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RECEIVED 20 November 2023

ACCEPTED 30 January 2024

PUBLISHED 21 February 2024

CITATION

Chen C, Bai M, Wang T, Zhang W, Yu H,
Pang T, Wu J, Li Z and Wang X (2024) An RGB
image dataset for seed germination
prediction and vigor detection - maize.
Front. Plant Sci. 15:1341335.
doi: 10.3389/fpls.2024.1341335

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An RGB image dataset for seed germination prediction and vigor detection - maize

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KEYWORDS

RGB image dataset, seed germination prediction, seed vigor detection, maize seed, agriculture, breeding

1 Introduction

The greatest food crop in the world, maize, is crucial to ensuring national food security and an efficient supply of agricultural goods (Collins et al., 2018; Hall et al., 2021; Song et al., 2022). The first step in increasing corn yields is to pick high-quality cultivars (Xanthopoulos, 2020; Tu et al., 2022). Seed vigor is an essential test item in the protocols for inspecting the quality of seeds due to it could accurately measure and predict the quality of seed development in the field as well as the potential germination rate, seedling emergence rate, seedling growth potential, plant resistance, and production potential. It is a key indicator for assessing the quality of seeds (Huayta-Hinojosa et al., 2022; Jin et al., 2022; Tetreault et al., 2023). High-vigor seeds are a crucial assurance of successful harvests and higher agricultural product yields since they have apparent growth advantages and output potential (Riveiro et al., 2020). The International Association of Seed Testing (IAST) recommends several methods for determining seed vigor, including germination, cold resistance, accelerated aging, conductivity, and enzyme activity (Fenollosa et al., 2020; Ma et al., 2020; Ali et al., 2022; Zhang et al., 2023). Traditional vigor testing techniques have drawbacks including lengthy measurement times, heavy seed usage, subpar measurement accuracy, and low sensitivity (Peng et al., 2018; Zhu et al., 2019; Pang et al., 2020, Pang et al., 2021). The advancement of seed vigor detection technology has raised the bar for modern agriculture. The hotspot and trend of current mainstream research is machine learning-based detection technology, which is a non-contact direct measuring method with the benefits of being direct, quick, true, and dependable (Medeiros et al., 2020; Wen-ling et al., 2020; Sun et al., 2021; Tu et al., 2023). By using RGB to obtain corn seed images, the authors combined HSI and 3DCNN to establish an optimal classified corn seed vitality model (Fan et al., 2023). In farming, measuring seed vigor is crucial, and a non-destructive machine vision method for detecting seed vigor can aid in a more accurate assessment of seed quality. This provides seed companies with a better basis for decision-

making when selecting cultivars and managing plantings (Yasmin et al., 2019; Tu et al., 2023). The digital image of soybean was obtained by using RGB, and the character of soybean was evaluated automatically by using Python Algorithm (Ghimire et al., 2023). The performance of a neural network-based model to identify plant species from paramo seeds via optical RGB images (Ropelewska et al., 2023). High-quality datasets are crucial for accurate machine vision algorithms in seed vigor detection and classification. Yet, current datasets still suffer from several problems below.

- (1) Sample imbalance: The dataset for seed vitality has an unequal distribution of seed samples across various categories, leading to a significant gap between the number of samples in each category. It could cause the model to be biased towards predicting categories with more seed samples, thus decreasing the accuracy of predicting categories with fewer samples. Eventually, the accuracy of the model will be negatively impacted.
- (2) Sample noise: Obtaining accurate seed vigor sample data is important to ensure proper analysis and model construction. Measurement errors, disturbances during data collection, sampling errors, and other factors can lead to inaccurate data that may mask the true pattern of the data and lead to misinterpretation. Additionally, seeded vitality datasets may contain noisy data, such as mislabeled and duplicate samples, which would negatively impact model training and testing and ultimately reduce model accuracy.
- (3) Lack of data diversity: An unbalanced and incomplete distribution of state data in a seeded vitality dataset, even failing to encompass the entire data space or relevant situations, is likely to have a negative impact on the performance of the model and its ability to classify effectively.
- (4) Incomplete data: When the data in the seed vitality dataset is incomplete, it means that there are missing values or important features of the seed that are not included, which will affect the accuracy and interpretability of the model.
- (5) Inconsistencies in data sources: The dataset contains samples from various seed data sources or collection methods, resulting in differences that cause issues like spatial and temporal inconsistencies between the data. Such inconsistencies would negatively affect the training and prediction of the model and eventually impacts the overall efficacy of the model (Liu et al., 2020).

To improve the accuracy of corn seed vigor detection, a new corn seed vigor dataset was created that included a standard germination test under six contrasting conditions. The dataset includes photographs of corn seeds taken at regular intervals and categorized based on their germination status, primary and secondary root growth. The dataset allows researchers to predicting and grading seed germination and vigor, providing a reliable data source for the study of improving corn seed vigor. Additionally, the method of data collection provides a reference for other seed vigor prediction data collection and improves the validity

of non-destructive seed vigor identification and testing data in smart agriculture. It also provides a more scientific approach to seed vigor data collection.

2 Values of the data

(1) We conducted an experiment to collect a substantial amount of data on the germination process of maize seeds. The goal was to observe the changes in characteristics, morphology, and color throughout the entire process. Non-fixed shooting was used to capture diverse germination data. By recording germination data at hourly intervals, it was possible to efficiently analyze the seed development process and create accurate and automated testing models for seed quality assessment. This dataset is reliable and useful as it reduces the impact of sample imbalances, inconsistent data sources, and incomplete data.

(2) Seed vigor detection greatly benefits from the seed dataset of RGB images, which is enriched in feature information including morphology, structure, and texture. Compared to traditional methods, RGB images of seeds offer advantages such as low cost, easy obtainability, non-contact capability, and low computational consumption. These advantages make nondestructive seed vigor detection more practical and valuable for research and application.

(3) The datasets complement databases for the detection of seed vigor and standard germination processes. These data are vital for researching seed vigor classification, predicting germination, and evaluating and detecting vigor. By analyzing the data, the researchers can accurately detect seed vigor and predict germination ability, leading to improved seed quality and crop yield.

3 Materials and methods

3.1 Selection of materials

In the experiment, we selected Meiyu 817 maize seeds. The seeds are known for their strong resistance, high production rate, and wide cultivation in Northeast China. Figure 1 displays the various stages of germination for the sample, including ungerminated, germinating, germinated, primary root, and secondary root. These stages depict the different phases of seed germination, and the sample is visible in Figure 1 below.

3.2 Experimental condition

The experiment consisted of six groups, with each group consisting of 200 seeds. Initially, the maize seeds were categorized into three groups based on the aging experiment, with aging times of 0d, 3d, and 6d, respectively, in a 45°C constant temperature oven. The remaining three groups were stored in environments with temperatures of 20°C, 0°C, and -20°C, respectively. The seed grouping and 100-grain weight are presented in Table 1 below.

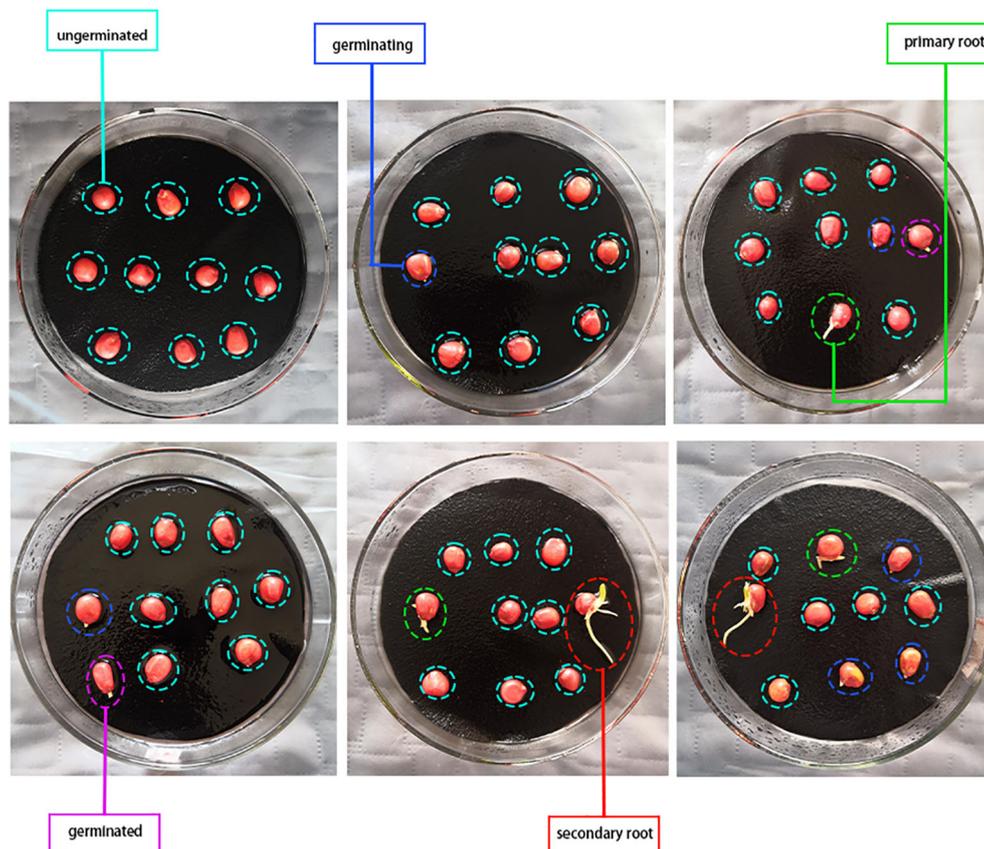


FIGURE 1
Different germination states of maize seeds in standard germination test.

3.3 Standard germination test

According to the Technical Regulations on Crop Seed Germination (GB/T 3543.4-1995), the seeds were placed in a germination chamber that maintained a constant temperature of 25°C. There were six subgroups, each consisting of 200 seeds, with varying temperatures (-20°C, 0°C, 20°C) and durations (3d, 6d, 9d). Then, placed 20 subgroups of each subgroup in Petri dishes, for a total of 120 Petri dishes with 10 seeds each (1,200 seeds in total). After that, the seeds were evenly spaced to ensure enough space for growth and to prevent mold. Finally, sprayed water every 2-3 hours

TABLE 1 Experimental groupings.

Experiment number	Number of grains (pcs)	Prerequisite	Hundred grains weight (g)
1	200	20°C	36.68
2	200	0°C	37.29
3	200	-20°C	37.04-37.05
4	200	age 3d; 45°C	36.93-36.94
5	200	age 6d; 45°C	36.5
6	200	age 9d; 45°C	36.57

to keep the bed moist, and did not cover the dishes to ensure sufficient oxygen supply. As for data collection, diffused light was used during the day and 45w incandescent light at night to photograph the germination process. A Huawei Honor V10 mobile phone was used to take photos from a height of 20-25cm every hour. However, we removed any moldy or dead seeds and labeled the remaining seeds into five categories based on their germination vigor. 1. ungerminated; 2. germinating; 3. germinated; 4. primary root; 5. secondary root.

The corresponding germination states were: (1) seeds were not germinated, decayed, or dead; (2) primary root 0-2mm; (3) primary root germinated 2mm; (4) there was and there was only one primary root, and the seed primary root exceeded more than 2mm; (5) there was more than one secondary root in addition to the primary root. Figure 2 below shows the time series of seed germination status of 6 groups of comparison tests:

3.4 Construction of the dataset

During the germination tests, photos were taken for a total of 6 days and 21 hours. The test was concluded 3 hours earlier than the specified 7-day time periods, as the samples had already reached their highest germination rate. One photo was taken per hour throughout the experiment, and the result was 120 photographs per

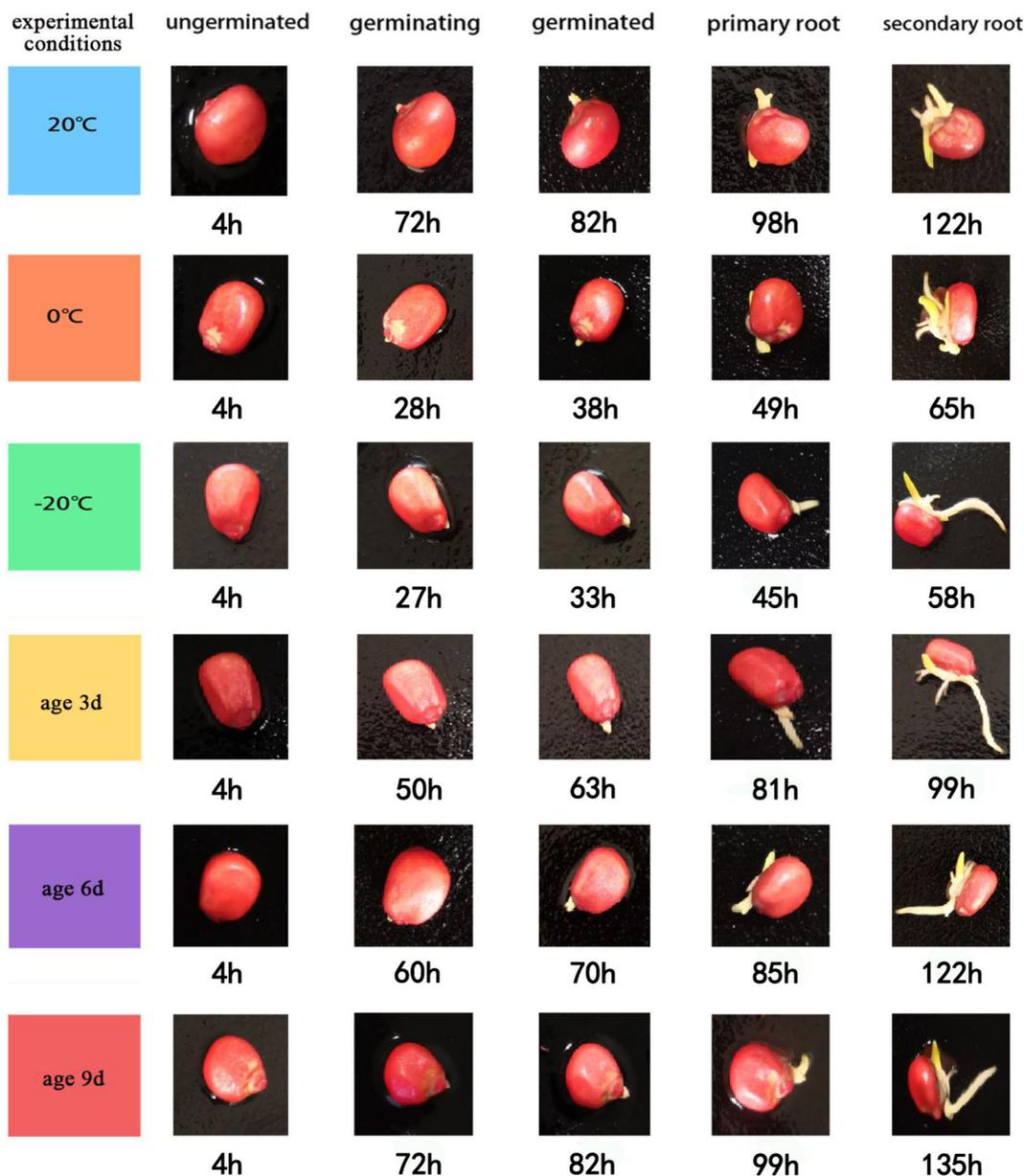


FIGURE 2
Chronological germination status of six seed groups.

hour. Throughout the experiment, one photo was taken every hour, resulting in 120 photos per hour. In total, 19,800 RGB images with 3456 x 4608 pixels, were collected and annotated using LabelImg. Data annotation is stored in the format of the PASCAL VOC dataset, and is set to.xml format. A total of 181,250 valid data were labeled, while fuzzy or obscured images were removed to reduce data noise. The number of labels corresponding to the five different states were: 1. ungerminated:149842; 2. germinating:7042; 3. germinated:1936; 4. primary root:5087; 5. secondary root:17343. For easier download, we uploaded the 120-folder dataset separately, which was generated each hour. It could be accessed on the Kaggle public dataset titled Seed Vigor Detection RGB Image. The dataset is available at the following two address: <https://www.kaggle.com/datasets/chengchengchen/seed-vigor-detection-rgb-image> [\[iee-dataport.org/documents/rgb-image-dataset-seed-germination-prediction-and-seed-vigor\]\(http://iee-dataport.org/documents/rgb-image-dataset-seed-germination-prediction-and-seed-vigor\)](http://</p>
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3.5 Seed viability object detection experiments

In order to verify the validity of the dataset, we perform experiments on the seeds vitality object detection using the two-stage object detection model Faster RCNN (Girshick, 2015), the one-stage model SSD (Liu et al., 2016), YOLOv3 (Redmon and Farhadi, 2018), YOLOv5 (Jocher et al., 2020), RTMDet (Lyu et al., 2022), and the anchor-free model FCOS (Tian et al., 2019); and we optimize the feature extraction capability by change the backbone.

TABLE 2 Seed Viability Object Detection Experiments.

Model	Backbone	mAP (%)	mAP .5(%)	mAP .75(%)	Ungerminated	Germinating	Germinated	Primary root	Secondary root
Faster RCNN	ResNet50	0.765	0.908	0.896	0.836	0.696	0.617	0.799	0.875
Faster+FPN	ResNet 50	0.783	0.921	0.912	0.854	0.734	0.640	0.815	0.873
Faster+FPN	ResNeXt101	0.808	0.943	0.931	0.862	0.758	0.705	0.83	0.887
YOLOV3-SPP	Darknet53	0.635	0.826	0.792	0.813	0.563	0.391	0.695	0.711
FCOS	ResNet50	0.637	0.796	0.763	0.839	0.566	0.379	0.703	0.699
SSD	VGG	0.512	0.689	0.625	0.779	0.168	0.318	0.633	0.664
RTMDet	CSPDarknet	0.757	0.887	0.87	0.85	0.682	0.562	0.801	0.889
YOLOv5-n	CSPDarknet	0.625	0.758	0.739	0.842	0.461	0.3	0.729	0.795
YOLOv5-s	CSPDarknet	0.739	0.868	0.855	0.863	0.709	0.47	0.8	0.851

The average accuracy mAP of several target categories, the recognition accuracy mAP50 and mAP75 for IoU thresholds of 0.5 and 0.75, and the recognition accuracy of each category are recorded in the experiment results.

All experiments are run on a server with an Inter(R) Xeon(R) Platinum 8336C CPU at 2.3 GHz, two NVIDIA GeForce RTX 3090 24G GPUs, and 256 GB of RAM. The experimental results are shown in Table 2, and it could be seen that the results of two-stage network structure detection are better than the one-stage and anchor-free models, where backbone is ResNeXt101, the network combined with FPN and Faster RCNN provides the best results. The recognition accuracy of RTMDet in one-stage is the highest. The recognition accuracies of the one-stage model and the anchor free model are lower in the categories Germinating and Germinated, but the two-stage model significantly improves the recognition accuracies of these two categories. It indicates that the average recognition accuracy as well as the recognition accuracy of a single category can be changed by adjusting the backbone, adding FPN structure, and adjusting the complexity of the model structure.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

CC: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. MB: Data curation, Formal analysis, Visualization, Writing – original draft. TW: Data curation, Formal analysis, Validation, Visualization, Writing – original draft. WZ: Data curation, Formal analysis, Visualization, Writing – original draft. HY:

Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. TP: Conceptualization, Formal analysis, Writing – review & editing. JW: Data curation, Funding acquisition, Writing – original draft. ZL: Conceptualization, Funding acquisition, Investigation, Writing – original draft. XW: Funding acquisition, Supervision, Writing – original draft.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. Shenyang Aerospace University Doctoral Talent Research Initiation Project (23YB05); National Key R&D Program Sub-projects (2022YFD200160202); National Natural Science Foundation of China under Grant (62376165); National Natural Science Foundation of China under Grant (62171295); Applied Basic Research Project of Liaoning Province under Grant (2023JH2/101300204).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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