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# Fast region based convolutional neural network ResNet-50 model for on tree Mango fruit yield estimation

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**ABSTRACT**

The foundation of the Indian economy is agriculture, the amount of land available for agricultural activities has decreased due to numerous factors. To fulfill the demands of the expanding population, the maximum yield must be produced on the least amount of land that is accessible. To overcome the challenges of agriculture, many researches have been carried out to adopt technology into agriculture. As India is one of the world's top producers of Mangoes and has a vast market, and has encouraged extensive Mango farm development. Automatic yield estimation of Mangoes in the early stage is important to improve the quality and quantity of production which improves both domestic and export markets. The work proposes a fast region (FR) based convolutional neural network (CNN) residual network (ResNet)-50 model for efficient deep learning-based Mango crop yield estimation system to count the Mango fruit from the images of individual trees. A temporal Mango fruit database is used to estimate the yield of on tree Mango fruits, and a framework is provided to estimate Mango fruit yield in red, green, and blue (RGB) image. This experiment shows that the suggested FRCNN ResNet-50 model attained a better accuracy of 98.20% on the proposed dataset.



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## 1. INTRODUCTION

Remote sensing technologies play a significant role in research on horticultural tree crops and precision agriculture. In horticultural regions, data sets from various remote sensing platforms, including satellites, airplanes, and unmanned aerial vehicles (UAVs), have been used to measure and map significant biophysical and functional aspects [1]. The methods used to estimate tree fruit yields include visual inspection of the state of the trees, manual fruit counting, and knowledge of prior production histories. The current best approach for estimating fruit load involves manually counting a sample of trees, however, this is labor-intensive and occasionally inaccurate [2]. The exact pixel-by-pixel instance segmentation of fruit and the proper identification of picking sites are two challenging tasks that the vision system of a fruit-picking robot must do. The picking performance of the robot is insufficient and its application is not widely used since the vision system performs these jobs in an unsatisfactory manner [3]. However, the manual assessment and recording of panicle number and stage is a tedious task that relies on the experience of the observer. Thus, Mango identification and categorization using an automated method might help with orchard management. Machine vision has been applied for the assessment of the level of Mango for several trees, where the Mango is easily distinguishable from the background based on color threshold [4]. Green Mangoes on trees may be visually detected using UAV technology. In this work, green Mangoes were photographed using a UAV, and training sets were created to teach the residual network (ResNet)-50 model to recognize the Mango. The suggested approach includes visual technology assistance for intelligent calculation of the amount of Mangoes, which could reliably identify green Mangoes [5]. Because of their enormous potential as carbon sinks, these types of tree-based ecosystems have received much research and promotion [6]. The resource present at satellite has near-infrared (NIR) with high spatial resolution which was used for estimating the Mango orchards. The texture of Mango orchards can vary depending on how thick and sparse they are as seen in satellite images [7]. Absolute percentage error (APE) of the estimate in comparison to a reference measurement of Mangoes can be used to describe how well fruit load estimation's function [8].

Detected Mango is tracked between frames and added to a cumulative count only when not present in a predicted position for several frames. This approach allows a greater proportion and possibly all Mangoes per tree to be detected [9]. Fourier-descriptor approach is used to categorize fruits based on their forms and determine the Mangoes' mass from captured photos. The volume of the Mango was calculated using a cylinder approximation analysis approach, and a correlation was created using the data gathered [10]. Although visual occlusion challenges the link between image-based fruit counts and the real amount of fruit on the tree, that cannot be resolved by increased classification performance [11]. A large portion of research has concentrated on increasing the accuracy of fruit detection inside imaging. Almost all of the literature on the subject mentions this issue [12]. Since fruit detection in colour imagery has improved over the past five years thanks to work by CNN and the machine vision community, it could be argued that attention should now turn to fruit counting systems, which are made to collect and analyze orchard imagery in a way that provides the highest accuracy in contrast to actual field and harvest fruit measurements [13]. Although continuous measurement of canopy spectra is useful for tracking plant biophysical and biochemical properties, it is not as simple as using sap flow sensors in the field [14]. Some of the significant issues encountered throughout the study were prominent flushed regions, occlusions from leaves, stems, and branches, as well as non-uniform lighting in distinct fruit segments [15]. Study proposes a review of over the past thirty years, of automating the process of sizing fruits and vegetables by moving from mechanical means to machine vision [16]. Proposed work suggests a visual object tracking network called YOLO-deepsort to count and identify tomatoes at various stages of growth. Predicated on the YOLOv5s framework [17]. The CNN-based detection model center net was used for an input picture series to identify the fruit areas in the detector and the image produces a collection of identified bounding boxes. The matching fruit model was used to identify and label the discovered same identities of fruits between subsequent images. A faster R-CNN (FR-CNN) with modified IoU (MIoU) for detecting fruits utilizing on-plant photos is proposed. FR-CNN with MIoU correctly finds the fruits. Mango and orange are two different fruits used assess the process [18]. A method based on direct calculation of the total fruit load per tree using deep learning CNN has been used to normalize the number of visible fruits and non-visible fruits that existed in the orchards [19]. Information of the five main crop phenology stages of the Mango using sentinel-2 is collected, the sentinel-2 analysis has high temporal resolution with greater analytical options in terms of mapping and modeling vegetation in orchards to produce valuable information for farm crop management [20].

The fast R-CNN technique outperforms R-CNN since, in contrast to R-CNN, which does a convolution forward pass for each item proposal per image, the fast R-CNN algorithm executes feature extraction only once per image in order to create the region of interest (ROI) projections. The primary contributions are mentioned below to enhance the performance of Mango estimation:

- A temporal Mango fruit dataset is utilized and the ROI pooling technique is applied.
- Once the data is processed, fast RCNN-ResNet-50 is introduced to reduce the dimensionality of extracted vectors, which increases system complexity and training time for the classification algorithm.
- Additionally, the performance of fast RCNN-ResNet-50 model is evaluated in terms of f-score, recall, precision, and detecting accuracy.

The organization of this research is mentioned as follows; section 2 provides the explanation and mathematical equations for the proposed method. In section 3 demonstrates the result analysis and its comparison. Finally, section 4 represent the conclusion of this research.

## 2. METHOD

Estimating the output of Mango crops is crucial for early yield prediction, which aids farmers in better yield planning. The segmentation problem is made more complex by the various difficulties that the Mango crop dataset presents in terms of illumination and the background. This section gives the methodology of proposed fast RCNN-ResNet-50 model for the Mango yield prediction which is depicted in Figure 1.

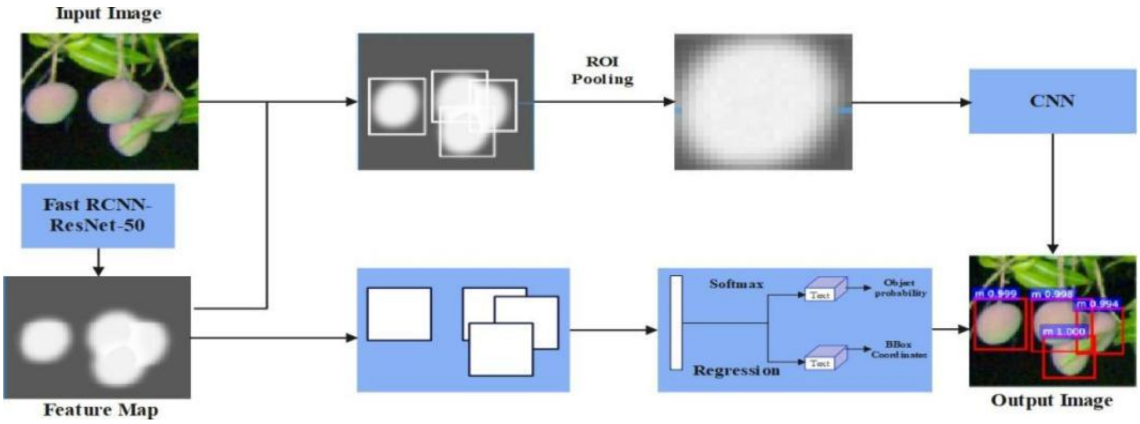


Figure 1. Block diagram for the proposed work

### 2.1. Data collection

The dataset includes images of Mango trees captured with a smartphone's primary camera during daytime using 1920×1080 pixel resolution. Dataset was collected for five monhs, during the first three months of the data collection period, data gathered for every 7 days. Based on fruit maturity, data collection frequency is then increased over the following two months. Each day, 800 shots were taken, including pictures of all the trees from the five different varieties. The photographs are taken during two periods, morning and afternoon, which are coordinated with the movement of the sun. Furthermore, the pictures of these trees have taken at 2 and 3 meters away. The selected trees range in age from 15 to 20 years old. The height of the trees above the ground varies between 7 to 8 feet and each acquired image is roughly 7 to 8 MB in size. There are a total of 21,000 photos in the dataset, only the matured Mango fruit images are used for this study. The dataset is gathered in two sessions over the course of a day, with session 1 taking place between 9:30 a.m. and 10:00 a.m. and session 2 between 2:30 p.m. and 3:00 p.m., respectively. As a result, the obtained photos include a tree's outline, top and bottom views, however, are not subject to the acquisition. The data was gathered over the course of a five-month [21], [22]. The proposed Fast RCNN-ResNet-50 model's efficacy in predicting Mango production is verified using training, validating, and testing databases as shown in Table 1. The research and development of machine learning tasks frequently involve developing algorithms that can learn from data and make predictions about Mangoes.

Table 1. Comparison results of fast RCNN-ResNet-50 model with the existing models

| Model | Fruit | Accurac y (%) |
|---|---|---|
| CNN [23] | Plum | 90.00 |
| FR-CNN [24] | Apple, Mango, Orange | 91.00 |
| Proposed (fast RCNN-ResNet-50) | Mango | 98.00 |

### 2.2. Pre-processing red, green, blue

Red, green, blue (RGB) color space is used in this work, which is useful for color-based object recognition and feature extraction. After the Mango images were captured, certain preliminary processing procedures were carried out and the camera's RGB data for the scene was recovered. The distance criterion of 1.9 m half of the tree spacing was thought to be sufficient to exclude canopy items from neighboring trees because the inter-tree space is around 3.8 m. The RGB pixels of the background area was represented by a different mixing as shown in (1).

$$minF_1 = \sum_{(i,j)\in p} h(||f_1(x_i) - f_1(x_j)| \quad |_2^2 - T_1) + \rho_1 \sum_{(k,l)\in N} h(T_1 + \tau_1 - ||f_1(x_k) - f_1(x_l)||_2^2 \quad (1)$$

were,
$\rho_1 - Weight$,
$x_k, x_l - Larger\ Threshold$,
$x_i, x_j - Smaller\ Threshold$,
$\tau_1 - Different\ class\ samples$ and $T_1 - Distance\ between\ negative\ sample\ pair$

### 2.3. ResNet-50 segmentation

The ResNet-50 is an advanced technique used to classify remotely sensed Mango in the yields to execute the task of Mangoes classification at the pixel-wise semantic segmentation. A typical neural network uses a succession of convolutional layers that are followed by multi fully related layers, which fundamentally abbreviate all input limits into a particular output value of the segmentation. The output of a fully convolutional neural network (CNN) is multi-valued because the layers are not entirely coupled, as well as semantic segmentation has the same pixel size as the input image. The ResNet-50 is also known as the residual network and the key benefit of the ResNet-50 model is that uses the skip connections function to eliminate all the network deficits. The most important concept to comprehend when it comes to the mapping of parameters for adding the input from one layer to the next is the term skip connection. Although, the dimension of the *x* and *F(x)* might not have identical. The spatial resolution of the input image gets a high network shortfall using the CNN network.

Furthermore, segmenting a Mango in the yields is carried out using the linear projection. To match the residual growth of uniqueness, widen the channel and align them with the residual function. In (2) represents a function where x is the input, with F(x), and then passed as input to the following function layer.

$$y = F(x, \{W_i\}) + W_s x \tag{2}$$

Proposed model suggests a foundational network for Mango classification that just uses picture data and perform very well at spotting early-stage illnesses. This network derives from the ResNet50 topology, which was chosen due to its ability to provide widespread usage and cutting-edge performance. However, different baseline topologies or inception can also be used with the proposed crop conditional technique. This network has 50 layers and two 3×3 convolutions that follow each other, followed by 3×3 ROI-pooling operations. This model consists of 7×7 high-level features of Mango images that are combined with average pooling operation to produce an image size of 2048. In this work, the ResNet-50 image segmentation is performed with the skip connection mapping function of the system. Initially, the input images are taken in the formation of RGB image type. Then the ResNet-50 function extracted the collected data with a three-dimensional layer of convolution layer and pooling layer to improve the ability of the image segmentation. Finally, the collected image is effectively segmented along with higher accuracy and sensitivity for better image classification of the function.

### 2.4. Process of fast RCNN

A schematic illustration of fast RCNN-ResNet-50 is shown in Figure 2. Fast RCNN-ResNet-50 was employed in this study to build the bottom-up pathway, each of its five convolution modules, C1 through C5 which contains numerous convolution layers. Every level from C1 to C5 sees a halving of the spatial dimension to lower the C5 channel depth to 256-d (P5). Further, 1×1 convolution filter is used which makes the first feature map layer for object prediction. The previous layer is up-sampled by a factor of 2 along the top-down approach using the nearest neighbour up-sampling technique. To create P4, the up-sampled P5 and the pixel-wise 1×1 filtered C4 were combined. P3 and P2 are produced using the same procedure. In order to build feature pyramids and make autonomous predictions at various levels (P2, P3, P4, P5, and P6) for multi-scale object detection, the network makes use of its built- in multi-scale pyramidal structure of deep convolutional networks.

The region proposal network cycles through the various prediction levels and fully utilizes the scale-dependent feature maps at 32×32, 64×64, 128×128, 256×256, 512×512. At every stage, three aspect ratios- 1:1, 1:2, and 2:1 is also used. The RPN may be trained from beginning to end to produce bounding-box recommendations and objectness scores at each position concurrently. Target objects may be present in these regions, which are then forwarded to the next classifier network to get the final classification and improved anchor positions. The ROI pooling layer employs maximum pooling to transform each ROI from the RPN into a feature map of fixed size at 7×7, since the same classifier model is distributed between the region proposals from the feature map pyramid of multiple levels.

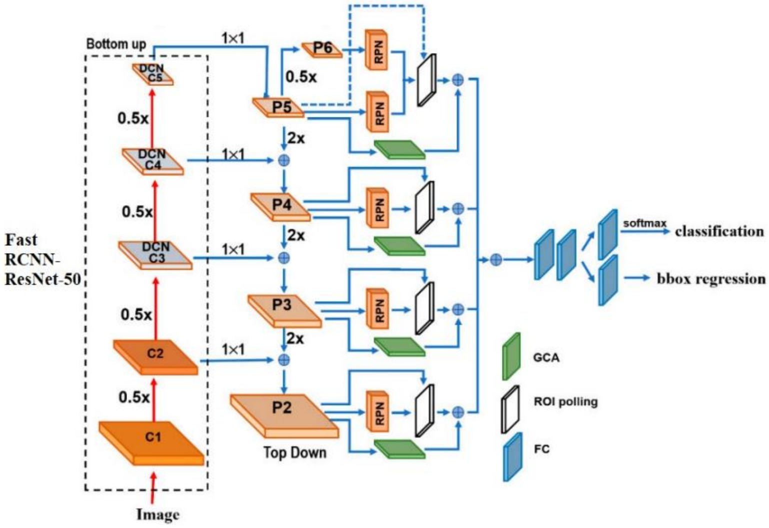


Figure 2. A schematic illustration of fast RCNN-ResNet-50 design

### 2.5. Region of interest pooling

The CNNs frequently employ the procedure known as "ROI" to recognize several pedestrians and Mango in a single image while performing object identification tasks. ROI pooling was used to extract a fixed-sized feature vector for classification from each cropped feature map. CNNs trained a single softmax layer that was adequate for prediction which was used to increase detection speed. However, a hurdle for further performance improvement remained the development of region recommendations utilizing selective search.

### 2.6. CNNs

Especially for computer vision problems, CNNs are among the most effective and popular deep learning systems. In this work, CNNs were used for phoneme identification of Mango with weights distributed throughout temporal receptive fields and back propagation training. Segmentation divides picture pixels into one or more groups that are more like actual things in the real world and maybe semantically interpreted. A graph cut issue can be used to model semantic picture segmentation, the graph model's edges and the energy function's different-order potentials may be used to represent contextual connections. The process of region proposal and annotation involves classifying the pixel values into discrete groups using CNN. Convolutional layer, max-pooling layer, and fully linked layers are the components of the CNN classification architecture. Max-pooling layers are intended for feature selection, whereas convolution layers are intended for feature detection. The backdrop region's pixels are modeled by CNN's which is represented in (3) and (4).

$$GMP(F) = max_{xy}F(X,Y) \tag{3}$$

$$GAP(F) = average_{xy}F(X,Y) \tag{4}$$

where $GMP - Global\ Max\ Pooling, GAP - Global\ Average\ Pooling, xy - Local\ features\ by\ CNN$

## 3. RESULTS AND DISCUSSION

The proposed fast RCNN-ResNet-50 model is trained using 5,000 images which is divided into 80% training set and 20% validation set. The training and validation accuracy is 98% and 96%, and the training and validation loss is 0.14 and 0.08 which is depicted in Figures 3 and 4. Due to the fact that photos of mature Mango fruits are used in training, along with the fact that both the leaves and the fruit are green, the dataset becomes more complex and learning accuracy slowly increases. The performance of the model is measured by below precision, recall, F1-score, and detection accuracy as regular measures of outcomes of four different cultivars i.e, Arkaarun, Malgova, Mallika and Raspuri is depicted in Figure 5. Figure 6 shows the detected and segmented Mango fruits, the proposed fast RCNN-ResNet-50 method to detect and segment the Mango fruit is performing better with 98% of accurate fruit detection and some fruits were missed due to occlusion, illumination and misclassification with leaves.

$$\text{Precision}=\frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall}=\frac{TP}{TP+FN} \quad (6)$$

$$\text{F1-score}=\frac{2\times P\times R}{P+R} \quad (7)$$

$$\text{Detection accuracy}=\frac{TP+TN}{T+F} \quad (8)$$

were, (TP)-true positive, (TN)-true negative, (FP)-false positive, (FN)-false negative.

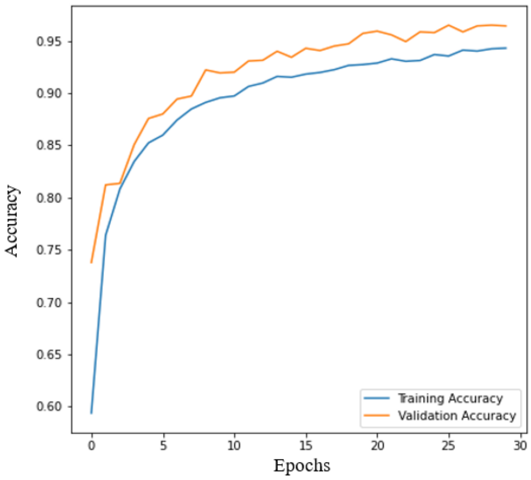


Figure 3. Training and validation accuracy

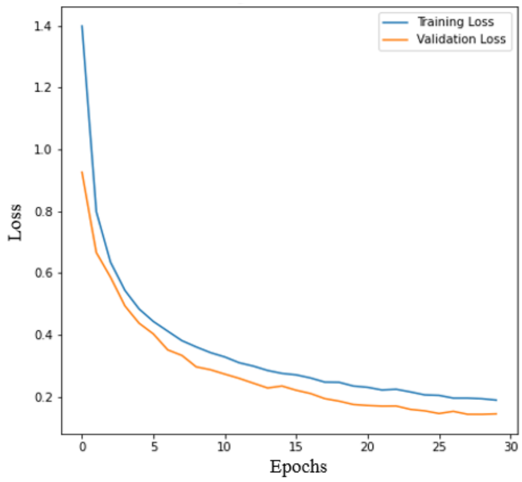


Figure 4. Training and validation loss

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Arkaarun | 0.98 | 0.95 | 0.97 | 88 |
| Malgova | 0.99 | 1.00 | 0.99 | 83 |
| Mallika | 0.96 | 0.97 | 0.97 | 79 |
| Raspuri | 1.00 | 1.00 | 1.00 | 14 |
| accuracy | | | 0.98 | 264 |
| macro avg | 0.98 | 0.98 | 0.98 | 264 |
| weighted avg | 0.98 | 0.98 | 0.98 | 264 |

Figure 5. Screenshot of model’s performance

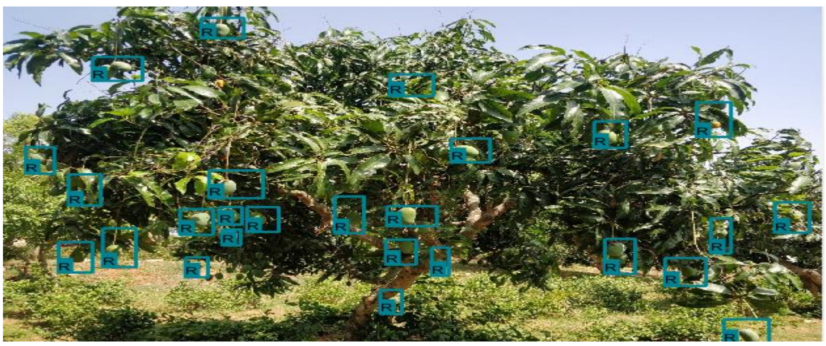

Figure 6. Mango fruit (Raspuri) detected image

### 3.1. Comparative analysis

Table 1 gives the comparison results of the proposed fast RCNN-ResNet-50 model for identifying and segmenting the Mango fruits is compared with the existing models which proposed a multiclass CNN model for plum selection, 1,928 samples of three classes were considered for experimentation, algorithm achieved accuracy of 90% [23]. The existing FR-CNN method proposed a multi class fruit classification system using dataset consisting of 4,000 images of apple, Mango and orange fruits, and achieved a more accurate and faster detection by improvement of the convolutional and pooling layers and achieved accuracy of 91% [24]. A method is proposed to recognize and count green immature citrus fruits by segmenting the pixels into fruit, foliage, and background, two back propagation neural network models were created to forecast apple fruit production in the early and ripening periods and achieved accuracy of 87% [25].

Compared to other models, the fast RCNN-ResNet-50 model outperformed in terms of Mango yield prediction with an accuracy of 98%. The main challenge of this study was with the dataset, the shape and color of leaves and fruits are similar which made object detection more difficult. The fast RCNN-ResNet-50 technique chooses discriminative feature vectors that significantly reduce the processing time for the CNN classifier and led to the better detection and segmentation, which are the main issues addressed in the above section and its comparison results are shown in Figure 7 and in Table 1.

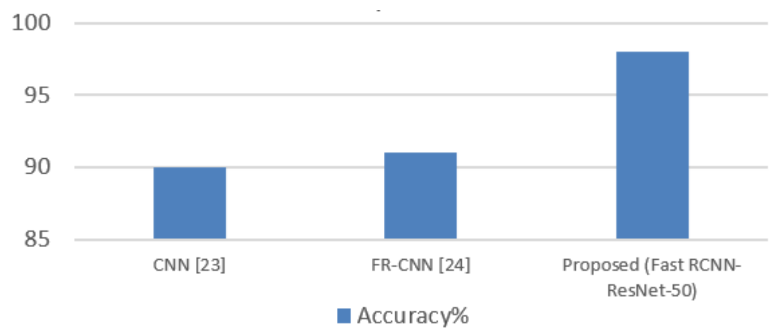


Figure 7. Comparison analysis of proposed and existing models

## 4. CONCLUSION

A novel fast RCNN-ResNet-50 model is presented in this paper for efficient identification and segmentation of Mango yields. After applying the RGB approach to identify the Mango in the picture sequences, CNN models are used to extract vectors from the segmented images. By suggesting a technique that significantly simplifies the training and validating of the model, the retrieved multi-dimensional feature vectors are optimized. The improved vectors of features are supplied input to the CNN classification approach for classifying images. The results of a thorough experiment showed that the proposed fast RCNN-ResNet-50 model outperformed other classifiers CNN, FR-CNN, and random forest (RF), achieving higher precision of 98.20%, recall of 94.20%, and F1-score of 98.62% for temporal Mango dataset. The suggested model will be improved in the future by adding a new ensemble classifier to provide a real time detection in the Mango yields.

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