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EXPLORING HU'S MOMENT INVARIANTS AND ZERNIKE MOMENTS FOR EFFECTIVE IDENTIFICATION OF TWO-ROW AND SIX-ROW BARLEY VARIETIES

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Abstract

Barley variety identification is a complex and economically significant task. The identification of two-row and six-row grains is particularly important due to their different characteristics, such as protein and starch content, which have specific implications in different applications. This paper evaluates the effectiveness of discriminating between two-row and six-row barley grains using Hu moment invariants and Zernike moments in combination with various classifiers including linear and SVM classifiers with linear, RBF, polynomial, and sigmoid kernels. The application of Zernike moments and an SVM classifier using an RBF kernel achieved an accuracy level of 99.2%. In comparison, the application of Hu's moment invariants resulted in an accuracy of 98.5%.

Introduction

Barley is one of the world's oldest and most important crops (along with wheat, rice, and maize) (RAMAGE 2011). It plays a significant role in the global economy, particularly as animal feed (which accounts for approximately 70% of barley harvests), in malt and alcohol production (about 21% of barley harvests),

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as a basis for nutritional products (to a lesser extent) (MARCUS 2013), and more recently as a feedstock for biofuel production (GRIFFEY et al. 2010). In 2022, global barley production exceeded 154 million tons (*World Barley production*. 2023).

Barley is one of the most genetically diverse cereals (GOZUKIRMIZI, KARLIK 2017). It is classified into two types based on its processing applications: feed and malt. Further classification is based on several factors, including planting season (spring and winter), the number of fertile spikelets (two-row and multi-row), and the presence or absence of husks (hulled or naked) (ROGALSKA 2011). Grains from different barley varieties often differ significantly in terms of physical characteristics and composition. As a result, they have different processing properties and affect the quality of the final product (BAIK, ULLRICH 2008).

Barley grains are characterized by an elongated shape, often described as "spindle-shaped", meaning that they are narrowest at the base and tip, and wider in the middle. The shape of two-row barley grains is similar to a symmetrical ellipsoid (Fig. 1*a*) (HEBDA, MICEK 2007). Typically, two-row barley grains are shorter and thicker and have a higher starch content. In contrast, grains of six-row varieties usually appear asymmetric and twisted (Fig. 1*b*) (FITZSIMMONS, WRIGLEY 1985). Six-row barley grains are longer and tend to contain more protein and less starch than their two-row counterparts.

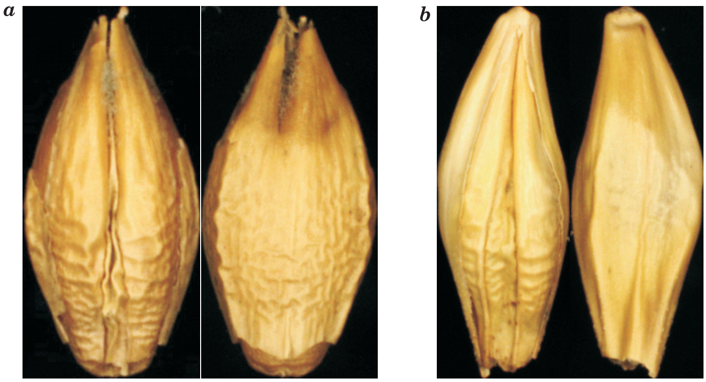

Fig. 1. Digital images of grains: *a* – two-row, *b* – six-row

The quality of grain delivered to processing companies is a critical factor determining the quality of the final product. Purchasing inferior grain can render part or all of a batch unusable in the production process, potentially generating significant losses for the producer.

Traditionally, the quality of barley is assessed by visual inspection by an expert. This method is time-consuming, limited to a certain sample size (100 g of grain collected according to proper procedures), and prone to human error. To ensure the repeatability of the tests and accelerate the grain evaluation and classification process, it is essential to automate the evaluation using image analysis.

The topic of discriminating barley varieties using image analysis covers a wide range. SZCZYPIŃSKI et al. (2015) applied attributes of shape, color, and texture to identify 11 varieties of two-row barley. Discriminant analysis was used along with a set of linear classifiers and an artificial neural network, with an accuracy of 86%.

KOZŁOWSKI and SZCZYPIŃSKI (2019) conducted studies using nine implementations of convolutional neural networks (CNNs) to identify varieties of barley grains. They successfully achieved an accuracy level of 93%. The research material consisted of barley grains belonging to six two-row varieties: Blask, Bordo, Conchita, Kormoran, Mercada, and Signora. These studies illustrate the potential of CNNs to improve the accuracy of grain variety identification, contributing to more efficient agricultural practices and processing methods.

SHI et al. (2022) distinguished between two-row and six-row barley varieties in their research. They used three varieties of six-row barley and some varieties of two-row barley for analysis. The study was divided into two parts: identifying the variety based on the image of a single grain and identifying the variety based on images containing multiple grains (images with different numbers of grains). Using the YOLOv5x6 network, they achieved an accuracy of 98.4% for single grains and 58.9% for the multi-grain dataset. This work focused on detecting specific varieties rather than classifying groups of two-row and six-row grains.

The application of Hu's moment invariants and Zernike moments as shape descriptors for the identification, evaluation, and recognition of various plant-based objects can often be found in the scientific literature. An example of such application is the use of Zernike moments for leaf identification of various plant species by research groups such as SALEEM et al. (2019), PALLAVI and VEENA DEVI (2014), TYYSTJÄRVI et al. (2011), SALVE et al. (2016), and TSOLAKIDIS et al. (2014). Meanwhile, Hu's moment invariants were used by LUKIC et al. (2017), DU et al. (2013), and KHAIRNAR and KHAN (2022) for leaf recognition in their studies.

In grain shape analysis, most of the publications are concerned with rice grain discrimination, such as in the works of WEE et al. (2002, 2006, 2009), where the application of Zernike moments, genetic algorithm, and multilayer perceptron (MLP) resulted in a recognition efficiency of 93.25%, and after modifications, 96.5% in the identification of damaged rice grains.

KURTULMUŞ et al. (2016) used both Hu's moment invariants and Zernike moments for the classification of eight varieties of pepper seeds. An MLP network consisting of 30 neurons in the hidden layer was constructed, and an accuracy of 84.94% was achieved using sequential feature selection and a robust backpropagation algorithm.

For the analysis of barley grains, Hu's moments invariants were used in the study by ADJEMOUT et al. (2007). The study presented the results of automatic analysis of maize, oat, barley and lentil grains. The combination of shape and texture features yielded an efficiency of 89.25%.

In the study by SZTURO (2023), the results obtained for Zernike moments and Hu's moment invariants for detecting damage in barley grains, such as separating broken grains and grains with ruptured embryos from healthy ones, were compared. Accuracy levels of 99.8% and 99.7% were achieved for distinguishing healthy grains from halves and healthy grains from ruptured embryos, respectively.

The use of Hu's moment invariants and Zernike moments for the discrimination of barley grain varieties has not been described in the literature. Due to the good results of classification of other plant objects (such as leaves, rice grains, and bell pepper grains) obtained using these methods in the works of other authors, it was decided to analyze the possibility of application to the recognition of groups of two-row and six-row barley varieties.

This study focuses on identifying groups of two-row and six-row grains (without identifying individual varieties). The aim of this work is to compare methods for detecting the shape of two-row and six-row barley, based on moments (Hu's moment invariants and Zernike moments) combined with five types of classifiers. Therefore, it was possible to choose the best method to discriminate between the two groups of barley varieties.

Methods

Moment invariants are methods that have been successfully used to recognize the shapes of various objects and have been used in applications such as the classification of citrus leaves (QADRI et al. 2019) and pepper seeds (KURTULMUŞ et al. 2016). Given their advantages, they also appear to be suitable for discriminating between two-row and six-row barley grains. The robustness of moment invariants in capturing shape characteristics makes them ideal for applications where precision in morphological differentiation is critical.

Moment invariants are among the most popular methods for extracting feature vectors that are invariant to RTS transformations (*rotation*, *translation,* and *scaling*). The basis of this approach is to describe objects using a set of measurable quantities called *invariants* (FLUSSER et al. 2009). An image moment is defined as the integral of the image function $f(x, y)$ over a polynomial basis, specified for a given region of interest (ROI) (BABATUNDE et al. 2014). Two-dimensional central moments of order $p+q$ with coordinates centered at the centroid $(\bar{x}, \bar{y})$ are calculated using the formula:

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q \, f(x, y) \, dx \, dy \tag{1}$$

where:

$$\bar{x} = \frac{m_{10}}{m_{00}},$$
$$\bar{y} = \frac{m_{01}}{m_{00}}.$$

The following sections describe Hu's moment invariants and Zernike moments, which are used to extract characteristic features from images. These allow to compare objects, classify and detect patterns based on their shape or brightness distribution in the image.

Hu's moment invariants

In 1962, Hu (SABHARA 2013) derived a set of seven complex moment invariants based on the theory of algebraic functions. *Hu's moment invariants* are a set of image features calculated from normalized central moments (2):

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \text{ where } \gamma = \frac{p+q+2}{2} \text{ for } p+q = 2, 3 \ldots \tag{2}$$

These properties remain invariant to image transformations such as translation, scaling, rotation and reflection. In particular, the seventh Hu's moment invariant (h_7) changes sign upon reflection. This property ensures that the features provide consistent and reliable image analysis across different transformations, which is crucial for applications in pattern recognition and digital imaging where orientation and size can vary.

Hu's moments are calculated using specific formulas (3) (HUANG, LENG 2010):

$$h_1 = \eta_{20} + \eta_{02}$$

$$h_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$h_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$h_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$h_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$
$$+(3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$h_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$h_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$
$$-(\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{3}$$

With the obtained magnitudes of features h_1-h_7 having a wide range of values (and therefore may not be comparable), the logarithmic transformation expressed by equation (4) must first be used to perform the analysis:

$$H_i = -\text{sign}(h_i)\log\ |h_i| \tag{4}$$

As a result, the logarithmic transformation transforms the original values of the Hu's moments in such a way as to preserve directional information and balance the distribution of values. It is important to ensure that the values of the original Hu's moment sign are preserved. Negative values of Hu's moments may include additional information about the shape of objects, such as symmetry or torsion.

Zernike moments

Hu's moment invariants perform adequately for images under translation, scaling, rotation and reflection, but they do not have orthogonal properties. Orthogonality in this context is understood as "the decomposition of an object into individual and uncorrelated components to simplify its analysis" (Martín et al. 2010).

The approach proposed by Teague (1980) aimed to address the issue of non-orthogonality in Hu's moment invariants by applying orthogonal moments, specifically Zernike moments (Ze). Zernike moments represent the projection of an image function $f(x, y)$ onto a set of Zernike polynomials (Asli et al. 2019), which are described as "complex, orthogonal polynomials forming a basis for integrable functions over the unit disk surface" (Luckner 2008). These polynomials provide a convenient means of decomposing an image into a series of uncorrelated features, thereby simplifying the analysis and improving the robustness and accuracy of feature extraction in image processing tasks.

Formally, Zernike polynomials are defined as (Marouf, Faez 2013):

$$V_{nm}(x,y) = R_{nm}(x,y)e^{jm\tan^{-1}(\frac{y}{x})} \tag{5}$$

for $x^2 + y^2 \leq 1$, $n \geq 0$, $|m| \leq n$ and radial polynomials $\{R_{nm}\}$

$$R_{nm} = \sum_{s=0}^{(n-|m|)/2} S_{n,|m|,s}(x^2+y^2)^{\frac{n-2s}{2}} \tag{6}$$

$$S_{n,|m|,s} = (-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!} \tag{7}$$

Zernike moments of the n-th order with m repetitions can be calculated using the formula:

$$ZM_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x,y) V_{nm}^*(x,y) \tag{8}$$

The moments determined in this way are characterized by orthogonal properties, which means that are independently of the choice of one Zernike function and there is no correlation with other functions. In this way, Zernike moments allow the decomposition of an object's shape into independent components, which simplifies shape analysis. Zernike moments are characterized by rotation and scaling invariance, as well as robustness to noise and deformation present in the image (MISHRA et al. 2017). Furthermore, they have a concrete geometric interpretation reflecting the shape features of the object. Zernike moments analysis allows the description of many object shape features such as symmetry, size, shape, orientation, stretch, obliquity, kurtosis, etc., making them successfully used for quantifying and comparing object shapes.

Evaluation Metrics for Classification

To evaluate the quality of classification in this study, measures such as accuracy, recall, precision (PPV), $F1$, $F1$ macro average and specificity were used.

The most common measure used to evaluate the quality of a classification model is accuracy (PPV). It determines the number of correctly classified objects relative to the size of the total set and is calculated using the formula (SOKOLOVA, LAPALME 2009):

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{9}$$

where:

TP – true positives,
TN – true negatives,
FP – false positives,
FN – false negatives.

Another commonly used metric is sensitivity (also known as recall or true positive rate, TPR), which is the number of true positives relative to the total number of true positives and false negatives (TP + FN) and is calculated using the formula:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{10}$$

The specificity or true negative rate (TNR), on the other hand, is the number of cases correctly classified as negative relative to the number of all true negatives and false positives (TN+FP):

$$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{11}$$

Precision (positive predictive value, PPV) is the proportion of cases classified as positive (TP+FP) that are correctly assigned to their class:

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{12}$$

When selecting a classification model with different measures of precision and specificity, it is useful to determine the F_1 index, which is the harmonic mean of PPV and TPR:

$$F1 = \frac{2 \cdot \mathrm{PPV} \cdot \mathrm{TPR}}{\mathrm{PPV} + \mathrm{TPR}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \tag{13}$$

The $F1$ macro average is calculated as the arithmetic average of the $F1$ results for all classes. Each class, regardless of the number of samples it represents, has the same significance in the calculation of this metric.

$$F1_{\mathrm{macro\_average}} = \frac{1}{k} \sum_{i} F1_i \tag{14}$$

where:

k – number of cases,

i – class index.

Each of these metrics provides different information about model performance and helps identify areas for improvement. A high precision value indicates fewer false positives, while a high recall value indicates successful identification of most true positives. Taken together, these metrics provide a comprehensive evaluation of the classification model.

Materials

In this study, barley grains representing two-row varieties: Bordo, Fariba, and Kormoran, and six-row varieties: Zenek, Kobuz, and Wintmalt, were utilized. This material was obtained under the project number NCBR PBS3/A8/38/2015, entitled “Development of industrial methods of automatic evaluation of technological parameters and classification of grain using image analysis”.

The grain images were obtained using a prototype assessment and classification device with identical lighting conditions, a resolution of 1292×964 pixels, and a high-contrast background (LAMPA et al. 2016). The setup included CCD Mako G-125C digital cameras with FL-CC1614-2M lenses equipped with LED ring lights (LAMPA et al. 2016). The barley grains were placed in the device on a rotating transparent glass transport disk with a radius of 10 cm, coming from a linear vibratory feeder. As the grain passed through the acquisition field, an optical sensor triggered the cameras. The images were then analyzed. The images were used to train and test convolutional neural networks, as described in publications (DOLATA, REINER 2018, KOZŁOWSKI et al. 2019, LAMPA et al. 2016, ZAPOTOCZNY et al. 2020).

Table 1

Number of barley kernel images used in the training and testing process

Varieties		Number of images		Total
		training dataset	testing dataset	
Two-row kernels	Bordo	540	540	3,256
	Fariba	550	550	
	Kormoran	538	538	
Six-row kernels	Zenek	520	520	3,200
	Kobuz	575	575	
	Wintmalt	505	505	
Total		3,228	3,228	6,456

The set of digital images of barley grains was divided into a teaching and a testing datasets according to the information in Table 1. A total of 6,456 images of two-row and six-row barley grains were used for the analysis.

Results

To compute Hu's-moment invariants and Zernike moments, the Python programming language and libraries such as Mahotas and OpenCV were used. A series of morphological operations were performed on the image. Once the contours have been determined, Hu's moments are calculated using a function from the OpenCV library. For the Zernike moments, a circle was defined on the perimeter of the grain contours, with the center at the centroid of the grain. Within this circle, the absolute values of the Zernike moments (Ze) are calculated for a given polynomial degree d and returned as a feature vector of varying lengths: 12 for $d = 5$, 25 for $d = 8$, 36 for $d = 10$, 72 for $d = 15$, 121 for $d = 20$, etc. The moments are not calculated for pixels outside the defined circle area, so it is important to set the radius size accurately. In this case, the radius was automatically determined on the grain contour by using the OpenCV *cv2.minEnclosingCircle()* function.

The number of features generated by the Zernike moments was quite significant (121 features for $d = 20$), so Fisher's Linear Discriminant Analysis (LDA) was used to reduce the feature vector. This provided a ranking of the most discriminative features distinguishing between two-row and six-row barley grains: Ze_8 (7.73601), Ze_9 (6.82933), Ze_{15} (4.90846), and Ze_4 (4.10166). These features have all been determined at a polynomial degree of 8, eliminating the problem of generating a larger number of features. This allows to reduce the computational time required to process each image, increasing the efficiency of the classification process while maintaining a high accuracy in distinguishing between different types of barley grain.

Table 2

Comparison of classification results for two-row and six-row barley grains when using Hu's moment invariants and Zernike moments and five types of classifiers

	Classification Evaluation Metrics	Class[1]	Linear classifier	SVM classifier			
				linear	polynomial	RBF	sigmoid
Hu's moment invariants	Accuracy	–	0.984	0.981	0.954	0.985	0.963
	Recall	1	0.982	0.975	0.953	0.981	0.959
		2	0.986	0.988	0.954	0.989	0.966
	Precision, PPV	1	0.986	0.988	0.955	0.989	0.967
		2	0.982	0.975	0.953	0.981	0.959
	*F*1	1	0.984	0.981	0.954	0.985	0.963
		2	0.984	0.981	0.953	0.985	0.963
	*F*1 Macro average	-	0.984	0.981	0.954	0.985	0.963
	Specificity	1	0.986	0.988	0.954	0.989	0.966
		2	0.982	0.975	0.953	0.981	0.959
Zernike moments	Accuracy	–	0.988	0.984	0.979	0.992	0.951
	Recall	1	0.983	0.975	0.965	0.989	0.940
		2	0.993	0.993	0.993	0.994	0.963
	Precision, PPV	1	0.993	0.993	0.993	0.994	0.962
		2	0.983	0.975	0.965	0.989	0.941
	*F*1	1	0.988	0.984	0.979	0.992	0.951
		2	0.988	0.984	0.979	0.992	0.952
	*F*1 Macro average	-	0.988	0.984	0.979	0.992	0.951
	Specificity	1	0.993	0.993	0.993	0.994	0.963
		2	0.983	0.975	0.965	0.989	0.940

[1]Class indicated: (1) – two-row barley; (2) – six-row barley.

The performance of five different classifiers was compared to determine which classifier was best at discriminating between two-row and six-row barley grains. The results are presented in Table 2. Hu's moment invariants, as well as Zernike moments in combination with all the classifiers tested, indicate high classification efficiency. Significant metrics values were obtained, higher than 94% for the various classifiers. For Hu's moment invariants, the average percentage of correctly classified cases was between 95.4% and 98.5%. Whereas for Zernike moments, the accuracy for different classifiers ranged between 95.1% and 99.2%. Both Hu's moment invariants and Zernike moments gave the best results with the Support Vector Machine (SVM) classifier using a Radial Basis Function (RBF) kernel. In particular, the $F1$ macro average for Hu's moments reached 98.5%, while for Zernike moments it was even higher at 99.2%.

Zernike moments with the RBF SVM was found to be as effective in classifying two-row and six-row varieties as it was in detecting the shape of damaged from healthy barley grains, where the accuracy was 99.8% and 99.7% (SZTURO 2023). This shows how effective the use of relatively simple methods can be for this type of task. It is also possible to combine these methods to achieve a more comprehensive solution, relieving the human labor involved in the tedious and responsible work of evaluating grains at collection points.

The proposed method has achieved high accuracy, however, it may be interesting to extend to detect specific varieties. Here, in addition to shape, other features of the grain are important, such as the shape of the lemma base, the length of the rachilla, the corrugation of the pales, or the depth of the furrow. For this analysis, a combination of different methods will be required to obtain satisfactory results. Among this topic, good results were obtained by SZCZYPINSKI et al. (2015) – 86%, KOZLOWSKI and SZCZYPINSKI (2019) – 93% and SHI et al. (2022) – 98.4%. Artificial neural networks were used in all cases.

Table 3

Average computation time per single barley grain image

Moments	Average computation time [s]
Ze, d=20	0.295
Ze, d=15	0.228
Ze, d=10	0.219
Ze, d=8	0.209
Ze, d=5	0.199
Hu	0.007

In Table 3, the average computation time for a single grain is shown with Hu's moment invariants and Zernike moments for degree d equal to 5, 8, 10, 15, and 20. As there are more image operations required to compute Zernike moments and more attributes are generated (121 attributes in the case of $d = 20$), a longer computation time than for Hu's moment invariants is noticeable.

The novel application of Hu's moment invariants and Zernike moments to the classification of two-row and six-row barley grains can significantly support agricultural quality control and grain sorting processes. It is possible to implement and integrate the proposed solution, which uses shape features and machine learning models, into the barley grain assessment system at collecting centers. Thus, the barley evaluation process, which is currently done manually, can be more objective and reliable.

Further studies are planned to extend the dataset to other varieties of two--row and six-row barley. The integration of deep learning methods is considered to have the potential to further improve classification accuracy. Furthermore, it is planned to compare the effectiveness of using Hu's moment invariants and Zernike moments to discriminate specific barley grain varieties. Further improvement and testing of these computational techniques is important for successful application in industrial practice.

Conclusion

The results of the evaluation of Hu's moment invariants and Zernike moments using five different classifiers can be interpreted according to different criteria: accuracy, number of extracted features and thus the processing time, as well as sensitivity to scaling, rotation and distortion. The following conclusions can be drawn:

1. Accuracy criterion: Zernike moments combined with the SVM RBF classifier provide a classification accuracy of 99.2% for the identification of two-row and six-row barley grains, compared to 98.5% for Hu's moment invariants.
2. Criterion of the number of features extracted:
   – Hu's moments: extracted a total of 7 features were extracted;
   – Zernike moments: the number of features depends on the degree of the polynomial used in the calculations. By applying Fisher's Linear Discriminant Analysis, the number of features was reduced. These most discriminative features are all generated within $d=8$.
3. Average processing time: The average time to obtain Hu's moments for a single image is shorter than for Zernike moments, as shown in Table 3.
4. Zernike moments are more resistant to distortions and noise.

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References

ADJEMOUT O., HAMMOUCHE K., DIAF M. 2007. *Automatic seeds recognition by size, form and texture features*. 2007 9th International Symposium on Signal Processing and Its Applications, ISSPA 2007, Proceedings. https://doi.org/10.1109/ISSPA.2007.4555428

ASLI B.H.S., FLUSSER J., ZHAO Y., ERKOYUNCU J.A. 2019. *Filter-generating system of Zernike polynomials*. Automatica, 108: 108498. https://doi.org/10.1016/j.automatica.2019.108498

BABATUNDE O.H., ARMSTRONG L., LENG J., DIEPEVEEN D. 2014. *Zernike Moments and Genetic Algorithm: Tutorial and Application*. British Journal of Mathematics & Computer Science, 4(15): 2217–2236. https://doi.org/10.9734/BJMCS/2014/10931

BAIK B.K., ULLRICH S.E. 2008. *Barley for food: Characteristics, improvement, and renewed interest*. Journal of Cereal Science, 48(2): 233–242. https://doi.org/10.1016/J.JCS.2008.02.002

DOLATA P., REINER J. 2018. *Barley variety recognition with viewpoint-aware double-stream convolutional neural networks*. Proceedings of the 2018 Federated Conference on Computer Science and Information Systems, FedCSIS 2018, p. 101–105. https://doi.org/10.15439/2018F286

DU J.X., ZHAI C.M., WANG Q.P. 2013. *Recognition of plant leaf image based on fractal dimension features*. Neurocomputing, 116: 150–156. https://doi.org/10.1016/J.NEUCOM.2012.03.028

FITZSIMMONS R.W., WRIGLEY C.W. 1985. *Australian Barleys: Identification of Varieties, Grain Defects and Foreign Seeds*. CSIRO Publishing, Clayton, Australia.

FLUSSER J., SUK T., ZITOVÁ B. 2009. *Moments and Moment Invariants in Pattern Recognition*. John Wiley & Sons, Hoboken. https://doi.org/10.1002/9780470684757

GOZUKIRMIZI N., KARLIK E. 2017. *Barley (Hordeum vulgare L.) Improvement Past, Present and Future*. In: *Brewing Technology*. Ed. M. Kanauchi. InTech. https://doi.org/10.5772/INTECHOPEN.68359

GRIFFEY C., BROOKS W., KURANTZ M., THOMASON W., TAYLOR F., OBERT D., MOREAU R., FLORES R., SOHN M., HICKS K. 2010. *Grain composition of Virginia winter barley and implications for use in feed, food, and biofuels production*. Journal of Cereal Science, 51(1): 41–49. https://doi.org/10.1016/J.JCS.2009.09.004

HEBDA T., MICEK P. 2007. *Cechy geometryczne ziarna wybranych odmian zbóż*. Inżynieria Rolnicza, 5(93).

HUANG Z., LENG J. 2010. *Analysis of Hu's moment invariants on image scaling and rotation*. ICCET 2010–2010 International Conference on Computer Engineering and Technology, Proceedings, 7. https://doi.org/10.1109/ICCET.2010.5485542

KHAIRNAR K., KHAN S. 2022. *Plant Leaf Disease Segmentation and Feature Extraction using Image Processing*. International Journal of Advance Research and Innovative Ideas in Education, 8(1).

World Barley production. 2023. Knoema. https://knoema.com/atlas/World/topics/Agriculture/Crops-Production-Quantity-tonnes/Barley-production

KOZŁOWSKI M., GÓRECKI P., SZCZYPIŃSKI P.M. 2019. *Varietal classification of barley by convolutional neural networks*. Biosystems Engineering, 184: 155–165. https://doi.org/10.1016/j.biosystemseng.2019.06.012

KURTULMUŞ F., ALIBAŞ İ., KAVDIR I. 2016. *Classification of pepper seeds using machine vision based on neural network*. International Journal of Agricultural and Biological Engineering, 9(1): 51–62. https://doi.org/10.25165/IJABE.V9I1.1790

Lampa P., Mrzygłód M., Reiner J. 2016. *Methods of manipulation and image acquisition of natural products on the example of cereal grains*. Control and Cybernetics, 45(3).

Luckner M. 2008. *Automatyczna identyfikacja wybranych symboli notacji muzycznej*. In: *Zastosowania metod statystycznych w badaniach naukowych III*, p. 35–43. StatSoft Polska, Kraków.

Lukic M., Tuba E., Tuba M. 2017. *Leaf recognition algorithm using support vector machine with Hu moments and local binary patterns*. SAMI 2017 – IEEE 15th International Symposium on Applied Machine Intelligence and Informatics, Proceedings, p. 485–490. https://doi.org/10.1109/SAMI.2017.7880358

Marcus J.B. 2013. *Chapter 4 – Carbohydrate Basics: Sugars, Starches and Fibers in Foods and Health*. Culinary Nutrition. The Science and Practice of Healthy Cooking, p. 149–187. https://doi.org/10.1016/b978-0-12-391882-6.00004-2

Marouf H., Faez K. 2013. *Zernike Moment-Based Feature Extraction For Facial Recognition of Identical Twins*. International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), 3(6). https://doi.org/10.5121/ijcseit.2013.3601

Martín H.J.A., Santos M., de Lope J. 2010. *Orthogonal variant moments features in image analysis*. Information Sciences, 180(6) : 846–860. https://doi.org/10.1016/J.INS.2009.08.032

Mishra D., Majhi B., Sa P.K. 2017. *Improved feature selection for neighbor embedding super--resolution using zernike moments*. Advances in Intelligent Systems and Computing, 460 AISC: 13–24. https://doi.org/10.1007/978-981-10-2107-7_2/FIGURES/6

Qadri S., Furqan Qadri S., Husnain M., Saad Missen M.M., Khan D.M., Muzammil-Ul-Rehman, Razzaq A., Ullah S. 2019. *Machine vision approach for classification of citrus leaves using fused features*. International Journal of Food Properties, 22(1), 2071–2088. https://doi.org/10.1080/10942912.2019.1703738

Pallavi P., Veena Devi V.S. 2014. *Leaf Recognition Based on Feature Extraction and Zernike Moments*. International Journal of Innovative Research in Computer and Communication Engineering, 2(2).

Ramage R.T. 2011. *A History of Barley Breeding Methods*. Plant Breeding Reviews, 5(4): 95–138. https://doi.org/10.1002/9781118061022.CH4

Rogalska U. 2011. *Podstawy hodowli jęczmienia*. EUREQUA. http://www.uwm.edu.pl/eurequa/pl/I_opr.met.htm

Sabhara R. 2013. *Comparative Study of Hu Moments and Zernike Moments in Object Recognition*. The Smart Computing Review, 3(3). https://doi.org/10.6029/smartcr.2013.03.003

Saleem G., Akhtar M., Ahmed N., Qureshi W.S. 2019. *Automated analysis of visual leaf shape features for plant classification*. Computers and Electronics in Agriculture, 157: 270–280. https://doi.org/10.1016/J.COMPAG.2018.12.038

Salve P., Sardesai M., Manza R., Yannawar P. 2016. *Identification of the Plants Based on Leaf Shape Descriptors*. Advances in Intelligent Systems and Computing, 379: 85–101. https://doi.org/10.1007/978-81-322-2517-1_10

Shi Y., Li J., Yu Z., Li Y., Hu Y., Wu L. 2022. *Multi-Barley Seed Detection Using iPhone Images and YOLOv5 Model*. Foods, 11(21). https://doi.org/10.3390/FOODS11213531

Sokolova M., Lapalme G. 2009. *A systematic analysis of performance measures for classification tasks. Information Processing & Management*, 45(4), https://doi.org/10.1016/j.ipm.2009.03.002

Szczypiński P.M., Klepaczko A., Zapotoczny P. 2015. *Identifying barley varieties by computer vision*. Computers and Electronics in Agriculture, 110: 1–8. https://doi.org/10.1016/j.compag.2014.09.016

Szturo K. 2023. *Integration of an information ontology-based expert system with machine learning methods for barley kernel defects recognition*. Lodz University of Technology, Łódź.

Teague M.R. 1980. *Image analysis via the general theory of moments*. Journal of the Optical Society of America, 70(8). https://doi.org/10.1364/JOSA.70.000920

TSOLAKIDIS D.G., KOSMOPOULOS D.I., PAPADOURAKIS G. 2014. *Plant Leaf Recognition Using Zernike Moments and Histogram of Oriented Gradients*. Lecture Notes in Computer Science 8445 LNCS. https://doi.org/10.1007/978-3-319-07064-3_33

TYYSTJÄRVI E., NØRREMARK M., MATTILA H., KERÄNEN M., HAKALA-YATKIN M., OTTOSEN C.O., ROSENQVIST E. 2011. *Automatic identification of crop and weed species with chlorophyll fluorescence induction curves*. Precision Agriculture, 12(4). https://doi.org/10.1007/S11119-010-9201-6/FIGURES/7

WEE C.Y., PARAMESRAN R., TAKEDA F. 2006. *Fast computation of zernike moments for rice sorting system*. Proceedings – International Conference on Image Processing, ICIP, 6. https://doi.org/10.1109/ICIP.2007.4379547

WEE C.Y., PARAMESRAN R., TAKEDA F. 2009. *Sorting of rice grains using Zernike moments*. Journal of Real-Time Image Processing, 4(4). https://doi.org/10.1007/S11554-009-0117-1/TABLES/3

WEE C.Y., RAVEENDRAN P., TAKEDA F., TSUZUKI T., KADOTA H., SHIMANOUCHI S. 2002. *Feature reduction of Zernike moments using genetic algorithm for neural network classification of rice grain*. Proceedings of the International Joint Conference on Neural Networks, 1. https://doi.org/10.1109/IJCNN.2002.1005614

ZAPOTOCZNY P., REINER J., MRZYGŁÓD M., LAMPA P. 2020. *The use of polarized light and image analysis in evaluations of the severity of fungal infection in barley grain*. Computers and Electronics in Agriculture, 169. https://doi.org/10.1016/J.COMPAG.2019.105154