INSPECTION OF TOMATOES USING IMAGE PROCESSING TECHNIQUES

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https://www.doi.org/10.59277/RJB.2023.4.01
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Abstract. This work aims to inspect tomato features and classify them based on color and morphological features into the three predefined regions using artificial neural networks (ANN). Different learning methods were analyzed for the task of inspecting tomatoes using image processing software in MATLAB. Tomatoes were collected from the eastern parts of Ethiopia. The neural classification was done by the shape and size feature alone. The ANN classifier on the selected color feature alone showed that from the total test examples of 180 images, 168 (93.3) were correctly classified and 12 (6.7 %) were misclassified. The ANN classifier on all features taken together showed that all the test images were correctly classified. This result is similar to the morphology (shape and size) features result, but if the number of data points is high, the result may vary significantly. The overall result revealed that shape and size features have more discriminating power than color features, and the discrimination power increases when individual features are trained together with shape and size features. This may be because the discriminating factor increases due to the increase in the number of included features. It was observed that the proposed method was successful as quantified by the cumulative error (CE) and percentage error (%E) of training, testing, and validation of color features: 6.35 %, 3.70 %, and 11.11 %, respectively, in evaluating the quality of tomatoes.

Key words: Tomato, image analysis, inspection, segmentation, MATLAB, ANN.

INTRODUCTION

Tomatoes are grown internationally because they are edible and provide many nutrients [19]. Thousands of cultivars were decided on with special fruit types and for optimum growth in diverse developing conditions [17]. They are typically part of day-to-day diets and are a major source of antioxidants [22].

According to [4], Europe is the primary importer of tomatoes. Italy imports the bulk from America, Spain, and China. Ethiopia has a bonus over America and China because of its geographic proximity, availability of land, and coffee production expenses. The United Arab Emirates imports $41.6 million worth of processed tomatoes, of which $17.9 million comes from China alone [4].

Received: May 2023
in final form August 2023.

Domestic production of tomatoes in Ethiopia relies on appealing funding opportunities, with the present farmers not being able to fulfill the growing local demand [4]. The population boom in Ethiopia is set at 4 % at the same time as GDP has been developing with the aid of greater than 7 %, according to annual data for the previous couple of years. As urbanization grows, there may be a shift toward the use of packaged goods. The demand for tomato paste is forecast to grow by 5 % yearly [4]. Ethiopia's tomato processing quarter represents an untapped marketplace capability for export to regional, European, and Middle Eastern markets.

Artificial intelligence is used for checking out fruit that is satisfactory and sorting it. Among the advantages of imaginative smart devices are non-destructiveness, accuracy, and consistency. According to [26], synthetic intelligence can appropriately pick out the inner and outer traits of agricultural merchandise, such as the level of maturity, defects, moisture, and nutrients. The charge-coupled device (CCD) virtual cameras are used to evaluate the traits of color to determine the satisfaction of merchandise illuminated with the aid of a mild supply. This method was used with the aid of [16] to categorize the lemons and tomatoes in line with their color, defects, and volume [19]. The equatorial diameter becomes measured in millimeters, and the floor vicinity becomes expressed in pixels as a median of the diameter optical evaluation.

Immaturity and ripening disorders in tomatoes are common defects seen in markets. According to [24], vulnerabilities and defects in tomatoes increase because of the overuse of pesticides and toxins and incorrect storage. Sorting is an important process in packaging and product supply to the market.

According to [13], the efficiency and effectiveness of sorting govern the quality standard of the product. Manual sorting is the most common method for sorting fruits, but it has problems with quality control carried out by humans. Using machine vision contributes to the automation of sorting and reduces labor costs and the number of employees required.

Therefore, it is very important to assess the quality of tomatoes using methods that can be implemented in automatic sorting machines [22]. The main aim of this work was to inspect tomatoes based on their morphological attributes by using an ANN-based image analysis technique.

LITERATURE REVIEW

DIGITAL IMAGE

A digital image is represented by a two- or three-dimensional array in a binary number system [11]. The digital image falls into two categories according to its format, which are called raster and vector images.

A raster image takes the form of a grid or matrix, with each element (pixel) having a unique location and independent color value. Raster is the most common category of image created and used within digitization projects. All scanners and digital cameras produce raster images, and most output devices (print and screen) also use raster formats. The most common examples of raster file formats are JIFF, JPEIF, JFIF, and GIF. The raster image records information for each pixel, and its file size can be large.

Vector image files are just a set of mathematical instructions that are used by a drawing program to construct an image. The common vector images include 2D and 3D architecture drawings, flow charts, logos, and fonts. They consist of lines, curves, and are shaped with editable attributes such as color. Vector images are resolution independent; they can be reshaped or rescaled without losing quality.

Types of digital images

A binary image is a digital image that has only two possible values for each pixel. The two colors used for a binary image are black and white. The color used for the object in the image is the foreground color, while the rest of the image is the background color. Binary images are stored as a single bit (0 for black and 1 for white).

A grayscale image is a digital image in which the value of each pixel is a single sample; that is, it carries only intensity information. The image of this type, also known as black and white image, is composed exclusively of shades of gray, varying from black at the weakest to white at the strongest intensity. The range of intensity is from zero (black) to 255 (white) [11].

In an eight-bit color image each pixel is represented by an 8-bit byte. The maximum number of colors that can be displayed at any time is 256.

DIGITAL IMAGE PROCESSING

Digital image processing is the technology of applying computer algorithms to process digital images. The outcomes of this process can be either images or a set of representative characteristics or properties of the original images [5]. The main purpose of digital image processing is to allow people to obtain an image of high quality with the descriptive characteristics of the original image. In addition, unlike the human visual system, which is capable of adapting itself to various circumstances, imaging machines or sensors are ineffective to automatically capture meaningful targets [10].

Image preprocessing

Image processing makes the resulting image more suitable for the subsequent tasks [34]. It is the process of converting an image to a digital format and then executing various operations on it to extract valuable information. When specific specified signal processing methods are used, the image processing system typically interprets all images as 2D signals.

Image segmentation is the division of an image into meaningful regions based on uniformity or non-uniformity criteria. It is used to extract special features that allow objects to be distinguished. These techniques include threshold, edge detection, morphology, and regions of interest. Each image processing operation transforms the gray value of a pixel. However, image processing operations can be classified into three classes based on the information required to perform the transform [18]. They are called transforms, neighborhood processes, and point processes.

Transformation is the process of decomposing an image into its sine or cosine components. Applying a simple function to each gray value in an image enables very efficient and powerful algorithms such as arithmetic operations [12]. So, $f(x)$ is a function that maps the range 0 to 255 onto itself. Functions include adding or subtracting values to pixels, or multiplying each pixel by a constant. Adding a constant brightens the image and subtracting a constant darkens the image.

Neighborhood is a process that can be measured as an extension of applying a function to each pixel's neighborhood.

Point processing is used to transform images by manipulating individual pixels. Point processing uses only the information of individual pixels to create a new image [18]. Transformations are calculated based on regional or global information and applied to each point. Image processing is the analysis of images using techniques that can identify hues, colors, and relationships imperceptible to the human eye.

Image processing is used to solve identification problems using mathematical operations, such as forensics or creating weather maps from satellite imagery. There are two basic types of images processing the spatial domain image processing and frequency domain image processing.

Spatial domain refers to the grid of pixels that represent an image. The relative positions and local neighborhoods of pixels are important for spatial domain techniques [20]. This is in contrast to the histogram method. A histogram is a graph that shows how many times each shade of gray occurs in an image. Shows intensity fluctuations.

Frequency domain image processing processes image characteristics in the frequency domain by modifying the Fourier transform coefficients, inverse Fourier transforming to modify the coefficients, and obtaining the processed image. The image is then processed to obtain a new image retaining the original properties and displayed using the inverse Fourier transform shown in Figure 1.

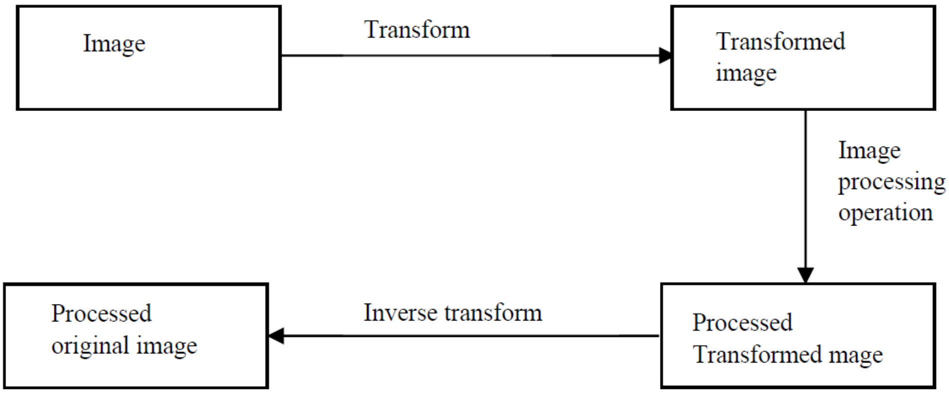

Fig. 1. Schema for transform process.

ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is a type of pattern classifier. It is a system based on the functionality of biological neural networks [21, 23]. More specifically, ANN is an information processing paradigm inspired by the way biological nervous systems such as the brain process information [8, 15]. ANN has been applied in the absence of theoretical evidence of function shape [19]. ANNs are data-based, not model-based. A key element of this is to get the new structure of information processing systems. It consists of several highly interconnected processing elements (neurons) that work together to solve a specific problem [8]. Among various network architectures, feed forward neural networks or multi-layer perceptrons (MLPs) are most commonly used in this work. MLP networks typically consist of three layers of neurons. They are input layer, hidden layer and output layer.

MATERIALS AND METHODS

DATA COLLECTION

A sample of different types of tomatoes was purchased from the local market in three different areas: Dire Dawa, Harar, and Jijiga. The tomatoes were placed on a white background and their images were taken with a digital camera. Data processing was performed by an image processing software written in the high-level programming language MATLAB (The MathWorks, Natick, MA, USA) to produce helpful information for classification and further work. The results of the detection of the samples were displayed on a computer screen.

Data collection method

We have taken tomatoes from each of the three regions mentioned before. One hundred eighty best tomato images (forty from every region) and the selection of images were used to extract features.

METHOD FOR DATA ANALYSIS

The developed system relies on a lot of digital images to operate and needs to read an image of pixel color in order to gain the best result to classify the fruits based on their quality. The image processing technique employed in this study is shown in Figure 2 [13].

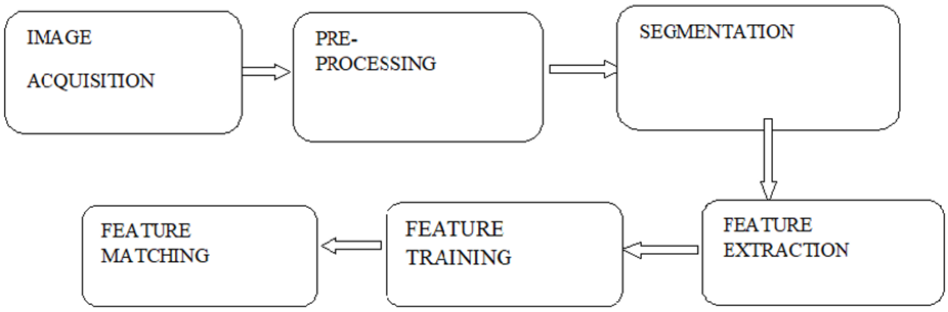

Fig. 2. Image processing stages [13].

The image acquisition was done using a digital camera, and it was loaded and saved using MATLAB [5].

Image segmentation is the process of partitioning an image into meaningful regions for a particular application. The segmentation was based on measurements taken from the image and might be gray level, color, depth, or motion [15]. As edge detection is a fundamental step in image processing, it is necessary to point out the true edges to get the best results from the matching process. So, it is important to choose edge detection.

The features were extracted from the relevant information in the input data to perform feature matching using this reduced representation instead of the full-size input. Here, shape, size, and color were used to extract features for inspecting tomatoes from three sites [1, 22].

The cumulative errors (CE) for the training and test subsets can be calculated using the following equation [2]

$$CE = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{M}\left(t_{ji} - O_{ji}\right)^2 \tag{1}$$

where O_{ji} is the output predicted by the network of ith output node from p^{th} sample; t_{ji} is the training (actual) output of the i^{th} output node from j^{th} sample; N is the number of the training samples and M is the number of the output nodes.

RESULTS AND DISCUSSION

RESULTS

In this study, one hundred twenty images of tomatoes were captured for classification into three regional groups. In this section, we present the segmentation, feature extraction, and classification results using MATLAB [7].

Segmentation

The histogram image shown in Fig. 3 is an example of an image suitable for image thresholding [25]. The tomato image histogram has two distinct modes: the narrowest and the broadest. The narrowest and most prominent one (on the left) corresponds to background pixels. whereas the broadest one (on the right) reflects the intensity distribution of pixels corresponding to the tomatoes.

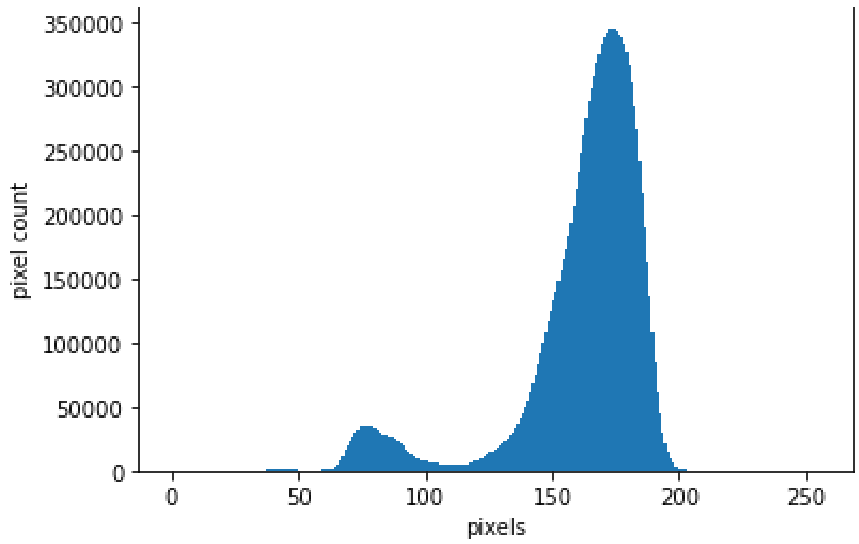

Fig. 3. Histogram of tomato images.

Illumination and reflectance patterns play a critical role in the threshold. Even an easy input image, that could be successfully segmented using global thresholding, poses a much harder challenge if the illumination pattern changes from uniform to gradual. The resulting image using the source code is good and works for all other images, and the corresponding histogram shown in Figure 3 is used to assess the quality of the image (it has to be bimodal) taken during capture and used to indicate the threshold point. The threshold point is found by trial and error, and hence the decision to be well-segmented for such a system is facile.

Noise can have a significant impact on thresholding. This is to say that a bright day and a foggy day give different results. So, we controlled our experiment in a dark region to eliminate such a source of variability.

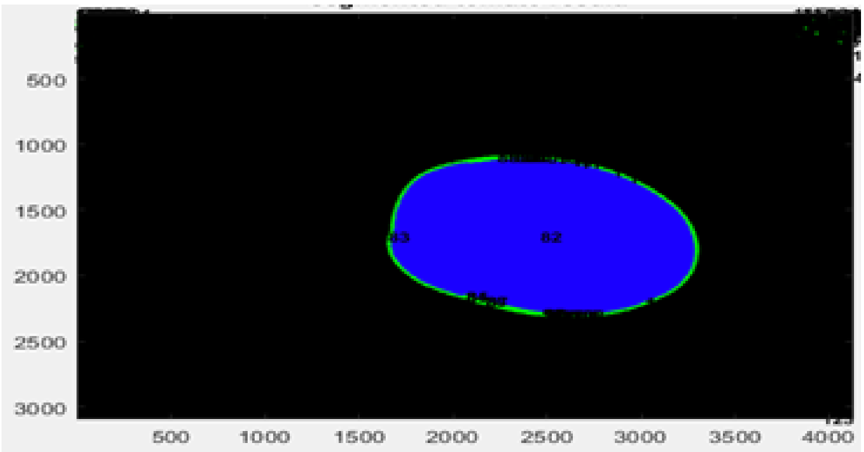

Fig. 4. Segmented tomato image using threshold from segmented images.

The basic problem of thresholding is the conversion of an image with many gray levels into another image with fewer gray levels, usually only two. This conversion is typically performed by comparing each pixel intensity with a reference value (threshold) and replacing the pixel with a value that means “white” or “black”, depending on the outcome of the comparison. Thresholding is a very popular image processing technique, due to its simplicity, intuitive properties, and ease of implementation, so we used this to segment the tomato from the background in this work.

Features analysis

The shape and size characteristics of tomatoes were extracted. We have stated six morphological features: eccentricity, area, perimeter, centroid, major axis, and the minor axis of a tomato. These features were computed from the binary image segmentation result described in the previous section. Table 1 presents the descriptive statistics of the extracted features. The eccentricity of tomatoes collected from Hara was greater than the other two sites. Similarly, the centroid, major and minor axis of tomatoes from Hara were greater than the other two sites.

Table 1

Shape and size features extracted from tomatoes

Tomatoes collected from	Eccentricity	Area [mm^2]	Perimeter [mm]	Centroid [mm]	Major axis [mm]	Minor axis [mm]
Harar	17874	505.4	349.7	(1173.3, 166.7)	137.1	150.9
Dire Dawa	10053	389.5	977.9	(544.3, 140.2)	91.8	113.1
Jijiga	11084	407.5	614.4	(571.3, 144.3)	98.4	118.8

Color feature analysis

The color characteristics of tomatoes were also extracted by our software according to the color feature extraction algorithm the hue, saturation, intensity, and color images were shown in Figure 5. The extracted parameters were hue, saturation, intensity components, and RGB color coordinates. Moreover, we have derived the nine color features shown in Table 2. The results shows that the mean hue colors for Dire and Jijiga tomatoes were similar whereas, Harar had a higher variance hue than the other two sites. Moreover, Harar had a wider intensity range tan the other two sites. The range of intensity of Hara was higher than the other two sites. Overall, color feature sampling from Harar and Dire Dawa samples showed similar characteristics.

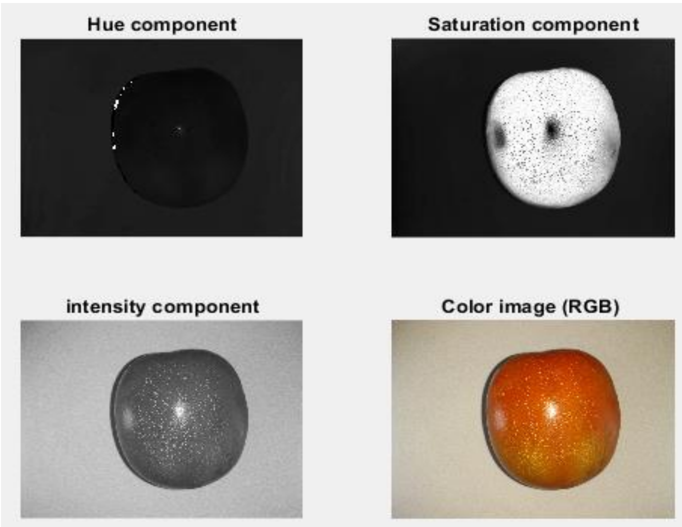

Fig. 5. Color features of a representative tomato.

Table 2

Color features sample extracted from Harar tomato fruits

Color features	Harar tomato	Dire Tomato	Jijiga Tomato
Mean of Hue	0.53	0.54	0.54
Variance of Hue	0.10	0.09	0.08
Range of Hue	0.62	0.61	0.72
Mean of Saturation	0.01	0.02	0.02
Variance of Saturation	0.01	0.01	0.003
Range of Saturation	0.01	0.01	0.01
Mean of Intensity	0.98	1.00	0.99
Variance of Intensity	0.87	1.00	0.60
Range of Intensity	0.94	0.93	0.69

Classification model using ANN

The artificial neural network refers to the connections between the neurons in each system's many layers. Figure 6 depicts an example system with three layers. The first layer contains input neurons which pass data through synapses to the second layer of neurons (hidden layer) and finally through further synapses to the third layer of output neurons. Neural networks have been used to address a wide range of problems that are difficult to answer with traditional rule-based programming. The neural network's output is determined by the connection form, weight value, and excitation function of each node. At the same time, the neural network model is almost all built to describe a specific logical process using some algorithm or function.

Classification of model results based on shape and size features has been selected that increase the performance of ANN, namely, eccentricity, area, perimeter, centroid, major axis, and minor axis [23]. As shown in Figure 6, the employed ANN classifier consists of 7 layers: input, hidden, and output. The input layer accepts the inputs, the hidden layer processes the inputs, and the output layer produces the result. Hence, the neuron numbers of the input layer were seven because the centroid has two values on the *x* and *y* axes and the remaining five features. The output neurons were three, which correspond to the three predefined tomato regions considered in this study. The number of neurons in the hidden layers was ten.

The ANN was trained on 70 % (126 images) of the total datasets. The performance of the trained network was validated by 15 % (27 images) and tested using 15 % (27 images) of the total data set. Table 3 shows the results for CE (cumulative error) and %E (percentage error) of training, testing, and validation of shape and size features. The CE for training, testing, and validation were 4.28, 12.37, and 12.20, respectively, while the percentage errors for each of them were zero percent.

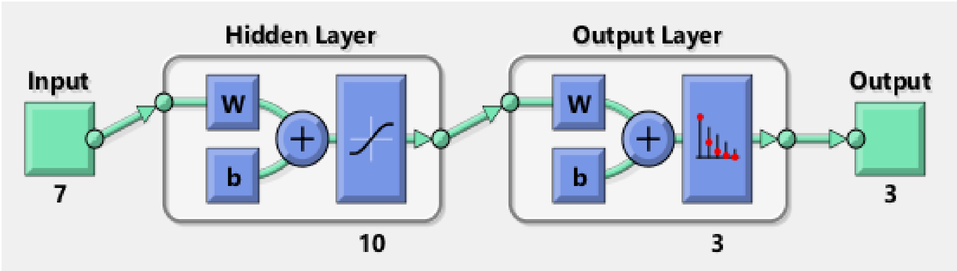

Fig. 6. Artificial neuron network structure layouts in MATLAB.

Table 3

The performance results of the ANN classifier based on shape and size features

Results

	Samples	CE	%E
Training:	126	4.27922e-0	0
Validation:	27	12.36745e-0	0
Testing:	27	12.19736e-0	0

The result of ANN classification using shape and size features showed that the classification accuracy of Dire Dawa, Harar, and Jijiga tomatoes was 100 %. Hence, the neuron numbers in the input layer were nine. The output neurons were three, which correspond to the three predefined tomato regions considered in this study. The number of neurons in the hidden layers was ten shown in Figure 7.

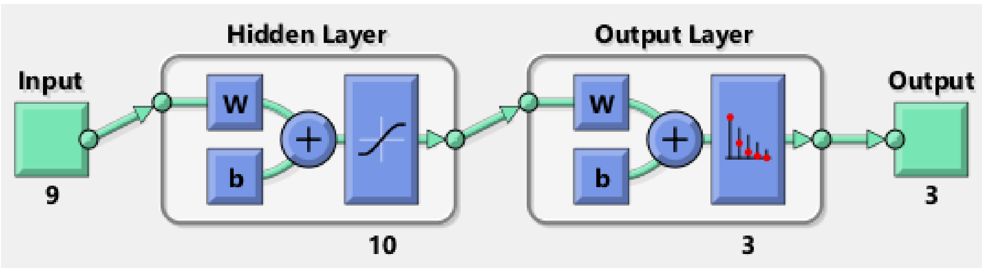

Fig. 7. The result of a network diagram of nine features of color.

The network was trained on 70 % (126 images) of the total data set. Then, the performance of the trained network was validated by 15 % (27 images) and tested using 15 % (27 images) of the total data set. Table 4 shows the results for CE (Cumulative error) for training, validation, and testing was 0.09, 2.67, and 2.67, respectively. The percentage error (%E) of training, testing, and validation of color features: 6.35 %, 3.70 %, and 11.11 %, respectively.

Table 4

The performance statistics of the ANN classifier based on nine color features

Results

	Samples	CE	%E
Training:	126	9.24221e-1	6.34920e-0
Validation:	27	2.66747e-0	3.70370e-0
Testing:	27	2.67431e-0	11.11111e-0

The classification models based on all features were selected as input to the network. Seven shape and size features and nine color features were extracted. Hence, the neuron numbers in the input layer were sixteen. The output neurons were three, which correspond to the three predefined tomato collection regions considered in this study. The total number of neurons in the hidden layers was ten shown in Figure 8.

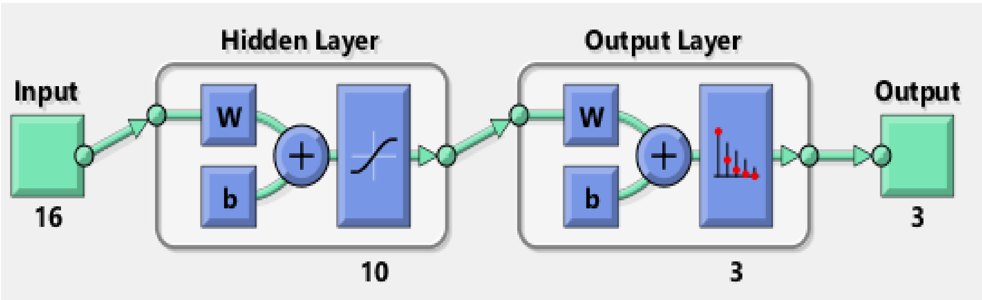

Fig. 8. Screen shoots result of a network diagram of all 23 features.

The network was trained by 70 % (126 images) of the total data set. The performance of the trained network was validated by 15 % (27 images) and tested using 15 % (27 images) of the total data set. Table 5 shows the results for CE (cumulative error) for training, validation, and testing were 3.77, 10.4, and 10.4, respectively. The percentage error was 0 for each feature.

Table 5

The performance results of the ANN classifier based on twenty-three features

Results

	Samples	CE	%E
Training:	126	3.77549e-0	0
Validation:	27	10.39439e-0	0
Testing:	27	10.41345e-0	0

DISCUSSION

Based on the method described in [14], this study demonstrates digital image processing classification of tomato fruit using ANN-based pattern classification. ANN provided high accuracy on the training set, but poor interpolation on the test data. This is possible by using the model developed in [1, 14]. The result shows that both the validation and test have cumulative errors and percentage errors.

The result of Artificial Neural Network (ANN) classification using shape and size features show that the classification accuracy of Dire Dawa, Harar, and Jijiga tomato was classified correctly (100 %). The level of accuracy of the classification based on this model was slightly higher than to [14]. In this study, tomato classification was based only on color and size. We did not add its weight for classification purposes as shown in [13]. Most of the research carried out in the fruit grading system focuses on the color or texture of the fruit in deciding the quality of the fruit.

As mentioned in [9], a feature training and testing approach is included in the tomato image collection. Tomato characteristics, color, size and shape are taken into account when choosing tomatoes.

The classification model based on color features, namely the variance and range of hue, saturation, and intensity components, was used as input to the network as described in the methodology section [1, 14]. The result of ANN classification using color feature showed in Table 5 that the classification accuracy of Dire Dawa, Harar, and Jijiga, the tomato was 100, 83.3, and 96.7 respectively (in percent) [1, 14]. Dire Dawa was perfectly classified, Harar was misclassified to Jijiga (10 images (16.7 %)) and Jijiga was misclassified to Dire Dawa (2 images (1.1 %)). The overall result shows that tomato sorting and grading of 96.7 % and 100 %, respectively.

This shows that the method proposed in this paper produces similar results as [1]. However, it has some main limitation that the color and the size functions alone are ineffective in sorting. In addition, the number of samples used in the experiment is very small compared to other works [1]. According to [6], tomato seed yield and quality are primarily determined by the variety selected for seed production. Many improved varieties and different agricultural packages have been recommended to users to overcome the low yield and quality of tomatoes in the country [3]. Because tomato seeds are not the same in Ethiopia or in any other country. This was one of the weaknesses of the study relative to other studies [1, 13].

CONCLUSION

The paper presented a method for automatic sorting of tomato using computer vision techniques. In this work, we successfully classified tomatoes using ANN-based image processing software written in MATLAB.

Moreover, experimental results showed that the shape and size traits had more discriminative power than the other two traits in the ANN classification in classifying halal tomatoes based on growing area. However, using all features together improves the classification accuracy of tomato fruit. This shows how important it is to include all the characteristics when distinguishing halal tomatoes from different regions. Increasing the estimation sample size improves accuracy and makes it easier to find subtler features.

Therefore, future research should investigate the use of different algorithms, color spaces, and dimensions**,** as well as combinations of other SVM, RGB, and HSL, Convolutional Neuron Network (CNN), Random Forest, Logistic regression, K-NN, and Decision tree models**,** to see which model provides a more accurate model. Besides color, other features can also be examined for parameter extraction.

The use of image processing for quality identification is applicable not only to tomatoes, but also to other types of fruit exported to external markets. As a result, this technology can improve the country's market opportunities.

Acknowledgments: The authors would like to thank the farmers in the three regions for providing the tomato samples required for the experiments and the Dire Dawa University research and community engagement vice President office for funding this research.

Conflicts of interest: The authors declare no conflicts of interest.

REFERENCES

1. ARAKERI, M.P., B. LAKSHMANA Computer vision-based fruit grading system for quality evaluation of tomato in agriculture industry, *Procedia Computer Science*, 2016, **79**, 426–433.
2. BASHEER, I.A., M. HAJMEER, Artificial neural networks: Fundamentals, computing, design an application, *J. Microbiol. Methods,* 2000, **43**, 3–31.

3. BALCHA, K., D. BELEW J. NEGO, Evaluation of tomato (*Lycopersicon esculentum* Mill.) varieties for seed yield and yield components under Jimma condition, South Western Ethiopia, *Journal of Agronomy*, 2015, **14**, 292–297.
4. ETHIOPIAN AGRICULTURAL TRANSFORMATION AGENCY (ATA), Annual Report, 2016.
5. FURTADO, J.J., Z. CAI, X. LIU, Digital image processing: supervised classification using genetic algorithm in MATLAB toolbox, *Report and Opinion*, 2010, **2**(6), 53–61.
6. GEORGE, R.A.T., *Vegetable Seed Production*, CABI Publishing, New York, 1999, pp. 1–327.
7. GONZALEZ, R.C., *Digital Image Processing*, 3rd edition, Pearson Education India, 2009.
8. HUANG, Y., Advances in artificial neural networks methodological development and application, *Algorithms*, 2009, **2**, 973-1007, ISSN 1999-4893.
9. HUIYU, Z., J. WU, J. ZHANG, *Digital Image Processing*, part I, Ventus Publishing Aps., 2011, ISBN 978-87-7681-541-4.
10. IMRAN, A.K., B.P.S. SENGAR, Implementation of technique for image authentication using regular LDPC codes, *International Journal of Computer Applications*, 2013, **67**(4), 14-18.
11. JACKMAN, P., DA-WEN SUN, Recent advances in image processing using image texture features for food quality assessment, *Trends in Food Science & Technology*, 2013, **29**(1), 35–43.
12. JARIMOPAS, B., N. JAISIN, An experimental machine vision system for sorting sweet tamarind, *Food Engineering J*., 2008, **89,** 291–297.
13. KALAIVANI, R., S. MURUGANAND, A. PERIASAMY, Identifying the quality of tomatoes in image processing using MATLAB, *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 2013, **2**(8), 3525–3531.
14. KUEH, H.Y., E. MARCO, M. SPRINGER, S. SIVARAMAKRISHNAN, *Image Analysis for Biology. MBL Physiology Course*, 2008.
15. LINO, A.C.L., J. SANCHES, I.M.D. FABBRO, Image processing techniques for lemons and tomatoes classification, *Bragantia*, 2008, **67**(3), 785–789.
16. MONERUZZAMAN, K.M, A.B.M.S HOSSAIN, W. SANI, M. SAIFUDDIN, M. ALENAZI, Effect of harvesting and storage conditions on the postharvest quality of tomato (*Lycopersicon esculentum* Mill) cv. Roma VF, *Aust. J. Crop. Sci.*, 2009, **3**(2), 113–121.
17. NICOLESCU, C., P. JONKU, A data and task parallel image processing environment, *Elsevier Science B.V., Parallel Computing*, 2002, **28**, 945–965.
18. RODRIGUEZ-LAFUENTE, A., C. NERIN, R. BATTLE, Active paraffin-based paper packaging for extending the shelf life of cherry tomatoes, *J. Agric. Food Chem*., 2010, **58**, 6780–6786.
19. SAXENA, N., N. RATHORE, A review on speckle noise filtering techniques for SAR images, *international journal of Advanced Research in Computer Science Electronics Engineering*, 2013, **2**(2), 243–247.
20. SEKAR, R.L., N. AMBIKA, V. DIVYA, T. KOWSALYA, Fruit classification system using computer vision: A review, *International Journal of Trend in Research and Development*, 2018, **5**(1), 22–26.
21. SGHERRI, C.F., A. NAVARI-IZZO, G.P. PARDOSSI, R. SORESSI, R. IZZO, The influence of diluted seawater and ripening stage on the content of antioxidants in fruits of different tomato genotypes, *J. Agric. Food Chem.***,** 2007**, 55**, 2452–2458.
22. TAMAKUWALA, S., J. LAVJI, R. PATEL, Quality identification of tomato using image processing techniques, *International Journal of Electrical, Electronics and Data Communication*, 2018, **6**(5), 67–70.
23. VELIOGLU, S.Y., G. MAZZA, L. GAO, B.D. OMAH, Antioxidant activity and total phenolics in selected fruits, vegetables, and grain products, *Journal of Agricultural and Food Chemistry*, 1998, **46**, 4113–4117.
24. YUD-REN, C., C. KUANGLIN, S.K. MOON, Machine vision technology for agricultural applications, *Comput. Electr. Agric*., 2002, **36**, 173–191.
25. ZHANG, Y., L. WU, Classification of fruits using computer vision and a multiclass support vector machine, *Sensors*, 2012, **12**(9), 12489–12505.