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Determination of seed sowing quality by dotted-nesting method using video file processing technology

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Abstract. The research work presents a method for assessing the qualitative performance of a sowing machine using the dotted-nest sowing method. The analysis of the subject area was carried out, within which the object of optimization was described. The sowing of agricultural crops is considered one of the most important technological operations in crop cultivation, as it directly affects crop yields. The control of the sowing process and the detection of any malfunctions during it are investigated using information technology. An algorithm for determining the accuracy of sowing using the dotted-nest method is presented. Two indicators were considered as optimization criteria: the coefficient of variation of the time intervals between seed emission from the sowing disc and seed placement, which were minimized. Two parameters affecting sowing quality were selected as optimization variables: the rotation frequency of the sowing disc and the position of the seed ejector of the sowing unit. The results of the experiments and research have been processed in the form of video files showing the seeding process using the YOLO v8 neural network.

1 Introduction

The rapid development of information technology increases the role of computing in many areas of human activity. Recently, computer systems have been used in various areas of agricultural production. When developing an intelligent system for assessing sowing quality, it is important to consider agrotechnical requirements (such as uniformity of sowing and seed damage) as well as technical and technological indicators (such as the diameter of the sowing disc, the position of the seed ejector of the sowing unit, seeding rate, speed, and productivity) that affect yield. This creates the need for a subsystem to assess the uniformity of seed sowing, which can serve as the basis for an intelligent system to evaluate the quality of sowing.

Developing algorithms for assessing seed sowing uniformity is an essential part of evaluating the quality of sowing processes. These algorithms play a crucial role in

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accurately determining various parameters of the sowing equipment, as well as in identifying double and missed seeds [1].

Modern vacuum seed drills are fitted with seed ejectors to eliminate grouped seed deliveries. Most contemporary devices have flat or stepped (serrated) ejectors. These ejectors push the seed group towards the axis of the seeding disc rotation, causing the least securely attached seeds to fall back into the seed chamber. The suction force holding a seed to the disc hole depends on the vacuum in the chamber and the hole area.

In the dotted-testing method, the initial distance between sets in a row varies, and this expected value differs from zero. This limits the use of the coefficient of variation as an indicator of sowing performance quality for this method. Thus, it is crucial to develop an intelligent system that enhances the assessment method for the accuracy of dotted-nesting sowing devices and allows for pre-sowing setup of row crop planters [2].

To develop such a system, it is necessary to establish a methodology for evaluating seeding uniformity and to ensure that the evaluation results meet agrotechnical requirements. Such a computer program will simplify the procedure for assessing seed placement accuracy and reduce the workload on specialists by using this algorithm for pre-sowing seeder setup on a test bench as well as during the seeding operation itself.

The implementation of the sowing quality assessment subsystem involves classifying the loaded files of seeding device operations and detecting any malfunctions or their absence in the recorded data. The goal of this work is to increase the number of correctly identified deviations in the sowing device's operation.

To achieve this goal, the following task must be addressed: given a sequence X and a set of reference records D that contain the results of the sowing device's operation under various structural and operational parameters, it is necessary to find the reference record matching X as closely as possible. This record should ensure an optimal match between the analyzed file and the reference, thereby improving the accuracy of the sowing device's performance assessment.

Currently, there are several approaches to solving problems in this area: exhaustive search methods; neural networks; methods based on comparison with a reference model.

The exhaustive search of all possible integer variations of the variables guarantees a solution. However, for high-dimensional problems, the calculation time can be extensive due to the large number of possibilities to be evaluated. Nonetheless, since the calculation of the criteria for each possible variant is independent of the others, parallel computing using clusters of computational devices, graphics cards, and cloud computing can be employed. For example, modern graphics cards are equipped with more than 20,000 computational cores, enabling a significant acceleration of computations.

Another approach to solving problems in a specific field is the use of neural networks. These are mathematical models that are inspired by the way the human brain works. This mechanism can be used to create an intelligent system capable of detecting deviations in the operation of the sowing device in recorded files, essentially performing a classification task.

2 Materials and methods

The first stage in developing a neural network involves designing its architecture and then training the system. There are two training methods: supervised and unsupervised. During supervised learning, a system learns to recognize objects that belong to predefined classes by using a pre-generated set of training data. The goal of the learning process is to minimize the margin of error between the desired output and the actual output obtained. In contrast, unsupervised learning allows the network to group objects into classes based on their characteristics and adjust the weights so that similar objects yield similar results. A properly trained system can significantly improve the accuracy of achieving correct results.

In the reference model-based method, a model (template) is created for each operational mode of the sowing device. During the recognition phase, the template that most closely matches the observed sequence is selected.

A Pareto front is constructed to solve multi-criteria optimization problems. This technique helps to visualize which optimization criteria are most important and what trade-offs can be made in selecting the best solution. The goal of constructing the Pareto front in the context of the current system design is to identify a set of non-dominated solutions, providing a compromise between performance and seeding quality.

One of the approaches that can be used in the development of a decision support system is the hierarchy analysis method. This method involves building a hierarchy and then comparing criteria pairwise [3].

Another approach to solving the problem is to use a production model. This model is based on the use of factors and rules. The advantage of this method is the visibility and ease of making changes and additions to the knowledge base containing the rules and facts. The algorithm works by using a direct chain of reasoning, i.e., by applying the rules sequentially until the desired result is obtained. A production rule is represented as follows:

Specification: IF <condition> THEN <action>

Where Specification is the specification of the rule and IF <condition> THEN <action> are the core components of the rule.

The combination of "IF... THEN..." represents a causal relationship. On the left part of this rule there is a statement which can be either true or false.

In this paper, the following global linguistic variables have been identified:

- *SR* – seeding rate.
- *CV* – coefficient of variation (less than 33%).
- *CS* – crushing of seeds (less than 3%).
- *DS* – driving speed (low (less than 5 km/h), medium (5-7 km/h), high (8-15 km/h).
- *PD* – position of the dumper (1 – fully open hole, 0 – completely blocked hole).

The rules for these variables are as follows:

1. IF *PD* = 0,5 AND *DS* = high THEN *CS* > 1%;

IF *PD* = 0,5 AND *DS* = high AND *CS* > 1% THEN *CV* > 33 %;

2. IF *PD* = 0,5 AND *DS* = low THEN *CS* < 1%;

IF *PD* = 0,5 AND *DS* = low AND *CS* < 1% THEN *CV* < 33 %;

3. IF *PD* = 0,5 AND *DS* = average THEN *CS* > 1%;

IF *PD* = 0,5 AND *DS* = average AND *CS* > 1% THEN *CV* < 33 %;

4. IF *PD* = 0,75 AND *DS* = high THEN *CS* > 1%;

IF *PD* = 0,75 AND *DS* = high AND *CS* > 1% THEN *CV* < 33 %;

5. IF *PD* = 0,75 AND *DS* = low THEN *CS* < 1%;

IF *PD* = 0,75 AND *DS* = low AND *CS* < 1% THEN *CV* < 33 %;

6. IF *PD* = 0,75 AND DS = average THEN CS < 1%;

IF *PD* = 0,75 AND *DS* = average AND *CS* < 1% THEN *CV* < 33 %;

7. IF *PD* = 1 AND *DS* = high THEN *CS* < 1%;

IF *PD* = 1 AND *DS* = high AND *CS* < 1% THEN *CV* > 33 %;

8. IF *PD* = 1 AND *DS* = low THEN *CS* < 1%;

IF *PD* = 1 AND *DS* = low AND *CS* < 1% THEN *CV* < 33 %;

9. IF *PD* = 1 AND *DS* = average THEN *CS* < 1%;

IF *PD* = 1 AND *DS* = average AND *CS* < 1% THEN *CV* < 33 %;

The rule base generated for the task is stored in the database. At the beginning of the decision-making process, a connection is established with the database and the tables containing the rules are queried. Then, using Python programming, code is generated based on the rules extracted from the knowledge base.

The mathematical support for this project consists of mathematical models of the designed objects, as well as methods and software-implemented algorithms for finding optimal solutions. Mathematical support is a crucial and challenging stage in the development of decision support systems [4].

Two indicators have been selected as optimization criteria for evaluating the quality of sowing: seed sowing accuracy (R_1) and seed crushing (R_2), which should be minimal.

When selecting optimization parameters, it's important to start by considering how each parameter should affect all of the optimization criteria. The factors affecting the quality of sowing were two indicators: the rotation frequency of the sowing disc (X_1, min-1), the position of the seed dumper (X_2).

The design and operating parameters of the seeding apparatus were determined by the method of planning a multifactorial experiment. Based on the results of experiments using a multifactorial experimental plan, using a planning matrix for two-factor Box-Wilson plans of the second order, regression equations were determined that adequately describe the sowing process under study, taking into account the significance of the regression coefficients.

$R_1(X_1, X_2) = 65.45 + 0.66X_1 - 169.74X_2 - 1.58X_1X_2 + 0.013X_1^2 + 132X_2^2$

$R_2(X_1, X_2) = 4.68 + 0.02X_1 - 10.1X_2 - 0.02X_1X_2 + 5.39X_2^2$

To solve the optimization problem, it was decided to use the full search method. The optimization criteria were determined by iterating through the parameters X_1 and X_2 with increments: for X_1 - 5, and for X_2 - 0.05. The values of X_1 ranged from 10 to 60, and the values of X_2 ranged from 0.5 to 1, where 1 is a completely open hole and 0.5 is half blocked. New values of R_1 and R_2 were recorded in a table.

Video recordings of the sowing process were obtained during experiments and research aimed at developing an intelligent decision support system for assessing the quality of seed sowing. Based on the review and analysis of the prior information, it has been decided to use the YOLO v8 neural network to process these videos [5-10]. YOLO is a neural network designed to detect objects and work with them in images.

The video contains recordings of the sowing apparatus in operation, featuring a rotating sowing disc with seeds captured on it. The Python script was written to split the video into frames at one-second intervals for retraining the neural network. The images were then annotated with two classes: “Seed” (seed on the disc) and “Hole” (empty hole on the disc). The labelImg utility was used to annotate the images on the sowing disc, selecting one of the classes and drawing a box around the object. After annotating all the files, the data was split into three parts: Train - 70%; Test - 20%; Valid - 10%.

Training was conducted using an Nvidia GeForce RTX 3050 4 Gb graphics card. The number of training epochs was set to 500 (YOLO stops automatically if there are no improvements after several epochs), the batch size was 16, and the image size was 640.

3 Results and Discussion

Training the model required 311 epochs, with the best training results being achieved at the 211th epoch.

As a result, the prediction accuracy for the seed class was 90.3%, and for the empty hole class it was 96.8% (Figures 1).

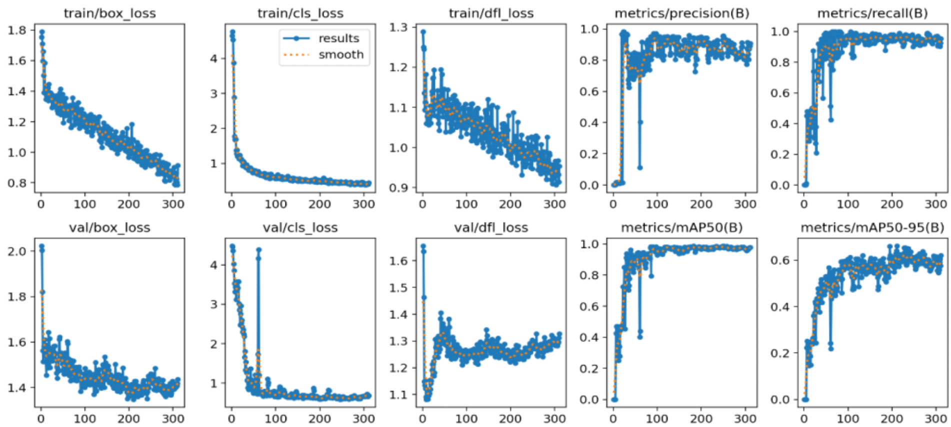

Fig. 1. Results of Neural Network Training.

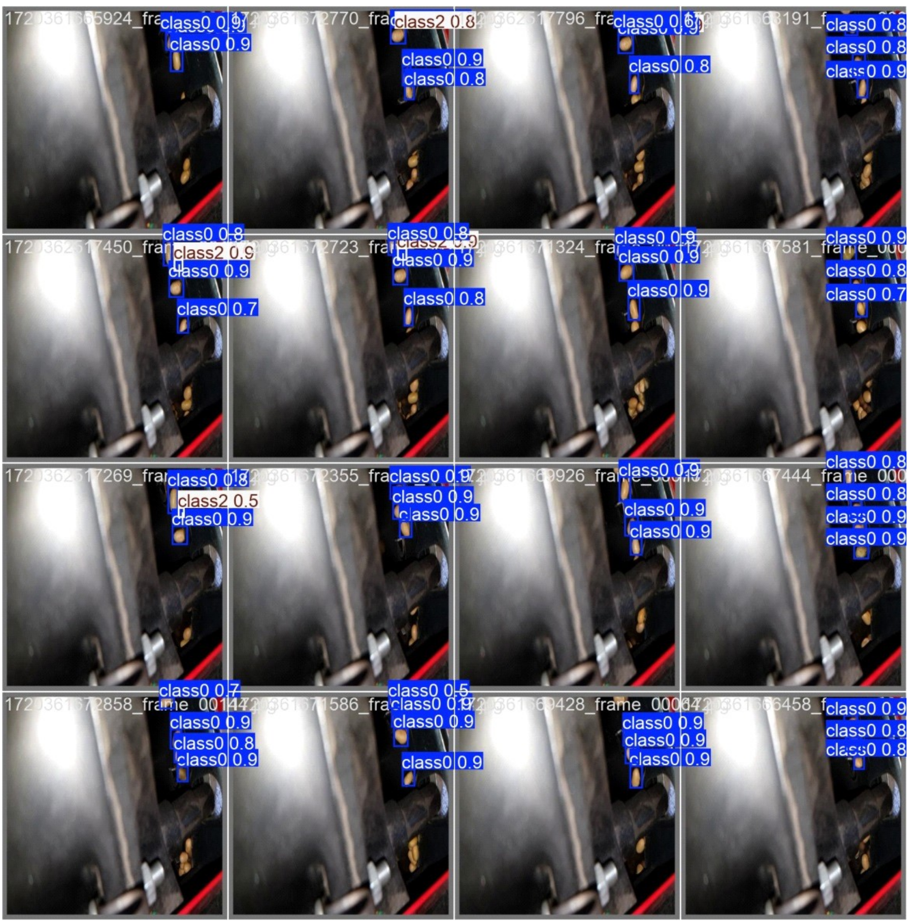

Fig. 2. Validation Set Prediction Results.

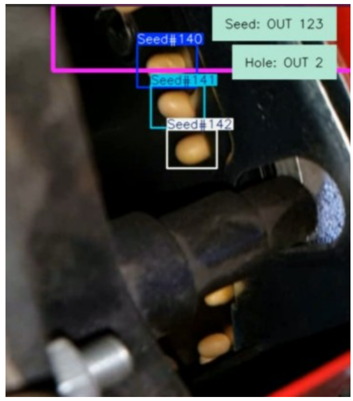

Fig. 3. Counting Seeds and Empty Holes.

Figure 1 shows a steady decrease in the number of errors in the model for both the training and validation datasets, indicating successful training. The loss graphs show that the error values for classification tasks have decreased, indicating an improvement in forecasting accuracy. The accuracy and memorization metrics have high values, indicating the effective identification and classification of objects by the model. The average accuracy index (mAP) also shows positive dynamics, confirming the high generalizability of the model. Overall, these results suggest that the model has been trained successfully and is ready to be applied to new data.

The obtained neural network model was used to count the number of seeds and empty holes on the sowing disc (Figure 2, 3). For this purpose, the script was written in Python.

4 Conclusion

During the work, an analysis of the subject area was conducted, and the main approaches to solving the task were reviewed. The most suitable method was then selected, and an algorithm for determining sowing quality was developed.

The intelligent sowing quality assessment system being developed within the framework of this work will allow classifying deviations in the functioning of sowing machines, as well as help the decision-maker choose the best sowing option depending on external factors. Using this approach will reduce the cost of specialists setting up seeders on a test stand before sowing, rather than in the field. In the course of the work, the issue of building a decision support subsystem was considered, as well as the main approaches to solving the task were considered. The search for a solution consists in using a direct chain of reasoning, i.e. sequentially applying the rules in order until the value of the resulting variable is obtained.

The YOLO v8 neural network was used to process video files of the sowing process obtained during experiments and research aimed at creating an intelligent decision support system for determining the quality of seed sowing.

Further work will be related to the development of software and hardware for an intelligent decision support system for determining the quality of sowing.

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