Analysis and Ranking of Informative Color Characteristics of Maize Kernels in the Recognition of Fusarium-Infected (Fusarium Moniliform) Maize Grains

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Abstract: This paper presents a study on the analysis and ranking of informative color characteristics for the recognition of maize kernels infected with *Fusarium moniliforme*. Digital images of healthy and infected kernels from several maize varieties were used to extract 17 color features from the RGB, HSV, Lab, YCbCr, XYZ, and xyY color models. The study aimed to determine the most informative descriptors for distinguishing infected kernels from healthy ones and to evaluate their classification performance using a Support Vector Machine with a radial basis function kernel. The results demonstrated that the informativeness of color features depends on the maize variety, while several descriptors showed consistently high discriminative potential. Among them, the S component of the HSV color model was identified as the most stable and informative feature for a number of varieties. The proposed approach achieved classification accuracy above 95% for "Uzbekistan 601 ESV," "Uzbekistan 300 MV," and "Moldavskiy 257 SV," confirming the feasibility of color-based machine vision for automated detection of Fusarium-infected maize kernels. The findings indicate that feature ranking makes it possible to identify compact and effective subsets of descriptors, thereby improving recognition efficiency and reducing computational cost. The developed approach may be applied in intelligent grain inspection and sorting systems for agricultural quality control.

1 INTRODUCTION

Automated quality assessment of various agricultural products based on their digital images [1]-[3] requires application of accurate and efficient procedures for acquiring, processing, and interpreting the most informative set of features related to the qualitative characteristics of the objects.

Quality assessment of the features themselves is closely associated with reducing the number of features used in recognition tasks, which makes it possible to significantly decrease computational costs without information loss.

The first condition in feature ranking is search for a minimal description of the feature space [4], while the second condition is identification of features that exhibit minimal correlation with each other [5].

The main objective of this study is to determine the informational significance of color features derived from different color models in the recognition of maize kernels infected with *Pink Fusarium*, as well as to establish the reliability of classification using the Support Vector Machine (SVM) method.

2 RESEARCH METHODS AND THE RECEIVED RESULTS

2.1 Main Functions of Automatic Quality Assessment of Grain Products

The main actions performed by the standard automated grain product quality assessment system in agriculture include: detecting defects, categorizing products by shape, size, color, maturity, sorting by quality and degree of maturity, automating food storage and processing processes.

The main functions in automatic quality assessment and quality sorting are as follows:

- obtaining primary information (based on visual images, spectral characteristics, measurement data, etc.) and determining quality indicators;
- classification – identification of the research object by qualitative characteristics and assignment to a certain class (quality);
- sorting – physical separation by classes into quality objects and removal of foreign impurities.

Analysis of the existing modern automated systems for quality assessment, proposed by a number of authors, shows that the main requirements that must be observed are: ensuring regular supply of objects to the inspection zone; complete scanning of objects; extraction of a useful signal (in the background of noise), containing the necessary information, on the basis of which the selected algorithm recognizes which of the given classes the evaluated agricultural products belong to.

The main components of typical automated systems are:

- grain delivery module to the automated system;
- a module for obtaining primary information about the object, including a camera or other optical device and a lighting system;
- analysis and decision-making module: a computer system equipped with image acquisition and processing modules and specialized software;
- a module for performing the mechanical separation of objects by corresponding categories.

2.2 Comparative Analysis of the Main Methods of Control and Classification in Automatic Quality Assessment Systems

The synthesis of corn grain quality classifiers was carried out using methods for selecting information characteristics based on an algorithm that uses several criteria for determining the informativeness of each characteristic, both individually and in combination, with subsequent assessment of classification accuracy using standard classification methods. All features from the initial feature space were analyzed to determine which of them are informative for belonging to one of the two classes of objects – infected and healthy. When determining the sets of the most informative features, the following steps are performed [6]:

1) Visual analysis of two-dimensional (and three-dimensional) characteristics and characteristic histograms by class. According to this type of image distribution in the feature space, the intervals and directions of increase (or decrease) of features for objects by classes are visually assessed. When representing experimental initial data in input vector spaces, it is evident that classes are displayed in overlapping domains.
2) Assessment of correlation between traits. It is desirable that the complex of the most informative features include only those that are independent of each other or minimally dependent on each other. The relationship between paired traits is assessed by calculating their correlation coefficients.
3) Assessment of the individual informativeness of each of the characteristics using the statistical criterion χ-square (Chi-square/CS. Determination of informative trait combinations for each variety using discriminant analysis and Wilks' Lambda criterion.
4) Finding combinations consisting of 7 traits using the "Scalar Ranking of Traits" method using Fisher's FDR criterion and assessing the correlation between traits.
5) Finding combinations consisting of 3 traits using the exhaustive search method – "Best Trait Combination" using the results of the "Scalar Ranking of Traits" method (6-point) and the J_3 criterion based on scatter diagrams.
6) Choosing the optimal set of characteristics – the same sample is classified using different sets of characteristics, which additionally determines the minimum number and type of characteristics.

2.3 Results of the Analysis of the Informativeness of Features Using the χ-Square (Chi-Square/cs) Individual Assessment Criterion

The characteristics are ranked according to the degree of informativeness in descending order according to the χ^2 value. The relationship shows how the χ^2 criterion value for the F trait is calculated:

$$\chi^2(P) = \sum_{i=1}^{m}\sum_{j=1}^{k}\frac{(A_{ij}-E_{ij})^2}{E_{ij}} \quad (1)$$

where C_j is the number of features in class j, and R_i is the number of observations in subgroup i;:

- m – number of subgroups formed according to the values of the *P* trait;
- k – number of classes;
- A_{ij} – the value of the characteristic in the *i*-th subgroup of the *j*-th class;
- E_{ij} – expected number of observations of the A_{ij} trait in the *i*-th subgroup;
- C_j– number of features in the j-th class;
- R_i – the number of observations in the *i*-th subgroup.

The ordering of traits by informativeness using the χ^2 method was implemented using the Feature Selection and Variable Screening (FSL) module, which is part of the STATISTICA package. Graphs have been obtained that illustrate the degree of informativeness that each of the studied color characteristics possesses individually in relation to the discrimination between groups of healthy and infected seeds.

The obtained generalized results [7] show that six of the 17 studied traits have repeatability as the most informative for most varieties. These are the following characteristics: y(xyY), Cb(YCbCr), b(Lab), S(HSV), x(xyY), and B(RGB).

However, for each variety, they are arranged in a different sequence according to their informativeness. It should be noted that the trait y (xyY) is leading for six varieties in the seed images taken from the smooth side and for nine varieties in the seed images taken from the embryo side.

The obtained results are not unambiguous, i.e., based on them, it is impossible to draw a universal conclusion about the degree of informativeness of traits. Nevertheless, they demonstrate trends that indicate which characteristics can potentially be useful when forming a classification algorithm.

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Results of the analysis of the information value of features and the selection of sets of informative features.

2.3.1 Approach Based on the Stepwise Discriminant Analysis Method

In the study, the General Discriminant Analysis (GDA) method was used to assess the informativeness of traits using Wilks' Lambda (λw) criterion.

$$F_{Wilks} = \left(\frac{n-g-p}{g-1}\right)\left(\frac{1-(\lambda_{p+1}/\lambda_p)}{\lambda_{p+1}/\lambda_p}\right), \quad (2)$$

where:

- p – total number of traits;
- g – number of classes;
- λ_p – Wilks' λ, calculated for the current combination of traits;
- λ_{p+1}– Wilks' lambda calculated for the current combination of features when adding/removing a new feature.

According to the number of traits in the original trait space, equal to 17, the total number of GDA-tested trait combinations for each sub-sample for each variety is 131,069.

2.3.2 Scalar Feature Ranking (SFR) Approach

Finding the set of informative features is carried out in several stages.

Initially, the characteristics are ordered in descending order of informativeness according to one of the criteria of one-dimensional divisibility, denoted for brevity as *C*, and $i_l$is the index of the most significant characteristic. In this study, *Fisher's Discriminant Ratio* (FDR) was chosen as the *C* criterion. The value of the FDR criterion is calculated using the following formula:

$$FDR = \left(\frac{m_1-m_2}{\sigma_1^2+\sigma_2^2}\right)^2 \ . \quad (3)$$

where:

- m_1 – is the average value of this characteristic for the first class;

- m_2– average value of the trait for the second class;
- σ_1^2– variance of the value of the trait in the first class;
- σ_2^2 – variance of the sign values in the second class.

The correlation coefficient r_{ij} is calculated between the first (most significant) characteristic and each subsequent characteristic not involved in the individual assessment of informativeness:

$$r_{ij} = \frac{\sum_{k=1}^{n} x_{ik}x_{jk}}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \sum_{k=1}^{n} x_{jk}^2}}. \quad (4)$$

The correlation coefficient r_{ij} between the first (most significant) feature and all subsequent features not included in the result obtained from the individual assessment of the informativeness of the features is calculated:

$$p_{ij} = \frac{\sum_{n=1}^{N} x_{ni}x_{nj}}{\sqrt{\sum_{n=1}^{N} x_{ni}^2 \sum_{n=1}^{N} x_{nj}^2}}. \quad (5)$$

The $i_2$index of the second most informative feature x_{i2} is calculated according to the following dependence:

$$i \ = max_j\{a_1C_j - a_2|p_{i_r,j}|\}, j \neq i_r \quad (6)$$

where $p_{i_r,j}$ – the correlation coefficient between the most significant feature i_1 and the feature $j \neq i_r$; a_1 and a_2 are adjustable parameters.

The following relationship is used to calculate the remaining indices:

$$i_k = max_j\left\{a_1C_j - \frac{a_2}{k-1}\sum_{r=1}^{k-1}|p_{i,j}|\right\}, j \neq i_r, r = 1,2,\dots,k-1,\dots,k = 3,4,\dots,m. \quad (7)$$

The characteristics are ordered in descending order of their informativeness according to the indices from i_1 to i_{17}.

According to the predetermined number of characteristics – *n* (for example, *n=7*), which are part of the complex of informative characteristics, the first n characteristics with indices from i_1 to i_n are selected.

2.3.3 Best Feature Combination (BFC) Approach

This approach uses the results of the Scalar Feature Ranking method, after which a new, smaller size is selected from the resulting combination of features. The criterion by which characteristic groups are selected is the scatter plot (Scatter matrices), denoted as J_3.

$$J_3 = \text{trace}\{S_W^{-1}S_b\}, \quad (8)$$

where S_W – is the so-called intra-class scatter matrix (*within-class scatter matrix*),

S_b– inter-class scatter matrix. The S_W matrix is calculated using the following formula:

$$S_W = \sum_{i=1}^{c} P_i S_i, \quad (9)$$

where P_i – a priori probability for the class *i*=1, 2, . . ., c; S_i– is the corresponding covariance matrix of class i.

The matrix S_b is calculated using the following formula:

$$S_b = \sum_{i=1}^{c} P_i(m_i - m_0)(m_i - m_0)^T, m_0 = \sum_{i=1}^{c} P_i m_i, \quad (10)$$

where m_0 – the total vector of average values calculated based on data from all classes. The following equation is also valid: $S_m = S_W + S_b$ Large values of the J_3criterion mean that the data in the corresponding feature space have a small intra-class scattering and a large inter-class distance.

According to the BFC method, finding optimal combinations consisting of three traits is carried out under the following two conditions:

- The characteristics that have the maximum possible values J_3 are selected;
- such three characteristics are selected that the cross-validation error during the *k*-nearest neighbors (*k=3*) classification is minimal.

The implementation of procedures for searching for informative feature sets is carried out in the MATLAB software environment. The procedures for determining informative trait sets for all varieties were carried out with two restrictions on the maximum number of traits: 7 – using the *Scalar Feature Ranking* method and 3 – using the *Best Feature Combination* method.

The Scalar Feature Ranking (SFR) and Best Feature Combination (BFC) approaches use databases with normalized feature values, while the GDA (General Discriminant Analysis) method uses unprocessed feature values corresponding to components of different color models.

According to which each input object can be attributed to one of the following four possible categories:

- TP – healthy grains classified as healthy;
- FP – healthy, classified as infected;
- TN – infected grains classified as infected;
- FN – infected, classified as healthy.

Based on these categories, the following indicators are calculated in the study: accuracy (*Accuracy*), sensitivity (*Sensitivity*), specificity (*Specificity*), precision (*Precision*), and overall error.

The value of the total error e_0 in the formula represents the percentage of all erroneously classified objects relative to the total number of objects:

$$e_0 = \frac{FP+FN}{TP+TN+FP+FN} \cdot 100, \%, \qquad (11)$$

represents the percentage of all erroneously classified objects relative to the total number of objects.

To obtain primary information about the external quality indicators of objects during the analysis of color, size, shape, external defects, etc., mainly CCD sensors are used, which are included in the considered automated system for sorting products by external defects. This system uses 3 color CCD cameras, processing 9 images per grain. Grain transportation is carried out using roller conveyors. A comparative analysis of the percentage of incorrectly classified products was conducted – 21.8%, 14.3%, and 4.2% respectively when using one, two, and three chambers.

When analyzing maturity, hardness, moisture content, sugars, starch, niches, internal defects, etc., it is necessary to obtain primary information about the internal quality indicators of objects. The main information is obtained through spectroscopy in the ultraviolet (UV), near-infrared (NIR), infrared (IR) regions. According to the trends identified by a number of authors, the most promising methods for image analysis are methods based on hyperspectral sensory systems. In these systems, the sensor collects and processes information from the entire electromagnetic spectrum (from ultraviolet to infrared spectrum).

The use of X-ray imaging, computed tomography, and nuclear magnetic resonance is limited due to the high cost of equipment for performing such systems, as well as the low operational speed.

2.4 Methods for Classifying Food Products Integrated into Automated Systems

When solving problems of real-time classification of agricultural and food products, “classification time” is of significant importance due to the specifics of sorting machines - quality assessment is carried out continuously, in a flow, and in the mode of free fall of the product. Image processing methods, which require a long time to solve and are based on a large volume of computational procedures, are practically “inoperable” when considering such problems. Classification is an information process that involves transforming information about the values of characteristics describing objects for classification into information about their belonging to a predetermined class. When selecting an adequate classifier, the main criteria considered are applicability, effectiveness, and classification time, provided the classification accuracy is sufficiently high. The effectiveness of various classifiers significantly depends on the statistical characteristics of the input data used to form the classifier, i.e., on the training sample and the prior information [8].

2.5 Application of Automated Systems in Assessing the Quality of Agricultural Products

The need for quick and effective quality assessment leads to numerous studies and developments on this topic.

The developed automated system, based on computer vision, sorts pomegranate seeds [2] by color into four categories at a speed of up to 75 kg/h. The prototype of the machine consists of three modules. Seeds are directed to the inspection zone using six transport belts; the camera's field of view simultaneously covers three belts, thanks to which images from several belts are processed simultaneously; mechanical sorting by category is carried out using air injection nozzles.

The automated system for sorting rice grains is presented in [9] across 8 categories. The system allows sequential transportation of a certain number of matrix-arranged rice grains using a transport belt to a module for image acquisition and individual classification of each grain according to its digital image. Synchronization of control signals is carried out through a programmable logic controller (PLC). A specialized software has been developed in the Windows environment that is programmed as a self-learning system, i.e., universal for various rice varieties, using a sorting algorithm that uses a range-selection method, neural networks, and a hybrid algorithm. The highest accuracy achieved is 91% at a rate of 1200 grains per minute.

In another automated system [4], an impulse optical LED system is used to detect and remove wheat grains with fuzarium disease-induced coating. The system is designed to identify infected grains in motion while they fall freely. When registering a contaminated grain, the system activates the air nozzle, and the object is removed. Identification algorithms are based on reflection spectral data in the range of 1032 to 1674 nm and discriminant analysis; the achieved overall recognition accuracy is 91%.

2.6 Determination of Informative Significance of Maize Kernels Color Characteristics and Classification Reliability

The objects of the study are color digital images of healthy and Fusarium-infected (*Fusarium moniliforme*) maize kernels of the following varieties: “Uzbekistan 601 ESV,” “Uzbekistan 300 MV,” “Karasuv 350 AMV,” “Dneprovskiy 181,” “Moldavskiy 257 SV,” and “Moldavskiy 215 AMV.” For each variety, 150 images of healthy kernels and 150 images of infected kernels were obtained.

The images were captured at a resolution of 352 × 289 pixels by using a PIH-7030 H/IR color camera with the following specifications: sensor - 1/3″ CCD; physical resolution - 752 × 582 pixels; active area - 352 × 289 pixels; image quality - 460 TV lines; color depth - 16 million colors; lens - Tokina with manual focal length adjustment ranging from 6 to 60 mm.

The distance between camera and an object during image acquisition was 26 cm. Illumination was ensured by two circular fluorescent lamps positioned above the working scene.

Further image processing included segmentation based on the H (Hue) component of the HSV color model in order to separate background pixels from pixels belonging to the object (kernel).

The maize kernel pixels were extracted to form color features from the respective color models by constructing a color feature vector. The knowledge and data base contains arithmetic mean values of the color components, averaged over all pixels of the image corresponding to an individual maize kernel.

Each maize kernel was evaluated by an expert and classified as belonging either to the “healthy” class or to the class of “infected with Fusarium” (pink form).

The choice of the method for determining the informational significance and definitive color features in the recognition of two classes of maize kernels (healthy and infected) is based on the fact that the data exhibit an asymmetric structure.

The Support Vector Machine (SVM) method performs classification by mapping the data through a nonlinear transformation into a higher-dimensional feature space in which the data become linearly separable.

In the SVM method, the so-called reference points are the boundary data points that are used in the feature space to construct the optimal separating hyperplane. This hyperplane is formed in such a way that the margin, i.e., the distance between the boundaries of the two classes, is maximal.

During both training and classification, the function Φ represents a mapping of the input space into a new feature space of higher dimensionality, expressed through the scalar product of pairs of vectors $\Phi(x)$ and $\Phi(y)$.

$$K(x, y) = \langle \Phi(x), \Phi(y) \rangle. \quad (12)$$

By means of a kernel function, this scalar product can be defined implicitly, which makes it possible to avoid an explicit transformation into a high-dimensional space. Depending on the selected kernel function, different types of classifiers can be constructed, including linear, radial basis function (RBF), polynomial, and multilayer perceptron (MLP) neural network classifiers [6], [7].

In this study, an RBF-type kernel function with width parameter σ was selected, which is expressed as follows:

$$K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right). \quad (13)$$

For the implementation of the Support Vector Machine (SVM) method, the STATISTICA 8 software package developed by *Stat Soft* was used. The method was implemented using a radial basis function (RBF) as the kernel function. The case of synthesizing a classifier for two classes was considered: healthy maize kernels and maize kernels infected with Fusarium [10].

At the next stage, the type of kernel function was selected, with the RBF function being used for this purpose.

The next step consisted in evaluating the model based on the achieved classification accuracy for the entire dataset (training and testing), separately for each of the 17 color features.

A total of 32 support vectors were formed-16 for each of the two classes. The achieved cross-validation accuracy was 98.889%. In addition, the figure also presents the classification accuracies obtained separately for the training dataset and for the testing dataset.

Presents the distribution plots of samples from the test dataset according to the selected features: red points denote samples of healthy kernels, while blue points denote samples of infected kernels.

For the *smean* feature, it can be observed that the samples are well separated, indicating a high level of informativeness of this feature. In contrast, for the *vmean* feature, a complete overlap of the classes is observed. This leads to the conclusion that this feature is not informative for the recognition task.

The analysis indicates that an increase in the number of generated support vectors is accompanied by a decrease in classification accuracy.

For the “Uzbekistan 601 ESV” variety, the largest number of informative features was identified, including B (RGB), S (HSV), b (Lab), Z (XYZ), Cb and Cr (YCbCr), as well as x and y (xyY).

The “Karasuv 350 AMV” and “Dneprovskiy 181” varieties are similar in terms of informative features, as they largely coincide [11].

Using the S (HSV) feature, satisfactory classification accuracy exceeding 95% was achieved for the “Uzbekistan 601 ESV” and “Moldavskiy 257 SV” varieties.

3 CONCLUSIONS

This paper presented a systematic analysis and ranking of informative color characteristics for the recognition of Fusarium-infected maize kernels based on digital image data. A set of 17 color features derived from the RGB, HSV, Lab, YCbCr, XYZ, and xyY color models was evaluated in order to determine their discriminative significance in separating healthy and infected kernels. The obtained results confirmed that color-based image analysis combined with Support Vector Machine classification is an effective approach for automated detection of Fusarium infection in maize grains.

The experimental study showed that classification accuracy above 95% was achieved for the maize varieties “Uzbekistan 601 ESV,” “Uzbekistan 300 MV,” and “Moldavskiy 257 SV,” which confirms the practical applicability of the proposed method. Among the analyzed descriptors, the S component of the HSV color model was identified as the most informative and stable feature, particularly for the varieties “Uzbekistan 601 ESV” and “Moldavskiy 257 SV.” At the same time, additional features from the RGB, Lab, XYZ, YCbCr, and xyY models also demonstrated strong discriminative potential for specific varieties, indicating that the effectiveness of recognition depends on a rational selection of variety-specific feature subsets.

The main contribution of this study lies in the identification and comparative evaluation of the most informative color descriptors for recognizing Fusarium-infected maize kernels and in demonstrating their suitability for reliable machine-vision-based classification. The practical significance of the proposed approach is associated with its potential application in automated grain inspection, quality control, and sorting systems, where rapid and objective assessment is required. Further research should be focused on expanding the image dataset, validating the model under different illumination and acquisition conditions, and integrating color features with texture and shape descriptors to increase the robustness and generalization ability of the recognition system.

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