Development and evaluation of a machine vision system for assessing the quality of wheat seeds

Mohammad Shaker[1*], Adel Bakhshipour[2], Dadgar Mohammadi[3]

(1. Department of Agricultural Engineering Research, Fars Research and Education Center for Agriculture and Natural Resources, AREEO, Shiraz, 7155863511, Iran;
2. Department of Biosystems Engineering, Faculty of Agricultural Sciences, University of Guilan, Rasht, 4199613776, Iran;
3. Department of Instructor, Economic, Social and Extension Research, Fars Research and Education Center for Agriculture and Natural Resources, AREEO, Shiraz, 7155863511, Iran)

Abstract: In this research, a machine vision system was built and evaluated for two wheat cultivars, Torabi and Azar. The system consisted of three parts: a suction box, a sampling box, and an imaging box. In each wheat type, the performance of the suction device was evaluated with two seed plates and four suction values. A completely randomized design with five replications was used for the statistical data analysis and the Duncan test was used to compare means. In each suction setting, the total number of seeds stuck to the seed plate, the number of singulated seeds and the seeds stuck together in each hole were counted and their percentage was calculated. The captured digital images were processed in MATLAB software to determine the percentage of breakage, impurity, and the number of wheat seeds. The research results indicated that the most suitable treatment for Turabi variety wheat was the seed plate with 1 mm holes and -100 mm Hg suction. For Azar variety wheat, the optimal treatment was found to be the seed plate with 1 mm holes and -120 mm Hg suction. The validation results of the algorithm showed an accuracy close to 100%. The economic study also showed that replacing the machine vision system with the conventional method has an economic justification in terms of the incurred costs.

Keywords: cereals, economic feasibility, image processing, non-destructive, quality.

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1 Introduction

Wheat is the most important agricultural plant in the world, which plays an important role in providing the food need of humans. Considering the increasing population of Iran and the world, as well as the global food shortage, it is important to investigate all solutions that can increase wheat production and optimize the utilization of the produced wheat. The process of seed control and certification plays an essential role in improving the quantity and quality of agricultural products and daily food supply. These aspects are of significant importance in the field of agricultural sciences.

The final stage of wheat seed approval and certification is sampling of the seed shipment for laboratory tests, including tests of purity, viability, seed moisture, etc., and finally labelling. Using an accurate and quick method of identifying different cultivars, the number of broken seeds and impurities, in accordance with the standard of the principles and regulations of control and seed certification, plays an effective role in preventing the great loss of this

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***Corresponding author: Mohammad Shaker, Assistant professor.** Fars Research and Education Center for Agriculture and Natural Resources, AREEO, Shiraz, Iran. Email: m.shaker1348@gmail.com.

mixing (Ghaderifar and Soltani, 2011). During the seed purity test, mechanical devices such as board, adequate light, magnifying glasses, binoculars, microscopes, etc., are used to increase the speed up the process and reduce the fatigue of the seed inspection expert. However, the separation of components is typically done manually and visually by the expert, which requires a significant investment of time and money. Additionally, due to eye fatigue, different criteria of people and human vision error, this approach can lead to inconsistent and non-standard evaluation results. To address these issues, machine vision can be used as a suitable alternative for human vision. Computer vision techniques enable the detection of objects in digital images or videos. These technologies have been rapidly adopted and widely used across various industries (Bakhshipour and Zareiforoush, 2020). One of the most important advantages of the machine vision system is the enhanced accuracy and speed it offers at a low cost, resulting in an overall high efficiency. Therefore, this method can be considered as an alternative to manual counting and inspection of seed samples.

Image processing is a vital tool in agriculture and food sciences, enabling the extraction of meaningful information from visual data to enhance quality assessment and automation (Tian et al., 2020). It involves acquiring, analyzing, and modifying digital images to highlight features or extract data (Kawade and Akant, 2021). Applications include evaluating fruit ripeness, detecting defects, grading crops, and monitoring food processes. For instance, color and texture analysis has proven effective in identifying bruises and assessing crop quality (Cubero et al., 2011). Such techniques offer precision and efficiency, improving productivity and quality control in the food and agriculture sectors. Numerous applications of computer vision and image processing in agriculture have been documented in the review literature (Dhanush et al., 2023; Restrepo-Arias et al., 2024).

Image processing has been successfully used for evaluating and separating seeds, as it is considered as a fast and effective method. Sapirstein et al. (1987) used a machine vision system to classify whole grain samples of wheat, barley, rye, and oats based on physical characteristics such as grain length, width, and surface, and obtained a linear recognition model. The results of this research showed that almost one percent of the 1100 tested seeds were misclassified among wheat, barley, rye and oats.

In a study conducted by Zayas et al. (1990), image analysis along with a statistical model were used to differentiate between whole and broken corn kernels. Twelve parameters describing the shape and size of corn kernels were used for this purpose. The results of this research showed that by using this method, all broken seeds and 98% of whole seeds in the tested samples were correctly identified.

Majumdar et al. (1997) employed an automatic machine vision system to classify spring wheat, durum wheat, barley, rye and oat grains. In another research by Majumdar and Jayas (2000), an algorithm was developed based on morphological features to classify wheat, barley, oat and rye grains using machine vision. In this research, 23 morphological features were used for diagnosis. The results showed that this method achieved the classification accuracies of 98.9% for wheat, 96.8% for barley, 99.9% for oat and 81.6% for rye grains.

In a research, the performance of an automatic inspection system was evaluated for classifying rice quality. Using this system, whole, cracked, chalky, unripe, dried, broken and damaged seeds were successfully separated from each other. A special rice quality inspection software was developed to improve the accuracy of seed separation and machine performance. The results showed that the automatic inspection system can correctly classify more than 90% of rice seeds compared to human inspection. Specifically, the system demonstrated high accuracy rates of 95% for whole seeds, 92% for chalky seeds, and 87% for cracked seeds. The average speed of the rice quality inspection process was more than 1200 seeds per minute (Wan et al., 2002).

The digital image processing method was utilized in a research to determine the geometric characteristics and surface color of rapeseeds. Also, this method was used to detect some difficult-to-separate impurities in the cleaning process (Tańska et al., 2005).

Tanabata et al. (2012) measured the seed shape in rice using SmartGrain software. Another research that was conducted on the germination of six varieties of rice using machine vision to evaluate seed color, size, shape and texture. The accuracy of this evaluation method in rice germination was 93.06% and the speed of the method was 8.31 seconds for each image (Lurstwut and Pornpanomchai, 2016).

Kapadia et al. (2017) reported that image processing plays an important role in seed tests for identifying the seed mass of different cultivars, as well as identifying and distinguishing new cultivars in order to introduce and register them. Due to its high speed and high accuracy, this technique helps the breeders in cultivar selection.

Yan et al. (2017) analyzed the purity of four hybrid corn seeds based on color characteristics, achieving a 93.75% identification accuracy using K-means algorithm.

Shaker et al. (2016) developed and tested an automatic machine vision and control system to enhance the performance of paddy peeling machine and reduce rice loss. They used an image processing algorithm in MATLAB software to determine the percentage of rice breakage with an accuracy of 91.81%.

Payman et al. (2018) developed a computer vision system for assessing rice appearance quality, utilizing a special tray, scanner, and software. The system accurately classified rice grains into whole and broken kernels with over 98% accuracy and effectively detected fissures (96.51%) and color defects. It also achieved high precision in measuring whiteness and chalkiness (R^2 of 99%). The results highlight the potential of image processing for evaluating rice quality.

Sileabat (2022) developed a model for evaluating wheat quality using digital image processing and Transfer Learning techniques, extracting 22 features to characterize wheat samples. A Vgg16-CNN classifier, utilizing a back-propagation learning algorithm with one hidden layer, three dense layers, and one dropout layer, was employed for classification. The model achieved an overall accuracy of 97.90%, with class-specific accuracies ranging from 95.20% to 100%. Their results demonstrated the model's effectiveness in classifying wheat quality, highlighting the potential of machine learning to automate and enhance wheat quality assessment.

Wonggasem et al. (2024) used traditional and deep learning image processing methods for baby corn quality inspection. The EfficientNetB5 model achieved the highest accuracy of 99.06%, surpassing the 95.28% accuracy of the traditional method. The study proposed an automated pipeline to enhance agricultural production by improving the differentiation of baby corn quality.

The research summary indicates that digital image processing can be used to analyze the physical traits of diverse agricultural products. This information can be utilized to develop and implement machine vision-based grain inspection systems. The objective of this research was to develop and evaluate a computer vision system to determine the amount of breakage, impurity, and the number of wheat seeds using the image processing techniques.

2 Materials and methods

2.1 Site specifications

The research was conducted in Zarghan region of Fars province (Southern Iran, 30°94′E, 52°48′N, average annual rainfall of 365 mm, maximum temperature of 41°C, minimum temperature of 9°C, and 1620 m above sea level) from 2021 to 2022.

2.2 Machine vision system

In this research, in order to determine the percentage of breakage, impurity and the number of wheat seeds, it was necessary to build a mechanism that can be used to take samples from a mass of wheat seeds and then separate the seeds from each other.

After that, by taking the images of the wheat samples and transferring them to MATLAB software, the above factors were determined using an image processing algorithm. For this purpose, a machine vision system was built and evaluated technically and economically.

This system consists of three sections: suction box, sampling box, and imaging box. The performance of developed system was evaluated for two wheat varieties, Tarabi and Azar (Figure 1). In the suction box, a 1600-watt electric motor with a suction fan was used. A dimmer device (variable resistance) was utilized to adjust the rotational speed of the electric motor and the suction strength. Additionally, a timer was employed to regulate the suction duration in the box. The level of suction production could be adjusted from -50 to -160 mm Hg. A standard suction measuring gauge was used to measure and calibrate the suction level. Subsequently, a label was affixed on the box to document the test results by the operator (Figure 2).

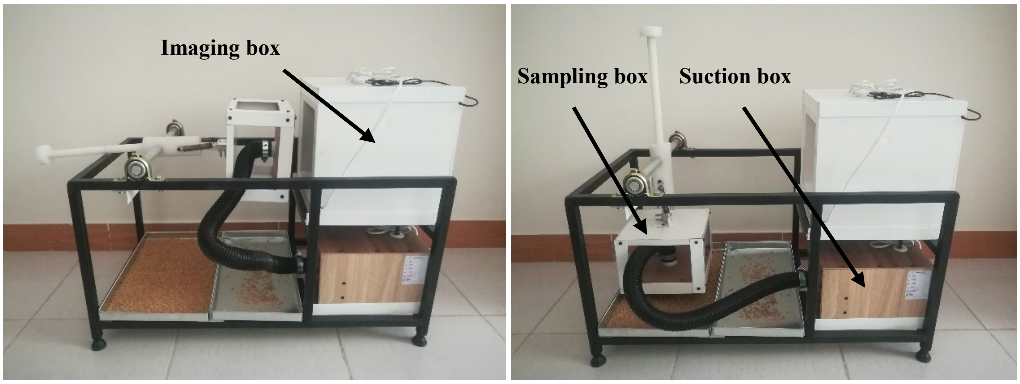


Figure 1 Different parts of machine vision system


Figure 2 The device for measuring the amount of suction and the label of its calibration results

To collect samples, a wooden frame box measuring 20 × 20 × 2 cm and two metal seed plates were used. Two seed plates were created: one with 1 mm diameter holes and the other with 1.5 mm diameter holes, spaced 15 mm apart. The plates were replaceable on the box. A total of 100 holes were placed on each seed plate. Matte black paint, which is suitable for imaging, was used for coloring on the seed plate (Figure 3). The sampling box was connected to the chassis using two tension springs and related connections. Based on this mechanism, the sampling box's movements were limited to only vertical and rotational movements around the axis connected to the chassis. Two suction and sampling boxes were connected to each other by a flexible pipe.

After activating the electric motor and generating suction in the sampling box, by pressing the box down on the seed tray and holding it for 2 to 3 seconds, the seed samples were taken (the seeds stuck on the holes of the seed plate). After that, by releasing the pressure, the springs would force the box to return to its original state. In this scenario, with the rotation of the sampling box around the axis connected to the chassis, the box was positioned in front of the imaging box (Figure 1). At this stage, a digital camera was used to capture an image of the seed plate. The suction was then stopped at the designated time by the timer to allow the seed samples to be dispensed onto another tray.

The imaging box was designed with a fluorescent lamp to provide illumination. When the lamp's light hit the middle screen and reflected downwards, it indirectly and uniformly illuminated the seeds. A Logitech-C170 digital camera with a 5-megapixel resolution was mounted on top of the box at a height of 30 cm. This setup ensured that the images were taken from a fixed height, eliminating any potential vibration or error in the images (Figure 4).

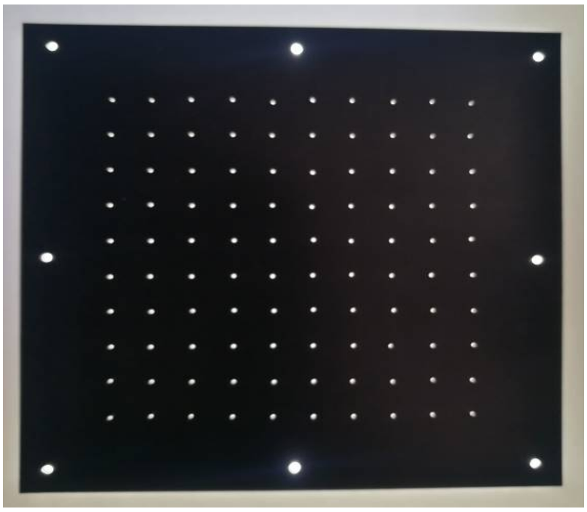


Figure 3 Seed plate

Figure 4 Imaging box

Table 1 Physical characteristics of the two evaluated wheat cultivars

Type of wheat	Length (mm)	Width (mm)	Thickness (mm)	Weight of 1000 seeds (grams)
Torabi	7.2	3.88	2.76	47.61
Azar	7.38	2.88	2.52	36.19

2.3 Technical evaluation of machine vision system

Torabi (irrigated) and Azar (rainfed) wheat varieties, common in Fars province, whith their physical characteristics are presented in Table 1, were used for the technical evaluation of the developed machine vision system. In both types of wheat, the performance of the suction device, with two seed plates (with hole diameters of 1 and 1.5 mm) and four suction values (-80, -100, -120 and -130 mm Hg) was evaluated.

In this research, the evaluated treatments (8 treatments) based on the type of seed plate and suction amount were as follows:

Treatment 1. Seed plate with 1 mm hole and -80 mm Hg suction

Treatment 2. Seed plate with 1 mm hole and -100 mm Hg suction

Treatment 3. Seed plate with 1 mm hole and -120 mm Hg suction

Treatment 4. Seed plate with 1 mm hole and -130 mm Hg suction

Treatment 5. Seed plate with 1.5 mm hole and -80 mm Hg suction

Treatment 6. Seed plate with 1.5 mm hole and -100 mm Hg suction

Treatment 7. Seed plate with 1.5 mm hole and -120 mm Hg suction

Treatment 8. Seed plate with 1.5 mm hole and -130 mm Hg suction

In order to determine the most effective settings for the machine vision system, the total number of seeds stuck to the seed plate, and the number of singulated seeds, and the seeds stuck together in each hole. The percentage of each category was also calculated. Finally, for each type of wheat, the appropriate seed plate and suction amount of the machine were selected, in which there was the highest percentage of singulated seeds and the lowest percentage of seeds sticking together.

2.4 Image processing algorithm coding

The images taken by the digital camera were transferred to the MATLAB software to determine the percentage of breakage, the percentage of impurity, and the number of wheat seeds using a developed image processing algorithm.

The input RGB images were converted to grayscale. By applying an appropriate threshold, initial binary images of the samples were obtained. Next, any potential empty regions inside the objects were filled using the “*imfill*” function. To eliminate potential noise, sequential erosion and dilation operations were performed with the “*imopen*” function. This process resulted in refined binary images of the samples, which were suitable for subsequent morphological analyses. Using these binary images, shape features such as area, perimeter, length, width, aspect ratio, eccentricity, and roundness were computed with the "*regionprops*" function. Additionally, the exterior boundaries of the wheat seeds were traced using the "*bwboundaries*" function. Moreover, by logically overlaying the binary and RGB images of the wheat samples, RGB images of the kernels with a completely zeroed-out background were generated. These refined images were then used to extract the Red, Green, and Blue color components for further analysis.

Using shape, color, and boundary data, the samples were categorized into five general classes: single whole kernels, touched grains (doubles), broken grains, and impurities (others). A conditional classification algorithm was developed based on five images, each containing 100 samples.

To evaluate the model's performance, 10 test images with known sample compositions were manually created by introducing impurities into pure wheat samples. The algorithm's accuracy and effectiveness were then assessed using these test images.

2.5 Cost analysis of machine vision system

In the economic evaluation of this project, the partial budgeting method was used. This method is applied when the manager of a production unit makes a change in the production management method. The purpose of partial budgeting is to organize and adjust information in such a way that a specific decision can be reached in the production department (Soltani et al., 2007). In this regard, the following calculations were made to make a decision.

A) Calculating benefits of different treatments: (Bi + C1)

Bi: the increase in income due to the new decision.

C1: Decrease in costs due to the implementation of a new decision.

B) Calculation of the cost of different treatments: (Ci + B1)

Ci: the increase in variable costs due to the new decision.

B1: the decrease in income due to the new decision.

If the increase in income plus the decrease in cost is greater than the increase in cost plus the decrease in income [(Bi + C1) > (Ci + B1)], the net profit has increased and the decision is economically justified. Otherwise, this decision is not economically justified.

Investment in the construction of a machine vision system has an economic life of more than one year, so its costs and benefits cannot be collected directly. For the economic evaluation of this project, it is necessary to discount the cost of building the machine vision system and its profit over the years of its useful life. For this purpose, using the method of the same payment amount and the discount rate (equivalent to the rate of agricultural facilities), the costs of the machine vision system are distributed uniformly in the years of useful life. In this method, the present value of the costs is multiplied in the recovery factor and the amount of the cost per year in the operation period is obtained. According to Skunjad (2013), the mathematical equation for calculating the same payment amount of the present value in different years of the exploitation period is Equation 1:

$$A = P\left[\frac{r(1+r)^n}{(1+r)^n-1}\right] \qquad i = 1.2.\ldots.n \qquad (1)$$

In this equation, A is the same amount of cost for each year in the exploitation period, $\left[\frac{r(1+r)^n}{(1+r)^n-1}\right]$ is the recovery factor, P is the present value, r is the discount rate, and n is the length of the exploitation period.

2.6 Statistical analysis

One-way ANOVA analysis were applied to the data collected from the experiments using SAS software and Duncan's multiple range tests was used to compare the treatments means.

3 Results and discussion

3.1 Technical evaluation of the machine vision system

As mentioned, in this research, 8 treatments were evaluated based on the type of seed plate and the amount of suction.

The analysis of variance of the percentage of singulated seeds and stuck-together seeds on the seed plate, related to Torabi wheat, is presented in Table 2. The results of this table show that the treatment has a significant effect on the percentage of singulated seeds and stuck-together seeds at a probability level of 1%.

The comparison of the means of the effects of the evaluated treatments on the percentage of singulated seeds and stuck-together seeds, related to the Torabi wheat variety, is presented in Table 3. The results of this table indicate that the highest percentage of singulated seeds is in treatment 1 (seed plate with 1 mm hole and suction of -80 mm Hg) with 98.38% and the lowest amount is in treatment 7 (seed plate with 1.5 mm hole and suction of -120 mm Hg) with 57.65%. The results of Table 3 also show that the highest percentage of stuck-together seeds is in treatment 7 (seed plate with 1.5 mm hole and suction of -120 mmHg) with 42.35% and the lowest amount is in treatment 1 (seed plate with 1 mm hole and suction of -80 mm Hg) with 1.62%.

Summarizing the results of Tables 2 and 3, it is evident that the most appropriate treatment for Torabi wheat is treatment 2 (seed plate with 1 mm hole and suction of -100 mm Hg) with 95.31% singulated seeds and 4.69% stuck-together seeds. This treatment is in the same statistical group with treatments 1 and 3 and there is no significant difference between them, but considering that the total number of seeds stuck to the seed plate in treatment 2 is more than the total number of seeds stuck to the seed plate in treatment 1, the treatment 2 was selected. The sample of images prepared for Torabi wheat in suction of -100 mm Hg with 1 and 1.5 mm seed plate is presented in Figure 5.

The analysis of variance of the percentage of singulated seeds and stuck-together seeds on the seed plate, related to Azar wheat, is presented in Table 4. The results of this table show that the effect of the treatment on the percentage of singulated seeds and stuck-together seeds is significant at the probability level of 1%.

The comparison of the means of the effects of the evaluated treatments on the percentage of singulated seeds and stuck-together seeds, related to the wheat of Azar variety, is presented in Table 5. The results of this table indicate that the highest percentage of singulated seeds is in treatment 3 (seed plate with 1 mm hole and suction -120 mm Hg) with 91.60% and the lowest amount is in treatment 8 (seed plate with 1.5 mm hole and suction -130 mm Hg) with 39.13%. The results of Table 5 also show that the highest percentage of stuck-together seeds is in treatment 8 (seed plate with 1.5 mm hole and suction -130 mmHg) with 60.87% and the lowest amount is in treatment 3 (seed plate with 1 mm hole and suction of -120 mm Hg) with 8.40%.

Summarizing the results of Tables 4 and 5 shows that the most suitable treatment for Azar wheat is treatment 3 (seed plate with 1 mm hole and suction -120 mm Hg) with the percentage of singulated seeds 91.6% and the percentage of stuck-together seeds 8.4%. This treatment is in the same statistical group with treatments 2 and 4 and there is no significant difference between them, but considering that there is the highest percentage of singulated seeds and the lowest percentage of stuck-together seeds in this treatment, so this treatment was selected. The sample of images prepared for Azar wheat in suction of -120 mm Hg with 1 and 1.5 mm seed plate is presented in Figure 6.

Table 2 Analysis of variance of the percentage of singulated seeds and stuck-together seeds (wheat of Torabi cultivar)

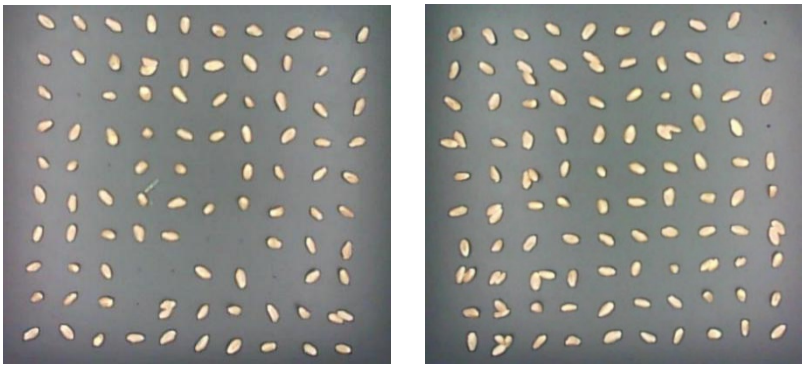
Row	Sources of change	Degrees of freedom	Mean of squares	
			Singulated seeds	Stuck-together seeds
1	Treatment	7	1509.44 **	1509.44 **
2	Trial error	32	15.61	15.61
3	Total	40		

Note: ** Significant at 1% probability level.

Table 3 Comparison of the means of treatment effect on the percentage of singulated seeds and stuck-together seeds (wheat of Torabi cultivar)

Treatment	Singulated seeds (%)	Stuck-together seeds (%)
1	^{a} 98.38	^{e} 1.62
2	^{ab} 95.31	^{de} 4.69
3	^{ab} 95.08	^{de} 4.92
4	^{b} 90.72	^{d} 9.28
5	^{c} 73.78	^{c} 26.22
6	^{d} 66.47	^{b} 33.53
7	^{e} 57.65	^{a} 42.35
8	^{e} 58.09	^{a} 41.91

Note: Similar letters indicate that there is no significant difference.



(a) Seed plate with 1 mm hole (b) Seed plate with 1.5 mm hole

Figure 5 Sample of images prepared for wheat of Torabi cultivar in suction of 100 mm Hg

Table 4 Analysis of variance of the percentage of singulated seeds and stuck-together seeds (wheat of Azar cultivar)

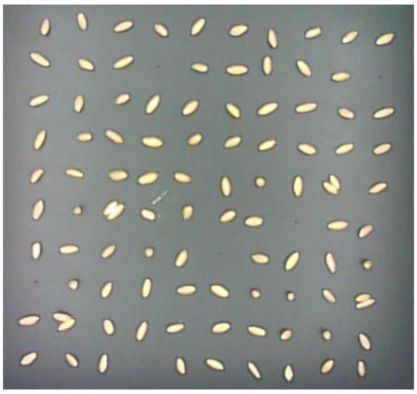
Row	Sources of change	Degrees of freedom	Mean of squares	
			Singulated seeds	Stuck-together seeds
1	Treatment	7	2297.53 **	2297.53 **
2	Trial error	32	29.19	29.19
3	Total	40		

Note: ** Significant at 1% probability level

Table 5 Comparison of the means of treatment effect on the percentage of singulated seeds and stuck-together seeds (wheat of Azar cultivar)

Treatment	Singulated seeds (%)	Stuck-together seeds (%)
1	b 83.66	d 16.34
2	ab 84.99	de 15.01
3	a 91.60	e 8.40
4	ab 87.13	de 12.87
5	c 54.61	c 45.39
6	cd 50.50	bc 49.50
7	d 46.91	b 53.09
8	e 39.13	a 60.87

Note: Similar letters indicate that there is no significant difference.


(a) Seed plate with 1 mm hole

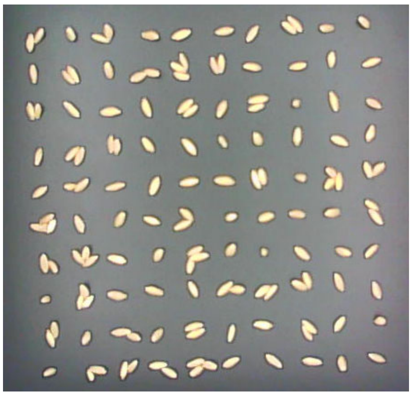

(b) Seed plate with 1.5 mm hole

Figure 6 Sample of images prepared for wheat of Azar cultivar in suction of 120 mm Hg

3.2 Validation of the image processing algorithm

Because there was no impurity in the wheat samples or there was only a small amount impurities present in wheat samples, some impurities were manually added to the samples. Thereupon, the images of the provided samples were captured and used to assess the algorithm for determining the percentage of breakage, the percentage of impurity, and the number of seeds in Torabi wheat variety (Figure 7).

This algorithm was developed to identify and label whole seeds, broken seeds, double seeds and impurities, after execution (refer to Figure 8). The accuracy of the algorithm was evaluated with 10 images (similar to Figure 7, but with varying number of whole, broken, double seeds and impurity. The evaluation showed that the accuracy of the algorithm was close to 100%.

3.3 Cost analysis

Given that the duration and cost of the treatments were equal, the economic evaluation was conducted to determine whether replacing the use of the machine vision system with labor in measuring the percentage of seed breakage and impurity would be viable. Because the benefits obtained from the use of both methods were nearly identical, therefore, the decision to replace one with the other was done from an economic point of view based on the cost of implementing the methods. Based on the technical findings of the study, the required time was about 20 seconds for sampling, separating, counting and determining the percentage of breakage of 100 wheat seeds using the machine vision system. In comparison, the traditional method using human vision took about 180 seconds. Moreover, this time increases to about 240 seconds if the fatigue of the person is taken into account during the activity in the traditional procedure. Therefore, it is evident that the use of the machine vision system reduces the required time for wheat seed control and certification by about one-ninth to one-twelfth compared to the traditional method. Considering that in the wheat seed control and certification process, 400 wheat seeds (four samples of 100 each) are counted and separated from each seed shipment, therefore, to compare the economic costs of different methods for determining seed purity, the costs were estimated for a total of four samples, each containing 100 seeds.

Figure 7 Wheat sample with broken seeds and impurity

Table 6 Estimating the costs of using the machine vision system in determining the of breakage and impurities percentage of wheat seed

Method used	Investment cost ($)	Useful life (years)	Equivalent uniform annual cost ($)	The cost of counting and separating 100 seeds ($)	The cost of counting and separating 400 seeds ($)	The cost of skilled labor to use the machine ($)	Total cost for counting and separating 400 seeds ($)
Machine vision system	80	5	26.8	0.00007	0.0003	0.0152	0.0154

The cost of using the machine vision system in determining the purity of wheat seeds is shown in Table 6. According to Table 6, the initial investment cost for constructing the machine during the year of project implementation was estimated at 80 dollars. Taking into account the useful life of the machine and the discount rate of 18%, the annual cost of the machine in the period of operation was calculated to be equal to 26.8 dollars. According to the average working days per year (290 days) and the number of working hours in one day (7.33 hours), the cost of using the machine vision system to count and separate 100 seeds (which takes 20 seconds) was estimated at 0.00007 dollars, and for 400 seeds (four packs of 100 kernels), it was calculated to be 0.0003 dollars. Additionally, the cost of expert labor to operate the machine to count and separate 400 seeds was estimated at 0.0152 dollars. Therefore, the total cost of using the machine vision system for counting and separating 400 seeds was calculated as 0.0154 dollars.

The cost of determining the purity of wheat seeds using the traditional method was compared in two cases (use of labor without fatigue and with fatigue), and the results are presented in Table 7. According to the results of this table, the cost of determining the purity of 400 wheat seeds in the traditional method was estimated at 0.08 dollars in the first case (without personal fatigue) and 0.11 dollars in the second case (with personal fatigue).

Based on the information in Tables 6 and 7, the cost of determining the purity of 400 wheat seeds using the machine vision system compared to the traditional method was reduced about 80% in the first case (use of labor without fatigue) and about 85% in the second case (use of labor with fatigue). Therefore, making a decision to replace the machine vision system with the usual method is economically justified in terms of costs. In addition to cost reduction, the use of a machine vision system offers other advantages, such as reducing the required time by one-ninth to one-twelfth, along with decreasing the error rate.

Table 7 Estimation of the costs of using labor and human vision in determining the of breakage and impurities percentage of wheat seed

Method used	Duration of counting and separating 100 seeds (seconds)		The cost of counting and separating without individual fatigue ($)		The cost of counting and separating with individual fatigue ($)	
	without fatigue	with fatigue	100 seeds	400 seeds	100 seeds	400 seeds
The usual method	180	240	0.02	0.08	0.03	0.11

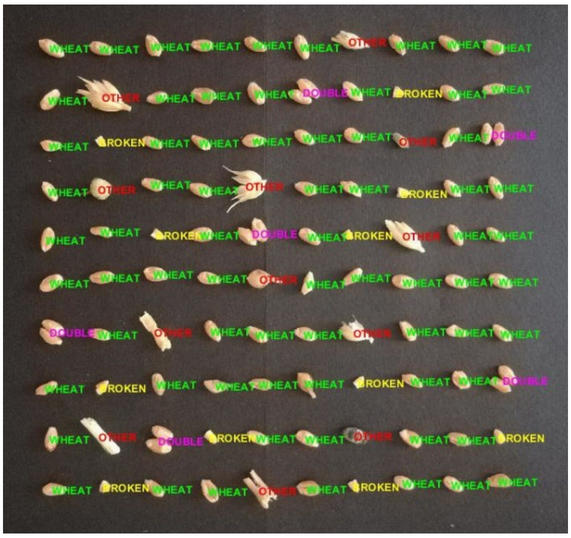


Figure 8 Implementation of the algorithm to determine the percentage of breakage, the percentage of impurity and the number of wheat seed

4 Conclusion

A machine vision system was developed and evaluated to inspect the quality and purity of wheat grains. The summary of the results indicated that for the machine vision system, the optimal conditions for Torabi and Azar varieties of wheat were found to be the use of a seed plate with a 1 mm hole and suction levels of -100 and -120 mm Hg. these combinations resulted in the highest percentage of singulated seeds and the lowest percentage of seeds sticking together. The accuracy of the algorithm in determining the percentage of breakage, the percentage of impurity, and the number of wheat seeds was close to 100%. Additionally, it identified the type of seeds (whole, broken, double and impurity). The time required for sampling, separating, determining of breakage percentage, impurity percentage, and counting the number of wheat seeds in this system takes about 20 seconds. This is a significant reduction compared to the traditional method, which requires the expertise and vision of human, reducing the required time by about one-twelfth. The economic study results also indicated that the decision to replace the machine vision system with the traditional method is economically justified in terms of the incurred costs.

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