**TomatoX: Vision-based Judgment of Tomato Maturity using**

**Extreme Learning Machines**

Roberto D. Saldaña Jr.

University of the Philippines Visayas Tacloban College

Magsaysay Boulevard, Tacloban City, Leyte 6500

**Abstract:** *Tomato is one of the economically important fruit in the world. Major supplies of tomatoes come from farms and greenhouses. The traditional way of sorting tomatoes are done by human graders. However, this procedure has a lot of shortcomings. Manual sorting is a very time consuming, tedious, and expensive task. Additionally, the human identification of colors is affected by many factors like brightness, intensity, etc. A lot of research has been conducted on the automation of this procedure. This research proposes the use of Extreme Learning Machines (ELM) in sorting and classifying tomatoes. The study utilizes color features as input to the ELM Network. The study proposes the use of L\*, a\*, Hue, and red-green difference. The experiment results show that ELM can be an efficient method in the classification of tomatoes. Also, the training time for ELM is fast compared to other researches. The proposed color features also performed better than other color feature combinations.*

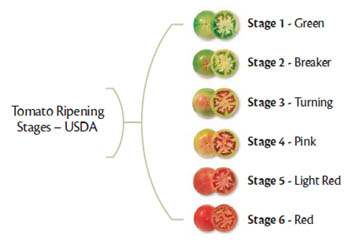
**Keywords:** Tomato Classification, Image Processing, Color Space, Machine Learning, Extreme Learning Machines

**1 Introduction**

Tomato, scientifically known as Lycopersicon esculentum, is a nutritious fruit known as a vegetable. It is arguably one of the economically important fruit in the world. This is because exports of tomato and its lateral products such as ketchup and tomato sauce have considerable income. In turn, tomato is the most investigated member of the fleshy fruits regarding fruit development and ripening [6].

The major sources of tomatoes are commercial farms and greenhouses. Traditionally, the classification and sorting of tomatoes is done using human labor. This process is very time-consuming, tedious and expensive. In fact, the high labor cost has been the main obstacle in the expansion of greenhouses. Additionally, human identification of colors is affected by sensations like brightness, intensity, lightness and vividness, thus in many cases color definition is a matter of subjective interpretation.

The surface color of a tomato is the most important external characteristic to assess the maturity and is a major factor in the consumer’s purchase decision. Degree of ripening is usually estimated by color charts [3]. Based on the external color, the United States Department of Agriculture (USDA) established six ripening stages reflecting human ability to differentiate ripeness. Figure 1 shows the different stages of a tomato as described in the USDA chart. It can be seen that the surface color changes from green to red. The summary of the description for each stage is shown in Table 1.



**Figure 1:** USDA tomato ripening stages [5]

**Table 1:** USDA Tomato ripening stages

|  |  |
| --- | --- |
| Stage | Description |
| Green | surface is completely green in color |
| Breaker | definite “break” in color of not more than 10% |
| Turning | change of color is more than 10% but not more than 30% |
| Pink | change of color is more than 30% but not more than 60% |
| Light Red | change of color is more than 60% but not more than 90% |
| Red | change of color is more than 90% |

**1.1 Image Processing**

Image processing is the manipulation of an image to produce either an image or a set of characteristics/parameters related to the image. According to [4], image processing is used in applications for two purposes: (1) improving the visual appearance of images to a human observer, including their printing and transmission and (2) preparing images for measurement of their features and structures which they reveal. Various techniques in image processing have been introduced, including visual enhancement, data extraction and the context of reproduction and transmission. These techniques include grayscale conversion, binary masking, scaling and cropping.

**1.2 Color Space**

A color space, also known as color model, is a mathematical or numerical representation of a set of colors. The purpose of a color model is to facilitate the specification of colors in some standard generally accepted way. This research utilized the RGB, HSI, and CIE L\*a\*b\* color models. All of the color spaces can be derived from the RGB information.

**1.3 Extreme Learning Machines**

The Extreme Learning Machines (ELM) is a recent breakthrough in machine learning and data analysis. It tries to solve the pressing issues encountered by traditional learning techniques such as neural networks (NN) and support vector machines (SVM). These issues include intensive human intervention and slow learning speed. Developed by Huang et al. [1], ELM works for the “generalized”single-hidden layer feed-forward networks (SLFNs) but the hidden layer (feature mapping) in ELM need not be tuned. In NN, all hidden nodes in SLFNs need to be tuned. ELM however shows that these hidden nodes need not be tuned and can be randomly generated. In fact, all parameters of the ELM can be analytically determined. The ELM algorithm is summarized on the next paragraph.

Given a training set , hidden node output function , and hidden node number *L*,



*step* 1Randomly generate hidden node parameters (), *i* = 1 ,…, *L*.



*step* 2Calculate the hidden layer output matrix **H**.

*step* 3 Calculate the output weight vector **β**: **β =**



If a positive value 1/λ or C is added the calculation of **β**, the resultant solution is more stable and tends to have better generalization performance. The formula for the calculation of the output weight **β** is as described in equations (1) and (2):

|  |  |
| --- | --- |
|  | **(1)** |
|  | **(2)** |

**2 Proposed Approach**

The flow of the process for this research is illustrated in Figure 2. The tomato image undergoes a number of preprocessing steps before it is subjected to classification.

**Figure 2:** The pipeline of TomatoX

**3 Experimental procedures**

The dataset used in this research is composed of six hundred (600) images, one hundred (100) images per tomato stage. It was divided into two subsets, the train set and the test set. The train set is composed of seventy percent (70%) of the dataset while the test set is composed of the remaining thirty percent (30%). Four experiments were conducted and for statistical acceptability, all experiments were subjected to 30 trials.

For experiment I, a fixed data and a random data is compared. For the fixed data, a fixed train and test set were used for all 30 trials. On the other hand, for the random data, a random train and test set were used for every trial. For experiment II, the number of hidden nodes was varied according to the number of samples. The variation in the number of hidden nodes used was N, 0.75N, 0.5N, 0.25N where N is the number of samples. Table 2 shows the variation in the number of hidden nodes.

**Table 2:** Varying the number of hidden nodes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | A | B | C | D |
| Number of Hidden Nodes | 105 | 210 | 315 | 420 |

For experiment III, the value of the regularization coefficient (C) is varied from 1 to 50. The fixed dataset used in experiment I was also used in experiment III but only the test set was used in testing the classifier, i.e. for every regularization coefficient (C), the train set was used for training but only the test set was used in testing the accuracy of the classifier. For experiment IV, the number of color features was varied. Table 3 shows the variation in the combination of the color features.

**Table 3:** Varying the input features

|  |  |
| --- | --- |
| **Set** | **Color Feature (s)** |
| **A** | R-G |
| **B** | H, R-G |
| **C** | L\*, a\* |
| **D** | L\*, a\*, H, R-G |
| **E** | R, G, R-G, H, a |

**4 Results and Discussion**

**4.1 Experiment I**

**Table 4:** Results for the comparison of fixed data and random data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Fixed | | Random | |
|  | **Test set** | **Train set** | **Test set** | **Train set** |
| Mean | 97.593% | 98.865% | 97.185% | 98.905% |

As shown in Table 4, for the test set, the fixed data has a higher average than that of the random data. This is due to the fact that the classifier for the random data was not trained well to handle more complicated inputs, i.e. there is a possibility that the images that are more difficult to classify were on the test set while the easier ones were on the training set. There is also a possibility that the opposite situation will happen, i.e. the images that are easier to classify were on the test set while the difficult ones were on the training set. This can be seen on the results for the train set, the random data has a higher average compared to the fixed data.

**4.2 Experiment II**

**Table 5:** Results of varying the number of hidden nodes for the test set and train set

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | A | B | C | D |
| Test set | 97.593% | 96.796% | 94.667% | 87.463% |
| Train set | 98.865% | 99.556% | 99.714% | 99.952% |

The fixed dataset used in Experiment I is used in this experiment. As shown in Table 5, for the test set, as the number of hidden nodes is increased, the accuracy of the classifier tends to decrease. This is because as the number of hidden nodes approaches the number of training samples, the ELM becomes a singular least-squares problem and gives an unstable solution. On the other hand, for the train set, as the number of hidden nodes is increased, the accuracy of the classifier increases accordingly. This can be contrasted to the results obtained in the test set. The reason behind is that as the number of hidden nodes approaches the number of training samples, the matrix H becomes square and invertible. Thus, according to [2], SLFNs can approximate these training samples with zero error.

**4.3 Experiment III**

**Table 6:** Results of varying the values of the regularization coefficient

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **No C** | **1** | **10** | **20** | **30** | **40** | **50** |
| **Mean** | 97.593% | 98.259% | 98.13% | 98.074% | 98.056% | 98.148% | 98.278% |

As shown in Table 6, the results for all values of C have greater accuracy compared to the result obtained without the introduction of C. This suggests that the introduction of the regularization coefficient (C) further improves the classification capability of ELM. However, as shown in the results, an increase in the value of C does not necessarily mean an increase in the accuracy

**4.4 Experiment IV**

**Table 7:** Results of varying the input features

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** | **E** |
| **Mean** | 96.037% | 94.444% | 96.741% | 97.593% | 95.833% |

As shown Table 7, the results show that set D, containing the proposed input features performed best among all the setups. The results also show that the use of more input features does not necessarily mean an increase in the accuracy. In fact, set A containing only one input feature performed better than set B that contains two input features and set E that contains five input features. For comparison, the result of this study is compared to the work of Opeña [15]. As shown in Table 8, the accuracy of this research is smaller but the training time is smaller compared to TotoBee [15]. Time is a necessity in industrial applications. The results of this research offer faster training time with a small decrease in accuracy.

**Table 8:** Results of varying the input features

|  |  |  |
| --- | --- | --- |
|  | Current Research | TotoBee [15] |
| Accuracy | 97.593% | 98.19 % |
| Training Time (sec) | 1.89 | 153.46 |

**5 Conclusions**

In this study, ELM was implemented to solve the tomato classification problem. Experimental results show that ELM can be an efficient method in the classification of tomatoes. In the first experiment, it has been shown that the ELM classifier is robust. It can handle complex data with little impact on the accuracy. In the second experiment, it has been shown that the number of hidden nodes can affect the performance of ELM. As the number of hidden nodes is increased, the accuracy for the train set increases while the accuracy for the test set decreases. In the third experiment, the introduction of a regularization coefficient (C) further improves the generalization capability of the ELM. However, based on the results, an increase in the value of C does not necessarily mean an increase in the accuracy. In the last experiment, it has been shown that the input features have a significant effect on the performance of the ELM. However, an increase in the number of input features does not guarantee a good result. Set A containing only one input feature has better performance than set B and set C containing two and five input features respectively. Overall, set D containing the proposed input features performed best amongst all the setups.

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