

B.Tech 7th Sem Project Report

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Certificate of Approval

This is to certify that the 7th Sem B.Tech. project report entitled “Estimation of Starch and Textural Feature Extraction in Foldscope image using GLCM” is a record of bonafide work carried out by Pragyanshu Verma under my supervision and guidance.

The report has partially fulfilled the requirements towards the degree of Bachelor of Technology in Electronics and Communication Engineering at Indian Institute of Information Technology, Guwahati.

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1. Introduction

In the market there are many fruit and vegetable in which chemical are being used to increase the production. Manual techniques to assess the food quality, the visual perceptions (usually bare eyes) dominate the other means, which is not only inefficient but also unreliable due to subjectivity, inconsistency etc. However, such obscures can be tackled by the computer vision technology that corresponds to the human vision, in inspecting quality of fruits and vegetables. It captures images electronically, then interpret and recognize the characters /information to examine the quality, and grading of agricultural products. In this direction, several attempts have been made for grading of food including apples [1, 2], mango [2] sweetpepper [3], papaya [4], tomato [5, 6] etc. However, all the methods consider the traditional camera images, taken from the surface of the vegetables and fruits, which are failed to provide inside details such as nutrients contents of a products. Such details are the key components to quantify the food quality or grading. Certainly, the microscopic images (resolution of 200 nm or smaller) provide insight information at cell level which could be appropriate to examine the food quality more precisely than the use of conventional camera images. Few works have been conducted in this direction based on such microscopic images to evaluate the quality of vegetable and fruits such as evaluation of potato and its starch [7], browning of apple due to storage [8], and effect of freezing in blueberries [9]. Here in this project we will focus on specific vegetable such as potato.

Keywords: Foldscope, Microscopic Image Processing, Potato Starch.

2. Motivation

Food quality assessment is always being an important part at the time of purchasing or consuming any sort of foods. Now-a-days, it becomes more evident as fertilizer and pesticides in crops are being used enormously without maintaining the nutrition value to meet the huge demand of food for rapidly growing population. In addition, harmful chemicals are also being used in vegetables and fruits for immoral purposes; for instance, Copper Sulphate (CuSO_4) is used to look the vegetable fresh; Calcium Carbide (CaC_2) is used to ripe fruits artificially and so on. Besides, several synthetic colors are applied on vegetables to maintain their freshness. Such malpractices make the food quality assessment more evident. Generally, in market the quality of the agricultural products are evaluated based on their shape, size, colour etc. which are performed by means of vision, touch, smell, odour, taste, flavour etc. Indeed, all these methods are tedious, time consuming, very, much subjective, but not even very reliable. Therefore, it is very significant to develop a rapid, reliable, easy to use system to examine the agricultural products.

3. Problem Definition

Differentiate the starch quantity in different Folscope images using segmentation and contour detection method. Furthermore, classify the Foldscope images on the basis of GLCM texture feature.

4. System Overview

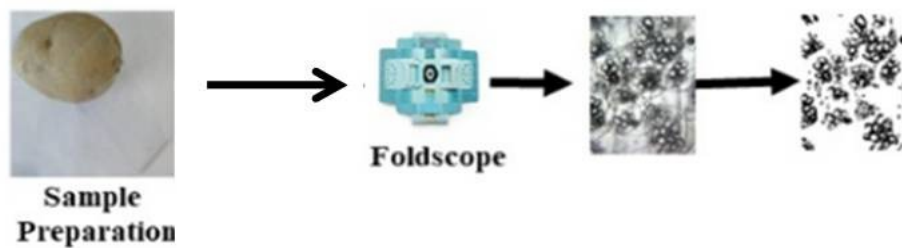


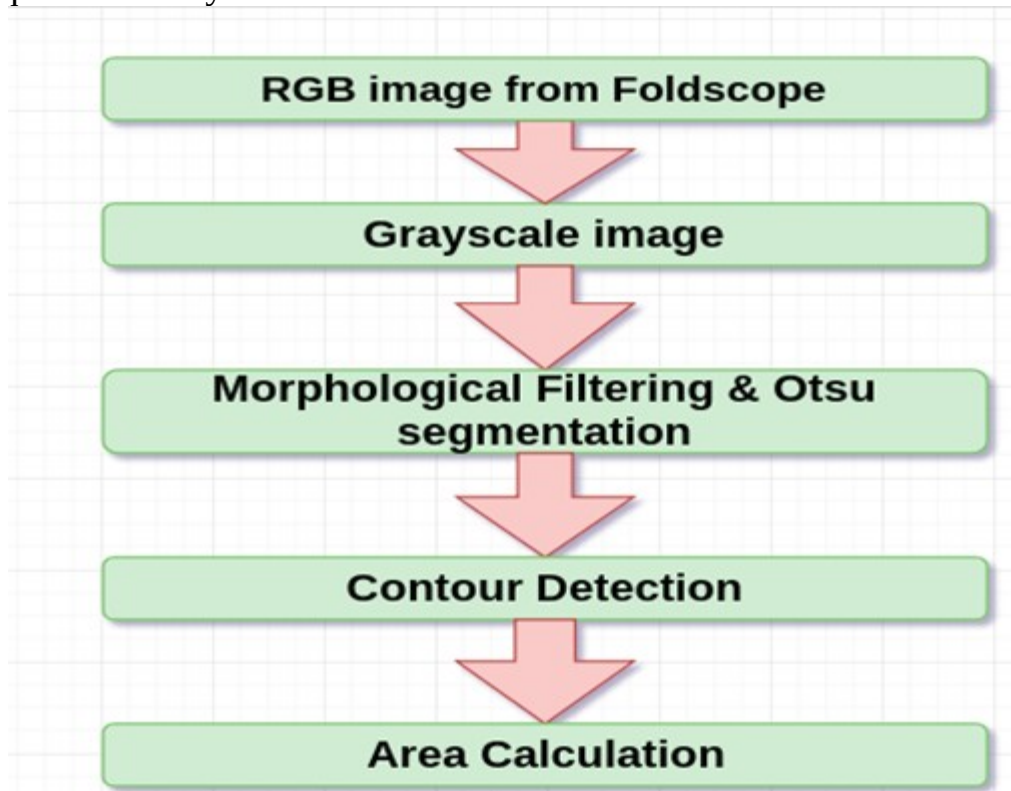
Figure-1

A system overview of the proposed method has been displayed in Fig. 1 which involves several stages including sample preparation, image acquisition, image processing, starch detection and estimation. Firstly, conventional methods for acquiring microscopic images such as sectioning of samples etc. are conducted to acquire microscopic image of potato. Next, images are generated using Foldscope. Further, image processing techniques such as morphological filtering followed by segmentation are conducted to detect the starch from those one set of images.

5. Methodology

Usually images generated by microscopes which are expensive, complex, bulky and need some sort of expertise to operate. In this regard, recently, a newly developed light weight (~9gm), low cost (~Rupees 250), and 140X magnification powered origami based paper microscopic called Foldscope [10] could be a good solution to generate the microscopic images. Besides, the generated images can be captured directly by simple mobile camera. Thus, a combining Foldscope with mobile camera for capturing microscopic images and further employing computer vision and image processing techniques to analyze those images could be a proper food quality assessment system. Therefore, in this work, microscopic images of potato have been considered to verify the usability of such device. The potato has been used as one of the most important crop consumed in India after rice, wheat and maize [11]. Usually, it contains water (80%) and dry matter (20%) which is well-known as starch [11]. Inevitably, this starch amount defines the quality of a potato [12]. In a microscopic image of potato, usually starches are glided on the surface of the cells which makes it challenging to distinguish from regular cells. In this purpose, staining method enhances either cell boundaries or starch, could be useful in such detection process.

But, it requires not only



involvement of additional arrangement (chemical process etc.), but also high-end microscope (like electron microscopes)[13]. Another way, use of image processing techniques such as morphological image enhancement on microscopic image directly could be very convenient to sidestep staining process [14]. Certainly, a well-established, simple and accurate image segmentation techniques such as Otsu's segmentation method [15] has been employed. It works with intensity of an image and considers thresholding technique to discriminate two set of classes of an image. Thus, it could be applicable to distinct starch from cell background. Nevertheless, such thresholding sometimes leads to improper segmentamentation techniques such as Otsu's segmentation method [15] has been employed. Therefore, measuring the starch content using microscopic images which will be captured by above mentioned setup and deploying image processing technique is the main objective of this work. This work focuses on the quality assessment of agricultural product based on microscopic image, generated by Foldscope. Microscopic image based food quality assessment always be an efficient method, but its system complexity, costly, bulk size and requirement of special expertise confines it usability. To encounter such issues, Foldscope which is small, lightweight, cheap and easy to use has been considered to verify its usability as food quality assessment device.

5.1 Morphological Filtering

Morphological operation analyses the geometrical structure of an image. It performs dilation, erosion, opening, closing operation with an image of definite shape and size (structuring element). Morphological filter can be constructed on the basis of morphological operations. It offers better result than the linear filtering as it deforms

the image geometry. The morphological filter has been designed based on two morphological operations called top-hat and bottom hat transform by opening and closing operations respectively. The whole operation performs on grayscale image. The brightest parts of the images are enhanced by top-hat transform; whereas, the bottom-hat transform does the reverse process. Top-hat transform followed by bottom-hat transform increases the contrast between cell boundaries and starch which further benefits to discriminate the starch distinctly. Figure-2 (i) is the original image that is taken and fig-2(ii) image is the output of the first image after applying morphological filtering. Generated images from the modalities consist of starch spreading over regular cells and its boundaries. However, the intensity difference between them is relatively small which confines to employ simple thresholding technique to discriminate starch from regular cells— leads to under segmentation. Certainly, a popular segmentation method known as Otsu's method which performs the thresholding, based on statistical measures can be used. Nonetheless, direct use of Otsu's method sometimes results over segmentation which can be overcome by a morphological filtering. Therefore, a morphological filtering has been conducted followed by Otsu's algorithm to improve the system performances by eradicating uneven illumination and the cell boundaries. Further, to estimate the starch quantity efficiently binarization and morphological operation have been performed.

5.2 Contour Detection

Contours can be explained simply as a curve joining all the continuous points (along the boundary), having same color or intensity. The contours are a useful tool for shape analysis and object detection and recognition. Contour tracing is one of many pre-processing techniques performed on digital images in order to extract information about their general shape. Once the contour of a given pattern is extracted, its different characteristics will be examined and used as features which will later on be used in pattern classification. Therefore, correct extraction of the contour will produce more accurate features which will increase the chances of correctly classifying a given pattern. Well, the contour pixels are generally a small subset of the total number of pixels representing a pattern. Therefore, the amount of computation is greatly reduced when we run feature extracting algorithms on the contour instead of on the whole pattern. Since the contour shares a lot of features with the original pattern, the feature extraction process becomes much more efficient when performed on the contour rather on the original pattern. To find the percentage of starch we have to first detect the starch. For that we are detecting the boundaries of the starch. To find the boundaries of the starch segment, contour detection method has been applied on the starch detected binary images. Contour detection method traces the boundary of the each starch and draw the red line on contours. There were many contour detected if we directly apply contour detection on these images because there is too many small-small borders. We don't want to detect the contour of that small portion. So to avoid small contour we took the area constraint. If the area of any contour is >500 px then only we have to draw the boundary. Furthermore, other measurement such as individual detection of starch has been done for ten Foldscope

images. The area has been calculated, considering number of pixels inside the boundary. Finally total percentage of starch area has been measured.



fig-2(i)

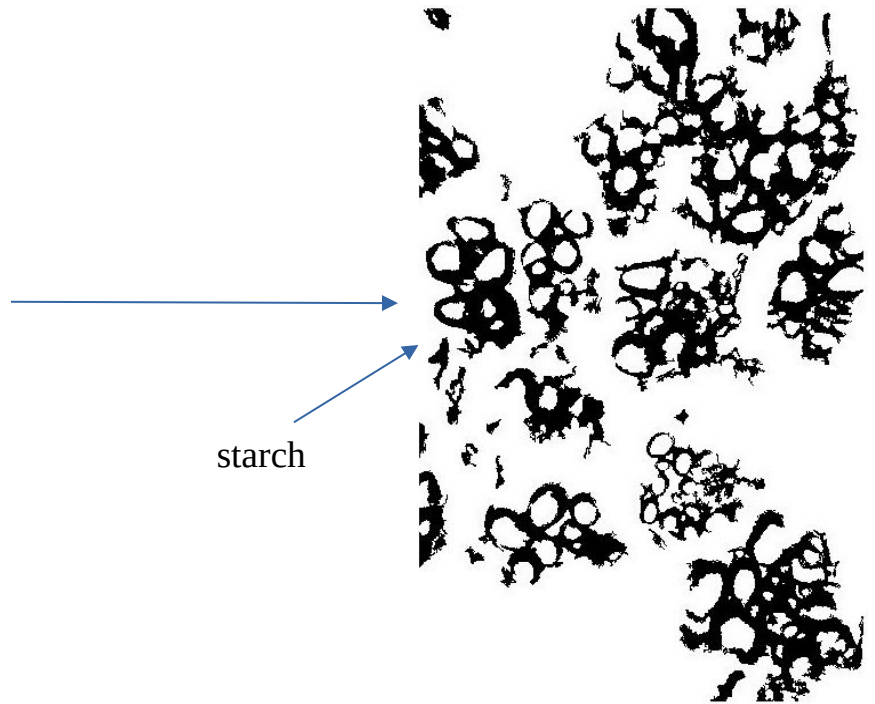


fig-2(ii)

5.3 Percentage Calculation of starch

For calculating the starch first we have to find the area of each contour and then sum all the area and then divided by total area. It will give the percentage of starch in image.

$$\% \text{ starch} = (\sum_{i=1 \text{ to } n} \text{area}_i) / \text{total area}$$

n = number of contours

area_i = area of i^{th} contour

Using this method we can find out the area of every contour and then % starch. In figure-3 (i) image is the output of the morphological filtering. We did our contour detection operation on this image so resultant image is fig-3(ii).

There are 5 steps to determine the % starch in an image. These steps have been shown in figure-5.

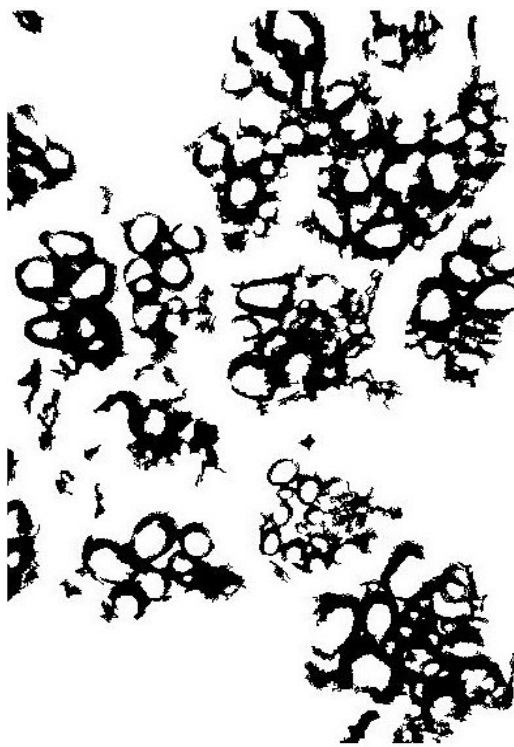


figure-3 (i)

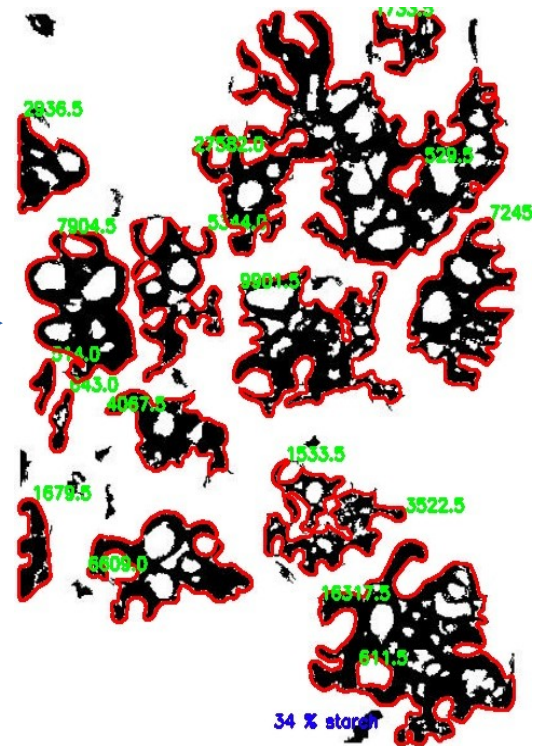


figure-3 (ii)

Figure-3

5.4 Texture Features

The textural features of the Foldscope images have been measured for segmentation and classification task. In image, visual texture is related to the spatial distribution of intensity values (grey level). It can be described as a pattern that spatially repeated. Statistical methods are used to analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features. The statistical methods can be classified into first order (one pixel), second order (pair of pixels) and higher order (three or more pixels) statistics. The first order statistics estimate properties (e.g. average and variance) of individual pixel values by waiving the spatial interaction between image pixels. The second order and higher order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. The most popular second order statistical features for texture analysis are derived from the co-occurrence matrix, known as grey level co-occurrence matrix (GLCM). Hence to get the textural information from microscopic images generates from the Foldscope, GLCM has been calculated. From GLCM, other measurement such as contrast, homogeneity, dissimilarity, energy, correlation and angular second momentum has been calculated for 10 microscopic images. The 'value' of the image originally referred to the grayscale value of the specified pixel, but could be anything, from a binary on/off value to 32-bit color and beyond. (Note that 32-bit color will yield a $2^{32} \times 2^{32}$ co-occurrence matrix!). Any matrix or pair of matrices can be used to generate a co-occurrence matrix, though their most common application has been in measuring

texture in images, so the typical definition, as above, assumes that the matrix is an image.

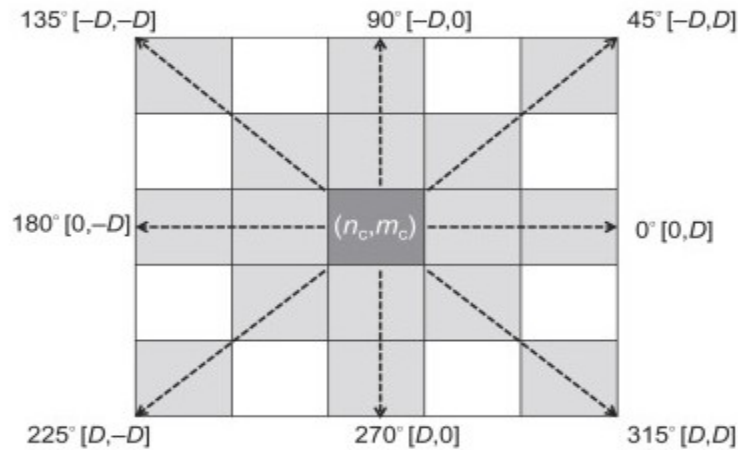
It is also possible to define the matrix across two different images. Such a matrix can then be used for color mapping.

The cooccurrence matrix is a statistical method of examining texture of a grayscale image. Let $I(k,k)$ be the neighbourhood grayscale image of a center pixel (n_c, m_c) . The cooccurrence value is define as the distribution of cooccurrence values ata given distance. from speciifc pixel (n_c, m_c) . For the image $I(k,k)$, the cooccurrence matrix $C_M = C_{(D_x, D_y)}(k, k)$ is defin as

$$C_M = \sum_{n=1 \text{ to } k} \sum_{m=1 \text{ to } k} \begin{cases} 1 & \text{if } I(n, m) = k \text{ and } I(n + D_x, m + D_y) = k \\ 0 & \text{otherwise} \end{cases}$$

where (D_x, D_y) are defin as

$D_x = D \cos(\theta)$ $D_y = D \sin(\theta)$ where θ is the offset that defines the direction of the matrix from the central pixel (n_c, m_c) and D is the distance from the pixel central pixel (n_c, m_c) as it is shown in Figure below.



Compute a feature of a grey level co-occurrence matrix to serve as a compact summary of the matrix. The properties are computed as follows : (here P represents the cooccurrence matrix)

$$\text{Contrast} = \sum_{i,j=0} P_{ij} (i-j)^2$$

$$\text{Dissimilarity} = \sum_{i,j=0} P_{ij} |i-j|$$

$$\text{Homogeneity} = \sum_{i,j=0} P_{ij} / (1 + (i-j)^2)$$

$$\text{Correlation} = \sum_{i,j=0}^{levels-1} P_{i,j} \left[\frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right]$$

6. Experiment

6.1 Experimental setup

The microscopic images are generated and captured by two modalities as mentioned earlier. One is the Foldscope which is an origami based optical microscope which can be assembled from a printed A4 size paper in 10minutes. The dimension of the device is 70X20X2 mm 3 and of weight 8 gm. The images are generated by 140 x magnifications with 2micron resolution. Another, a traditional microscope Olympus CH20i using 10X objective lens has been used to generate images. Two set of images of same sample has been generated and captured by a smart phone camera (MotoG4 Play, 1280x720HD, 294ppi, 5 inches diagonal display, 8MP).

6.2 Data

For experimental validation, potato starch has been taken into account. Among different varieties of potatoes, the 'Jyoti' variety is been selected as it is largely consumed in India. The specification of the 'Jyoti' variety has been briefed in Table 1. To generate the microscopic images, thin sections of potato are placed under the Foldscope as well as the traditional microscope and consequently the images are captured. In total 20 images from both of the modalities are taken.

Table : Specification of potato sample

Perticulates	Specifications
Common name	Alu, Alo, Aaloo
Season Varities	KufriJyoti (1968)
Family	Solanace
Botanical Name	Solanumtuberosu L

7. Results

Here first we get the % starch in an image. Previously it was calculated by considering the black pixels only. Where the white pixels have been eliminated which belongs to the starch portion. So, for starch calculation area of the starch cell has been calculated for ten Foldscope images. The result shows the % of starch area as 32.9 ± 6.0646 . Texture features has been measured using GLCM. Furthermore, contrast, dissimilarity, homogeneity and correlation has been calculated from GLCM. The higher value of homogeneity when contrast in texture is lower

Table-2:

Sr No	Contrast	Homogeneity	Correlation	Dissimilarity
img 1	124.231	0.215	0.983	7.129
img 2	167.52	0.176	0.98	8.549
img 3	103.624	0.216	0.987	6.636
img 4	156.262	0.208	0.981	7.931
img 5	153.478	0.187	0.981	8.115
img 6	173.103	0.198	0.977	8.322
img 7	147.398	0.16	0.958	8.106
img 8	121.468	0.185	0.962	7.127
img 9	144.75	0.175	0.953	7.783
img 10	148.264	0.155	0.96	8.341

8. Conclusion and Future work

Area of starch calculated successfully using contour detection. Ten image has been taken from foldscope Next, morphological filtering followed by and Otsu's method has been employed. After that we get a binary image in which cell boundaries were deleted. Then contour detection has been applied for area calculation. From the calculated area we can predict the presence of starch in an image. To classify the foldscope images texture features have been extracted. In future, more set of images along with several crops will be verified. In addition, deep learning-based based recognition system will be incorporated to improve is efficiently. In our future work we will try to represent the area in micro level. and on the basis of the texture features, further Foldscope images can be classified. In future cell boundary and area for potato microstructure will be performed for several Foldscope images.

References

- [1] S. Cárdenas-Pérez, J. Chanona-Pérez, J. V. Méndez-Méndez, G. Calderón-Domínguez, R. López-Santiago, M. J. Perea-Flores, "Evaluation of the ripening stages of apple (Golden Delicious) by means of computer vision system," *Biosyst. Eng.*, vol. 159, pp. 46–58, 2017. doi.org/10.1016/j.biosystemseng.2017.04.009.
- [2] M. A. Ali and K. W. Thai, "Automated fruit grading system," in *IEEE Int. Sympm. Robotics Manufact. Automation (ROMA)*, Kuala Lumpur, Malaysia, Sept 2017, pp. 1–6.
- [3] I. Sa, Z. Ge, F. Dayoub, B. Upcroft, T. Perez, and C. McCool, "Deepfruits: A fruit detection system using deep neural networks," *Sensors*, vol. 16, pp. 1222, 2016.
- [4] L. F. S. Pereira, S. Barbon Jr, N. A. Valous, and D. F. Barbin, "Predicting the

ripening of

papaya fruit with digital imaging and random forests,” *Comp. and Elect. Agri.*, vol. 145,

pp. 76–82, 2018.

[5] T. Mehra, V. Kumar, and P. Gupta, “Maturity and disease detection in tomato using

computer vision,” in *Int Conf Parallel, Distributed, Grid Comput.(PDGC)*, Solan, India, Dec. 2016, pp. 399–403.

[6] M. P. Arakeri, “Computer vision based fruit grading system for quality evaluation of

tomato in agriculture industry,” *Proc, Comp. Science*, vol. 79, pp. 426–433, 2016.

[7] Q. Liu, E. Donner, R. Tarn, J. Singh, and H.-J. Chung, “Advanced analytical techniques

to evaluate the quality of potato and potato starch,” in *Adv. Potato Chem. Tech.*, Ed: Elsevier, 2009, pp. 221–248.

[8] J. Cropotova, U. Tylewicz, E. Cocci, S. Romani, and M. Dalla Rosa, “A novel fluorescence microscopy approach to estimate quality loss of stored fruit fillings as a result of browning,” *Food Chem.*, vol. 194, pp. 175–183, 2016.

[9] P. Allan Wojtas, H. Goff, R. Stark, and S. Carbyn, “The effect of freezing method and

frozen storage conditions on the microstructure of wild blueberries as observed by cold stage scanning electron microscopy,” *Scanning*, vol. 21, pp. 334–347, 1999.

[10] Foldscape, <https://www.foldscope.com>

[11] S. Borah, B. Bowmick, and C. Hazarika, “Production behaviour of potato in Assam-A

critical analysis across zones and size groups of farms,” *Eco. Affairs*, vol. 61, pp. 23, 2016.

[12] N. Litaladio and L. Castaldi, “Potato: The hidden treasure,” *J. Food Comp. Anal.*, vol.

22, pp. 491–493, 2009.

[13] Q. Liu, L. J. Zhang, and X. P. Liu, “Microscopic image segmentation of Chinese herbal

medicine based on region growing algorithm,” in *Adv. Materials Research*, pp. 4110–4115, 2013.

[14] S. Ravi and A. Khan, “Morphological operations for image processing: understanding

and its applications,” in *Proc. 2nd Nat. Conf on VLSI, Signal Proc. ,Comm. NCVSComs*,

Guntur, India, Dec 2013.

[15] N. Otsu, “A threshold selection method from gray-level histograms,” *IEEE Trans*

Systems, Man, and Cybernetics, vol. 9, pp. 62–66, 1979.

