IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 4, March 2026

Impact Factor: 8.2

Seed Germination Detection System Using AI

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Abstract: *Seed germination analysis is an important process in agriculture, as it helps evaluate seed quality and overall crop productivity. Conventional methods rely on manual observation, which can be time-consuming, labor-intensive, and subject to human error. This work proposes an automated deep learning-based approach for detecting and classifying seed germination from images. The system uses an object detection model to identify individual seeds and a transformer-based classifier to determine their germination status. The approach follows a two-stage pipeline where seeds are first localized and then categorized as germinated or non-germinated. Experiments were performed on a publicly available dataset containing multiple seed species, demonstrating strong performance in both detection and classification tasks. In addition, a desktop application was developed to support image input, result visualization, performance evaluation, and real-time analysis using a webcam. The proposed system reduces manual effort and provides an efficient solution for automated germination monitoring.*

Keywords*:* *Seed germination, YOLOv8, DINOv2, Vision Transformer, object detection, agricultural AI, deep learning, computer vision*

I. INTRODUCTION

Seed germination is a key biological process that plays an essential role in crop growth, seed quality evaluation, and overall agricultural productivity. Accurate assessment of germination allows farmers and researchers to determine seed viability before planting. Traditionally, this process is carried out through manual observation of radicle emergence, which can be time-consuming, labor-intensive, and subject to human variability, especially when dealing with large numbers of seeds.

Advancements in computer vision and deep learning have enabled automated analysis of agricultural images, improving efficiency and consistency. Object detection models have proven effective in identifying and localizing multiple objects in real time, while transformer-based architectures provide strong capabilities for capturing detailed visual features required for classification tasks. Based on these developments, this work proposes an automated framework that integrates object detection and transformer-based classification to analyze seed germination from images.

The main contributions of this work are as follows:

- A two-stage deep learning pipeline for automated seed germination analysis.
- Integration of YOLOv8 for seed detection and DINOv2 Vision Transformer for seed-level classification.
- A practical desktop application for visualization, confusion matrix analysis, and webcam-based real-time inference.
- Experimental validation on a multi-species seed dataset using standard evaluation metrics.

II. RELATED WORK

Automated analysis of plant and seed characteristics has become increasingly important for achieving reliable and scalable agricultural monitoring. Traditional approaches in computer vision primarily relied on manually designed

DOI: 10.48175/IJARSCT-31843

features such as color, texture, and shape, which were then used with conventional machine learning models. While these methods performed adequately in controlled conditions, they often struggled to adapt to variations in lighting, seed orientation, background complexity, and differences across species.

With the advancement of deep learning, convolutional neural networks have significantly enhanced image analysis by automatically learning meaningful features from data. Object detection models, particularly those based on the YOLO architecture, have enabled efficient identification of multiple objects within a single image, making them well-suited for tasks like seed detection and counting. In addition, transformer-based models have recently shown strong capability in capturing complex patterns and detailed visual relationships.

The proposed SproutAI framework integrates the detection capability of YOLOv8 with the feature representation strength of a transformer-based classifier. By adopting a two-stage approach, the system first localizes individual seeds and then performs classification at the seed level. This design improves both detection accuracy and classification reliability compared to single-stage methods.

III. DATASET DESCRIPTION AND PREPROCESSING

A. Dataset

The dataset used in this work was obtained from Kaggle and contains seed germination images from three seed species: Zea mays, Secale cereale, and Pennisetum glaucum. Each image includes multiple seeds captured during germination experiments. The dataset statistics used in this study are summarized in Table I.

TABLE I: Dataset Statistics

Dataset Split	Number of Images
Total Images	2693
Training Images	2663
Validation Images	231
Test Images	60

Each image contains approximately 8–28 seeds. Images were resized to 640 × 640 pixels for object detection training. Seeds were labeled into two classes:

- Germinated
- Non-germinated

A seed is considered germinated when the radicle emerges from the seed coat.

B. Annotation and Preprocessing

The dataset did not originally contain detection annotations suitable for YOLO training. Therefore, seed-level annotations were prepared as part of the workflow to enable object detec- tion. After localization, detected seed regions were cropped and used for classification.

The preprocessing steps used in the pipeline are:

- Input image resizing for detector training to 640 × 640
- Seed crop extraction using bounding box coordinates
- Crop resizing to 224 × 224 for DINOv2 classification
- Standard train-validation-test split for development and eval- uation

IV. PROPOSED METHODOLOGY

A. System Overview

SproutAI follows a two-stage pipeline consisting of seed de- tection and germination classification. The overall architecture is shown in Fig. 1.

B. Stage 1: Seed Detection Using YOLOv8

YOLOv8 segmentation was used to detect seed instances from the input images. The detector predicts bounding boxes corresponding to seed locations, enabling per-seed analysis even when multiple seeds are present in a single image. The model was trained on a Windows 11 system with an Intel i5 processor and 16 GB RAM without GPU acceleration.

Parameter	Value
Input Size	640 × 640
Epochs	50
Batch Size	8
Optimizer	AdamW
Learning Rate	0.002
Momentum	0.9
Hardware	CPU

TABLE II: YOLOv8 Training Configuration

Stage 2: Seed Cropping and Classification Using DINOv2

After seed detection, the predicted bounding boxes are used to crop individual seed regions from the original image. These cropped seed images are resized to 224×224 pixels and passed to the classifier.

For classification, a DINOv2 Vision Transformer model (dinov2_vits14) was used as the feature extractor. A lightweight classification head was attached to predict two classes: germinated and non-germinated. The classification head consists of:

- Layer Normalization
- Fully connected layer (384 → 2)

The DINOv2 classifier was trained for 12 epochs.

B. Rationale for the Hybrid Design

The hybrid design was selected to exploit the strengths of both models. YOLOv8 provides efficient multi-object localization, which is necessary because a single image may contain many seed instances. DINOv2 is well suited for capturing fine- grained visual characteristics relevant to germination status, such as radicle emergence and subtle morphological differ- ences. By separating localization and classification, the system becomes modular, interpretable, and extensible.

V. EXPERIMENTAL SETUP

A. Implementation Environment

The models and user interface were implemented in Python using PyTorch, Ultralytics YOLOv8, OpenCV, NumPy, and Tkinter.

B. Evaluation Metrics

The object detection stage was evaluated using precision, recall, mAP@50, and mAP@50–95. The classification stage was evaluated using accuracy, precision, recall, and F1-score. These metrics are defined as follows:

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

Accuracy = (TP + TN) / (TP + TN + FP + FN)

F1-score = (2 * Precision * Recall) / (Precision + Recall)

C. Desktop Application

To enhance usability, a desktop application was implemented using Tkinter to provide an interactive interface for the system. The application allows users to upload images, view prediction outputs, analyze results through a confusion matrix, and perform real-time detection using a webcam. It combines both detection and classification models into a unified pipeline, ensuring efficient processing and intuitive visualization of results.

The interface is designed to be straightforward and easy to use, enabling users to operate the system without requiring specialized technical knowledge. Detected seeds are displayed with bounding boxes along with their corresponding germination labels. Additionally, the application presents important evaluation metrics to support performance assessment. Overall, the developed interface improves the accessibility and practical deployment of the proposed system in real-world agricultural scenarios.

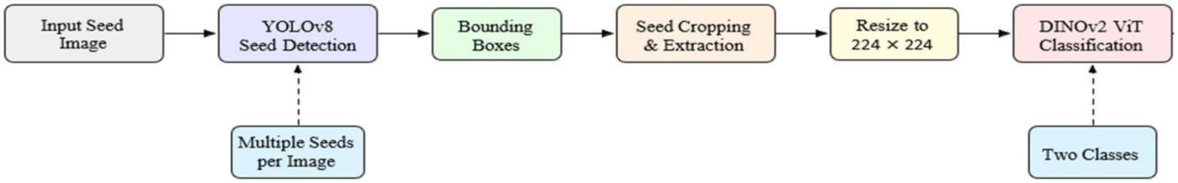


Fig. 1: Proposed SproutAI architecture. The system detects seeds using YOLOv8, extracts individual seed regions, and classifies them using a DINOv2 Vision Transformer to determine germination status.

VI. RESULTS AND DISCUSSION

A. Detection Performance

The YOLOv8 detection model achieved the performance summarized in Table III.

TABLE III: Detection Performance

Metric	Value
Accuracy	0.904
Precision	0.959
Recall	0.955
mAP@50	0.982
mAP@50–95	0.729

B. Classification Performance

The classification results are presented in Table IV.

TABLE IV: Classification Performance

Metric	Value
Accuracy	94.4%
Precision	97.0%
Recall	96.2%
F1-score	96.6%

The confusion matrix used for classification analysis is given in Table V.

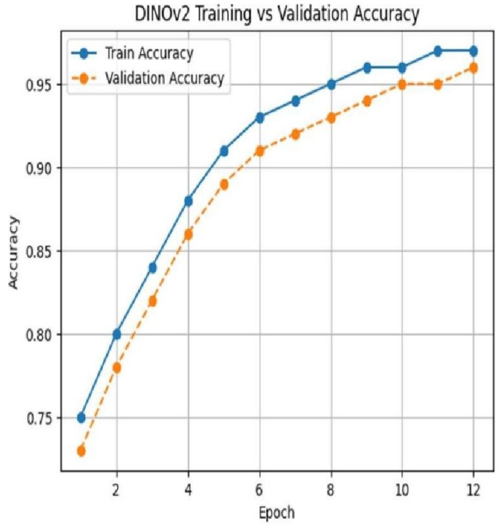
TABLE V: Confusion Matrix

Actual / Predicted	Germinated	Non-germinated
Germinated	40	7
Non-germinated	9	231

C. Training Graphs

The training behavior of the proposed SproutAI framework was analyzed using accuracy and loss curves for both the detection (YOLOv8) and classification (DINOv2) stages. The training and validation accuracy curves show a consistent upward trend across epochs, indicating effective learning and convergence of the models. The gap between training and validation accuracy remains minimal, suggesting that the models generalize well and do not suffer from significant overfitting

(a) YOLOv8 training/validation loss and metric curves.



(b) DINOv2 classification training and validation curves.

D. Discussion

The obtained results demonstrate that the proposed com- bination of YOLOv8 and DINOv2 is effective for automated seed germination analysis. The detector accurately identifies seed locations, while the transformer- based classifier reliably distinguishes germinated and non- germinated instances. The strong F1-score indicates a good balance between precision and recall, which is important in practical agricultural settings where both missed germinated seeds and false detections can affect analysis quality.

Another notable aspect of this work is that the system was trained and evaluated without GPU acceleration, indi- cating that the proposed framework remains feasible even in resource-constrained environments. The addition of a GUI further enhances real-world usability by allowing intuitive interaction with model predictions.

VII. LIMITATIONS AND FUTURE SCOPE

Although the proposed method demonstrates strong performance, several limitations remain. First, the dataset includes only three seed species, which may restrict generalization to other crops and germination conditions. Second, prediction performance may be influenced by image quality, lighting variation, background complexity, and occlusion. Third, the current work focuses on a two- class germination decision and does not model intermediate germination stages.

Future work can address these limitations by:

- Expanding the dataset to include more seed species and imaging conditions

Comparing the proposed framework with baseline CNN and transformer classifiers

- Investigating single-stage end-to-end approaches
- Deploying the system on mobile, web, edge, or IoT- enabled agricultural platform.

VIII. CONCLUSION

This paper presented SproutAI, an automated seed germination detection framework that integrates YOLOv8-based seed detection with DINOv2 Vision Transformer classification. The proposed system provides a complete pipeline for localizing seeds and predicting germination status from images containing multiple seed instances. Experimental results demonstrate strong detection and classification performance, and the inclusion of a desktop application improves the practical usability of the framework. Overall, the results highlight the value of combining object detection and transformer- based visual classification for agricultural monitoring and seed quality assessment.

ACKNOWLEDGMENT

The authors thank CMR Technical Campus for academic support and infrastructure. The authors also acknowledge the publicly available Kaggle dataset used in this work.

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DOI: 10.48175/IJARSCT-31843