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Automated devices for quantitative phenotyping of sunflower seeds

Abstract. To develop new sunflower varieties, it is important to accurately assess phenotypic traits that influence yield, disease resistance, and stress tolerance. Automation allows for systematic data collection and more informed decision-making in the breeding process. The goal of the work was to enhance the efficiency of selecting and predicting the development of sunflower genotypes through the development of new methods, hardware, and software tools for quantitative phenotypic characterisation of seeds. The methods for determining phenotypic characteristics of sunflower seeds, including geometric dimensions, mass, colour, rheological properties, and seed surface properties, have been presented and improved. A module for determining the morphological properties of seeds (geometric dimensions, mass, surface colour, etc.) was developed. This module was configured for high precision in the individual measurement of the geometric dimensions of sunflower seeds, with the determination of their shape and colour. It ensured low labour intensity and high technological efficiency in the implementation of the phenotyping procedure (determination, identification, and separation) of seeds. The methodology for analysing the rheological properties of seeds was refined, and a method for their automatic determination, along with a corresponding module, was substantiated. The proposed module maintains the accuracy of individual measurement of the rheological properties of seeds, consistent with modern measurement tools, while ensuring low labour intensity and high technological efficiency. Additionally, the module significantly reduced the influence of the human factor on the accuracy of measuring the rheological properties of seeds. The proposed module for determining seed surface properties ensured the accuracy of individual measurements of the coefficients of static and sliding friction of seeds, aligning with modern measurement tools, while also ensuring low labour intensity and high technological efficiency. This also significantly minimised the influence of the human factor on the accuracy of these measurements. The use of automated devices in practical conditions can help optimise the selection of seeds with the best characteristics

Keywords: module; software; geometric dimensions; surface colour; rheological properties; frictional properties

INTRODUCTION

Plant phenotyping involves a comprehensive evaluation of complex traits such as growth, development, resilience, architecture, physiology, ecology, and yield, along with basic measurements of individual quantitative parameters that contribute to these traits. The plant phenotype includes these complex characteristics, with measurable parameters such as root morphology, biomass, leaf traits, fruit (seed) characteristics, yield-related factors, photosynthetic

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efficiency, and responses to biotic and abiotic stress. With the rapid advancement of high-throughput genotyping in plant breeding and genomics, there is an increasing demand for more efficient and reliable phenotyping data to support modern crop genetics.

To accomplish this objective, phenotyping integrates knowledge from biology, computer science, mathematics, and engineering. C. Costa *et al.* (2019) and Y. Jiang & C. Li (2020) highlighted that quantitative measurement greatly benefits from advanced imaging technologies, but also depends on standardised experimental protocols, including sensor calibration and accurate data processing methods, which are essential for best practices in plant phenotyping.

Modern imaging methods offer high resolution and allow for the visualisation of multidimensional and multiparametric data. These methods are used to quantitatively assess complex plant traits during their growth in both controlled environmental systems and field conditions. According to M. Deb *et al.* (2024) and B. Daviet *et al.* (2022) image analysis algorithms are the primary drivers advancing image-based research that requires quantitative phenotyping of plant parts such as roots, stems, leaves, seeds, flowers, etc. Phenotyping of seeds was not possible without the use of modern equipment. One of the first such automatic phenotyping devices that addressed the complex issue was phenoSeeder, mentioned in the article by S. Jahnke *et al.* (2016).

The study by S. Yang *et al.* (2021) introduced a novel phenotyping method based on image processing of soybean seeds using neural networks and Mask R-CNN training. The primary advantages of this method include automatic image segmentation and pre-defined model weight coefficients. However, the method has some drawbacks: the phenotyping analysis of soybean seeds was based on two-dimensional images; the computational costs for training the instance segmentation model are relatively high; and the method for generating and augmenting synthetic images is limited to a single object class for image segmentation.

Researchers at the Earlham Institute, J. Colmer *et al.* (2020), introduced the SeedGerm system, which integrates affordable hardware with open-source software to conduct seed germination experiments, automate seed imaging, and apply machine learning for phenotypic analysis. A significant advantage of this system is its ability to process multiple image series simultaneously while providing accurate analysis of traits associated with seed germination and viability.

Additionally, the study by Y. Nehoshtan *et al.* (2021) introduced the SeedNet technology and system for studying the germination of vegetable crop seeds, which is based on deep learning and RGB image data. The proposed technology's advantage is its ability to be used for industrial seed sorting based on germination rates across various crops. However, the SeedGerm and SeedNet systems are primarily designed for assessing seed germination dynamics.

In the work by K. Tu *et al.* (2023), new software called AIseed was developed, which automatically captures and analyses morphological traits such as shape, colour, and texture features of individual seeds. The AIseed software is based on machine vision technology and provides high-throughput processing and phenotyping of seeds of various sizes. The advantage of this system is its high efficiency in detecting phenotypic traits of seeds. However, the system is not open for general access.

Therefore, the goal of this work was to improve the efficiency of selecting and predicting the development of sunflower genotypes by developing new methods, hardware, and software tools for the quantitative phenotypic characterisation of seeds.

MATERIALS AND METHODS

The primary phenotypic characteristics of sunflower seeds were shape, geometric dimensions, mass, colour, rheological, and frictional properties (Pieruschka & Schurr, 2019). The shape and geometric dimensions of the seeds were determined using an image processing methodology. The developed algorithm for determining the shape and geometric dimensions of seeds was based on a new image analysis method. This method reduced the time required for seed preparation and image acquisition. The contours of the seeds were automatically detected on digital images, and several shape parameters were calculated. These parameters included seed length (L), width (W) or thickness (T), area (S), and perimeter length (P). The algorithm and corresponding software, based on Visual Studio C++ (USA) and the OpenCV library (USA), analysed all the images obtained from the camera. After analysis, the seeds were automatically identified by taking successive points along the seed perimeter and maximising or minimising values in the following sequence of stages.

The process involved loading the image and converting it to a 1-bit format (black seeds on a white background). Morphological analysis was conducted to remove noise and gaps. Contours were detected, all seeds on the image were labelled, and the length (L), width (W) or thickness (T), area (S), and perimeter (P) of the seeds were calculated.

Image processing consisted of three stages. The first stage was converting the image of the selected rectangular region of the seed material from 24-bit (full-colour) to 1-bit (black and white) using a segmentation method. This isolated the black seeds on a white background. This method was stable even with changes in lighting levels. The second stage involved removing any noise or gaps. For this purpose, the software used OpenCV (Kumar *et al.*, 2023) functions Erode and Dilate, based on morphological operations. The third stage was the automatic detection of each seed's contour in the 1-bit image using the Canny edge detector and Hough transform via the OpenCV FindContour function. This process yielded a set of coordinates for each seed contour. To measure the length L, the algorithm found the maximum distance between points along the perimeter by calculating all possible distances between points in the segment $l_{i,j}$ located on the contour boundary (Fig. 1):

$$l_{i,j} = \sqrt{\left(x_{li} - x_{lj}\right)^2 + \left(y_{li} - y_{lj}\right)^2}, \quad (1)$$

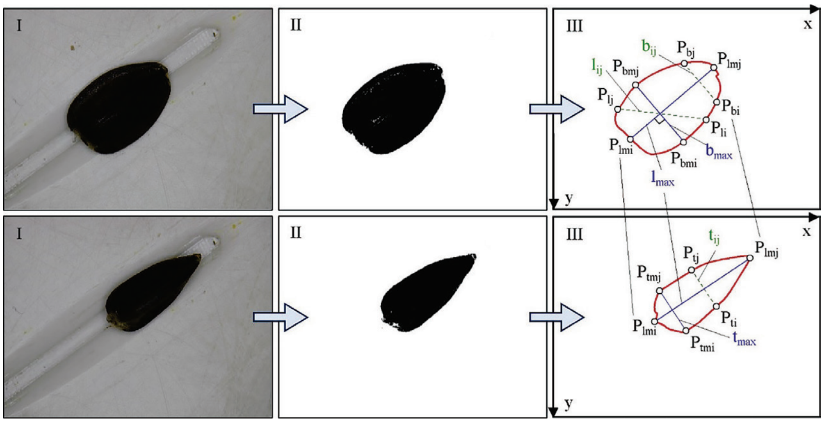

Figure 1. Stages of determining the geometric dimensions of seeds from photographic images
Note: *x, y* – coordinates, mm; l_{max} – length of the seed, mm; b_{max} – width of the seed, mm; t_{max} – thickness of the seed, mm; $l_{i,j}$, $b_{i,j}$, $t_{i,j}$ – distances between points of the segment, mm; P_{lj}, P_{bmj}, P_{bj}, P_{lmj}, P_{bi}, P_{li}, P_{bmi}, P_{lmi}, P_{tmj}, P_{tj}, P_{ti}, P_{tmi} – points on the seed contour; *I, II, III* – stages of determining geometric dimensions
Source: compiled by the authors

The determination of the largest segment *L* was carried out using the following method:

$$L = l\max_{i,j}\left(l_{i,j}\right)_{lmi\left(x_{lmi}, y_{lmi}\right) lmj\left(x_{lmj}, y_{lmj}\right)}{}_{max}. \qquad (2)$$

To measure the width *W* or thickness *T*, the algorithm found the largest segment that was perpendicular to the length *L* (Fig. 1):

$$w_{i,j} = \sqrt{\left(x_{wi} - x_{wj}\right)^2 + \left(y_{wi} - y_{wj}\right)^2} \left(if\ \frac{\left(y_{lmi} - y_{lmj}\right)}{\left(x_{lmi} - x_{lmj}\right)} \frac{\left(y_{wi} - y_{wj}\right)}{\left(x_{wi} - x_{wj}\right)} = -1\right), \qquad (3)$$

$$W = w\max_{i,j}\left(w_{i,j}\right)_{wmi\left(x_{wmi}, y_{wmi}\right) wmj\left(x_{wmj}, y_{wmj}\right)}{}_{max}, \qquad (4)$$

$$t_{i,j} = \sqrt{\left(x_{ti} - x_{tj}\right)^2 + \left(y_{ti} - y_{tj}\right)^2} \left(if\ \frac{\left(y_{lmi} - y_{lmj}\right)}{\left(x_{lmi} - x_{lmj}\right)} \frac{\left(y_{ti} - y_{tj}\right)}{\left(x_{ti} - x_{tj}\right)} = -1\right), \qquad (5)$$

$$T = t\max_{i,j}\left(t_{i,j}\right)_{tmi\left(x_{tmi}, y_{tmi}\right) tmj\left(x_{tmj}, y_{tmj}\right)}{}_{max}. \qquad (6)$$

The seed mass *M* was measured using a load cell with strain gauges, an HX711 module (China), and an Arduino control board (USA). The strain gauges and HX711 module were connected in a bridge configuration. The HX711 module, produced by Avia Semiconductors, was an analog-to-digital converter (ADC) with a 24-bit sampling frequency and an integrated operational amplifier.

The seed colour was determined using image processing techniques on images obtained under different lighting conditions. The seed was placed in a chamber beneath the camera, where controlled lighting was isolated from external light. RGB LEDs (*R* – red (465-470 nm), *G* – green (515-520 nm), *B* – blue (620-625 nm)) were used to provide light of specific colours, and the camera captured images of the seed either stationary or in motion, which were then transmitted to a personal computer.

The software algorithm consisted of the following stages:

1. Image Acquisition: capturing images from the video camera.
2. Colour Space Conversion: translating the image from RGB colour space to HSV (*H* – Hue, *S* – Saturation, *V* – Value).
3. Colour Filtering: setting the colour mask for filtering.
4. Morphological Transformations: applying basic morphological transformations such as dilation and erosion.
5. Contour Detection and Labeling: finding the contours of the detected object and drawing labels.

The advantages of this algorithm included: colour ranges were selected using *H*, *S*, and *V* scales, resulting in an immediate formation of a three-dimensional region in the colour space.

The algorithm was implemented using the OpenCV library. Various seeds of different colours, sizes, and shapes were tested. As noted, each seed required a specifically tuned colour mask. To isolate the desired colour, the *H* component boundaries had to be adjusted. The *S* parameter controlled colour saturation, while V determined colour brightness. A shaded object would have a low *V* value. From the obtained images, for each seed, a corresponding colour data matrix was determined under three types of illumination:

$$\begin{pmatrix} H_R & H_G & H_B \\ S_R & S_G & S_B \\ V_R & V_G & V_B \end{pmatrix}, \qquad (7)$$

where *H* represented the hue; *S* denoted the colour saturation; and *V* indicated the amount of light. The indices *R*, *G*, and *B* corresponded to the wavelength of electromagnetic radiation (lighting) affecting the area under the camera. When the software for automated seed phenotyping was launched, five windows appeared (see (Fig. 2):

1. Camera Window: displayed the original image from the camera under white lighting (with all LEDs turned on),

highlighting the contours of the seeds and their geometric dimensions.

2. Filter Window: showed the image from the camera after converting the colour image from the HSV colour space to a black-and-white mask. In this mask, pixels falling within the specified range turned white, while others turned black.

3. HSV Window: featured sliders for adjusting the HSV colour mask.

4. RGB Bar Chart Window: displayed histograms of colour distribution in the RGB colour space.

5. CMD Window: provided an input and output interface for messages and data.

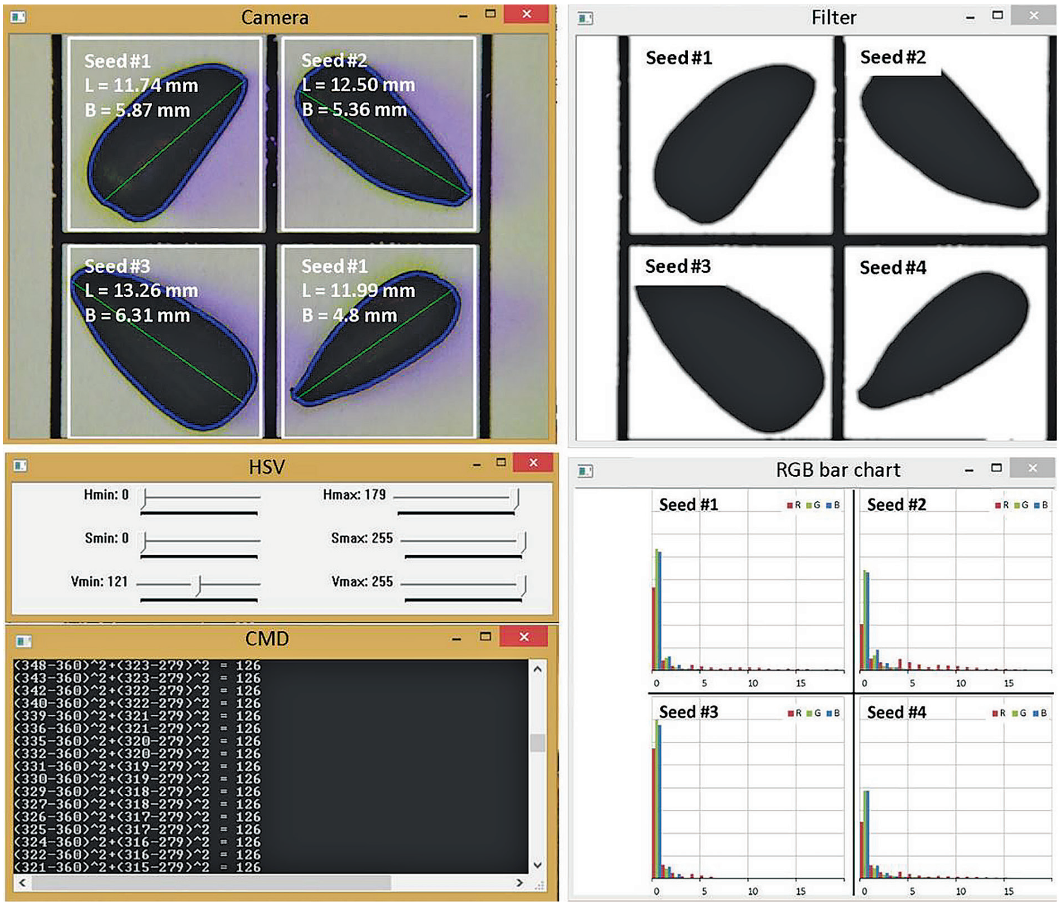

Figure 2. Software for automated phenotyping of sunflower seed material

Note: *L* – length of the seed, mm; *B* – width of the seed, mm; H_{min}, H_{max} – minimum and maximum value of hue; S_{min}, S_{max} – minimum and maximum value of saturation; V_{min}, V_{max} – minimum and maximum value of value; *R, G, B* – red, green, blue

Source: compiled by the authors

Determining the rheological properties of seeds involves the following stages:

1. *Stage one*. The seeds were placed in the required position on a flat horizontal surface of the working table in the area under a cylindrical indenter (diameter – 20 mm) mounted on a load cell that moved in the vertical plane. The load cell with the attached indenter had to be calibrated, and in its resting state, it had to correspond to a force of 0 N.

2. *Stage two*. The indenter started descending from the top point at a uniform, straight-line speed of 10 mm/s. Upon reaching the seed, the force on the load cell began to increase from 0 N. This moment was recorded as the start of the measurement process. Subsequently, the geometric size of the seed X was determined, with the working table set to the coordinate origin of 0 mm.

3. *Stage three*. During the measurement process, the time *t*, absolute deformation ΔX, and compression force *F* were determined. After the absolute deformation reached 10% of the seed size, the value of the force $F_{0.1}$ was recorded, and the seed stiffness coefficient k was calculated:

$$k = \frac{F_{0.1}}{0.1X_{max}}, \tag{8}$$

when the force *F* started to decrease, the maximum strength of the seed coat F_{max} was recorded.

The surface properties of seeds were primarily determined by roughness and/or the coefficient of friction (Fig. 3c). To determine the coefficient of friction of the seeds on the surface, a traditional method was used, which involved moving a load-bearing mass *M* of seeds (with mass M_s) across the working surface.

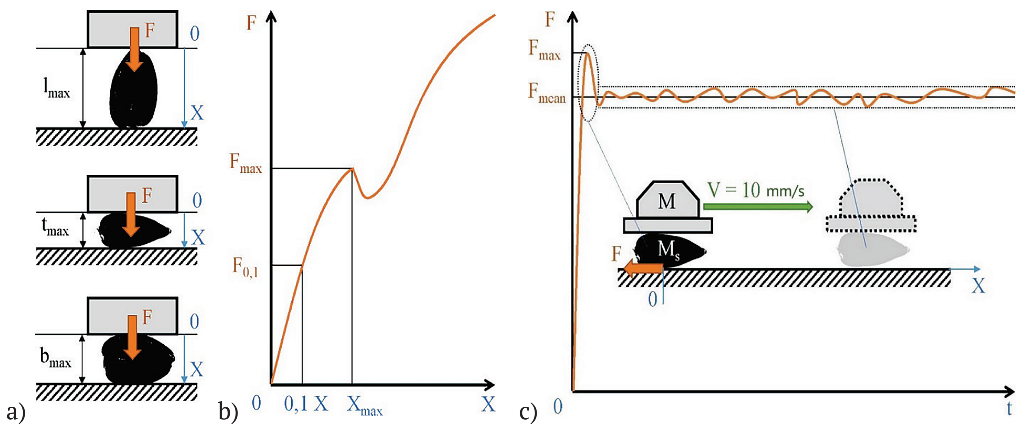

Figure 3. Process of determining rheological properties (a, b) and surface properties (c) of seeds
Note: *a* – seed placement options under the indenter; *b* – graph of the force *F* versus deformation *X* during seed compression; *c* – graph of the force *F* versus time during seed movement on the working surface; l_{max} – length of the seed, mm; b_{max} – width of the seed, mm; t_{max} – thickness of the seed, mm; F_{max} – the maximum strength of the seed coat, N; $F_{0,1}$ – force at 10% deformation, N; F_{mean} – the average force, N; *V* – speed of movement, mm/s; *M* – mass of the load, g; M_s – mass of the seeds, g; *t* – time, s; X_{max} – the maximum of the seed deformation, mm
Source: compiled by the authors

The change in the opposing force *F*(*t*) during the movement was measured dynamically using a resistive load cell. The coefficient of static friction μ_r was calculated as the ratio of the maximum force at the initial moment F_{max} to the total mass of the seeds M_s and the load *M*, multiplied by the acceleration due to gravity *g*. The coefficient of sliding friction μ_s was determined as the ratio of the average force F_{mean} to the total mass M_s of the seeds and the load *M*, multiplied by the acceleration due to gravity *g*.

RESULTS

According to the accepted methodologies for determining phenotypic characteristics of seeds, experimental samples of three modules were developed and manufactured: a module for determining the morphological properties of seeds (shape, geometric dimensions, mass, surface coloration), a module for determining the rheological properties of seeds (seed stiffness coefficient, seed coat strength), and a module for determining the surface properties of seeds (static and sliding friction coefficients). The design and technological scheme, overall appearance, and electrical diagram of the module for determining the morphological characteristics of seeds were shown in Figure 4. The principle of operation of the seed morphological properties determination module was as follows. Seeds for examination were placed in the seed feeder tray. The desired seed feed rate was set on the conveyor belt using an adjustable gate.

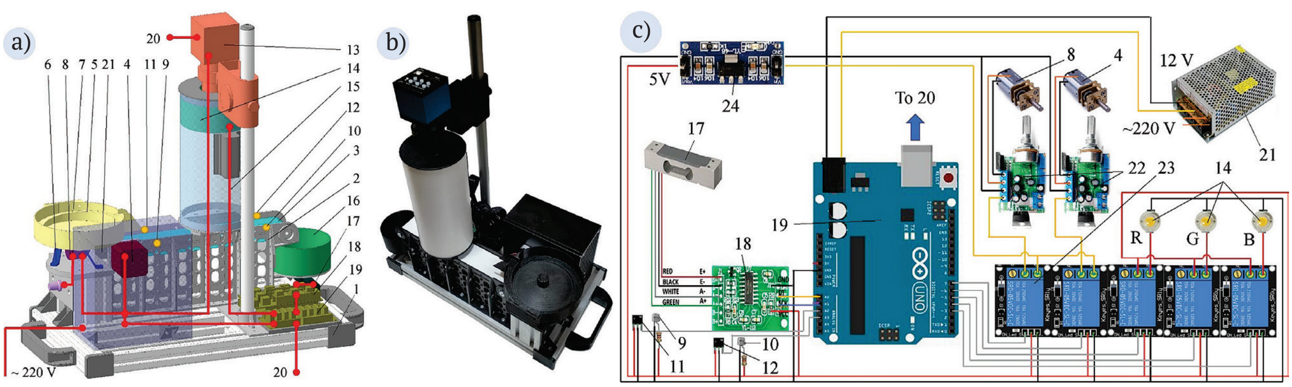

Figure 4. Structural-technological diagram (a), general view (b), and electrical schematic (c) of the seed morphological property determination module
Note: 1 – frame; 2 – belt conveyor; 3 – belt; 4 – electric motor; 5 – seed feeding tray; 6 – shock absorbers; 7 – gate; 8 – vibration motor; 9, 10 – infrared LEDs; 11, 12 – photoreceivers; 13 – camera (Eakins Video Microscope Camera (China)); 14 – RGB LEDs; 15 – lightproof tube; 16 – strain gauge; 17 – load cell; 18 – amplifier (weight sensor HX711); 19 – control unit (Arduino Uno ATmega328P-PU); 20 – personal computer; 21 – power supply; 22 – PWM controllers; 23 – relay block; 24 – voltage converter; *R, G, B* – red, green, blue
Source: compiled by the authors

The operator started the software on the personal computer, which was based on the OpenCV computer vision algorithms library. The personal computer sent a start signal to the control unit, which activated the vibration motor and the electric motor. The vibration motor generated vibrations in the seed feeder tray, causing the seeds to fall onto the belt, which moved due to the electric motor. The seeds passed between an infrared LED and a photodetector, generating a signal that was transmitted to the personal computer via the control unit. The personal computer activated the camera and sent a signal to the control unit to sequentially turn on the RGB LEDs. Images of the seeds under three different lighting conditions were stored in the personal computer's database. The seeds then passed between the infrared LED and the photodetector again, generating a signal that was sent to the personal computer through the control unit. After the conveyor belt movement was complete, the seeds fell into the collection tray. The signal from the load cell was transmitted through the amplifier and control unit to the personal computer, where the seed mass value was recorded in the database. The seed images were processed by the personal computer. During this process, the colour of each seed was determined under each activation of the RGB LEDs in red (*R*), green (*G*), and blue (*B*) spectra in the HSV colour space. Additionally, the personal computer determined the shape and geometric dimensions of each seed under examination based on the obtained images. All collected information was stored in the database and displayed on the personal computer's screen for the operator's review.

The design and technological scheme, general appearance, and electrical schematic of the seed rheological properties determination module were shown in Figure 5.

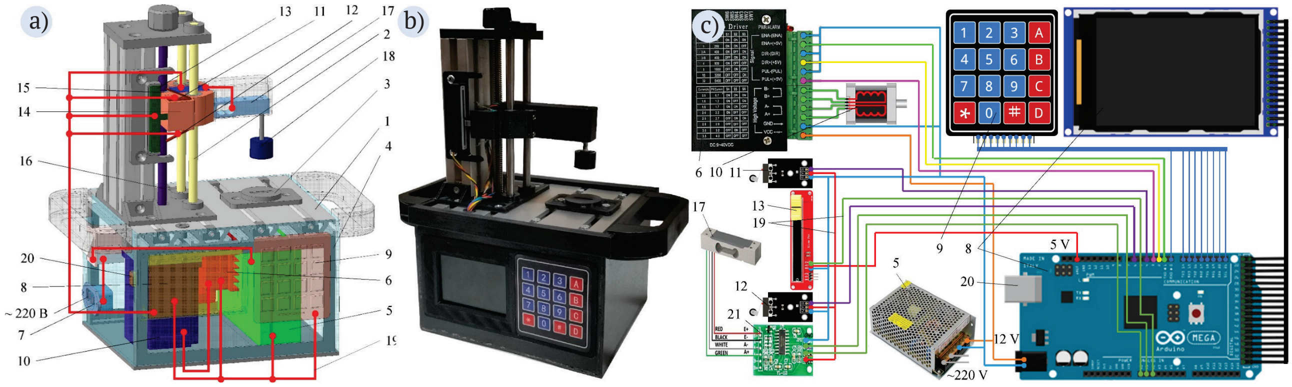

Figure 5. Structural-technological diagram (a), general view (b), and electrical schematic (c) of the seed morphological property determination module

Note: 1 – base; 2 – guide rail; 3 – worktable; 4 – housing; 5 – power supply; 6 – stepper motor controller (TB6600); 7 – socket with switch; 8 – control unit with LCD display (Arduino MEGA 2560 + 3.5 Inch TFT Color Display 320x480 Screen (China)); 9 – keyboard; 10 – stepper motor; 11 – upper limit switch; 12 – lower limit switch; 13 – variable resistor; 14 – carriage; 15 – nut; 16 – screw; 17 – load cell; 18 – indenter; 19 – electrical wires; 20 – USB output for connection to personal computer; 21 – amplifier (weight sensor HX711)

Source: compiled by the authors

The principle of operation of the seed rheological properties determination module was as follows. The operator placed the seeds on the working surface of the table and started the measurement process. The control unit with an LCD display sent a signal to the stepper motor controller, activating the stepper motor. The stepper motor shaft drove a screw, which rotated in the direction opposite to the thread of the screw. This caused the nut to unscrew, lifting the carriage along with the load cell and indenter along the guide. When the free wiper of the linear variable resistor reached the upper limit switch, the signal from the switch was sent to the control unit with the LCD display. The control unit with the LCD display sent a signal to the stepper motor controller, which stopped the stepper motor, and the indenter reached the topmost position.

The next step was the control unit sending a signal to the stepper motor controller, which activated the stepper motor. The stepper motor shaft started rotating the screw in the direction opposite to the screw thread direction. This caused the nut to start unscrewing, leading to the descent of the carriage along with the load cell and indenter along the guide. The indenter's movement speed remained constant at 10 mm/s. During the carriage movement, data from the load cell and linear variable resistor were sent to the control unit with the LCD display.

Starting from the zero value measured by the load cell, the force on the seed increased from 0 N as it was pressed. This moment was registered by the control unit with the LCD display as the beginning of the measurement. The thickness of the seed X was then determined via the linear variable resistor, assuming the working table corresponded to the initial coordinate of 0 mm. During the measurement process, the time t from the internal clock of the control unit, the absolute deformation ΔX from the linear variable resistor, and the compression force F from the load cell were recorded. After reaching the maximum force value or the lower limit switch of the linear variable resistor, the control unit sent a signal to the stepper motor controller, which turned off the stepper motor, stopping the indenter's movement. The control unit then returned the carriage to the topmost position.

All obtained data was stored in the database of the control unit with the LCD display and transferred via USB to the personal computer. Subsequently, the rheological properties of the seeds were calculated based on the obtained data. The design and technological scheme, general appearance, and electrical schematic of the seed surface properties determination module were shown in Figure 6.

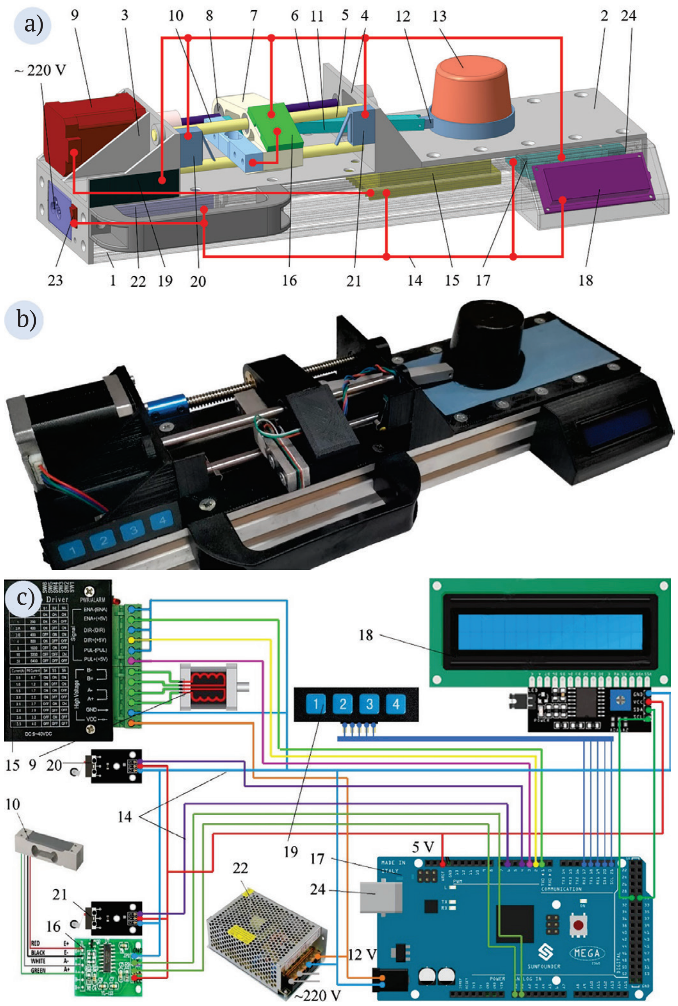

Figure 6. Design and technological scheme (a), general view (b), and electrical schematic (c) of the seed surface properties determination module

Note: 1 – base; 2 – working table; 3, 4 – left and right mounts; 5 – two guides; 6 – screw; 7 – carriage; 8 – nut; 9 – stepper motor; 10 – load cell; 11 – rigid connection; 12 – cup; 13 – weight; 14 – electrical wires; 15 – stepper motor controller; 16 – amplifier (weight sensor HX711); 17 – control unit (Arduino MEGA 2560); 18 – display (LCD 1602 I2C (China)); 19 – keyboard; 20, 21 – left and right limit switches; 22 – power supply; 23 – power button; 24 – USB port for connection to a personal computer

Source: compiled by the authors

The principle of operation of the seed surface properties determination module was as follows. The operator placed the seed on the working table surface and started the measurement process. The control unit sent a signal to the stepper motor controller, which in turn activated the stepper motor. The stepper motor drove the screw, which rotated in the direction opposite to the thread's winding direction. This caused the nut to unscrew, moving the carriage to the right along the guides. Once the carriage reached the right limit switch, a signal from the switch was transmitted to the control unit via electrical wires. The control unit sent a signal to the stepper motor controller, which stopped the stepper motor, placing the cup with the weight in the far-right position.

Next, the control unit sent a signal to the stepper motor controller, which activated the stepper motor again.

The stepper motor drove the screw, which rotated in the direction of the thread's winding. This caused the nut to screw back on, moving the carriage with the load cell, rigid connection, cup, and weight to the left. The speed of the carriage movement remained uniform and was set to 10 mm/s. During the movement, data from the load cell was transmitted to the control unit.

The control unit calculated the data and determined the coefficients of static and rolling friction. The obtained data was displayed on the screen. When the carriage reached the left limit switch, a signal from the switch was sent to the control unit. The control unit, via electrical wires, sent a signal to the stepper motor controller, which stopped the stepper motor, placing the cup with the weight in the far-left position. All obtained data was stored in the control unit's database and could be transmitted via the USB port to a personal computer.

DISCUSSION

As noted, the inspiration for creating an automatic phenotyping system that could be financially accessible to all breeders and geneticists came from the phenoSeeder systems (Jahnke *et al*., 2016) and SeedGerm (Colmer *et al*., 2020). The specialisation of the presented modules for automatic seed phenotyping is still limited and is currently applied only to sunflower seeds. However, all the specific characteristics of sunflower seeds have been considered, which allows for confident claims regarding the accuracy of the obtained results.

There are many methods for determining seed sizes, as used in the works of T. Tanabata *et al*. (2012) and F. Liu *et al*. (2022). In summary, these methods included forming a seed sample, scanning it, and processing the image to determine the actual sizes of the sample components. The image processing is performed using a computer program that automatically recognises the object and divides it into a predefined grid, determining the maximum, minimum, and average sizes in millimeters in two mutually perpendicular two-dimensional planes. To implement the proposed method, the body of the device has a shelf for the object under investigation. Two digital cameras are placed at a 90° angle to each other in specific slots. To improve the quality of images of seeds placed in the same direction on the shelf, they are illuminated by a lamp. The digital cameras are connected to a computer. The drawbacks of this method include the complexity of forming a row of seeds that must fall under the camera lenses. Another disadvantage is that this method allows the identification of seeds based on only two morphological characteristics – size and shape. There is no possibility of determining mass and colour. The proposed method and device for automatic seed phenotyping address these issues.

The known device for automatic seed phenotyping, described in the previous works of E. Aliiev (2020; 2023), contains a frame, a base, a matrix, a camera, and a personal computer. On the top of the frame, on the base, around the camera, and in the centre of the matrix, multi-coloured lamps of three electromagnetic radiation spectra (red (R), green (G), and blue (B)) are installed, which are controlled via a control unit connected to the personal computer. The matrix has square holes formed by movable horizontal and vertical plates, with springs on one side and pulling electromagnets (solenoids) on the other side, activated by the control unit via the personal computer. The new seed morphological property determination module addresses identified shortcomings, specifically the need to manually place seeds in the square holes of the matrix, which increases the labour intensity of determining the morphological properties of seeds. Additionally, previous devices lacked the ability to determine seed mass and conduct measurements in field conditions.

In the study by S. Wang *et al*. (2022), the physical characteristics of sunflower seeds were determined using physical tests, which were applied during simulation. To determine the rheological properties, the TMS-Pro physical property analyser (United Kingdom) with a sensor range of 0-2.5 kN was used. This equipment operates in accordance with the ASAE S368.4 DEC 2000 (R2017) standard. As part of the presented studies, the seed morphological property determination module was developed, which not only matches the accuracy of the known methods but also has several additional automated functions. However, compliance with the ASAE S368.4 DEC 2000 (R2017) standard has not been tested yet, which will be done soon.

Devices for determining the coefficient of friction, used in the works of S. Wang *et al*. (2022) and S. Bai *et al*. (2022), consist of a body, a sample, and a counter-sample with flat working surfaces, a counter-sample holder designed as a platform mounted on an axis, which can change its angle relative to the body, and a means for measuring the tilt angle of the counter-sample holder. The device also includes an intermediate platform that can rotate relative to the body and is fixed to the same axis as the counter-sample holder. Moreover, the device is equipped with a small displacement drive, for example, thermodynamic or spring-force, installed between the intermediate platform and the counter-sample holder. The disadvantages of such devices include low measurement accuracy, difficulty in processing information, and the inability to conduct research in field conditions. These drawbacks have been addressed in the newly developed seed surface properties determination module.

The known device for determining the coefficient of friction of agricultural materials, the FPT-H1 (United Kingdom), used in the research of E. Jotautiene *et al*. (2024), consisted of a frame, a chute, a carriage, and a drive. An analogous device is the ST-MXZ-1 (China), used in the work of M. Hu *et al*. (2022). The devices are equipped with a DC motor and an electronic dynamometer, capable of recording the final force. The drive system features spring-loaded rollers. The devices are equipped with a level and adjustable supports. These devices determine the average coefficient of friction of agricultural materials. Since seeds of agricultural crops, particularly sunflower, exhibit different adhesion to the working surfaces of agricultural machinery depending on the direction of movement due to the anisotropy of their surface, the disadvantage of these devices is the inability to determine the corresponding dependence of the coefficient of friction on the direction of seed movement along the working surface. The seed surface properties determination module developed in the article solves this problem.

The results presented in the works of S. Yang *et al*. (2021) and X. Jin *et al*. (2022) on seed image processing methods using neural networks and learning enable further development of research. This allows automating the seed image analysis process, reducing the likelihood of errors that may occur during manual classification. Moreover, modern machine learning methods enable the processing of large datasets, contributing to increased accuracy in predicting seed characteristics and accelerating breeding programs. The integration of such technologies into scientific research significantly expands the possibilities for developing new plant varieties with specific properties. The classification of seeds by their images and a complex of physico-mechanical properties will make it possible to create a complete workstation for breeders and plant geneticists.

CONCLUSIONS

The methods for determining the phenotypic characteristics of sunflower seeds were presented and improved, specifically geometric dimensions, mass, coloration, rheological properties, and surface properties of the seeds.

A module for determining the morphological properties of seeds (geometric dimensions, mass, surface coloration, etc.) was developed. The module was designed for high precision in individual measurement of sunflower seed dimensions, including shape and coloration, and ensured low labour intensity and high technological efficiency in the phenotyping procedure (identification, classification, and separation) of seeds. The methodology for analysing the rheological properties of seeds was improved, and a method for their automatic determination along with a module for this purpose was substantiated. The proposed module maintained accuracy in individual measurement of seed rheological properties, which met current measurement standards, and ensured low labour intensity and high technological efficiency. Furthermore, the proposed module enabled the determination of elasticity strength, elastic modulus, and static hysteresis indicators, which could not be measured directly. This significantly improved the overall productivity of the research and greatly reduced the influence of human error on the accuracy of measuring seed rheological properties.

The proposed module for determining the surface properties of seeds allowed for the maintenance of accuracy in individual measurement of static and sliding friction coefficients of seeds, meeting current measurement standards, and ensured low labor intensity and high technological efficiency. It also significantly minimised the impact of human error on measurement accuracy.

The prospects for further research include integrating the presented modules into a unified system for automatic sunflower seed phenotyping. Additionally, there is a need to refine the image processing software using neural networks and machine learning. Overall, the proposed improvements will enable the use of the automatic phenotyping system as a universal workstation for plant breeders and geneticists.

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CONFLICT OF INTEREST

None.

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Автоматизовані пристрої для кількісного фенотипування насіння соняшнику

Анотація. Для створення нових сортів соняшнику важливо точно оцінити фенотипові ознаки, які впливають на врожайність, стійкість до хвороб і стресостійкість. Автоматизація дозволяє систематично збирати дані та приймати більш обґрунтовані рішення в процесі селекції. Метою роботи було підвищення ефективності добору та прогнозування розвитку генотипів соняшнику шляхом розробки нових методів, апаратних і програмних інструментів для кількісної фенотипової характеристики насіння. Представлено і удосконалено методи визначення фенотипових характеристик насіння соняшнику, а саме геометричних розмірів, маси, забарвлення, реологічних властивостей і властивостей поверхні насіння. Розроблено модуль визначення морфологічних властивостей насіння (геометричні розміри, маса, забарвлення поверхні тощо). Модуль налаштовано на високу точність індивідуального вимірювання геометричних розмірів насіння соняшнику із визначенням їх форми і забарвлення та забезпечують низьку трудомісткість і високу технологічність реалізації процедури фенотипування (визначення, ідентифікації і сепарації) насіння. Удосконалено методику аналізу реологічних властивостей насіння й обґрунтовано спосіб їх автоматичного визначення і модуль для цього. Запропонований модуль зберігав точність індивідуального вимірювання реологічних властивостей насіння, що відповідає сучасним вимірювальним засобам, та забезпечував низьку трудомісткість і високу технологічність. При цьому також значною мірою зник вплив людського фактору на точність вимірювання реологічних властивостей насіння. Запропонований модуль для визначення властивостей поверхні насіння дозволив зберегти точність індивідуального вимірювання коефіцієнтів тертя спокою і ковзання насіння, що відповідає сучасним вимірювальним засобам та забезпечує низьку трудомісткість і високу технологічність. При цьому також значною мірою виключався вплив людського фактору на точність вимірювання. Використання автоматизованих пристроїв у практичних умовах може допомогти оптимізувати відбір насіння з найкращими характеристиками

Ключові слова: модуль; програмне забезпечення; геометричні розміри; колір поверхні; реологічні властивості; фрикційні властивості