A Comprehensive Review on Image-Driven Seed Germination Prediction Using Machine Learning Techniques

Ekeshwari Rangari[1], *Vishwas* Gaikwad*[2]

[1] Research Scholar, Department of Electronics and Telecommunication, Sipna College of Engineering & Technology, Amravati. ekeshwari.rangari@gmail.com
[2] Professor ,Department of Electronics & Telecommunication , Sipna College of Engineering & Technology, Amravati.

Abstract Predicting seed germination can be beneficial for precision agriculture, leading to increased yield, better seed quality assessment, and saving resources. Imaging-based instrumental techniques are becoming more popular as conventional germination tests are manual, destructive, and time-consuming. In this paper, we offer a critical review on machine learning (ML) and deep learning (DL) for the prediction of seed germination from RGB, hyperspectral (HS), thermal, and fluorescence images. Although CNNs and ResNet-based models have demonstrated very high accuracy in laboratory settings, the performance is highly dependent on dataset size, imaging conditions, and validation strategies. The choice of the system must consider the trade-off between the cost of hardware and accuracy. RGB systems are low-cost and scalable, but of moderate accuracy, whereas hyperspectral imaging offers better biochemical sensitivity at a higher cost in hardware and computation. However, despite promising results from field applications, large-scale access is restricted by the non-standardisation of datasets, the lack of cross-crop and real-field assessments, and practical constraints on energy efficiency, maintenance costs, and environmental variability. These gaps also motivate the creation of standard benchmarks, field (multi-crop) validation support, and energy-efficient edge AI through co-design between algorithms and hardware.

Keywords: Seed germination prediction; Image processing; Machine learning; Deep learning; Precision agriculture

1 Introduction

Modern agriculture is at the crossroads of sustainability pressures, climate uncertainty, and the critical need to double world food production. Crop establishment in the early stages is still one of the most critical determinants of yield stability and input-use efficiency. Of these

*Corresponding Author: vtgaikwad@sipnaengg.ac.in

initial stages, seed germination and seedling establishment directly affect the uniformity of a plant population, nutrient uptake efficiency, and crop productivity [1].
Germination assessment, however, still relies heavily on traditional laboratory-based testing procedures despite this critical factor. Common approaches for seed quality evaluation include standard germination tests, visual inspection of seeds, and biochemical assays (for example, tetrazolium staining) [2]. These methods are laborious, destructive, time-consuming, and frequently prone to human interpretive bias. More critically, they are not scalable and poorly applicable within high-throughput breeding programs, seed certification workflows, and phenotyping under field conditions [3].

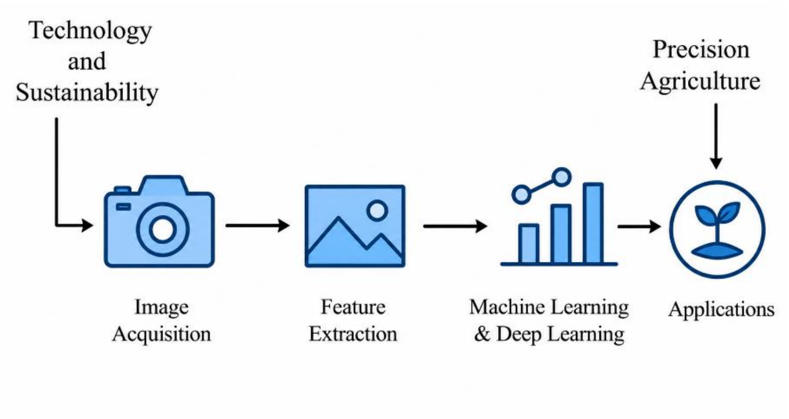

Fig. 1. Process of image-driven seed germination prediction

As agriculture moves towards data- and precision-based systems, a non-destructive, rapid, and scalable method for germination prediction is highly desirable. Imaging technologies partnered with artificial intelligence (AI) were of great interest as alternative options [4]. Machine learning (ML) and deep learning models, especially convolutional neural networks (CNNs), are the most common image-based approaches for analysing morphological, spectral, and physiological indicators of germination. In conjunction with Internet of Things (IoT) devices and edge-computing platforms, these systems support near real-time monitoring and decision intelligence [5].
However, most of the existing literature focuses on algorithmic accuracy in laboratory settings. Practical deployment considerations remain underexplored. Specifically, current reviews seldom address:

- Adoption challenges in resource-limited agricultural systems due to hardware cost restrictions
- Limited on-the-ground real-world validation, as most studies took place in controlled environments
- Lack of standardized and publicly available data for benchmarking and reproducibility
- Insufficient coverage of scaling, green AI, and directions for edge-AI

Its contributions include:

- Hardware–algorithm co-design analysis (sensor selection, imaging modalities, computation platforms, learning architectures).
- Cost–accuracy trade-off comparison across RGB, hyperspectral, thermal, and fluorescence imaging systems
- A talk on challenges in the deployment of edge-AI, constrained by energy efficiency, robustness, and real-field scalability.

- With an emphasis on integrating advances in methodology with practical deployment, this review aims to guide the development of aggregate, scalable, cost-effective Image-based seed germination prediction systems that can be used as part of contemporary precision agriculture.

2 Background

Conventional seed germination measurement methods are highly dependent on human observation and rule-based judgments, resulting in diminished scalability, objectivity, and early detection power. These methods are subjective and cannot characterize the complex, non-linear relationships between genetic variation in soil moisture response traits (RGEN) and its interactions with environmental conditions, including growth and developmental stages in FG that impinge on the germination process. Therefore, their application in large-scale precision agriculture is limited [6].

Imaging-based germination studies assisted by machine learning (ML) and deep learning (DL) offer an efficient approach and open avenues for non-contact, real-time monitoring of morphological and spectral alterations. Digital imaging transforms visual cues into quantifiable inputs, and ML/DL models learn discriminative patterns from images without expressing the underlying biological principles [7]. Learning features implicitly could improve prediction accuracy, robustness, and generalization ability in different settings. Learning-based methods also utilize spatiotemporal information to dynamically monitor the germination development, where subtle variations of structure and texture are difficult for humans to identify. This differs from prior manual or rule-based approaches and enables earlier prediction and scalable deployment [8].

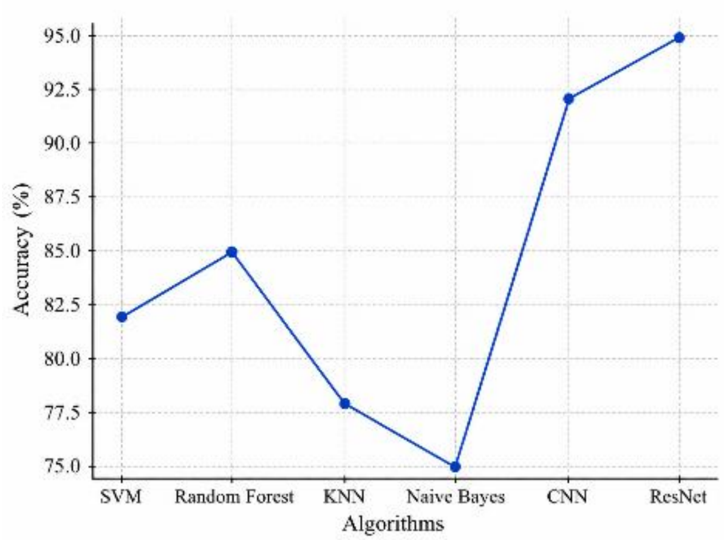

Fig. 2. Algorithm comparison

Figure 2 shows Deep learning approaches for seed germination prediction are compared with classical machine learning models in Figure 2. It shows that while DL models can achieve higher predictive accuracy with hierarchical feature learning, it requires more computations. This comparison is crucial in selecting models that effectively balance the feasibility to deploy model(s) with performance requirements [9].

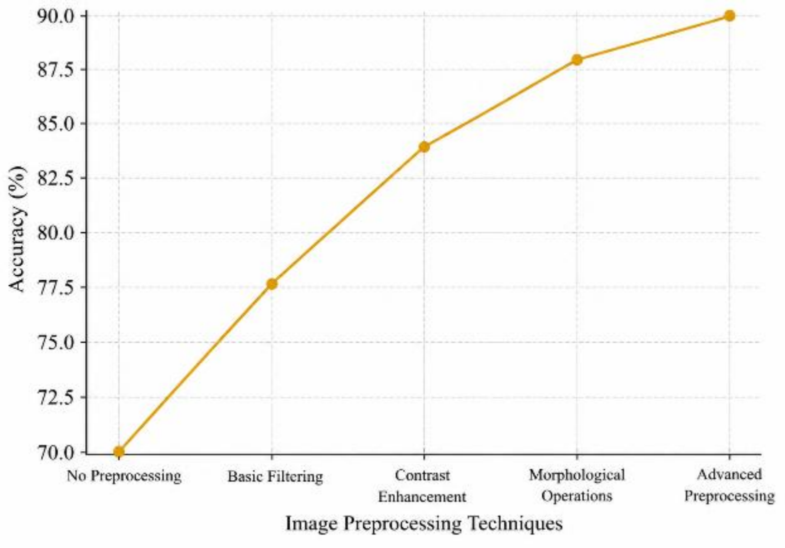

Fig. 3 Impact of preprocessing

Figure 3 shows the effect of preprocessing on prediction accuracy. Although noise reduction and contrast enhancement can help in making features clearer, excessive preprocessing may lead to artifacts or a decrease in generalization [10].

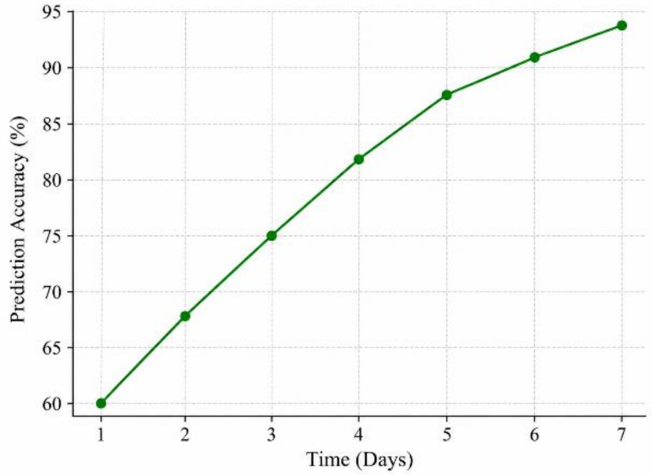

Fig. 4. Germination over time

The trade-off between early prediction and predictive accuracy over time is shown in Figure 4.

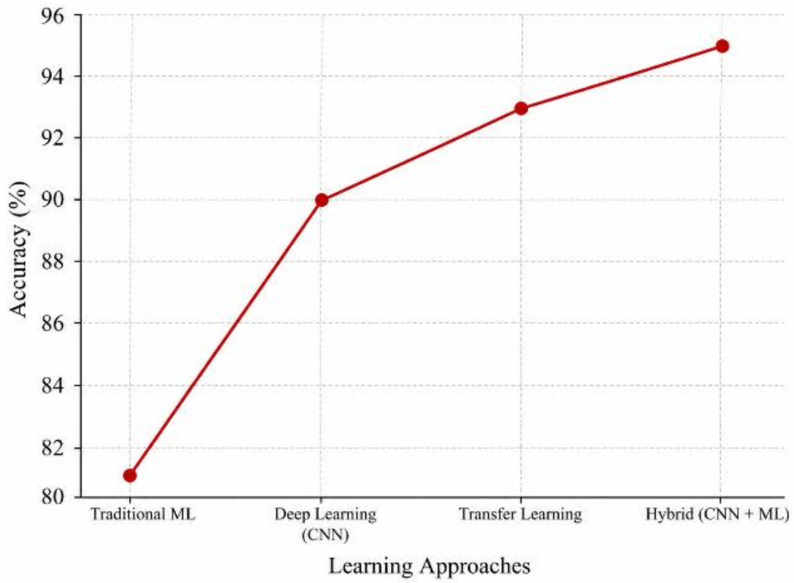

Fig. 5. Learning approach comparison

Figure 5 shows a comparison of the predictive performance and computational demand of traditional ML, deep learning, and hybrid models. Hybrid and DL models achieve significantly higher accuracy, but the size of the dataset, hardware cost, and energy demands limit their deployment. This means that we need to do a cost-accuracy trade-off analysis for scalable agricultural applications [19].

2.1 Digital Imaging and Preprocessing

Digital images for non-contact assessment were reported, with an RGB camera as an inexpensive, readily available solution, while hyperspectral and thermal cameras offer richer biochemical information at a higher cost. The classical pipelines rely on handcrafted preprocessing, which makes them sensitive to illumination, background clutter, and seed orientation. These limitations have prompted a transition towards end-to-end DL frameworks, which reduce reliance on pre-processing and are more robust, scalable, and applicable to precision agriculture in real-world settings [11].

3 Image Acquisition and Preprocessing Techniques

Figure 6 shows the general architecture of the seed germination prediction based on image acquisition and preprocessing. Visual data are captured by RGB, hyperspectral, thermal, or fluorescence imaging systems and post-processed using noise removal, contrast enhancement, segmentation, and morphological operations to enhance the visibility of objects [12]. Geometric, textural, and spectral features are computed for classification and prediction. The robustness of ML/DL models downstream depends heavily on the quality and consistency of image acquisition and preprocessing [13].

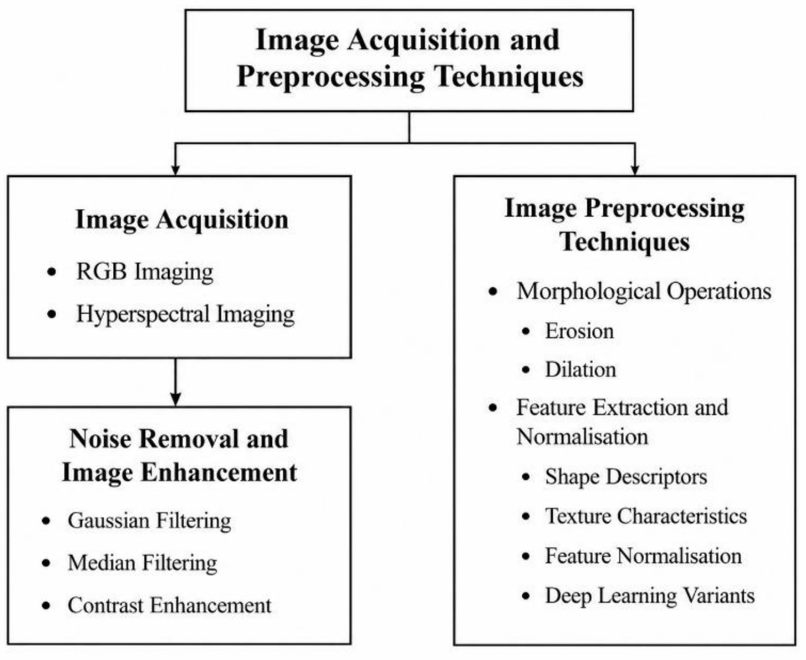

Fig. 6: Block diagram illustrating image acquisition and preprocessing techniques for seed germination prediction.

3.1 Acquisition of RGB Images

The detection of seed germination is mainly based on RGB imaging. This is due to the low cost, ease of implementation, and compatibility with standard CMOS cameras. It identifies visible morphological features such as radicle emergence, seed coat rupture, and early seedling growth [14]. RGB systems are lightweight, low cost, and scalable to deployment. Their low spectral sensitivity limits early biochemical detection prior to any visible morphological change. But RGB imaging offers the most reasonable compromise between scalability and predictive performance for real-world agricultural settings [15].

3.2 Multispectral and Hyperspectral Imaging

Visible imaging is less valuable than multispectral and hyperspectral imaging for detecting physical and biochemical changes during germination. Multispectral systems acquire a few discrete spectral bands, providing better discrimination but a moderate amount of data. The technology of hyperspectral imaging records narrow spectral bands in close proximity and can be used to determine accurately the moisture content, chlorophyll activity, and metabolic changes. But high spectral resolution means high data dimension, high computational load, and high system cost [16].

Moreover, hyperspectral systems demand accurate optical filter cascades, appropriate lighting conditions, and significantly more memory bandwidth than the common RGB platforms available today.

3.3 Hardware Problems in Deployment

3.3.1 *CMOS and CCD*

CMOS sensors are widely used because of their low power consumption (≈100-500 mW), on-chip processing, and low cost. Fluorescent lenses allow high frame rates but have relatively higher fixed-pattern noise. CCD sensors are characterized by better charge-transfer efficiency, readout noise, and uniformity, at the expense of power consumption (≈ 2-5 W), including external processing circuitry. That is why CMOS is preferred for edge and battery-dependent systems, and CCD is still the king for laboratory-grade precision imaging [17].

3.3.2 *Spectral Data & Computation Load*

Spectral resolution has a strong impact on memory, processing latency, and transmission cost. A hyperspectral camera consumes 10-25 W of power and generates large volumes of data, which need to be reduced in dimension or band-selected for real-time inference on embedded devices [18].

3.3.3. *Illumination Stability*

Illumination has a strong effect on the consistency of features. Variability can be reduced by regular irradiance design, general spectrum, or constant-current LED drivers. Field systems have illumination levels of 2-20 W and often exceed sensor power [6].

3.3.4 *Calibration and drift*

Dark frame subtraction is required for long-term deployment, flat-field correction, and synthesized spectral calibration to compensate for sensor aging, temperature variation, and optical drift.

3.3.5 *Limitations of Edge Device*

Edge platforms are constrained by tight power (typical 5–15 W), memory, and thermal constraints [21]. To achieve efficient deployment, lightweight architectures and quantization and pruning of the model are required to maintain real-time inference [4].

3.3.6 *Discrete Power-Consumption Levels*

Deployment systems are classified as:

- Ultra-low-power nodes: 0.5 to 3 W
- Portable edge AI systems 5-15 Watts
- High-Performance Edge Workstations 20-60 W
- Laboratory platforms: 150 – 500+ W

3.3.7 *Deployment Problems*

Electronics-photonics-algorithm co-design for scalable germination monitoring in practice, the spectral richness needed to produce accurate predictions must be balanced with the hardware cost and energy efficiency needed for sustainable adoption in the field [21].

4 Feature Extraction and Selection Methods

The trade-off between interpretability, robustness and scalability is encountered in the extraction of features for predicting seed germination from images. The classical handicraft features (shape, texture and color) provide biologically interpretable information on the radical extension and water uptake [22]. However, the descriptors are very sensitive to illumination variations, orientation of seed objects and environmental noises, which makes it difficult for them to be widely applied under non-standard imaging conditions. The feature representations learned by DL can directly address the image evidence and learn the spatial and temporal patterns in a hierarchical manner. CNN-based embeddings can capture subtle germination cues that hand-crafted descriptors may miss but require large, well-annotated datasets and high computational resources. Deep models are more prone to overfit and generalize poorly, especially in the case of limited data [23]. They are also referred to as hybrid feature strategies, i.e., a mixture of handcrafted and deep representations offering a tradeoff between interpretability and discriminative power for medium-scale databases. However, the high dimensionality and redundancy of these models lead to scalability issues, necessitating feature selection or dimensionality reduction for practical deployment [24].

Table 1: Feature Extraction Method Comparison

Feature Type	Example Methods	Biological Significance	Strength	Limitation	Best Used With
Shape-Based	Area, Perimeter, Hu Moments	Radicle emergence	Simple & interpretable	Limited for early stage	SVM, RF
Texture-Based	GLCM, LBP, Gabor	Internal structural changes	Captures micro-variation	Sensitive to noise	SVM, CNN
Color-Based	RGB histogram, HSV	Moisture uptake & maturity	Low cost	Illumination sensitive	ML + DL
Deep Features	CNN embeddings	Hierarchical patterns	High accuracy	Black-box	DL models
Hybrid Features	Handcrafted + Deep	Comprehensiv e	Robust & accurate	Higher complexity	Ensemble models

Table 1 also presents a number of feature extraction strategies, each with an impact on computation cost and deployment feasibility [25].
This overview table 1. reflects the robustness of features, comparing simple, predefined, deep, and mixed features in terms of biological relevance, sensitivity, and scalability. It emphasizes that, though hand-crafted features are interpretable, they are sensitive to noise in real-world variability, whereas deep and hybrid features are more stable because they are more complex. This comparison is an argument for the use of feature selection techniques in robust germination prediction systems [4].

5 Machine Learning and Deep Learning Models

Seed germination prediction models' performance varies widely with dataset size, crop species, imaging system, and validation method. Fine-tuning classical machine learning algorithms, such as support vector machines (SVMs) and Random Forests, leads to competitive performance on small-to-medium laboratory-condition RGB datasets, particularly in k-fold cross-validation. Nevertheless, their performance significantly drops

when it evaluates on an external or field image because of the hand-engineered features, which means a poor generalization ability.
Deep learning techniques show enhanced performance when large-scale, well-annotated datasets are used for training, and this is attributed to their capacity for automatic feature extraction and robustness, particularly for multimodal inputs that include RGB images with thermal or hyperspectral data. However, hyperspectral methods are still challenged by high dimensionality, the cost of the sensor, and computational load, which restricts their practical application. Hybrid and transfer learning models often achieve the highest accuracies, but they are mainly observed under laboratory-controlled conditions, with very few externally validated, which may result in overestimation of true performance.

6 Datasets and Benchmark Studies

Benchmarks for high-quality datasets are crucial for image-based seed germination prediction, since the performance and generalization ability of models strongly depend on data quality, diversity, and annotation consistency. While controlled laboratory environments are powerful for evaluating scales of seed quality using ML and DL models, developing effective solutions requires datasets that reflect the variability across seed species, imaging modalities used to image them, and environmental conditions to avoid overfitting. However, unlike other tasks in agricultural vision (e.g., plant disease or fruit detection), available seed germination datasets are limited and publicly unavailable, thereby constraining reproducibility and cross-study comparison. In this section, we survey public datasets, popular custom-built datasets, and benchmarking practices.

6.1 *Publicly Available Datasets*

Public datasets on seed germination are few because experimental protocols and seed species vary widely. An example of such a dataset would be SeedGerm-2023, a multi-crop RGB dataset comprising over 15,000 annotated images of maize, soybean, and rice. The images are annotated by germination stage (ungerminated, radicle emergence, partial, and full germination) and were collected over seven days under controlled environment conditions, making them suitable for convolutional neural network (CNN)-based classification. PHM-Seed is another dataset consisting of 3,000 hyperspectral image cubes of wheat and barley spanning 400–1000 nm for biochemical and moisture analysis using either 3D-CNN or transformer-based models. More general-purpose public datasets, such as Agri Vision and Seed Net, available at larger scales with non-germination-specific images, are important for transfer learning and generalization.

6.2 *Custom-Built Experimental Datasets*

The limited availability of public resources means most studies rely on private datasets collected with high-resolution RGB cameras mounted over germination trays under controlled temperature and humidity conditions. Some studies also use thermal or fluorescence imaging to record early metabolic activity. They vary in size from a couple of hundred to tens of thousands of images, with annotations covering different stages of germination. Commonly used data augmentation techniques, generating both geometric transformations and by leveraging Generative Adversarial Networks, synthesizing novel views from a limited set of images, bring ∼ 4–8% improvements in classification accuracies.

6.3 *Benchmark Studies and Metrics*

Standard benchmarks use classification metrics such as accuracy, precision, recall, F1-score, and ROC-AUC for these tasks, and RMSE and MAE for regression. While classical ML models typically achieve F1 scores of 0.85–0.92, DL models can outperform, achieving scores above 0.95 on large, well-annotated datasets.

6.4 *Benchmark Analysis Findings*

Deeper learning 5–10% top ML with better feature study. Hybrid CNN–SVM and transfer learning approaches yield improved results, especially for imbalanced and small datasets. However, there are key limitations due to the absence of general standards for benchmarks.

6.5 Cost-Sensitive Comparison

Accuracies reported should be interpreted in relation to the size of the data set, the imaging modality, and the cost of the system. Hyperspectral systems have a high biochemical sensitivity but tend to be limited in deployment due to expense and computational requirements. On the other hand, the RGB-based DL systems can achieve an accuracy close to competitive accuracy but at a significantly lower cost, making them more suitable for large-scale agricultural applications.

Table 2. Comparative Benchmark Studies in Image-Based Seed Germination Prediction

Study	Crop	Imaging	Model	Dataset Size	Accuracy
SeedGerm-2023 (2023)	Maize, Soybean, Rice	RGB	ResNet50 (CNN)	15,000 images	97% (5-fold CV)
PHM-Seed (2022)	Wheat, Barley	Hyperspectral (400–1000 nm)	3D-CNN	3,000 spectral cubes	94% (5-fold CV)
Rice Thermal Study (2021)	Rice	Thermal + RGB	Custom CNN	12,000 images	96.8% (80–20 split)
Soybean Segmentation Study (2020)	Soybean	RGB	U-Net	7,800 images	95% Dice Score
Tomato HSI Study (2019)	Tomato	Hyperspectral	Random Forest	4,800 samples	93% (10-fold CV)
Hybrid CNN–SVM Study (2023)	Maize	RGB	CNN + SVM	10,000 images	98.5% (5-fold CV)

In Table 2 of Marquez-Nostra et al. (2023), the reported accuracy is related to dataset size, crop type, imaging modality, and validation strategy, which allows for a qualified performance interpretation. However, larger RGB datasets and more strict cross-validation schemes will lead to higher accuracy, only while hyperspectral or hybrid ones add to the cost and complexity of the system. Crucially, most studies have no external or field validation and so the reported accuracies are often laboratory upper bounds. RGB-based systems that employ CMOS cameras (from USD 50 to 500; 0.5–5 W) reach a performance of accuracy between 95 and 98.5 % on datasets of up to ~15,000 photos, which shows promising results with affordable hardware. Hyperspectral systems (USD 15,000–60,000; 20–60 W), on the other hand, can provide similar but not better classification accuracy and therefore their large-scale deployment is hindered.

7 Applications and Case Studies

All reported case-study results here are obtained from controlled experiments. For wheat, a CNN trained on 9,000 RGB images recorded under the same laboratory-controlled lighting conditions achieved 96% accuracy in stage classification. A hybrid CNN–SVM model trained on 11,500 RBG images of maize exhibited 94% accuracy in a k = 5 cross-validation fold for the detection of the early radicle from imbibed seeds at 24 h.
For Mean Dice: U-Net segmentation of soybean at an average 5-fold cross-validation yielded 95% mean dice scores on 7,800 RGB images with an 80–20 train–test split, and rice viability prediction using thermal (12,000 image samples) gave a result exceeding the accuracy of predictions of plate counts. On the tomato dataset, at least 4,800 hyperspectral samples and PRF yielded an accuracy of 93 % with 10-fold cross-validation. Together, these results show that 94–98% accuracy can be achieved in the laboratory under highly controlled conditions and with many labelled examples; however, little is known about generalization at the field level.

8 Challenges and Limitations

While prediction performance is high in several studies, these results need to be interpreted within the context of each experiment. For instance, RGB-based CNN models trained on 10,000–15,000 images of maize, soybean, or rice under controlled lighting conditions reported accuracies ranging from 95–98.5% using k-fold cross-validation. Likewise, 93% and 94% accuracy are achieved with hyperspectral models trained on either 3,000 or 4,800 spectral cubes of barley or wheat under controlled laboratory conditions. These values are reported under controlled conditions with fixed camera geometry and limited environmental changes and illumination.
This, however, introduces a significant risk of performance degradation during field deployment. Changes in outdoor illumination, temperature variations, sensor aging, dust buildup, and crop variability shift the image distributions from the training conditions in the laboratory. Most published studies are internally validated (e.g., 80–20 splits or k-fold cross-validation), not field-validated, so reported accuracy likely reflects a ceiling of laboratory performance rather than actual, field-validated real-world rates.
Hardware constraints further limit scalability. Hyperspectral systems offer greater biochemical sensitivity but generally require expensive sensors and high-power budgets (20–60 W or more), hindering large-scale adoption. Due to the system-level constraints of edge devices available in farms (5–15 W power consumption and limited memory capacity), model complexity and real-time processing capabilities are constrained.

Table 3: Field Deployment Constraints

Challenge	Impact	Example	Mitigation Strategy
Illumination variability	Reduced accuracy	Outdoor sunlight	Adaptive normalization
Small dataset size	Overfitting	Rare crop seeds	Data augmentation, GAN
Hardware cost	Limited adoption	Hyperspectral cameras	RGB + DL hybrid

Edge computation limits	Latency	Farm devices	Model compression
Sensor calibration drift	Performance degradation	Long-term deployment	Periodic recalibration

The relevant constraints that prevent deployment in the field are summarized in Table 3. Varying illumination and calibration drift directly lower the stability of our predictions. Small datasets also increase the risk of overfitting, especially with rare crop varieties. Although accuracy is high in laboratories, scalability is limited by hardware costs and edge-computation constraints. In contrast, mitigation strategies such as adaptive normalization or data augmentation argue that, for successful deployment, system-level optimization rather than model selection is critical

9 Future Directions

Future studies should move from algorithm-cantered solutions to hardware–algorithm co-optimized designs that can compromise accuracy, cost, energy efficiency, and scalability. Edge AI and recently proposed quantum-inspired learning approaches seem promising for processing high-dimensional imaging data with affordable overhead; their effectiveness depends on practical hardware feasibility and model compression. Generalization and benchmarking can be further enhanced by creating large, standardized cross-crop, multimodal datasets. There will be a need to develop model-based approaches that can take advantage of environmental combined imagery data, as well as to focus on lightweight models for embedded and drone–based platforms to obtain faithful, low-cost, real-time germination estimation.

10 Conclusion

In this review, we provide a deployment-centric overview of image-based seed germination prediction by combining recent advancements in machine learning and deep learning with the context of electronics and photonics hardware. Although rapid and accurate models are often developed in the laboratory, real-world performance is limited by sensor cost, data availability, energy expenditure, and validation stringency. Critical research gaps include the lack of universal benchmarks, the lack of cross-crop generalization, and edge deployment in the context. Tackling these challenges through cost–accuracy trade-off analysis, hardware–algorithm co-design, and field-level validation will be crucial to enabling the translation of laboratory success into scalable and sustainable solutions for agriculture.

References

1. Y. Niroshan, E. Carmon, O. Yaniv, S. Ayal, O. Rotem, Robust seed germination prediction using deep learning and RGB image data. Sci. Rep. 11, 22030 (2021). https://doi.org/10.1038/s41598-021-01712-6
2. C. Chen, M. Bai, T. Wang, W. Zhang, H. Yu, T. Pang, J. Wu, Z. Li, X. Wang, An RGB image dataset for seed germination prediction and vigor detection–maize. Front. Plant Sci. 15, 1341335 (2024). DOI: https://doi.org/10.3389/fpls.2024.1341335
3. Y. Gulzar, Y. Hamid, A. B. Soomro, A. A. Alwan, L. Journaux, A Convolution Neural Network-Based Seed Classification System. Symmetry 12(12), 2018 (2020). https://doi.org/10.3390/sym12122018

4. T. Gao, A. K. N. Chandran, P. Paul, H. Walia, H. Yu, HyperSeed: An End-to-End Method to Process Hyperspectral Images of Seeds. Sensors 21(24), 8184 (2021). DOI: https://doi.org/10.3390/s21248184
5. Y. Fan, T. An, Q. Wang, G. Yang, W. Huang, Z. Wang, C. Zhao, X. Tian, Non-destructive detection of single-seed viability in maize using hyperspectral imaging and multi-scale 3D CNN. Front. Plant Sci. 14, 1248598 (2023). https://doi.org/10.3389/fpls.2023.1248598
6. T. Pang, C. Chen, R. Fu, X. Wang, H. Yu, An end-to-end seed vigor prediction model for imbalanced samples using hyperspectral image. Front. Plant Sci. 14, 1322391 (2023). DOI: https://doi.org/10.3389/fpls.2023.1322391
7. Q. Yao, X. Zheng, G. Zhou, J. Zhang, SGR-YOLO: A method for detecting seed germination rate in wild rice. Front. Plant Sci. 14, 1305081 (2024). DOI: https://doi.org/10.3389/fpls.2023.1305081
8. Z. Zou, J. Chen, W. Wu, J. Luo, T. Long, Q. Wu, Q. Wang, J. Zhen, Y. Zhao, Y. Wang, Y. Chen, M. Zhou, L. Xu, Detection of peanut seed vigor based on hyperspectral imaging and chemometrics. Front. Plant Sci. 14, 1127108 (2023). DOI: https://doi.org/10.3389/fpls.2023.1127108
9. H. Qi, X. Zhang, L. Wang, Rice seed vigor detection based on near-infrared hyperspectral imaging and transfer learning. Front. Plant Sci. 14, 1283921 (2023). https://doi.org/10.3389/fpls.2023.1283921
10. B.G. Ram , P. Oduor, C. Igathinathane, K. Howatt, X.A. Sun, Systematic review of hyperspectral imaging in precision agriculture: Analysis of its current state and future prospects. Computers and Electronics in Agriculture, 222, 109037 (2024). https://doi.org/10.1016/j.compag.2024.109037
11. K. Wonggasem, P. Wongchaisuwat, P. Chakranon, D. Onwimol, Utilization of Machine Learning and Hyperspectral Imaging Technologies for Classifying Coated Maize Seed Vigor: A Case Study on the Assessment of Seed DNA Repair Capability. Agronomy 14(9), 1991 (2024). DOI: https://doi.org/10.3390/agronomy14091991
12. P. Xu, L. Fu, Y. Pan, D. Chen, S. Yang, R. Yang, Identification of maize seed vigor based on hyperspectral imaging and deep learning. Bull. Natl. Res. Cent. 48, 84 (2024). https://doi.org/10.1186/s42269-024-01239-6
13. N. Wu, J. Huang, L. Zhang, Deep convolutional neural network with weighted loss for non-destructive rice seed vigor detection under imbalanced samples. Comput. Electron. Agric. 194, 106741 (2022). https://doi.org/10.1016/j.compag.2022.106741
14. A. Picon, D. Major, S. Sampson, Crop conditional convolutional neural networks for plant phenotyping and seed analysis. Comput. Electron. Agric. 165, 104964 (2019). https://doi.org/10.1016/j.compag.2019.105093
15. F. Zhu, P. Paul, W. Hussain, K. Wallman, B. K. Dhatt, J. Sandhu, L. Irvin, G. Morota, H. Yu, H. Walia, SeedExtractor: An Open-Source GUI for Seed Image Analysis. Frontiers in Plant Science 11, 581546 (2021). https://doi.org/10.3389/fpls.2020.581546
16. H. Xue, L. Zhao, Y. Chen, Rapid and non-destructive prediction of moisture content of maize seeds using hyperspectral imaging and PLSR. Sensors 24, 1855 (2024). https://doi.org/10.3390/s24061855
17. T. Cheng, F. Li, S. Wei, Hyperspectral and imagery integrated analysis for vegetable seed vigor. Comput. Electron. Agric. 212, 104605 (2023). https://doi.org/10.1016/j.infrared.2023.104605
18. A. Al Siam, M. M. Salehin, M. S. Alam, S. Ahamed, M. H. Islam, A. Rahman, Paddy seed viability prediction based on feature fusion of color and hyperspectral image with multivariate analysis. Heliyon 10(17), e36999 (2024). https://doi.org/10.1016/j.heliyon.2024.e36999

19. K. Vairavan, B. M. Kamble, A. G. Dergue, S. R. Ingle, Hyperspectral imaging of soil and crop: A review. J. Exp. Agric. Int. 46, 48-61 (2024). https://doi.org/10.9734/jeai/2024/v46i12290
20. A. Griffo, F. Usai, S. Sehmisch, F. Laager, A. Börner, L. Pasotti, A. Macovei, Application of machine learning models for non-invasive seed quality detection. Current Plant Biology 44, 100557 (2025). https://doi.org/10.1016/j.cpb.2025.100557
21. S. W. Jeong, J. I. Lyu, H. Jeong, J. Baek, J.-K. Moon, C. Lee, M.-G. Choi, K.-H. Kim, Y.-I. Park, SUnSeT: Spectral unmixing of hyperspectral images for phenotyping soybean seed traits. Plant Cell Rep. 43, 164 (2024). https://doi.org/10.1007/s00299-024-03249-0
22. M. F. Pomelle, A. Jarma-Orozco, L. A. Rodríguez-Páez, Imbibition and Germination of Seeds with Economic and Ecological Interest: Physical and Biochemical Factors Involved. Sustainability 15, 5394 (2023). https://doi.org/10.3390/su15065394
23. X. Liu, Z. Zhang, Y. Li, C. Igathinathane, J. Yu, Z. Rui, A. Azizi, X. Wang, A. Pourreza, M. Zhang, Early-stage detection of maize seed germination based on RGB image and machine vision. Smart Agricultural Technology 11, 100927 (2025). https://doi.org/10.1016/j.atech.2025.100927
24. M. O. Ojo, A. Zahid, Deep Learning in Controlled Environment Agriculture: A Review of Recent Advancements, Challenges and Prospects. Sensors 22, 7965 (2022). https://doi.org/10.3390/s22207965
25. H. Yan, Z. Zhang, Y. Lv, Y. Nie, Integrated multispectral imaging, germination phenotype, and transcriptomic analysis provide insights into seed vigor responsive mechanisms in quinoa under artificial accelerated aging. Front. Plant Sci. 15, 1435154 (2024). https://doi.org/10.3389/fpls.2024.1435154