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Multi Classification Of Potatoes Using Cubic Support Vector Machine

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Abstract

In an attempt to classifiy potatoes based on features of gray level co-occurrence matrix properties using support vector machine classifier in to five classes.Potato images are captured using developed setup. The developed image capturing setup has a resolution of 0.22 mm per pixel. The four parameters of gray level co-occurrence matrix such as variance, correlation, uniformity and homogeneity are calculated from each image and the data set has been prepared. Labelling of images is decided by visual appearance of potato, crack, rotten, sprout, good and skin peel potatoes are 75, 39, 153, 96 and 635 respectively. Crack, rotten, sprout, good and skin peel images has been labelled as 1, 2, 3, 4 and 5 respectively. Adding labelling to the feature data set, by which data set size increases to 998-by-five. Feature data set having size of 998-by-5 is fed into classification learner app in Matlab. Combined parameters of gray level co-occurrence matrix such as variance (contrast), correlation, uniformity (energy) and homogeneity are used in potato classification. Cubic support vector machine has an classification accuracy of 99.5 per cent. Quality parameters like true positive and positive predictive values are studied for cubic support vector machine model. True positive rates of 100, 97, 98, 99 and 100 are observed for crack, rotten, sprout, good and skin peel categories respectively. Crack and skin peel categories have same number of potatoes in manual and cubic support vector machine classification. Misclassified potatoes in cubic support vector machines are less than compared to manual classification with one, two and two potatoes in rotten, sprout and good categories.

INTRODUCTION

One of the most famous cultivations on earth, which is widely consumed as raw or cooked, is potato (*Solanum Tuberosum L.*). Farming of potatoes accounts for almost 80 per cent of countries. Following rice, wheat and maize, it is India's main crop. The need for potatoes for processed products is strong and not for fresh use. This increases the demand on the market for high-quality potatoes[1]. In India, 5129.4 million ton potatoes[2]are produced for the year 2017-18, and it occupied third position in the world[3]. In India, potato production has increased substantially over the last six decades. The analysis shows that the potato yield and production increased respectively at the national level at 1.10 and 5.98 million per year during the last decade[4]. As very less number of results available in artificial classification of potatoes, this study has been undertaken by developing a image capturing setup followed by classification results. Potato grading are very important unit operation in price fixing and minimum supporting price for farmers.

REVIEW OF LITERATURE

Image processing technology is in a developing phase which is being used for qualitative inspection of food[5], detect external defects in apples[6,7,8]; figs sorting[9]; potatoes external defects[10,11,12,13,14,15]; saffron quality checking[5]; biscuits crack inspection[16,17]; Mango shape[18] and wight estimation[18,19]; pecans quality evaluation[20]; potato sorting based on size and color[21]; area and volume determination of food materials[22]; banana maturity assessment[23]; physical properties of fruits[24]; berry yield prediction[25]; grape drying modelling[26]; sugarcane physical and chemical properties[27]; leaf area estimation[28] and pizza color estimation[29].

Classifier assigns classes to objects based on feature identification[30]. Classification is the major task after extracting the features[31]. Support vector machine (SVM) is a trained method to classify input data into two or more classes[32]. It is a new method of classification, which works on statistical concepts and does not require more samples for training data[33]. SVM develops an optimum separating line for multiple classification and it classifies the data without knowing their distribution model. SVM changes itself into next method of classification and it is made by a combination of binary classes. It classifies the data between each category and the rest of the categories[32]. SVM classification depends upon one versus one and one versus all classification types. Gaussain support vector machine classification of disease causing microscopic bacteria have an accuracy of 90.52 per cent[34]. Linear kernel SVM multi classification of different image data sets have an accuracy's of 67.54 and 61.05 per cent respectively. Gaussian SVM classifications having an accuracy's of 60.12 and 54.87 per cent respectively[35]. SVM algorithm maximises a partcular mathematical formula corresponding to input features. SVM's can correctly add a lot of features for training to find best and desirable separating line. They maximises the faults involved in the training set and maximises the gap between data and separating line. SVM's are used for the purpose of comparison and it results a single result[36]. Out of remaining classifiers SVM has highest accuracy but high traing time.

MATERIALS AND METHODS

Setup For Image Processing

The image processing units were consisting of acquisition devices, followed by image analysis unit like computer with image storage unit as shown in Figure 1. Image capturing requires an artificial light, image sensor and image storage unit as shown in Figure 1. A setup was developed with the help of a 40×40×40 cm box using a 20-gauge galvanized iron sheet. Four still web cameras (Model no. QHM495LM) equipped with inbuilt six LED lights and potentiometers were installed on inner four side walls of the box focussing in the centre of the box (Figure 1).

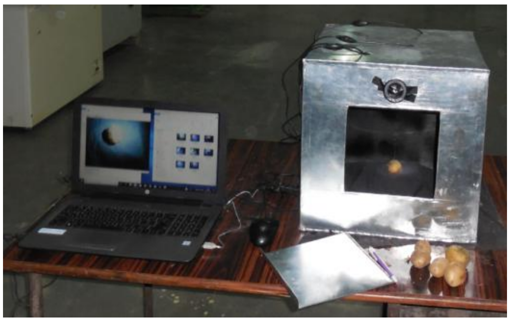

Figure 1. Image processing setup developed for potatoes

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These six LED bulbs will reduces the additional installation space required for lighting. The four ends of cameras were connected to laptop through USB (Zebronics, ZEB-04HB) Hub. While capturing care must be taken by allowing light to settle on potatoes. Potentiometers were used for adjusting the light intensity. Walls of the box were painted with black color to eliminate reflections. A door was provided at the front to place and remove potatoes. After developing setup, next step is image capturing.

Image Capturing

For good classification accuracy, a sample of nine hundred and ninety eight potatoes with crack, rot, good, sprout and skin peels was selected and each of them was placed on a 6 cm raised platform. Four images were captured at the upper portion of potatoes and again four images were captured by rotating the potato upside down with hand. While capturing eight thousand potato images, sixteen images are fully filled with shade. So a total of nine hundred and ninety eight potatoes were taken for classification. Out of eight images of each potato, single image with defect was taken for classification. Images containing shades were mostly eliminated for experimentation. Light intensity was adjusted by potentiometer. Images captured were in the size of 640×480 pixels which were cropped according to potato boundary. The process of image capturing is given in Figure 1. These images are processed using Matlab[37].In order to procede furthur for classification, next step is feature extraction of captured 998 images. A sample of five different types of images is given in Figure 2.

Figure 2. Different types of potato classes. 1. Crack, 2. Rotten, 3. Sprout, 4. Skin peel and 5. Good

Dataset Preparation and Classification Procedure

From GLCM, the properties like variance (contrast or inertia), correlation, uniformity (energy) and homogeneity values are measured based on pixel properties of an image. The lower limit of the contrast is zero and upper limit is calculated by the squaring the value of GLCM size value minus one. Variance is a measure of contrast intensities among a picture element and its adjacent picture element in whole image (Matlab, R2018b). Variance has been expressed in the following equation.

$$\text{Variance} = \sum_{x,y} |x-y|^2 \, p(x,y) \qquad \dots (1)$$

Correlation computes the combined chances of appearing some fixed match of pixels. The upper and lower limit of correlation is 1 and -1 respectively and for constant image it is zero (Matlab R2018b). Correlation has been expressed as

$$\text{Correlation} = \sum_{x,y} \frac{(x-\mu x)(y-\mu y)\,p(x,y)}{\sigma_x \sigma_y} \qquad \dots (2)$$

Uniformity is the summation of squared elements of GLCM. It lies within 0 and 1. Constant image has an uniformity value of one (Matlab, R2018b). It can be expressed as

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$$\text{Uniformity} = \sum_{x,y} p(x,y)^2 \qquad \ldots (3)$$

Homogeneity gives the clarity on how GLCM elements are spread to matrix diagonal. It lies 0 to 1. For diagonal elements of GLCM, homogeneity is one[30]. Homogeneity is given as

$$\text{Homogeneity} = \sum_{x,y} \frac{p(x,y)}{1+|x-y|} \qquad \ldots (4)$$

Four properties of GLCM, such as variance, correlation, uniformity and homogeneity of nine hundred and ninety-eight potato images were calculated and formed a matrix of size 998 by 4. Arranged contrast values in ascending order. Number of potato classes going to be classified was determined by choosing labels. Complete dataset contains five columns including labelling. In labelling five classes, number one indicated for crack potato, second indicated for rotten potato, third indicated for sprout potato, fourth indicated for good potato and fifth indicated for skin peel. In labelling two classes, number one indicated good potato and number two indicated for damaged potato. Flow diagram for classification of potatoes using classification learner app is given in Figure 3.

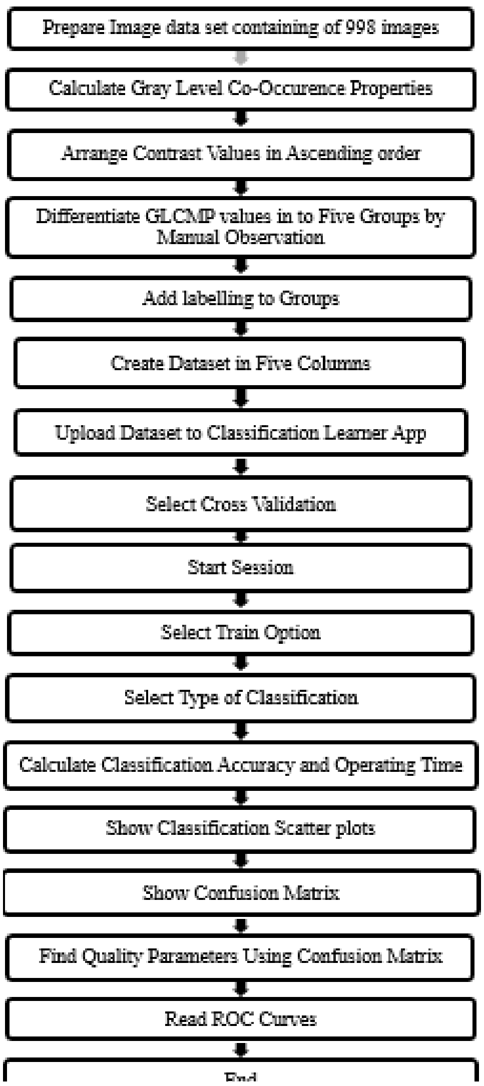

Figure 3 Flow diagram for operating potato classification based on gray level co-occurrence matrix properties.

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Criteria used in Cubic support Vector Machine Classification

Kernel scale was selected as automatic for cubic because software used a set of rules intended to increase the probability of solving problem using sub-sampling. Box-constraint level parameter was taken as one for cubic support vector machine classifier. This parameter was indicated by 'C'. To classify potatoes according to multi-classes, one versus one class method was used in cubic support vector machine. As predictor values having large variations in data, to improve the data to fit into classifiers, standardization of data has been set as true. Cross validation of data was taken as five i.e. data has been divided into five groups of almost equal sizes.

RESULTS AND DISCUSSION

The setup developed has a resolution of 0.22 mm per pixel. In manual classification of nine hundred and ninety eight potatoes, crack, rotten, sprout, good and skinpeel potatoes are 75, 39, 153, 96 and 635 respectively. Classification was performed using six kernel of support vector machines was given Table 1.

Table 1 Results of different kernel support vector machine classifiers

Type of the kernel	Accuracy, %
Linear	98
Quadratic	99
Cubic	**99.5**
Fine Gaussian	95.3
Medium Gaussian	95.7
Coarse Gaussian	92.7
Average	**96.7**

From results (Table 1), cubic support vector machine has highest accuracy (99.5 per cent) compared to quadratic (99 per cent), linear (98 per cent), medium gaussian (95.7 per cent), fine gaussian (95.3 per cent) and coarse gaussian (92.7 per cent). Gaussian kernel average accuracy value (94.56 per cent) was in acceptance with gaussian function accuracy of 91.5 per cent (Zhang and Sha, 2013) and linear SVM accuracy (98 per cent) (Table 1) was higher compared to the linear SVM accuracy of 82 per cent (Zhang and Sha, 2013). The scatter plots of classified potatoes using contrast and correlation features, contrast and energy features and contrast and homogeneity features were presented in Figures 4, 5 and 6 respectively.

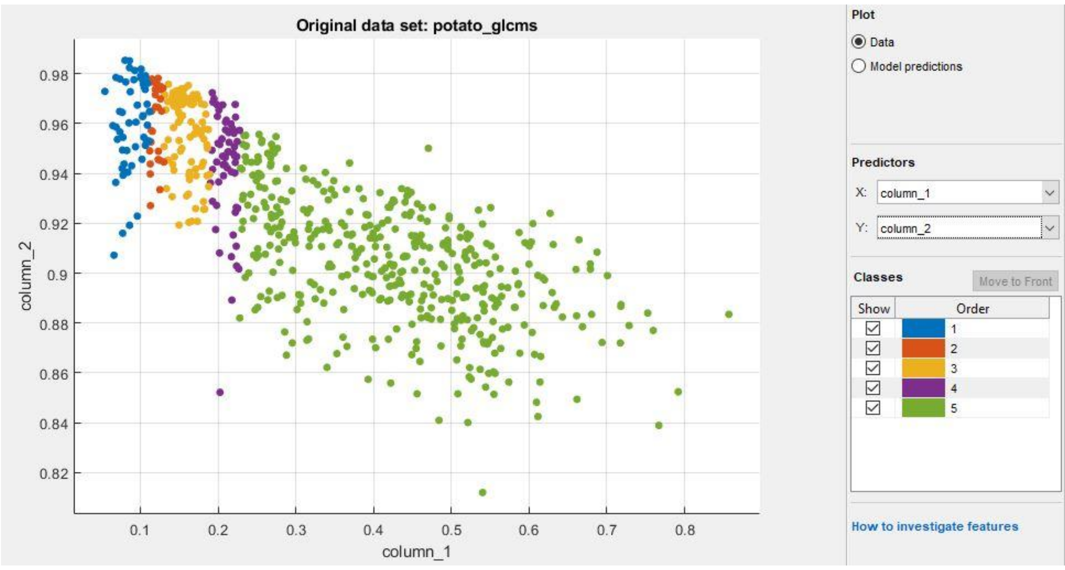

Figure 4 Classified potatoes using contrast and correlation features

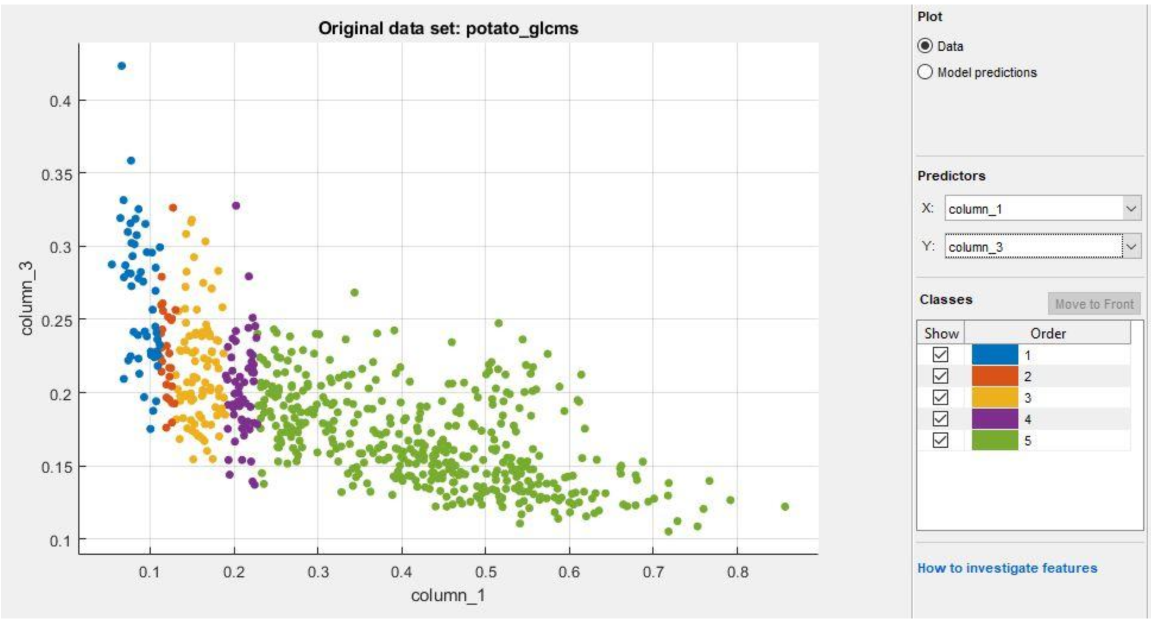

Figure 5 Classified potates using contrast and energy features

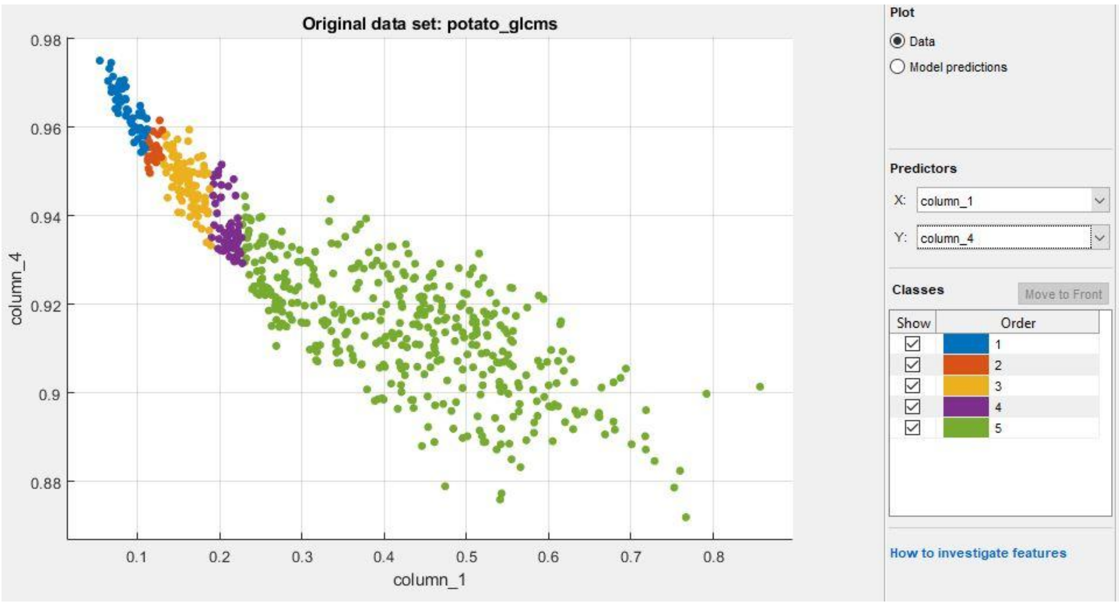

Figure 6. Classified potatoes using contrast and homogeneity features

The blue, red, yellow, purple and green data observations in Figure 4, 5 and 6 are crack, rotten, sprout, good and skin peel respectively. So, only quality parameters of cubic support vector machine was given.

Confusion matrices for cubic support vector machine model

Plot between true and predictive classes of cubic kernel support vector machine classifier based on number of observations worked efficiently on first true class (crack category) and fifth true class (skin peel category). Seventy five potatoes fell into true crack category without misclassifications. Thirty eight potatoes were fell into true class two (rotten category) with one misclassification into predicted sprout class (three). One hundred and fifty one potatoes fell into true class three (sprout category) with two misclassifications each one on predicted class two (rotten) and class four (good).

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Figure 7. Confusion matrix based on number of observations

Ninety four potatoes were fell into true class four (good category) with two misclassifications on predicted sprout class (two). Six hundred and thirty five potatoes fell into true skin peel class without any misclassifications (Figure7).

In cubic support vector machine model, crack category (true class 1), rotten category (true class 2), sprout category (true class 3), good category (true class 4) and skin peel categories (class 5) were having the true positive rates of 100, 97, 99, 98 and 100 per cent respectively.

Figure 8. Confusion matrix based on true positive and false negatives rates

Similarly, rotten, sprout and good true classes were having the false positive rates of 3, 1 and 2 per cent respectively (Figure8).
In cubic support vector machine classification model, crack category (true class 1), rotten category (true class 2), sprout category (true class 3), good category (true class 4) and skin peel category (class 5) were having the positive predictive values of 100, 97, 98, 99 and 100 per cent respectively.

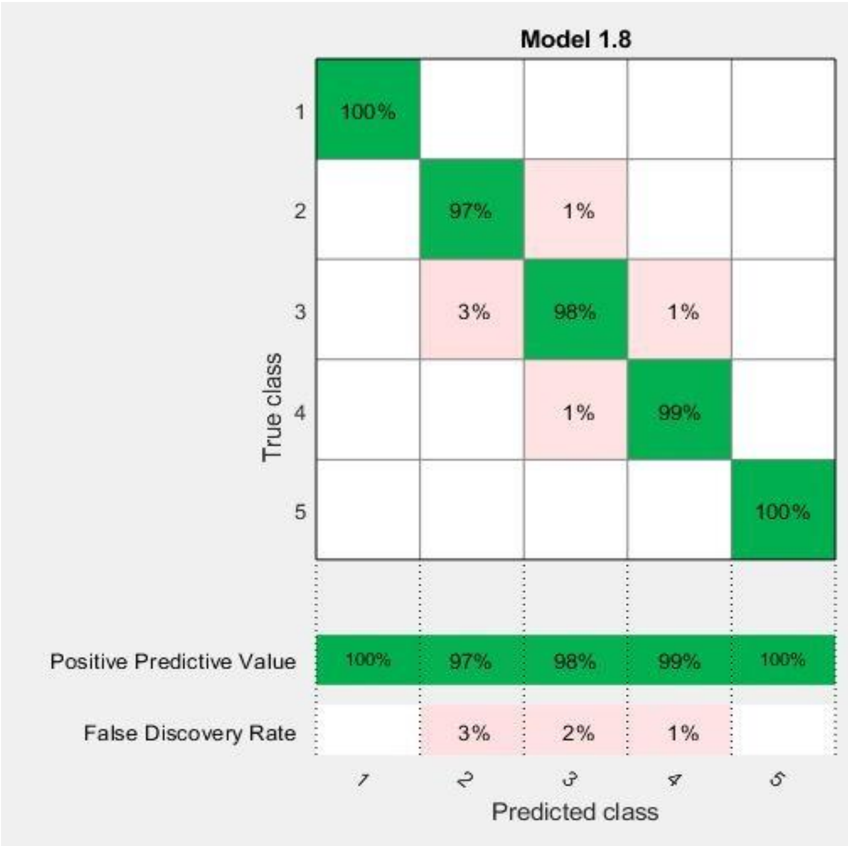

Figure 9. Confusion matrix based on positive predictive value and false discovery rate

Similarly, rotten, sprout and good true classes were having the false discovery rates of 3, 2 and 1 per cent respectively (Figure9). Classification accuracy of cubic support vector machine is 99.5 percent.

CONCLUSIONS

In comparison of manual classification versus cubic support vector machine classification, crack and skinpeel categories have equal number of potatoes but rotten potatoes have one potatoes less in number compared to manual. Sprout categories have two potatoes in number and similarly for good category two potatoes are less in number compared to manual classification.

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