Automated tomato harvesting system using image processing methods

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Abstract

The efficiency of farming is increasingly dependent on precision farming. This is due to significant competition, the emergence of new pests and bacteria that spoil the crop, environmental problems, and many other factors from which products lose their value. One of such factors is the timeliness of harvesting. This is especially true in greenhouse complexes, where harvesting occurs regardless of the season, regularly after the ripening of products. The ripening of tomatoes is quite unpredictable, so it is necessary to identify the ripening process to harvest in time. Machine vision can solve this problem by highlighting a separate spectrum of color, which is characteristic of already-ripe tomatoes. Therefore, the article proposes a method for identifying the processes of tomato ripening using image processing methods based on color detectors. The OpenCV library was used for software implementation. A Rasbberry Pi unicameral computer was used to solve this problem.

Keywords

Image recognition, tomatoes, machine vision, ripening, growing

1. Introduction

Methods of automated image analysis are manifestations of artificial intelligence, and the area of their use can be attributed to machine learning, which allows you to implement object recognition tasks by various criteria. Such criteria include the size of the object under study, its color and shape, and particular points in the image as a whole.

It is logical that the need to solve such problems increasingly appears in agriculture. This is due to fierce competition between agribusiness entities, increasing food requirements, and many other needs that increase the need to use artificial intelligence to process images.

However, the availability of machine vision technologies for small farmers does not always exist, especially when, due to lack of funds, they are forced to set up their own automation of their own production. Therefore, unresolved issues related to small farmers make such tasks extremely difficult.

Another problem that can be solved by introducing precision farming using machine vision technology can be considered an increase in the human need for food. Thus, the world's ever-growing population needs to increase food production by 70% over the next 40 years to feed everyone. Representatives of the Food and Agriculture Organization of the United Nations voiced this opinion. And while climate change will increase yields in some regions, it will also bring new challenges to growing healthy crops. Therefore, to meet such demand, it is necessary to increase the efficiency of agriculture in terms of resources and time, and, not surprisingly, farmers turn to assistive technologies.

CMiGIN 2022: 2nd International Conference on Conflict Management in Global Information Networks, November 30, 2022, Kyiv, Ukraine
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All this can be met in terms of precision farming, which is increasing, in the face of increasing consumption of food resources on the planet, makes itself felt. This is combined with the uncertainty of risks and threats, creating what is repeatedly mentioned in the scientific literature.

Today, the urgent need of farmers is to identify the various processes of pre-ripening of plants, in order to harvest in time and without losses.

As an example of solving this problem, we take the fruits of tomatoes, which farmers grow in their greenhouses, regardless of the season. Timely identification of the sowing processes of such crops is extremely important because the quality of the obtained products depends on their solution.

Due to the fact that today there are many approaches to recognizing tomatoes, determining their characteristics by color and shape, simple and accessible to farmers methodologies are quite difficult to find.

Thus, today, the most common methods can be considered machine learning using neural networks, various algorithms for finding features in images, color detectors, special points, as well as other methods of analysis [1 - 3]. However, there is a problem with computing power for implementing many algorithms [4-6], which is quite critical for use in agriculture [7]. Therefore, depending on its application, the solution should be as simple as possible.

Determining tomatoes in the greenhouse by color will require only matrix calculations, which will result in an acceptable result because the primary criterion for growth is the color, not even size.

Illumination and the presence of noise may be separate obstacles to such identification.

In this case, the identification of the maturation process requires the selection of a single spectrum by color in the image [8, 9] and comparing it with a similar image obtained after a certain period of time.

To do this, the process of photo fixation must be organized so that the size of the image does not differ, and the angle of the photo recorder was unchanged. The lighting during photo fixation should not be variable.

Such requirements can be implemented using a simple movable platform, which can move on a stretched wire (Fig. 1). This solution will be the most optimal in greenhouse conditions.

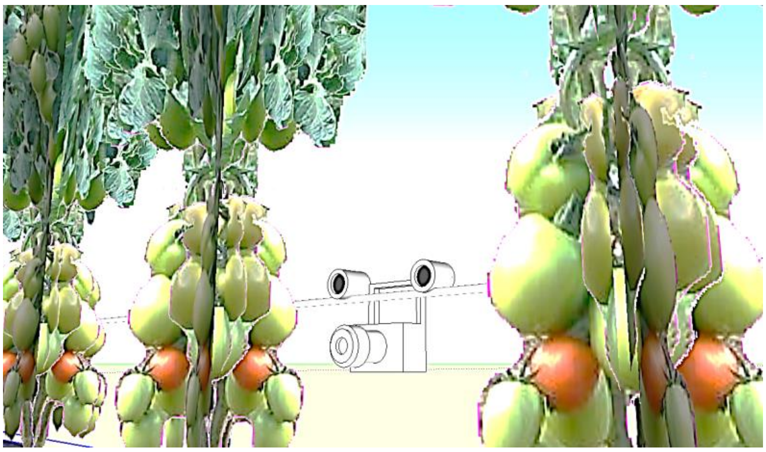


Figure 1: Movable photo lock model

Thus, it is possible to diagnose the right time to harvest tomatoes, which will allow farmers to respond in time to the yield.

2. Literature Analysis and Problem Statement

Spectral analysis of images during the identification of different fruits is widely used in many areas. Thus, a significant part of the work is aimed at identifying the individual contours of the fruit [10, 11] and their shape [12]. However, it is not always possible to record the shape of a tomato fruit due to its accumulation, so you should pay attention to works that use spectral analysis of images to identify objects.

In [13], it was proposed to collect fruits from fruit trees based on a color detector using a special device, the approbation of which showed an accuracy of 90%. Methods of face identification by spectral features have become widely popular. For example, in the article [14] it is offered to consider new spectral features created on the Sonic Wavelet transformations [15], which allow recognizing the texture of the face. In [16], an algorithm for recognizing fruits to determine further their weight was implemented.

However, although the identification of fruits by color has a number of advantages, compared with, for example, methods of identifying fruits by specific points, or by contours, there are certain problems associated with the noise formed as a result of shadows or changes in the light.

Therefore, a number of filters are used to solve such problems, such as the Otsu method, which is often used to reduce noise by low-pass filters [17]. These problems are solved by smoothing and blurring, for example using median filters [18, 19].

Due to the wide popularity of methods of spectral analysis of images [20-22], the vast majority of works [23] are devoted to combined identification methods, both in shape and color. For example, scientists from Oklahoma in a study of hyper-spectral image analysis methods have identified the most effective approaches to estimating the color spectrum in the image [24].

To highlight the color saturation, you often use the RGB model for identification purposes. This model contains pixels of at least 3 colors with different wavelengths. Such as red, blue, and green (Fig. 2), but for the convenience of working with the color spectrum, usually use the HSV model, where the characteristics of the spectrum also reflect the saturation, which is more in line with human perception of color.

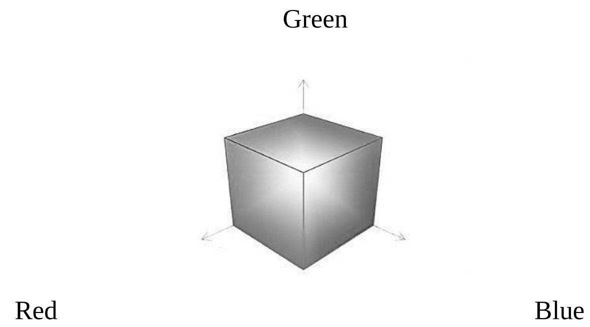


Figure 2: RGB model

Thus, HSV (English Hue, Saturation, Value - tone, saturation, value) is a color model in which the color coordinates are:

- Hue – color tone in the range of 0-360;
- Saturation – saturation, in the range of 0-100 or 0-1;
- Value – the value of color (brightness). Set from 0-100, or 0-1. (Fig. 3).

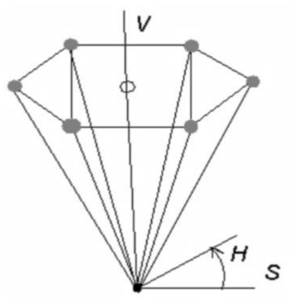
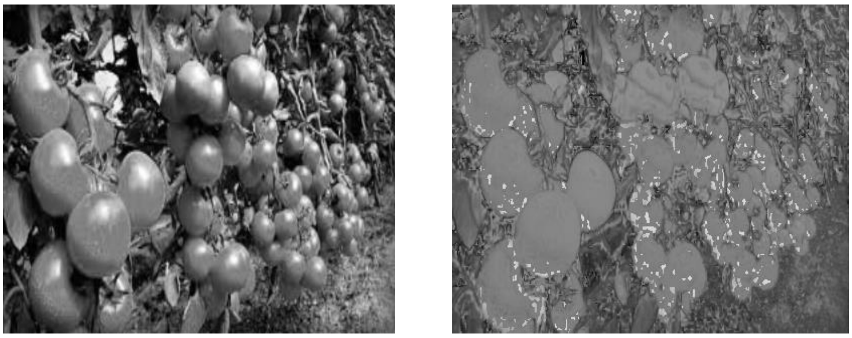


Figure 3: HSV model

The selection of individual color spectra of the image can be done using the library for pattern recognition OpenCv, which includes the possibilities of software implementation of both models. For HSV, the range of shades in this library will be [0,179], the range of saturation - [0,255], and the range of values - [0,255]. If you convert the image of a tomato bush from the format RGB y HSV, we obtain the following images (Fig. 4).



RGB HSV

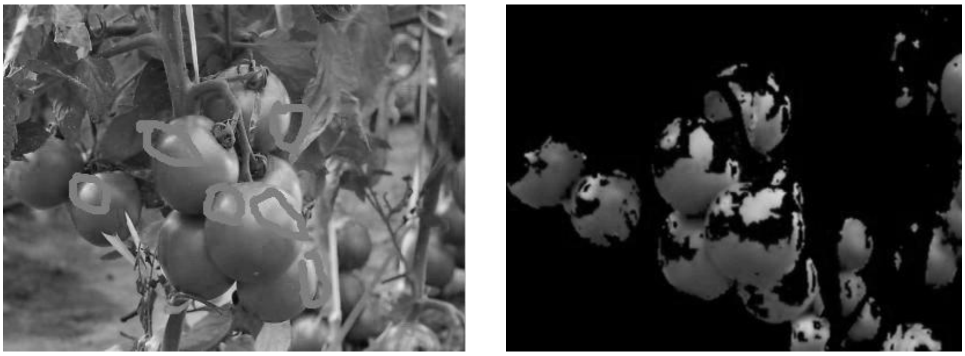
Figure 4: Convert RGB to HSV

Such, you can use image saturation elements.

To identify the fruit of the tomato, you can select the cream pixels by color using this library. Creating a mask that characterizes only the fruit. To reduce noise, you can use a Gaussian filter [17].

To determine the spectrum that corresponds to the color of the tomato, you can select its range, but the surface of this fruit has a glossy base, so there is a reflection, which is the cause of certain errors.

For example, the image of a tomato was taken, the range of its characteristics by color was established and as a result, incomplete identification was obtained. Fig. 5 shows the following inaccuracies.



A B

Figure 5: Select individual points in a given color range

But despite some error, you can count the pixel IDs of the selected color and set the criteria for the growth of tomatoes by calculating the selected color spectrum at different times, following certain requirements for lighting and angle of the photo-recorder.

3. Identification of tomato ripening processes by color

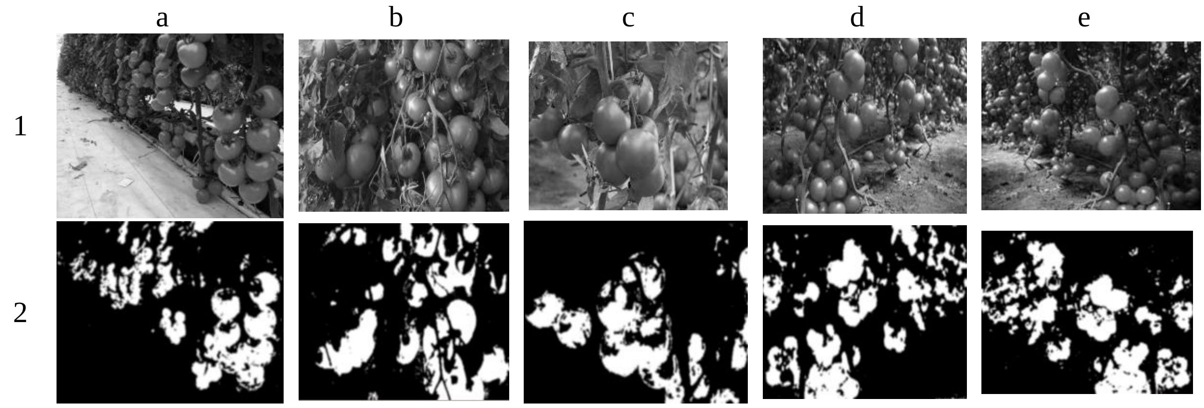
To verify the effectiveness of the method of identifying the growth of tomatoes by color spectrum, we obtain a sample of images (Fig. 5). To reduce noise, which is presented in the form of glare in the images, apply a Gaussian filter to the selected spectrum. Thus, blurring is required in order to reduce unnecessary noise. Gais blur is a typical image blur filter that uses a normal distribution

to calculate the conversion applied to each pixel of the image. The Gaussian distribution equation in N dimensions has the form:

$$G_{(r)} = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} e^{\frac{-r^2}{(2\sigma^2)}} \tag{1}$$

where r is the blur radius; σ is the standard deviation of the Gaussian distribution.

Using the GaussianBlur function of the OpenCv library, which implements Gaussian blur, we can get a more optimal version of the selection of tomatoes (Fig. 6). In order to determine the number of selected objects, the set color range of tomatoes was turned into the white peak of the village, and others into black. This is done using the threshold function, which returns an image where all pixels that are darker (less) 127 are replaced by 0, and anything brighter (more) 127 is replaced by 255.



	a	b	c	d	e
3	79258	68482	80003	67870	66814
4	40742	51518	39997	52130	53186

Figure 6: The process of identifying tomatoes by color

Thus, the image shows that the number of tomatoes can not be estimated, because there are no clear criteria in the images. Still, at the same time, by color, it is possible to study the ripening process.

In Fig. 7 the number of dots that characterize the selected color and black (line 3 - black, 4 - white) is presented. From this we can represent the proportion of the selected color in the images (Fig. 7).

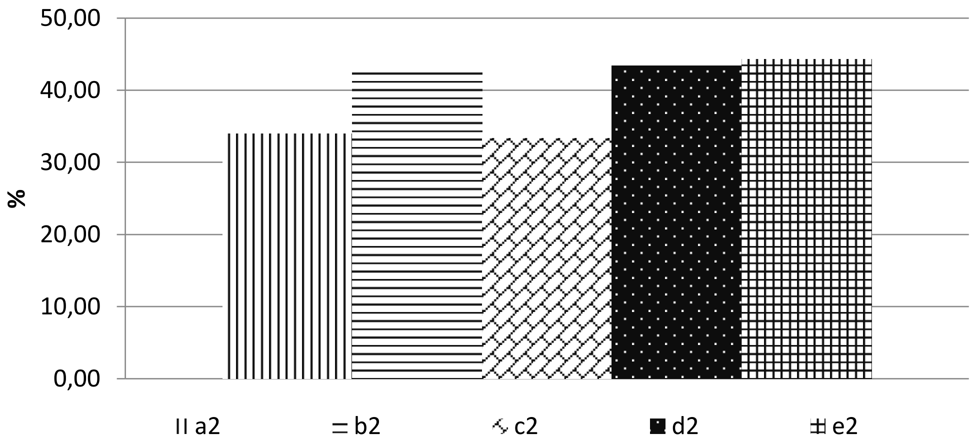


Figure 7: Specific gravity of selected tomatoes by color in the images $a_2 - e_2$, (%)

Thus, to identify the fruits of tomatoes, you can use the following sequence of steps:

- obtaining the original raster image from the photo-capture (.jpg or other sim-ilar format);
- color filtering;
- smoothing with a Gaussian filter and converting the selected area to black and white;
- counting the pixels that characterize the selection of tomatoes (white)
- count other pixels (black).

```
import cv2
import os
im = cv2.imread('im.jpg')
im = cv2.resize(im, (400, 300))
img_hsv = cv2.cvtColor(im, cv2.COLOR_BGR2HSV)
m1 = cv2.inRange(img_hsv, (0,50,20), (5,255,255))
m2 = cv2.inRange(img_hsv, (175,50,20), (180,255,255))
mask = cv2.bitwise_or (m1, m2)
cr1 = cv2.GaussianBlur(mask, (7,7), 0)
print (len(cr1[cr1==0]), 'black')
print (len(cr1[cr1>0]), 'white')
cv2.imshow("msk", m1)
cv2.imshow("cr", cr1)
cv2.waitKey()
```

4. Development of tomato ripening monitoring system

Detection of changes in the images of tomatoes can be implemented on the basis of a movable mechanism (Fig. 1), which is controlled by a single-board computer RaspberryPi. To establish the places of photography, on such a device you can install an infrared sensor that will respond to specially selected places (Fig. 8).

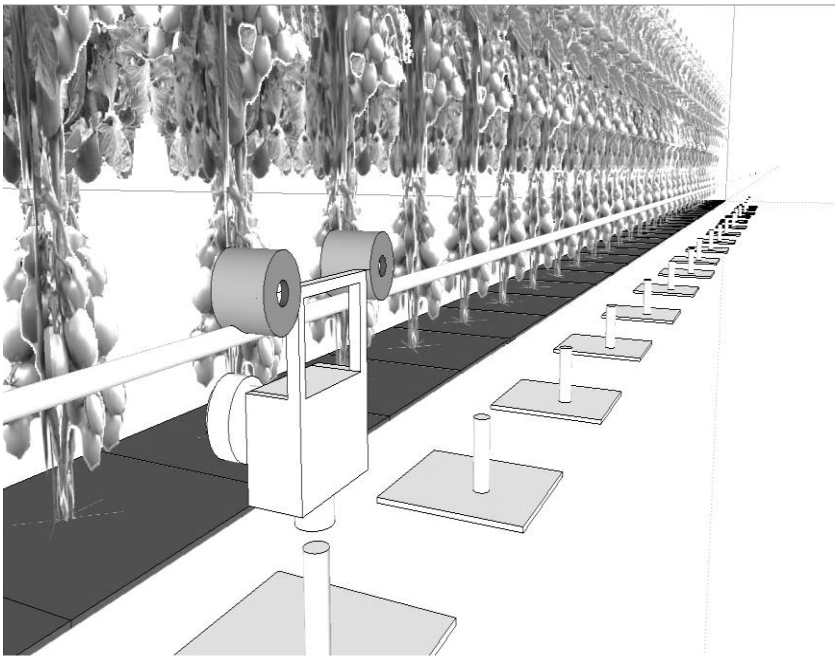


Figure 8: Placing labels on the travel route for infrared sensors

Standard infrared distance sensors allow you to respond to approximations at a distance of up to 30 cm. This is sufficient to identify the stopping point of a moving device.

The implementation of the software algorithm can be performed based on Python interpreter and libraries: sqlite3, for database operation, OpenCv, for image processing, RPi, for work with RaspberryPi COM port, which will be used to provide control signal to drive the transport platform.

The algorithm of operation of the movable photo-clamp is presented in Fig. 9.

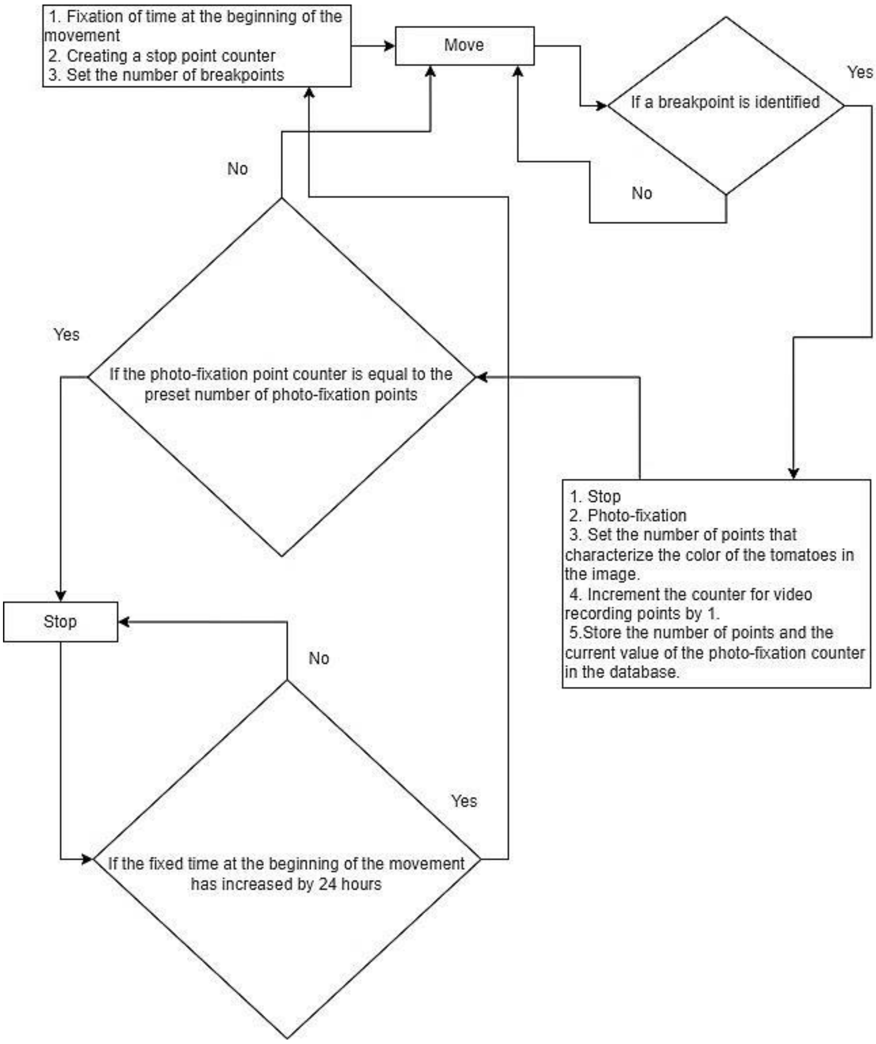


Figure 9: Algorithm of mobile platform operation for photo-fixation of tomato ripening process

The model of implementation of the specified algorithm in Python language can be implemented as follows:

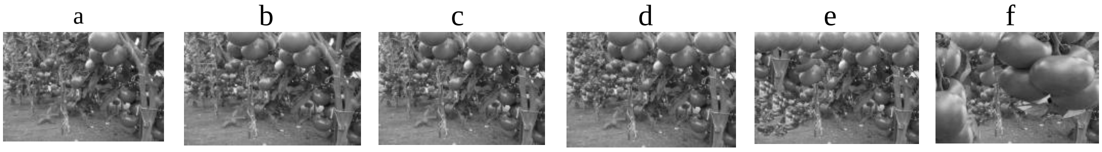
```
import pendulum
import cv2
import os
import time
import sqlite3 as sq
base=sq.connect('bese.db')
b=base.cursor()
try:
 b.execute('create table im (data text, stop_point text, qant text)')
except:
 print ('pass')
 pass
global time_now
global qantyti_points
global point_stop
global counter
def start ():
 moove()
 global time_now
 time_now = pendulum.now().int_timestamp
 global qantyti_points
```

```
 qantyti_points = 5
 global counter
 counter=0
 global point_stop
 point_stop=0
 return ident_point()
def moove():
 print ('move')
 time.sleep(1)
def ident_point():
 a=input()
 print (Breakpoint № {}'.format(a))
 return foto_fix()
def foto_fix():
 print ('stop')
 print (‘Photo-fix')
 print ('input name image')
 s=input()
 im = cv2.imread(s)
 im = cv2.resize(im, (400, 300))
 img_hsv = cv2.cvtColor(im, cv2.COLOR_BGR2HSV)
 m1 = cv2.inRange(img_hsv, (0,50,20), (5,255,255))
 m2 = cv2.inRange(img_hsv, (175,50,20), (180,255,255))
 mask = cv2.bitwise_or(m1, m2 )
 cr = cv2.bitwise_and(im, im, mask=mask)
 m1 = cv2.GaussianBlur(mask, (7,7), 3)
 cr1 = cv2.GaussianBlur(cr, (3,3), 0)
 print ('Coefficient of coincidence', len(cr1[cr1>0])/len(cr1[cr1==0]))
 global counter
 counter = counter + 1
 b.execute("insert into im values('{0}',{1},{2})".format(pendulum.now(), str(counter),
str(len(cr1[cr1>0])/len(cr1[cr1==0]))))
 base.commit()
 return check_timer()
def stop():
 print ('stop')
 while time_now + 12 <= pendulum.now().int_timestamp:
 print ('weit')
 time.sleep(1)
 return start()
def check_timer():
 if counter==qantyti_points:
 return stop()
 else:
 return ident_point()
start()
```

In this case, the start, stop and input functions can be implemented using a single-chamber RspberryPi computer. Approbation of this algorithm can be implemented with the following sample of photographs, where there is a moderate increase in the number of red tomatoes (Fig. 10). After receiving data on the number of color-defined points and storing them in a database, you can work with them.

a b c d e f

1



2	120000	120000	120000	120000	120000	120000
3	17324	22946	29481	31111	40113	65287

Figure 10: Identification of tomatoes by color during ripening

Thus, the growth is identified by increasing the red color in the images, which can be visualized as the ratio of the obtained points to their total number (Fig. 11), where line 2 is the total number of points in the image, line 3 is the number of identified points.

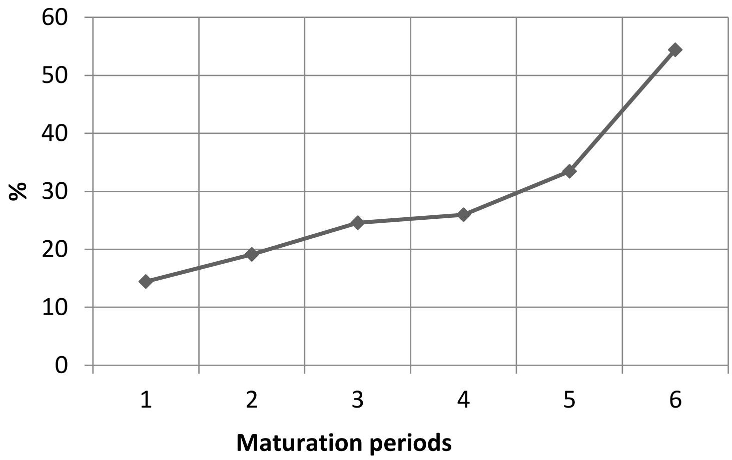


Figure 11: Dynamics of tomato ripening is obtained as a result of the ratio of highlighted points to the total quantities for a conditional period of time

5. Conclusion

The color of tomatoes is the most crucial factor in their growth. Using traditional color filters and the provided parameters of the color range, it is possible to alter the selected color in photographs. Due to the lack of complicated computations, this method is simple to apply. It is sufficient to utilize a single-chamber computer and a mobile photo clamp, which can record changes in the picture at a certain time, to detect the ripening of tomatoes. Due to the error due to the formation of light concentration, the resulting growth dynamics indicates the feasibility of using this method. However, this requires a number of conditions, namely: detailed images must be taken, using a mobile photo-fixer, during photo-fixation, the light must be the same as in the previous photo-fixation, the angle and location of photo-fixation should be non-variable.

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