Interactive Learning Media for Fruit Recognition in Early Childhood Using Backpropagation

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Abstract. The challenges faced by early childhood education in rural areas include an inadequate number of teachers, inadequate facilities and infrastructure, and limited foreign language skills of students. To solve these problems, an interactive, easy, and interesting learning media was created to make students participate actively, help them recognise objects in foreign languages, and adjust the school need (especially schools with a limited number of teachers). Fruit was chosen as the subject of the study because students recognise various popular fruits but do not know their names in English. Computer vision with the backpropagation method was applied to classify and identify 11 types or 789 images of popular fruits. There are seven parameters learned such as red, green, blue, area, perimeter, shape, and diameter colour features. The optimal learning rate of 0.4 and maximum iterations of 500 resulted in a system accuracy rate of 100%.

Keywords: Backpropagation, Computer Vision, Fruit Recognition, Interactive Learning Media

1 Introduction

Early childhood education is very important [1]. According to the National Education System Law of the Republic of Indonesia No.20 of 2003 article 28 paragraph 1 states that early childhood is a child with an age range of 0-6 years where the child's brain experiences very rapid development, so this period is called the golden age [2]. Children in the golden age have short attention spans and are easily distracted by objects that attract their attention, so interesting and fun learning media are needed to get students excited about learning. Teachers are important in early childhood learning, so teachers need to update their learning media to make it interesting and fun for students [3]. Three learning models (visual, auditory, and kinesthetic) [4] simulate children's cognitive development to help them classify objects based on shape, size, and colour [5]. Furthermore, language is also important to develop as a communication tool for socialising with the child's environment [6].

ICoSHIP 2023, November 18-19, Surabaya, Indonesia

DOI 10.4108/eai.18-11-2023.2342565

The challenges faced by early childhood education in rural areas include an inadequate number of teachers, inadequate facilities and infrastructure, and limited foreign language skills of students [1] as is the case with our partners KB Nurul Kharomah and Pos PAUD Alamanda 105. Based on our observations, both schools use learning media such as posters and books to introduce objects such as fruits, vegetables, and animals to the students. However, these media have the disadvantage that the students are easily bored, so the teachers have to communicate the material in an interesting way [8]. Furthermore, both schools teach using Indonesian and Madurese, as both schools are still influenced by Madurese culture and few students understand English. Contrary to Penfield's theory of brain mechanisms, childhood is acknowledged as the optimal period for acquiring second languages, given the brain's flexibility at this developmental stage, which enables more rapid language absorption than individuals over the age of six. [7]. To solve these problems, the researcher created a learning media that is interactive, easy, and interesting because students actively participate, help recognise objects in foreign languages, and is suitable for schools with a limited number of teachers. This learning media applies computer vision technology which is a combination of image processing and artificial intelligence for children aged 4 to 6 years. This research aims to find an artificial intelligence method that can classify and identify popular fruit varieties with a high rate of accuracy.

2 Method

There are three primary phases in this research, namely data collection, the design and creation of applications, and the testing of applications. The design and application creation stage consists of four stages, such as converting RGB images to HSV color space, image segmentation, feature extraction, and fruit classification using the backpropagation method as shown in Figure 1.

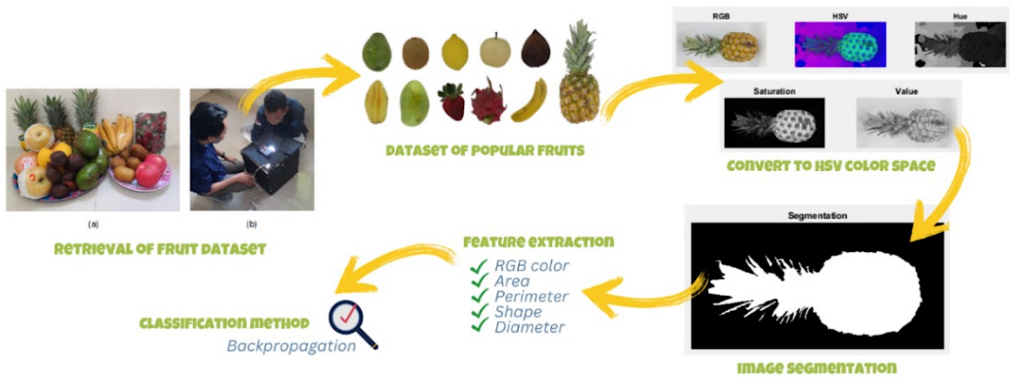

Fig. 1. The research stages

2.1 Dataset of Popular Fruits

This research is an extension of the previous research. We added 75 data on mango fruit, increasing the number of fruit classes from ten to eleven. The dataset of fruit was collected using a box equipped with five LED lights and a smartphone camera. There are 11 fruit types or 789 popular fruit image data, which are described in Table 2.

Table 2. Name and number of fruits data [4]

No	Fruit Class	Number of Data	No	Fruit Class	Number of Data	No	Fruit Class	Number of Data
1	Avocado	75	5	Pear	100	9	Strawberry	125
2	Kiwi	49	6	Banana	56	10	Dragonfruit	90
3	Lemon	51	7	Snakefruit	55	11	Mango	75
4	Pineapple	61	8	Starfruit	52			
Total Number of Data								**789**

2.2 Convert colors to HSV color space

The original image is an image with RGB colour space where the colour space is difficult to segment so it must be converted to another colour space such as HSV colour space. HSV color space is one of the color spaces whose approach model is similar to the human vision model with equations (1-3) [4]:

$$Hue = tan\left(\frac{3(Green-Blue)}{(Red-Green)+(Red-Blue)}\right) \tag{1}$$

$$Saturation = 1 - \left(\frac{min(Red, Green, Blue)}{Value}\right) \tag{2}$$

$$Value = \frac{Red+Green+Blue}{3} \tag{3}$$

2.3 Image Segmentation

Image segmentation is the second stage in the application development process. This process aimed to separate the object from the background using an equation (4) :

$$g'(x, y) = \{1,\ g(x, y) \geq T\ 0,\ g(x, y) < T \tag{4}$$

Where g(x,y) is the input image, g'(x,y) is the output image and T is the gray threshold value for the segmentation process.

2.4 Feature Extraction

A process used to obtain a unique value [14] that is used to classify or identify the object classes. Three colour features (red, green, and blue) and four shape features, namely area, perimeter, shape [17], and diameter [16] are used in this research with the formula equation (5) - (8) :

$$Area = \sum pixels\ in\ 1st\ row + 2nd\ row + \cdots + 8th\ row \tag{5}$$

$$Perimeter = \sum even\ code + \sqrt{2}x\sum odd\ code \tag{6}$$

$$Shape = \frac{Perimeter^2}{Area} \tag{7}$$

$$Diameter = \frac{major\ axis\ length + minor\ axis\ length}{2} \tag{8}$$

2.5 Backpropagation Method

This method also includes artificial neural network methods where the classification method is supervised learning. This method classifies when the system output does not match the target then the system will update the weights on each layer in the system.

3 Results and Discussion

Based on previous research, the fruit image is converted to the HSV color space, and the Saturation channel image is taken which is the best in representing the shape of the fruit because the RGB image has a large value range of 24 bits so it is difficult to segment. Saturation image is input to the image segmentation process using a threshold value of 0.13 using formula (4). If the gray degree pixel value has a value of more than 0.13, the segmentation image pixel result will have a value of 1 (white), while if the gray degree pixel value has a value of less than 0.13, the segmentation image pixel will be 0 (black), but in the image, there is a white object which is noise. To remove the noise, a further process is needed, namely segmentation based on area or Channel Area Thresholding (CAT) by finding the object area value of more than 6000 units as in Figure 3. After obtaining the binary image of CAT segmentation results, the next step is feature extraction based on color and morphology (shape) as shown in Table 3. The seven feature values in Table 3 become input for the backpropagation classification method which will later be compared based on variations in the ratio of training data and test data such as 50: 50, 60: 40, 70: 30, 80: 20, and 90: 10.

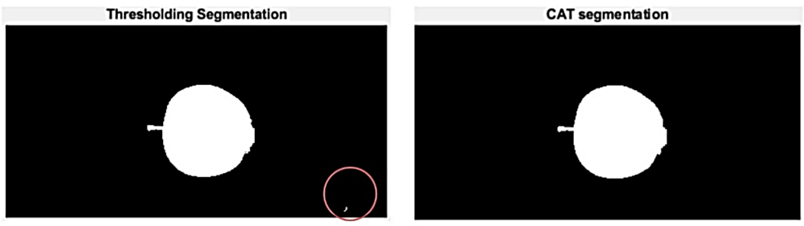

Fig. 3. Threholding segmentation (left) and CAT segmentation (right)

Table 3. The color and morphological feature extraction results.

Class	Color Features			Morphological Features			
	Red	**Green**	**Blue**	**Area**	**Perimeter**	**Shape**	**Diameter**
Avocado	195	195	190	614533	4125,02	32,04	846,57
Starfruit	187	197	191	707939	3312,69	16,30	989,15
Lemon	171	170	161	339533	2569,42	19,51	665,14
Kiwi	176	175	170	324171	2250,87	15,06	646,84
Mango	190	196	167	2133462	5547,38	14,61	1689,31
Dragonfruit	161	145	146	1088247	6985,29	46,32	1201,34
Pineapple	179	174	157	2307359	24665,31	273,16	713,66
Pear	176	173	164	684575	3518,89	19,02	919,94
Banana	173	171	163	458288	3926,85	33,83	948,34
Snakefruit	170	170	167	185916	1857,41	18,89	495,97

Strawberry	166	166	163	83916	1642,56	32,59	351,93

The research was conducted using a network architecture of 7 input neurons, 9 hidden layer neurons, and 11 output neurons with a maximum epoch of 500. Some of the variations made are learning rate variations (Table 4) and epoch variations (Table 5).

Table 4. The system accuracy is based on learning rate variation.

Learning rate (α)	Accuracy (%)				
	50: 50	**60: 40**	**70: 30**	**80: 20**	**90: 10**
0,1	97,97	98,10	97,89	100	100
0,2	98,73	98,73	97,89	100	100
0,3	98,73	99,05	98,73	99,37	100
0,4	**99,24**	**99,05**	**99,16**	**100**	**100**
0,5	99,24	99,68	98,73	98,73	100
0,9	98,98	99,05	98,73	99,37	100

The results in Table 4 show that the most optimal learning rate (α) is 0.4, which has been implemented on variations in the comparison of training and testing data. The accuracy of data comparisons of 50:50 is 99.24%, 60:40 is 99.05%, 70:30 is 99.16% and 80:20 or 90:10 is 100%. This shows that the more data that is trained, the better the system will recognize the pattern so that the system can classify the test data according to the target. Whereas in Table 5, the epoch variation is carried out on the variation of data comparison so that we get the time and accuracy of the system. Based on the results shown in Table 5, there is no significant difference in system accuracy for epochs 500 and 5000, except when comparing data 60:40. This comparison shows that when the 5000 epoch is used, the system accuracy actually decreases from 99.05% to 98.73%. This also happens when the system uses a maximum epoch of 100.

Table 5. The accuracy and time on the system against epoch variation

Comparison of data	Accuracy (%)			Time (s)		
	100	**500**	**5000**	**100**	**500**	**5000**
50: 50	97,72	99,24	99,24	0,2	0.99	9,81
60: 40	98,73	99,05	98,73		0,98	9,76
70: 30	97,47	99,16	99,16		0,97	9,78
80: 20	98,73	100	100		1	9,75
90: 10	98,73	100	100		0,98	9,82

Table 6. Comparison of system accuracy in KNN and backpropagation methods

Method	Accuracy (%)				
	50:50	**60:40**	**70:30**	**80:20**	**90:10**
KNN	99,49	99,37	99,58	99,37	100
Backpropagation	99,24	99,05	99,16	100	100

Previously, we used the K-Nearest Neighbor (KNN) method to classify and identify popular fruits, so in this study, we compared it with the backpropagation method by varying the ratio of training and test data to reach the highest accuracy method, as shown in Table 6. The table shows that the best comparison between training data and test data is 90: 10 for all types of classification methods used. Because both KNN and backpropagation produce system accuracy of 100%. Although the KNN method has an accuracy rate of 100% when K = 1, using K>1 is recommended due to the risk of overfitting (similarity of values between training and test data). The advantage of using the backpropagation method is that if the output does not match the target, the system will continue to update the weights so that the accuracy of the system becomes better than before. The implementation of computer vision technology can provide innovative learning media at KB Nurul Kharomah and Pos PAUD Alamanda 105 schools. This learning media also motivates students to actively and enthusiastically participate in learning real fruit recognition in both Indonesian and English. The findings in this study are in line with the ones found in previous studies. This approach was effective because the students enthusiastically participated in the learning process of fruit introduction [4]. The learning media is also updated to be website-based which can be accessed anywhere, anytime, and not limited to the device used. We also use other artificial intelligence methods such as the backpropagation neural network method which can recognize fruit with an accuracy of more than 96% [19]-[23].

4 Conclusion

This research shows that the backpropagation method can recognise 11 popular fruit variations with a system accuracy of 100%, based on a learning rate of 0.4 and a maximum iteration of 500. For future application development, we plan to add fruit classes with image variations and use other classification methods such as convolutional neural networks (CNN), which are very good at recognising varied image objects in a large number of classes.

Acknowledgment. We would like to thank P3M Politeknik Negeri Jember and TEFA JTI Innovation for funding our research. Thank you to KB Nurul Kharomah and Pos PAUD Alamanda 105 schools for facilitating our application testing.

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