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MUSHROOM SPECIES DETECTION USING IMAGE PROCESSING TECHNIQUES

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ABSTRACT: There are many kinds of mushrooms in the world, some of them are edible and some are poisonous. People may want to eat the mushrooms they encounter in nature, as a result of which they may become poisoned or even die. In this research image processing techniques, K-NN and Naive Bayes algorithms were used to classify mushroom species in Selçuk University Campus. As a result of the research, K-NN algorithm achieved 80% and Naive Bayes algorithm achieved 96% accuracy.

Keywords: Image Processing, Mushroom Species, K-NN, Naive Bayes.

1. INTRODUCTION

There are many mushrooms that are edible and poisonous in nature. People may want to eat the mushrooms they see when they come to nature, but they can poison or kill them.

The poisoning applications made to the National Poison Information Center of the Ministry of Health between April 1 and May 13, 2019 increased by 34 percent compared to 2018. Antidote is required for the treatment of poisonings; this situation requires additional costs for the national economy. If people are conscious of mushroom recognition, they will not both poison themselves and cause additional costs for the national economy [1].

This research was carried out by using image processing techniques, K-NN and Naive Bayes algorithms to prevent poisoning from 25 mushroom species in Selçuk University Campus.

Many researches have been done using image processing techniques in plant science. In these researches, mainly color properties were studied. Other research using image processing techniques in plant science are given below.

Neuman et al. [2] developed an image processing method to evaluate the color of grains and other objects in digital images in their study. According to RGB color characteristics of different wheat classes were examined, and differences were observed.

Neuman et al. [3] examined wheat colors by differentiation according to RGB properties in

order to distinguish grains depending on the class and types of wheat. As a result, the differences between different wheat classes were successfully revealed.

Göknur Dursun [4] determined wheat, barley, corn, chickpeas, lentils, beans, kidney beans and soybean, such as some grain products projected by image processing techniques the work done. Thanks to this research, the projection areas of small grain products have been determined precisely.

Njoroge et al. [5] stated that fruit can be classified according to internal and external characteristics of fruit in automatic fruit sorting systems. They stated that CCD cameras are used to determine the external (color, size and shape, etc.) properties of fruits, and X-ray rays are used to measure internal properties such as sugar content and acidity content.

Feng and Qixin [6] classified Crystal Fuji apples according to their color characteristics in their study. The color ratios of the fruits were calculated by HSI color space and the system worked 90% accuracy.

Chamelat et al. [7] used image processing techniques to identify grape fruit. They have extracted color attributes from RGB and HSV. They trained a support vector machine with these attributes and tested the developed algorithm on images taken under different conditions. The system worked 99% accuracy.

Lino et al. [8] used image processing techniques to classify lemon and tomato quality. The quality is determined according to shape, size, mass, hardness and stains. ImageJ program was used to determine the properties.

Tonguç and Yakut [9] have done apple sorting with image processing techniques. In this research, apples were classified according to their color and size characteristics. The system works at an improved level.

Omid et al. [10] conducted a study on the citrus volume and mass estimation using image processing technique. Lemon, lime, orange and mandarin were used as citrus varieties. Two cameras were used to take pictures of fruits in upright position. Image processing was performed in 3 steps: background segmentation, image enhancement and calibration. The results showed that the size of the citrus fruit had no effect on the accuracy of the calculated volume.

Al-Mallahi et al. [11] used image processing techniques to separate potatoes and clods. This research was tested between 380 contact tubers and 112 contact tubers and soil clods. The results show that 99% of the contacts were successfully exposed. The reason for the failure is that there are no sharp corners between the tubers and clods.

Liming and Yanchao[12] studied strawberry classification according to shape, size and color characteristics. As a result of the research, strawberry size detection error is not more than 5%, color classification accuracy is 88.8% and shape classification accuracy is above 90%. 1 strawberry is classified under an average of 3 seconds.

Aggelopoulou et al. [13] used image processing method by looking at the density of flowers found in apple trees to determine the harvest yield. In their research, they took color images from the trees at the time of flowering and measured the yields of the trees at the end of the

harvest. They revealed white flowers in the tree by thresholding. In their research, they were able to determine the harvest yield of 53 trees with an error of 18%.

Gastélum-Barrios et al. [14] conducted research using image processing techniques to improve tomato quality. In determining the quality of tomatoes, basic properties such as color, ripening rate, hardness, shape, size and content of minerals were examined.

Balestani et al. [15] used image processing techniques to classify cherries by size, maturity, and defect. They took 250 images with CCD camera. According to the RGB color properties were examined. As a result, the accuracy in size classification was 96%, the accuracy in maturity classification was 92%, and the accuracy in classification according to the failure status was 90%.

Sofu et al. [16] using the image processing method to determine the color, size and stains on apples and to classify stains, have studied various apples. In their study on a total of 201 apple images, they determined the accuracy of classification in color estimates as 99% and the accuracy in classification by apple species as 95.52%. The study classified 7 of the 10 stained apples as stained.

Font et al. [17] have initiated a study to avoid problems such as the simultaneous harvesting of nectarine of six varieties and the daily average of 500 tons of harvested at the same time in Aitona (South Lleida). During the nectarine packaging process, nectarines are classified according to their histogram properties. For this purpose, a small data set was prepared which kept histogram properties of each nectarine and a comparison was made between these nectarines.

Bhange and Hingoliwala [18] conducted a study using image processing to detect diseases on pomegranate. In this study, they aimed to provide a web-based service to the farmers for the definition of pomegranate disease by loading the image of pomegranate into the system. The system has a dataset with pomegranate images. When users enter their own pictures, they are compared with the pictures in the system. The system works 82% accuracy.

This research consists of 6 chapters. In the second chapter materials and methods, in the third chapter application, in the fourth chapter results and recommendations were explained.

2. MATERIAL AND METHOD

2.1. Material

In this research, images of mushroom species grown naturally in Selçuk University Campus were collected by faculty members and students of Selçuk University Faculty of Science Biology Department. A total of 25 mushroom species were studied and 8 of them were edible and 17 of them were poisonous mushrooms. Figure 1, has showed the two mushroom species on the Campus of Selçuk University. Species of mushrooms are showed in Table 1.

Table 1. Species of mushrooms.				
Names of Mushrooms	Species			
1-Agaricus altipes	Edible			
2-Agaricus bitorquis	Edible			
3-Agaricus bresadolanus	Poisonous			
4-Agaricus campestris	Edible			
5-Agrocybe arvalis	Poisonous			
6-Agrocybe paludosa	Poisonous			
7-Bjerkandera adusta	Poisonous			
8-Coprinellus disseminatus	Poisonous			
9-Coprinopsis episcopalis	Poisonous			
10-Coprinopsis marcescibilis	Poisonous			
11-Coprinus comatus	Edible			
12-Hygrocybe conica	Poisonous			
13-Inocybe nitidiuscula	Poisonous			
14-inocybe splendens	Poisonous			
15-Protostropharia semiglobata	Poisonous			
16-Psathyrella candoleana	Poisonous			
17-Psathyrella corrugis	Poisonous			
18-Psathyrella hirta	Poisonous			
19-Psathyrella prona	Poisonous			
20-Psathyrella senex	Poisonous			
21-Suillus bovinus	Edible			
22-Suillus collinitus	Edible			
23-Suillus flavidus	Edible			
24-Suillus luteus	Edible			
25-Tricholoma orirubens	Poisonous			

Figure 1. Two mushroom species in Selçuk University Campus.

2.2. METHOD

2.2.1. K-NN(K NEAREST NEIGHBOR) ALGORITHM

This algorithm is one of the most common used algorithms. While the classification is made, the distance of each record in the database with the other records is calculated. However, only k piece of the other records is considered for one record. k piece recording is the closest distance to the calculated point compared to other records. k value is pre-selected in the algorithm [19,20].

The working principles of the algorithm are summarized in the following steps.

Step 1: Determine an appropriate distance measurement space (Euclid distance measurement is the most used).

Step 2: Identify k piece point closest to each other.

Step 3: Determine the most common class of the specified group.

Step 4: Assign this group the name of the specified class [21].

Euclid distance measurement was used in this research. Euclid distance measurement is calculated according to Eq. (1). x and y are coordinates of points [22].

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$
(1)

2.2.2. Naive bayes algorithm

The Bayesian classification technique is a method that calculates the likelihood of a new data entering any of the existing classes by using existing, already classified data.

Developed algorithms and classification techniques based on Bayesian rule are called with this name [21].

Bayes' theorem is given in Eq. (2).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$
(2)

P (A | B) = Probability of event A when event B occurs. P (A) = Probability of event A.

P (B | A) = Probability of event A. P (B | A) = Probability of event B when event A occurs.

P(B) = Probability of event B [21].

2.2.3. Emgucv

EmguCV is an Open CV wrapper library that can be used in .Net languages. OpenCV (Open Source Computer Vision) is an open source image processing library.

2.2.4 Thresholding

Thresholding is the process of separating objects from the background and is the simplest segmentation method. It is used for different purposes such as reducing noise on the image or identifying objects. (i, j) is pixel value and T is the threshold value, If (i, j) > T, (i, j) is point of the object,

If $(i, j) \leq T$, (i, j) is point of the background.

2.2.5. Dilation and erosion

A binary image is a description of the image in black and white. Dilation is a morphological process used to magnify or highlight objects in binary images, erosion used to minify objects in binary images. Principle of dilation and erosion has showed in Figure 2.

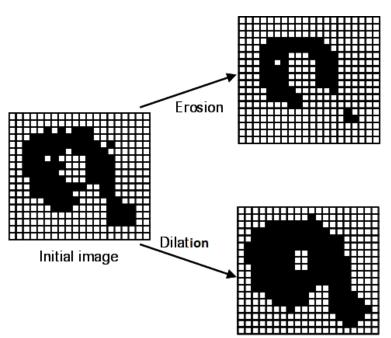


Figure 2. Principle of dilation and erosion [23].

3. APPLICATION

The research was carried out using Microsoft Visual Studio 2012 software. Opening window of program is given in Figure 3. There are 3 buttons on the opening window of program. After opening the picture, two buttons that are inactive will be opened. Figure 4 is the screen after opening the picture.

骎 Mushroom Recognition Program	— [) X
Open Image KNN	NAIVE BAYES	

Figure 3. Opening window of program.



Figure 4. Opening the picture.

Mushroom pictures were reduced to 300 * 300 size for effective working of program. RGB values and the ratio of mushrooms were selected for feature extraction in this research.

To find the ratio, the width of the cap of the mushroom is divided by the height of the mushroom. The RGB values and ratio of mushrooms were studied with the help of Emgucv Library. Thresholding, dilation and erosion were used for feature extraction. Thresholding, dilation and erosion were performed before RGB values and ratio were found. Figure 5 is the screen erosion and Figure 6 is dilation applied picture. Thresholding applied picture is given in Figure 7.

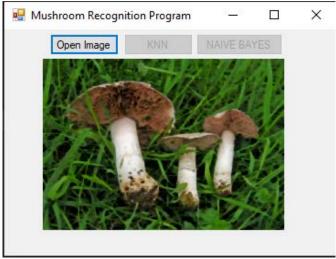


Figure 5. Erosion applied picture.

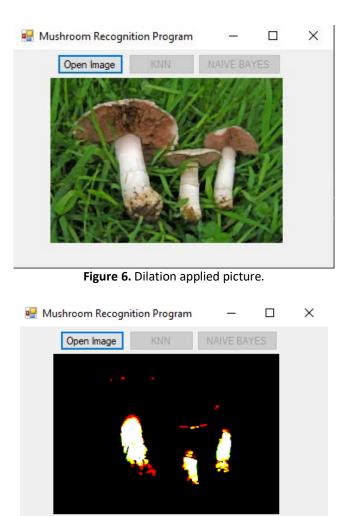


Figure 7. Thresholding applied picture.

There are 3 listboxes, 4 labels and 4 textboxes in the background of program. 255 of the RGB values are counted and these numbers are written on the labels.

Found RGB values and ratio of mushrooms has showed in Figure 8. Values of R, G, B and ratio of mushrooms is given in Table 2.



Figure 8. Found RGB value and ratio of mushrooms.

Table 2. Values of R, G, B and ratio of mushrooms.					
Names of Mushrooms	R	G	В	Ratio of mushrooms	
1-Agaricus altıpes	3045	3993	4686	0,959	
2-Agaricus bitorquis	5588	6634	6714	1,242	
3-Agaricus bresadolanus	2221	4188	7040	1,112	
4-Agaricus campestris	3083	2646	2657	0,966	
5-Agrocybe arvalis	483	1488	2200	0,996	
6-Agrocybe paludosa	3984	7003	7453	1,707	
7-Bjerkandera adusta	2102	1711	3189	1,004	
8-Coprinellus disseminatus	950	2784	4415	1,348	
9-Coprinopsis episcopalis	1000	1023	1269	1,351	
10-Coprinopsis marcescibilis	112	376	201	0.993	
11-Coprinus comatus	3418	3762	3971	0,76	
12-Hygrocybe conica	0	40	9367	1,324	
13-Inocybe nitidiuscula	0	1517	14963	0,993	
14-Inocybe splendens	1787	1782	6846	1,093	
15-Protostropharia semiglobata	1436	5573	4694	0,925	
16- Psathyrella candoleana	1202	748	1418	1,014	
17- Psathyrella corrugis	301	1273	1815	0,93	
18- Psathyrella hirta	298	1286	5949	0,843	
19- Psathyrella prona	4813	9060	11983	0,84	
20- Psathyrella senex	71	2996	6322	0,993	
21- Suillus bovinus	495	3254	16629	0,89	
22- Suillus colinitus	4387	3725	2654	0,993	
23- Suillus flavidus	585	5658	7994	0,795	
24- Suillus luteus	482	749	1539	0,913	
25- Tricholoma orirubens	2513	2405	1848	1,004	

RGB values and ratio of mushroom images were coded to improve the performance of K-NN and Naive Bayes algorithm. Coding of ranges for RGB values were presented in Table 3. Coding of ranges for ratio of mushrooms were presented in Table 4.

at	ble 3. Coded of number ranges for	RGB valu
	Ranges	Coding
	0-1000	1
	1001-2000	2
	2001-3000	3
	3001-4000	4
	4001-5000	5
	5001-6000	6
	6001-7000	7
	7001-8000	8
	9001-10000	10
	11001-12000	12
	14001-15000	15
	16001-17000	17

Table 3. Coded of numb	er ranges for RGB values.
Ranges	Coding

Ranges	Coding
0.000-1.000	1
1.001-2.000	2

Values after coding is given in Table 5.

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Names of Mushrooms	R	G	В	Ratio of mushrooms
1-Agaricus altıpes	4	4	5	1
2-Agaricus bitorquis	6	7	7	2
3-Agaricus bresadolanus	3	5	8	2
4-Agaricus campestris	4	3	3	1
5-Agrocybe arvalis	1	2	3	1
6-Agrocybe paludosa	4	8	8	2
7-Bjerkandera adusta	3	2	4	2
8-Coprinellus disseminatus	1	3	5	2
9-Coprinopsis episcopalis	1	2	2	2
10-Coprinopsis marcescibilis	1	1	1	1
11-Coprinus comatus	4	4	4	1
12-Hygrocybe conica	1	1	10	2
13-Inocybe nitidiuscula	1	2	15	1
14-Inocybe splendens	2	2	7	2
15-Protostropharia semiglobata	2	6	5	1
16- Psathyrella candoleana	2	1	2	2
17- Psathyrella corrugis	1	2	2	1
18- Psathyrella hirta	1	2	6	1
19- Psathyrella prona	5	10	12	1
20- Psathyrella senex	1	3	7	1
21- Suillus bovinus	1	4	17	1
22- Suillus colinitus	5	4	3	1
23- Suillus flavidus	1	6	8	1
24- Suillus luteus	1	1	2	1
25- Tricholoma orirubens	3	3	2	2

Table 5. Values after coded.

k value was selected 3 for K-NN algorithm. Result of K-NN algorithm was presented in Figure 9. Result of Naive Bayes algorithm was presented in Figure 10.

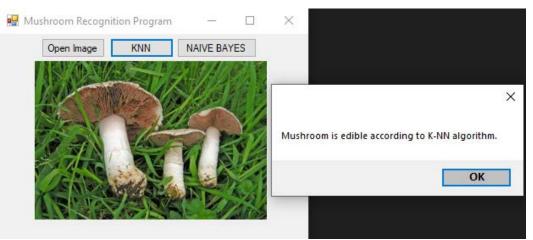


Figure 9. Result of K-NN algorithm.

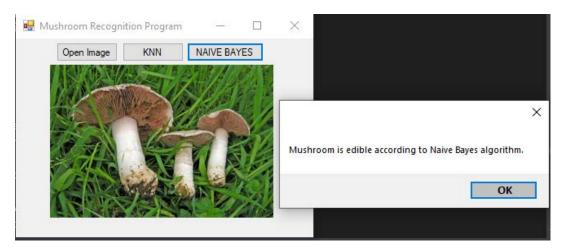


Figure 10. Result of Naive Bayes algorithm.

4. RESULTS AND RECOMMENDATIONS

In this study, K-NN and Naive Bayes Algorithm were used to determine mushroom species with image processing. The K-NN algorithm incorrectly classifies 5 of 25 mushroom species images and achieves 80% accuracy. Naive Bayes algorithm misclassifies one image and achieves 96% accuracy. Result of K-NN and Naive Bayes algorithms are presented in Table 6.

Table 6. Results of K-INN and Naive Bayes algorithms.					
Names of Mushrooms	K-NN Algorithm	Naive Bayes Algorithm	Edibility		
1-Agaricus altipes	Edible	Edible	Edible		
2-Agaricus bitorquis	Poisonous	Edible	Edible		
3-Agaricus bresadolanus	Poisonous	Poisonous	Poisonous		
4-Agaricus campestris	Edible	Edible	Edible		
5-Agrocybe arvalis	Poisonous	Poisonous	Poisonous		
6-Agrocybe paludosa	Poisonous	Poisonous	Poisonous		
7-Bjerkandera adusta	Poisonous	Poisonous	Poisonous		
8-Coprinellusdisseminatus	Poisonous	Poisonous	Poisonous		
9-Coprinopsis episcopalis	Poisonous	Poisonous	Poisonous		
10-Coprinopsis marcescibilis	Poisonous	Poisonous	Poisonous		
11-Coprinus comatus	Edible	Edible	Edible		
12-Hygrocybe conica	Poisonous	Poisonous	Poisonous		
13-Inocybe nitidiuscula	Poisonous	Poisonous	Poisonous		
14-Inocybe splendens	Poisonous	Poisonous	Poisonous		
15-Protostropharia semiglobata	Edible	Poisonous	Poisonous		
16-Psathyrella candoleana	Poisonous	Poisonous	Poisonous		
17-Psathyrella corrugis	Poisonous	Poisonous	Poisonous		
18-Psathyrella hirta	Poisonous	Poisonous	Poisonous		
19-Psathyrella prona	Poisonous	Poisonous	Poisonous		
20-Psathyrella senex	Poisonous	Poisonous	Poisonous		
21-Suillus bovinus	Poisonous	Edible	Edible		
22-Suillus collinitus	Edible	Edible	Edible		
23-Suillus flavidus	Poisonous	Edible	Edible		
24-Suillus luteus	Poisonous	Poisonous	Edible		
25-Tricholoma orirubens	Poisonous	Poisonous	Poisonous		

Table 6. Results of K-NN and Naive Bayes algorithms.

Edible mushroom species are less than poisonous mushroom species in this research. The low accuracy of K-NN algorithm compared to Naive Bayes algorithm may be due to lack of mushroom species. Mushroom images can be reproduced.

The importance of this research is to classify mushroom species in Selcuk University Campus for the first time by using image processing techniques, K-NN and Naive Bayes algorithm. An application about Selçuk University Campus's mushroom classification can be made on the mobile system in the future.

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