of subjects and samples will be sufficient compared to the listed datasets to meet the needs of deep learning-based applications.

**Table 1.** Public Palmprint Databases.

| Datasets | Number of Subjects | Number of Images | Image Format |
|---|---|---|---|
| CASIA Palmprint Image Database [16] | 312 | 5502 | JPEG |
| CASIA Multispectral Palmprint Database [17] | 100 | 7200 | JPEG |
| PolyU-IITD Contactless Palmprint Database [18] | 600 | 12000 | BMP |
| IIT Delhi Touchless Palmprint Database [19] | 230 | 2601 | BMP |
| Tsinghua Palmprint Database [20] | 80 | 1280 | JPEG |

### 2.2. Contactless Acquisition Device Designs

In this section, some of the contactless palmprint imaging devices are listed. Chen et al. [21] designed a system to illuminate palmprints with a digital camera and 23-watt lights which are positioned appropriately. They proposed a low-cost and touchless acquisition mechanism to capture palmprint and hand shape simultaneously. Hao et al. [17] built a multispectral imaging system. They used a group of LEDs and switched them sequentially to collect data under different lighting conditions. Using multispectral imaging techniques on a contactless imaging platform via a dedicated device, they evaluated the effect of multispectral imaging on the obtained verification performance. Kumar [19] utilized fluorescent light to illuminate palmprints in a semi-closed box. Using a pegless design, the palmprint images were captured despite not being user-friendly and narrow box design. Poinsot et al. [22] used a web camera and they captured palmprint images under natural light without any lighting equipment. In a controlled environment using green background, they located the user's hand and extracted palmprint images. Michael et al. [23] built a palmprint imaging system with a low-cost web camera and a 9-watt light bulb inside a semi-closed box. Without any markers and gloves, ROI images of palmprint and knuckle print were captured. Using a black box as an enclosure, they tried to avoid the negative effect of background light reflection. Ferrer et al. [24] designed a biometric system that works fine under visible light and infrared light owing to its bi-spectral structure. They used 2 low-cost web cameras to capture hand geometry and palmprint at the same time. Morales et al. [25] designed a multisampling image acquisition device that captures images of a hand with vertical movement between two plates. With its contactless structure, the proposed design could capture hand shape and palmprint images to increase the obtained performance using multimodality. Aykut and Ekinci [26] developed a system using a low-cost CCD camera with an iris lens. With the proposed design by fixing the distance between the camera and the user's hand, they resolved the problem of the varying distance between the user's hand and the camera. Xiao et al. [27] designed a low-cost palmprint acquisition device under natural light using a semi-closed box structure. This device captures the whole hand-based acquisition rather than part hand-based acquisition. Liang et al. [28] built an acquisition device to take high-quality palmprint images. Using a binocular CMOS camera, the imaging system captured the user's palm vein and palmprint simultaneously. They used a height reference to make volunteer subjects place their hand. We have designed a system by considering the main advantages and disadvantages of these listed imaging devices. In this study, the distance between the user's hand and the camera has been calculated and fixed with the help of the image projected on the tablet screen with a software solution. This provides a user-friendly structure while guiding users on the imaging platform. Without using any closed or semi-closed box, palmprint images have been captured using a low-cost camera which enables a low-cost system design. With a low-cost camera and MediaPipe Hands framework, palmprint image samples have been collected in real-time under natural light. Thus, the design system has worked accurately without using any lighting equipment. The details of the proposed palmprint acquisition device are given in the next section.

## 3. Results and Discussion Design and Implementation of Acquisition Device

### 3.1. Experimental Setup

The experimental setup is shown in Figure 1. The image acquisition hardware consists of a processing unit, camera, and tablet screen. We have used Raspberry Pi 4 Model B and Raspberry Pi Camera V2.1 since they have a low-cost and compact design. The camera has been mounted on a tripod to capture the hands. The camera and the user's hand have been placed both on top of a table to capture effective images. First, images are captured with the camera. Then the user's hand distance to the camera is calculated and the hand image is processed with the help of the MediaPipe Hands framework on Raspberry Pi. Lastly, extracted images are monitored on the tablet screen.

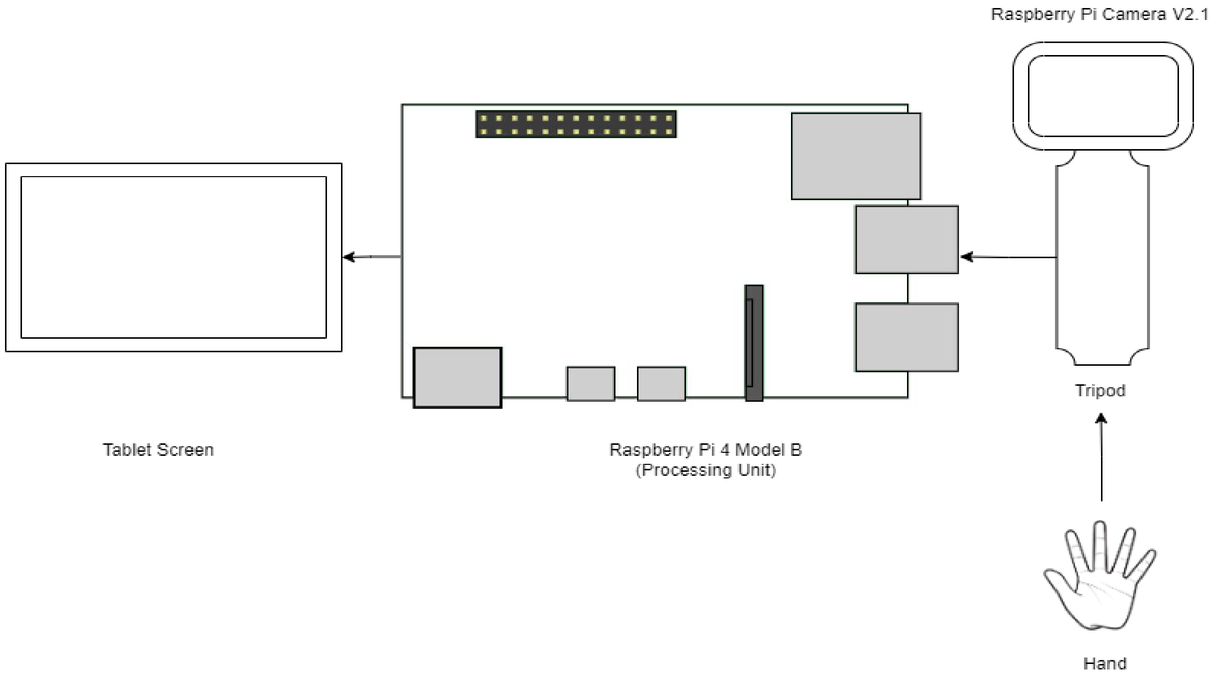


**Figure 1.** The experimental setup

### 3.2. Proposed ROI Extraction Method

The proposed dynamic ROI extraction method has 5 major steps. These steps are shown in the block diagram in Figure 2.

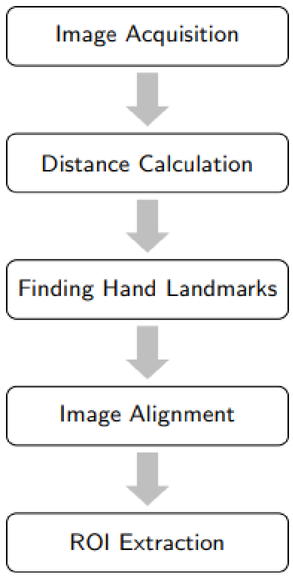


**Figure 2.** Primary steps in the proposed method

#### 3.2.1. Image Acquisition

The webcam captures palmprint images in a continuous video stream. The user can freely place his hand across the camera and he can move his hand during the acquisition.

#### 3.2.2. Distance Calculation

A Python-based software solution has been used to give feedback to the users about the positioning of the hand. Using the hand landmarks provided by the MediaPipe Hands framework, the position of the index finger, middle finger, and ring finger is fixed. The positions of the knuckles of these fingers are tracked. After getting positional approval from these 3 fingers with color indicators on the screen, the ROI extraction process for palmprint continues with distance calculation. To find the distance between the hand and the camera, firstly the hand is detected by the MediaPipe Hands. If the hand is present on the platform, landmark 5 and landmark 17 are used to calculate the actual distance in centimeters. Based on the distance between the x and y pixel coordinate values of these 2 landmarks, the Euclidean distance is calculated so as not to deal with rotation problems while finding the actual distance accurately. By defining a quadratic function to find the relation between the Euclidean distance of landmarks and their corresponding actual camera distance, the actual distance is estimated roughly with the help of curve fitting. The tablet screen is used to display the real-time video stream of the capture. Thus, the distance between the user's hand and the camera is fixed without using any physical distance sensor.

#### 3.2.3. Finding Hand Landmarks

MediaPipe Hands is an open-source framework developed by Google to estimate the coordinates of 21 hand landmarks from a web camera [15]. These landmarks are enumerated as shown in Figure 3.

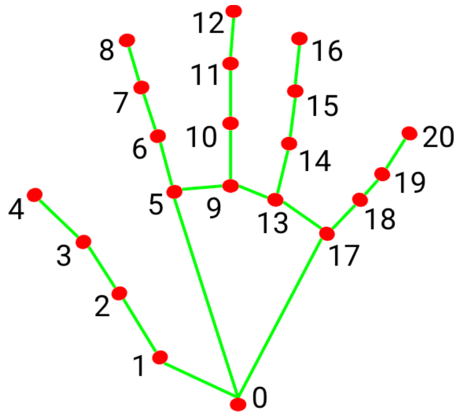


**Figure 3.** Hand landmarks of MediaPipe Hands [29]

MediaPipe Hands is mainly used for hand-tracking purposes on video data by estimating the pixel coordinates of these landmarks from 2D images. Roughly, MediaPipe Hands consists of 2 machine-learning pipelines. These are the palm detection model and hand landmarking model [29]. However, MediaPipe Hands hides the complexity of these 2 models and provides a lightweight solution. With its well-trained and considerably robust model in hand detection, it can catch hand landmarks even in extreme cases. Since it has a quick response time, it has been used to get the coordinates of each landmark while extracting dynamic ROI from the acquired video stream as shown in Figure 4. Without any parameter adjustment, the vanilla version of this framework has been applied to the real-time video stream.

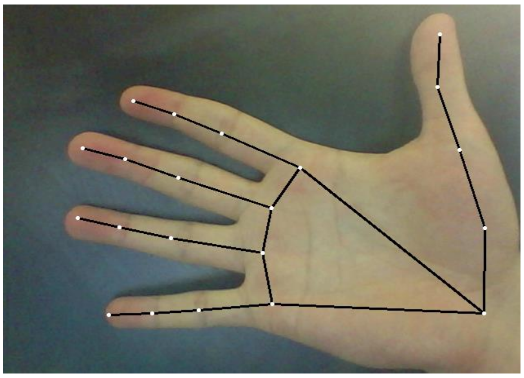

**Figure 4.** Detected hand landmarks on video data

### 3.2.4. Image Alignment

In the real-time video stream, hand displacement exists due to touchless and unguided imaging system preference. Hand displacement can be clarified as a case where the middle finger does not parallel the y-axis. For these images, hand displacement adjustment is conducted according to the extracted landmark of the middle finger to avoid the loss of a portion of the palm area in the ROI extraction. By using the angle between landmark 5 and landmark 9, or the angle between landmark 17 and landmark 9, the candidate rotation angles are computed. The greater of 2 angles to estimate the alignment angle is preferred. So the rotation angle θ can be computed as in Equation 1 [30]. In this equation, x_1, y_1 are the coordinates of landmark 9 and x_2, y_2 are the coordinates of landmark 5 or landmark 17.

$$\theta = \left(\frac{y_2 - y_1}{x_2 - x_1}\right)\left(\frac{180}{\pi}\right) \tag{1}$$

### 3.2.5. ROI Extraction

The detected hand landmarks of MediaPipe Hands have been used to find the borders of the palmprint. On the aligned image with detected landmarks, the boundaries of the extracted ROI have been determined by using the x and y pixel coordinates of landmarks 0, 5, and 17. While extracting the ROI, the farthest points, that provide an ROI of palmprint without any background, have been chosen horizontally and vertically. y coordinate of landmark 0 has been used as a lower limit on the y-axis, and the maximum of the y coordinate of landmarks 5 and 17 has been used as the upper limit on the y-axis. As a lower limit on the x-axis, the x coordinate of landmark 0 has been used, and lastly, as an upper limit on the x-axis, the x coordinate of landmark 17 has been used.

MediaPipe Hands framework tracks and detects the ROI automatically when a hand object is detected in the video stream at a certain distance from the camera. Despite varying illumination, the utilized hand-tracking framework enables the system to find key points to align hand images. Thus, the proposed system locates and extracts the ROI efficiently as shown in Figure 5.

**Figure 5.** A sample ROI image

## 4. Results and Discussion

All experiments have been carried out on Raspberry Pi 4 Model B with 4GB RAM and 64-bit quad-core processor. The proposed ROI extraction method has been implemented in Python 3.7 using Visual Studio Code IDE. The Python script has been used to build the system and MediaPipe Hands has been imported using OpenCV.

The performance of the proposed imaging system has been evaluated qualitatively rather than quantitatively. By using a dedicated thread, which is separate from the main thread, the frames have been read from the Raspberry Pi Camera. The frame-per-second (fps) rate of the camera sensor has been increased gradually. Thus, the most recent frame, which is read by the camera, has been grabbed at any moment in time. The performance of the proposed system has been evaluated on these grabbed images. Despite varying fps rates, MediaPipe Hands locates the palm and detects the reference points efficiently for each frame. As depicted in Figure 5 with a sample ROI image and in Figure 6 with detected reference points for flat and stretched hand positions under varying illumination, the proposed system can extract the palmprint ROI accurately. As a metric, the accuracy can be defined as the ratio between the number of perfectly extracted ROI and the total number of samples in the database. Correctly extracted ROI is an image that does not contain any background and only contains the palmprint. In these experiments, various scenarios have been used to test the efficiency of the proposed method such as hands with different poses and hands with accessories such as rings, hand tattoos, etc. Some of the sample images of these scenarios are given in Figure 6. However, the proposed method extracts ROIs dynamically even in these extreme cases. The delay interval between capturing sequential palmprint images is about 3 seconds. Since hand boundary detection or border tracing algorithms are not robust enough to ensure the stability of the proposed method due to complicated background noise, none of these algorithms have been used. The ROI segmentation accuracy could have been increased with additional preprocessing operations before the application of MediaPipe Hands or it could have been maximized with more proper parameter selection during the application of conventional methods. However, the main goal of this study is to show how well the MediaPipe Hands framework worked in detecting palmprint boundaries and extracting ROI from acquired videos. Our motivation is to develop a device without any physical sensor or guidance which restricts the user. The proposed ROI extraction method can be also used for palm vein and hand geometry biometrics since these biometric traits also focus on the same region that provides biometric features on the hand images.

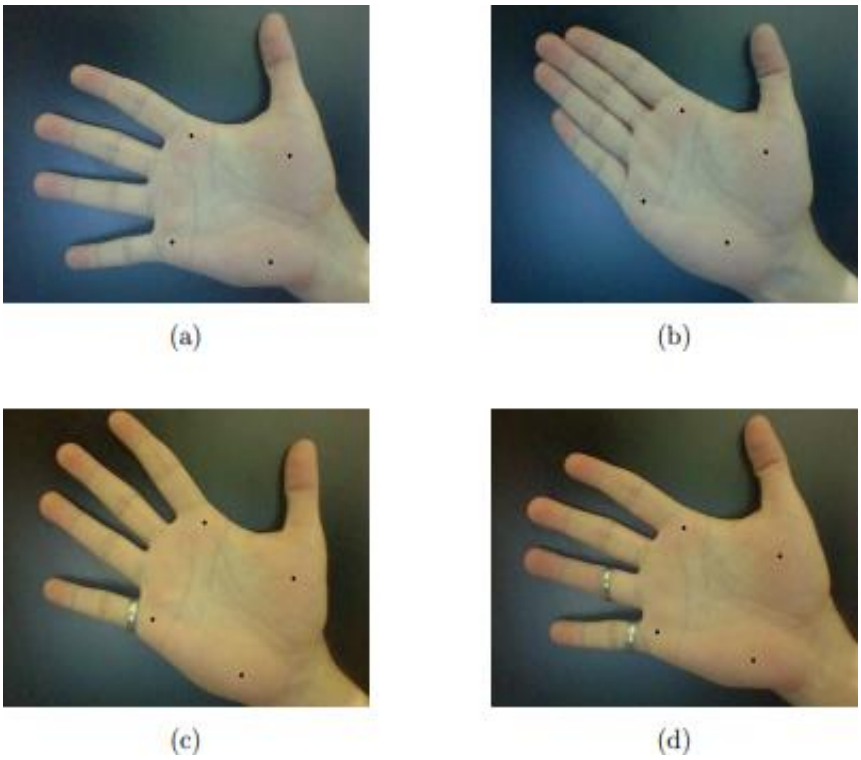


**Figure 6.** Image samples with detected hand landmarks (a) Stretched hand, (b) Flat hand, (c) Stretched hand with a ring, (d) Stretched hand with 2 rings

To increase the user's comfort, a contactless method has been proposed for image acquisition since the current trend in device design is towards an out-of-box structure. Although the contactless method causes translation and rotation problems, MediaPipe Hands and the proposed software resolve these problems efficiently. Thus, there will be no physical contact between the device surface and the user's hand during the image acquisition in the post-COVID-19 pandemic world. Moreover, the usage of MediaPipe Hands provides information about the hand on the platform. Whether the acquired image contains a right hand or a left hand, this information can be extracted with the help of this framework.

## 5. Conclusion

By their nature, recognition systems offer quick solutions, and they are used for security and privacy purposes in daily life. In this study, we have proposed to use MediaPipe Hands, which is a machine learning-based hand-tracking framework, to track hands on the imaging platform. Rather than analyzing the spatial domain and frequency domain, this study uses hand landmarks provided by this framework for ROI extraction. Since recognition performance does not solely depend on ROI localization but also on other factors such as applied feature extraction methods and used parameters, it has been only aimed to design an imaging system and extract ROIs of captured palmprint images. The developed imaging platform is effective, contactless, and hygienic. Its ROI extraction method is superior to conventional methods while finding palmprints in terms of time parameters. In future work, a large-scale palmprint database will be released with a sufficient number of users, samples, and sessions.

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