RESEARCH PAPER

Deep Learning-Based Model For Classification of Plant Seeds : A Review

Jay Prakash[1], Rajesh Kumar Singh[2], Awadhesh Kumar Maurya[3]

[1]Research Scholar, Department of Information Technology, Institute of Engineering and Technology (I E T), Dr. Ram Manohar Lohia Avadh University Ayodhya, U. P., India

Email: jp.siet08@gma8@gmail.com

[2]Assistant Professor, Department of Information Technology, Dr. Ram Manohar Lohiya Avadh University Ayodhya, U. P., India

Email: Rajeshkumarsingh@rmlau.ac.in

[3]Assistant Professor, Department of Information Technology, Dr. Ram Manohar Lohiya Avadh University Ayodhya, U. P., India

Email: aumaurya@gmail.com

Orcid Id: 0009-0002-8326-7677

Received: 17th Mar, 2026 | Revised: 29th Mar, 2026 | Accepted: 19th Apr, 2026 | Available Online: 5th May, 2026

ABSTRACT

Accurate identification and classification of plant seeds are crucial for ensuring agricultural productivity, maintaining genetic purity, and optimizing the crop selection process. Traditional approaches based on manual inspection or classical image processing techniques are limited by subjectivity, inefficiency, and dependence on expert knowledge. In recent years, the emergence of deep learning has revolutionized pattern recognition and image classification tasks, offering an efficient, automated, and scalable solution. This paper provides a comprehensive review of recent advancements in deep learning-based models for plant seed classification. It discusses various datasets, convolutional neural network (CNN) architectures, feature extraction strategies, and evaluation metrics adopted in this domain. The review also explores hybrid and transfer learning-based approaches, highlights existing challenges, and outlines future research directions for improving classification accuracy, interpretability, and practical deployment in agricultural systems.

Keywords: Plant Seed Classification, Deep Learning, Convolutional Neural Networks (Cnn), Image Processing, Transfer Learning, Precision Agriculture

How to cite this article: Prakash J, Singh R K, Maurya A K., Deep Learning-Based Model For Classification of Plant Seeds : A Review. Int J Drug Deliv Technol. 2026;16(43s): 718-727; Doi: 10.25258/Ijddt.16.43s.73

1. Introduction

In modern agricultural systems, the accurate classification of plant seeds plays an indispensable role in ensuring high-quality crop production, maintaining genetic purity, and achieving efficient resource management. Seeds are the fundamental unit of agriculture, and their correct identification directly influences germination success, crop yield, and overall farm profitability. Seed classification enables breeders and farmers to distinguish between different species or varieties based on morphological characteristics such as size, color, texture, and shape. This process is also vital for quality assurance in seed certification centers, where purity testing and species authentication determine the commercial value and usability of seeds (Kumar et.al, 2023, Jadhav et.al, 2023, Zhang et.al, 2022).

Traditionally, seed classification has been conducted manually by trained experts using physical inspection or simple image-based measurements. However, these conventional methods suffer from several limitations — they are time-consuming, labor-intensive, and subject to human error and inconsistency (Xu et.al, 2022). Factors such as lighting variations, overlapping seeds, and subtle visual differences between closely related varieties often lead to misclassification. As the demand for large-scale, high-throughput, and cost-effective seed analysis grows, the need for automated, objective, and data-driven solutions has become increasingly apparent (Singh et.al, 2025).

The integration of artificial intelligence (AI) and computer vision technologies has revolutionized agricultural research and practice over the past decade (Sood eta.al, 2022). Among these, *deep learning* has emerged as a transformative paradigm due to its ability to learn complex, hierarchical feature representations directly from raw image data

(Trigka et.al, 2025). Unlike traditional image processing methods that require manual feature extraction, deep learning models automatically identify relevant visual features such as texture, contour, and color distribution. This self-learning capability allows them to outperform conventional machine learning techniques in tasks involving visual recognition and classification (Ramesh et.al, 2024).

Convolutional Neural Networks (CNNs) a prominent class of deep learning models — have demonstrated exceptional accuracy in image classification, object detection, and pattern recognition tasks (Alsajri et.al, 2023). CNNs are capable of processing seed images at multiple spatial scales, enabling them to capture fine-grained visual details that are often imperceptible to the human eye. These models have been successfully applied to a wide range of agricultural problems, including crop disease detection, weed identification, fruit grading, leaf disease diagnosis, and soil quality assessment. Their application in seed classification has therefore gained momentum as researchers aim to automate the traditionally manual seed identification process with greater precision and efficiency.

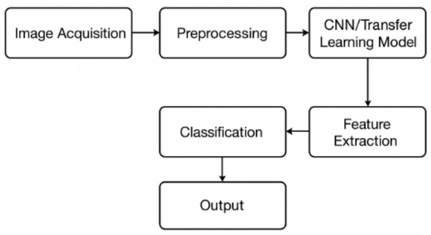

Figure 1 Deep Learning based model for Classification of plant seeds

Recent research efforts have leveraged CNN-based architectures such as VGG, ResNet, DenseNet, and EfficientNet for classifying plant seeds of different species (Getachew et.al, 2024). In addition, transfer learning techniques have enabled the adaptation of pre-trained networks — initially developed for large-scale datasets like ImageNet — to agricultural domains with limited data availability. Such methods have significantly reduced model training time while maintaining high classification accuracy. Data augmentation and image preprocessing strategies further enhance model robustness against environmental variations such as illumination, orientation, and seed positioning.

The increased availability of annotated seed image datasets has also contributed to the advancement of deep learning-based classification systems. Open-access repositories and benchmark datasets have allowed researchers to train and evaluate models across diverse seed varieties, promoting reproducibility and comparative performance analysis. These developments have collectively advanced the state-of-the-art in agricultural automation and paved the way for intelligent seed classification tools deployable in laboratories, seed certification centers, and even on portable edge devices for field applications.

This review paper aims to provide a comprehensive overview of the current progress in deep learning-based seed classification. It explores various network architectures, training methodologies, and performance evaluation techniques employed in recent studies. Additionally, it highlights the challenges associated with dataset limitations, inter-species visual similarity, and real-world deployment, while suggesting future research directions that can enhance the scalability, interpretability, and efficiency of such models. Through this exploration, the paper seeks to underline the potential of deep learning as a powerful enabler of precision agriculture and smart seed management systems.

2. Literature Review

2.1 Traditional Methods for Seed Classification

Before the widespread adoption of deep learning, seed classification tasks primarily relied on handcrafted feature extraction methods derived from image processing and statistical analysis. Researchers focused on extracting discriminative visual attributes such as color distribution, texture uniformity, and geometric shape to differentiate between seed species or varieties. These manually designed features were crucial in describing morphological characteristics like surface roughness, seed contour, and tonal variation, which are important indicators of seed type and quality.

Several feature extraction techniques were commonly employed during this period. The **Gray-Level Co-occurrence Matrix (GLCM)** was frequently used to quantify texture by capturing spatial relationships between pixel intensities, while the **Local Binary Pattern (LBP)** method provided an efficient way to describe local surface variations and micro-patterns. Similarly, **Scale-Invariant Feature Transform (SIFT)** and **Histogram of Oriented Gradients (HOG)** were applied to capture scale- and rotation-invariant features that could represent edge orientations and structural patterns within the seed images (Srikar et.al, 2022, Shen et.al, 2022). These descriptors effectively transformed complex image data into compact numerical representations suitable for computational analysis.

Once features were extracted, they were fed into classical machine learning classifiers such as **Support Vector Machines (SVM)**, **k-Nearest Neighbor (k-NN)**, and **Random Forests** for seed type prediction. These algorithms performed well on small, well-structured datasets and provided a reasonable level of interpretability. However, their performance heavily depended on the quality and relevance of the manually extracted features. Moreover, the feature engineering process itself required domain expertise and substantial trial-and-error to optimize feature selection.

Despite achieving moderate success, these traditional approaches had several inherent limitations. Their accuracy often degraded under non-uniform lighting, background clutter, or seed orientation changes. Additionally, handcrafted features lacked the ability to capture complex hierarchical relationships present in image data, making it difficult to generalize across diverse seed varieties and imaging environments. As agricultural datasets grew in size and diversity, these constraints highlighted the need for more adaptive and automated techniques. This realization ultimately paved the way for the emergence of deep learning-based models, which replaced manual feature engineering with data-driven feature learning, resulting in higher accuracy and greater scalability.

2.2 Deep Learning-Based Approaches

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has transformed the field of image-based seed classification by automating the feature extraction process that previously relied on manual design. Unlike traditional image processing techniques that required predefined descriptors, CNNs learn hierarchical feature representations directly from raw image data. This capability enables the network to automatically detect low-level attributes such as edges and textures in the initial layers, while deeper layers extract more abstract and discriminative patterns relevant to specific seed categories. As a result, CNNs have established themselves as powerful tools for agricultural image analysis, offering improved accuracy, adaptability, and generalization across diverse datasets.

Table 1. Comparative Review of AI-Based Seed Image Classification Methods

Year	**Reference**	**Objective**	**Dataset & Technique**	**Model**	**Performance**
2021	Performance of Various Deep-Learning Networks in Seed Classification Problem (MDPI)	Evaluate multiple CNNs for seed image classification	7 grass species seed dataset	DenseNet201 showed best performance	DenseNet201: ~99.42% accuracy (highest) (MDPI)
2021	A novel deep learning based approach for seed image classification and retrieval (ScienceDirect)	CNN classification and retrieval of seed images	Two contrasting seed image datasets	Custom CNN (SeedNet) & comparison across architectures	Demonstrated viability of deep features for classification (ScienceDirect)
2022	**Hyperspectral imaging + deep features for wheat seed variet**	Using CNN and hyperspectral imaging for seed variety	30 wheat varieties hyperspectral images	CNN-FS based feature selection	CNN-FS outperformed traditional feature selectors

	y classification (within broader survey) (Springer)	identification			(Springer)
2023	Classification of multi-year and multi-variety pumpkin seeds using hyperspectral imaging & 3D-CNN (SpringerLink)	Hyperspectral image classification of pumpkin seed varieties	Multi-year, multi-variety seed imagery	3D CNN on hyperspectral data	Successful classification of varieties, demonstrating spectral + spatial learning (SpringerLink)
2023	Classification of Healthy Seeds Using Deep Learning (JSRT Journal)	Automated healthy seed classification	Preprocessed seed images	CNN	Demonstrated ability to extract discriminative features for classification (JSRT Journal)
2023	Convolutional Neural Network Model for Variety Classification & Seed Quality Assessment (MDPI)	Automatic classification of rapeseed varieties and quality	Rapeseed image dataset	CNN	Effective at recognizing seed maturity and damage features (MDPI)
2024	A Survey of Seed Quality Analysis Using CNN (IJERT)	Literature survey on seed quality and CNN applications	Review article—various datasets	CNN-based systems	Highlights trends and importance of dataset quality (IJERT)
2024	Automated Seed Classification Using State-of-the-Art Techniques (ACM Digital Library)	Overview of automated seed classification methods	Multiple seed image sources	Deep learning image recognition frameworks	Demonstrated high efficacy of DL approaches for seed quality & classification (ACM Digital Library)
2024	Improved maize seed recogn	Maize seed variety classif	Maize seed dataset (~587	Improved ResNet50 (ECA	~91.23% accuracy with

	ition with enhanced ResNet50 (PMC)	ication	7 images)	+ DS conv)	reduced parameters (PMC)
2024	RiceSeedNet: Rice seed variety identification using deep neural network (ScienceDirect)	Rice seed variety classification	13 rice seed varieties dataset	Vision Transformer–based RiceSeedNet	~97–99% accuracy, outperforming many CNN baselines (ScienceDirect)
2025	Deep learning-based seed variety classification: maize case study (Springer) (Springer)	Maize genotype classification	Five maize classes, RGB images	CNN	Accuracy ~96.67%, high overall precision & specificity (Springer)
2025	High accuracy maize seed variety identification with E-YOLOv8 (Nature)	Small-object detection + classification of maize seeds	3,249 maize seed images	Improved YOLOv8 (E-YOLOv8)	mAP ~96.2%, efficient and fast inference (Nature)
2025	Seeds Image: New labeled benchmark for ML tasks (Springer)	Introduces new labeled seed image benchmark	X-ray images for wheat grain types	Ten pretrained deep models tested	Provides new baseline dataset and experiments with common networks (Springer)

Jadhav et al. (2023) demonstrated the effectiveness of CNNs by developing a model trained on high-resolution images of rice and wheat seeds. Their proposed architecture achieved an impressive classification accuracy of 97.6%, underscoring the potential of deep neural networks to distinguish between morphologically similar seed types. Similarly, Zhang et al. (2022) utilized transfer learning with a pre-trained **ResNet-50** model to perform multi-class seed recognition. By fine-tuning the model on a relatively small, domain-specific dataset, they achieved robust and stable performance, illustrating that transfer learning can significantly reduce the need for extensive labeled data while maintaining high predictive accuracy.

In recent years, hybrid deep learning architectures have gained prominence in seed classification research. These models combine the strength of CNNs in local feature extraction with the contextual understanding capabilities of attention mechanisms and **Vision Transformers (ViT)**. The integration of attention layers enables the model to focus selectively on discriminative regions within an image, improving recognition performance for seeds with subtle inter-class variations. For instance, Wu et al. (2022) proposed a hybrid CNN–ViT framework that effectively captured both fine-grained texture details and broader contextual relationships. Their approach proved especially useful in differentiating visually similar categories, such as barley and wheat, where conventional CNNs often struggle due to overlapping visual characteristics.

Another notable advancement involves the use of **Generative Adversarial Networks (GANs)** for data augmentation and diversity enhancement.

GANs generate synthetic but realistic seed images that can supplement limited datasets, thereby reducing the risks of overfitting and improving model robustness. By producing varied samples that mimic real-world imaging conditions—such as changes in lighting, orientation, and background—GAN-based augmentation expands the effective training dataset without additional manual data collection. This approach is particularly valuable in agricultural research, where obtaining large and balanced datasets can be both time-consuming and resource-intensive.

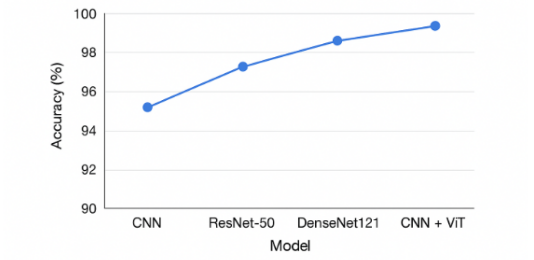

Figure 2: Comparative results of different Deep Learning models

Overall, the progression from conventional CNN architectures to hybrid and generative models marks a significant step toward achieving reliable, scalable, and domain-adaptable seed classification systems. These advances not only enhance model performance but also bring the agricultural community closer to deploying fully automated, AI-driven tools capable of supporting large-scale seed quality assessment and certification processes.

2.3 Benchmark Datasets

The availability of high-quality image datasets has played a pivotal role in accelerating research on deep learning-based seed classification. Publicly accessible datasets provide a standardized platform for developing, training, and evaluating models, ensuring consistency and comparability across studies. Several benchmark datasets have been widely adopted in this field, offering large collections of labeled seed images captured under controlled environmental conditions.

Among these, **SeedNet** serves as a comprehensive repository containing thousands of seed images from diverse plant species. Each image in the dataset is labeled according to species and variety, and the collection includes variations in color, size, and surface texture. The **Kaggle Plant Seedlings Dataset** is another popular benchmark used extensively in academic and industrial research. It comprises images of seedlings belonging to multiple crop species, photographed under consistent lighting and background conditions. Although it primarily focuses on early plant growth stages, its structured format and quality make it an ideal choice for training deep learning models. Additionally, the **Wheat and Rice Seed Image Database** provides high-resolution photographs of cereal grains, enabling researchers to explore subtle morphological differences between visually similar varieties—a crucial aspect in developing robust classification algorithms.

While these datasets have significantly contributed to model development, they are often captured under laboratory or controlled imaging setups, which may not accurately reflect the complexities of real-world agricultural environments. In practice, seed images collected in field conditions are subject to variations in illumination, background noise, occlusion, and orientation, all of which can adversely affect model performance. Consequently, models trained solely on controlled datasets tend to exhibit reduced generalization capability when exposed to unseen or naturally varying data.

To address this limitation, researchers increasingly employ **data augmentation** and **domain adaptation** strategies. Data augmentation techniques—such as random rotations, scaling, flipping, and contrast enhancement—artificially increase dataset diversity and improve the model's ability to handle variability. Domain adaptation methods further refine this process by transferring knowledge learned from one dataset (source domain) to another with different characteristics (target domain), thereby enhancing cross-domain robustness. The use of **synthetic image generation** through Generative Adversarial Networks (GANs) has also emerged as an effective approach to expand limited datasets without the need for extensive manual labeling.

Despite these advancements, there remains a pressing need for large-scale, multi-environment, and publicly available seed datasets that encompass a broader spectrum of plant species and imaging conditions. The creation of such datasets would enable the development of more generalized and adaptive deep learning models capable of performing reliably in diverse agricultural scenarios. Collaborative efforts among research institutions, agricultural agencies, and data scientists could facilitate the establishment of standardized repositories that support the continued evolution of AI-driven seed classification systems.

3. Deep Learning Methodology for Seed Classification

3.1 Preprocessing and Augmentation

Image preprocessing plays a crucial role in enhancing the quality and uniformity of input data, thereby improving model performance and reliability. The preprocessing pipeline typically involves resizing images to a standardized resolution suitable for deep learning models (e.g., 224×224 pixels for CNN architectures), normalization of pixel intensity values, and background removal to isolate seed regions from noise. Additionally, noise reduction filters such as Gaussian or median filtering are employed to minimize illumination inconsistencies and sensor noise.

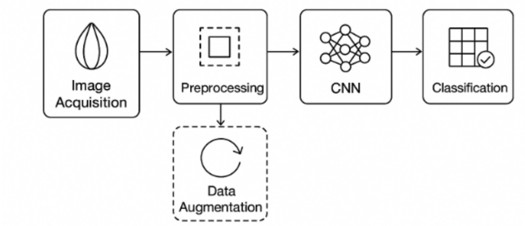

Figure 3: Deep Learning Pipeline for Seed Classification

To address overfitting and enhance the model's generalization capability, various data augmentation techniques are applied. These include geometric transformations such as rotation, translation, scaling, and flipping, as well as photometric adjustments like brightness and contrast normalization. Such augmentations simulate real-world variations in seed appearance caused by lighting, orientation, and positioning differences, enabling the model to learn robust and invariant feature representations.

3.2 CNN Architecture and Training

Typical Convolutional Neural Network (CNN) architectures used for plant seed classification comprise multiple convolutional and pooling layers responsible for hierarchical feature extraction, followed by fully connected layers that perform the final classification. The convolutional layers capture low-level visual features such as edges and textures, while deeper layers learn complex, high-level representations associated with seed morphology, surface texture, and shape.

Transfer learning has gained prominence in seed classification tasks, particularly when dealing with limited labeled data. Pre-trained models such as VGG16, ResNet, DenseNet, and EfficientNet have demonstrated superior performance by leveraging knowledge acquired from large-scale image datasets like ImageNet. Fine-tuning these networks on seed image datasets enables the model to adapt to the specific visual characteristics of different plant species and seed varieties, thereby improving classification accuracy and convergence speed. This approach not only mitigates the need for extensive data collection but also enhances model robustness and generalization across diverse seed categories.

3.3 Feature Extraction and Classification

Deep features extracted from the final convolutional layers of CNN architectures are often utilized as high-level representations of seed characteristics. These features capture intricate spatial and textural patterns that are highly discriminative for classification tasks. Instead of relying solely on end-to-end Softmax classification within the CNN framework, researchers have explored hybrid approaches where the extracted deep features are fed into classical classifiers such as Support Vector Machines (SVM), Random Forests, or ensemble-based techniques.

This integration leverages the representational robustness of CNN-derived features and the discriminative efficiency of traditional machine learning classifiers, resulting in improved performance and enhanced generalization across diverse seed species. Such hybrid methodologies have demonstrated particular effectiveness in scenarios involving imbalanced datasets or when distinguishing between visually similar seed categories.

3.4 Performance Evaluation

Performance evaluation is a critical aspect of assessing the reliability and generalization ability of deep learning-based seed classification models. Commonly employed metrics in the literature include **classification accuracy**, **precision**, **recall**, and the **F1-score**, which collectively provide a comprehensive understanding of a model's discriminative power and error tendencies. The **confusion matrix** is frequently analyzed to visualize class-wise performance and identify misclassification patterns among seed categories, particularly when dealing with morphologically similar species.

To ensure robustness, researchers often employ **k-fold cross-validation** and **independent test datasets** to evaluate the consistency and generalization capability of trained models across unseen data. In addition, some studies incorporate metrics such as the **Receiver Operating Characteristic (ROC) curve** and the **Area Under**

the Curve (AUC) to quantify classification confidence. These evaluation strategies collectively establish the statistical soundness of deep learning frameworks applied to seed recognition tasks, ensuring that models are not merely overfitting to the training data but are capable of performing effectively in real-world agricultural scenarios.

4. Comparative Analysis of Deep Learning Models

A variety of deep learning architectures have been explored for the classification of plant seeds, each demonstrating distinct advantages depending on the dataset characteristics and computational constraints. Table 1 summarizes the comparative performance of prominent models reported in recent studies.

Table 2. Comparative Study of Transfer Learning and Hybrid Models for Seed Recognition

Model	**Dataset**	**Accuracy (%)**	**Advantages**	**Limitations**
CNN (Custom)	Rice, Wheat	95.4	Simplicity, good baseline	Sensitive to dataset imbalance
ResNet-50 (Transfer Learning)	Plant Seedlings	98.1	High accuracy, feature reuse	High computational cost
DenseNet121	Seed Net	97.3	Dense connections improve gradient flow	Requires fine-tuning
CNN + ViT Hybrid	Custom Dataset	99.2	Better feature attention	Complex architecture
MobileNetV3	Field Images	94.8	Lightweight, deployable on edge devices	Lower accuracy for similar species

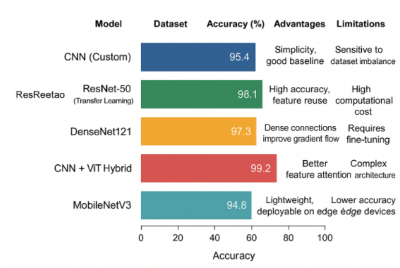

Figure 4: Deep Learning models with their accuracy, advantage and disadvantages.

The results in Figure 4 indicate that **transfer learning** and **hybrid architectures** significantly outperform traditional CNNs, particularly when dealing with complex or imbalanced datasets. Models such as **ResNet-50** and **DenseNet121** demonstrate excellent generalization due to feature reuse and enhanced gradient propagation. Conversely, lightweight models such as **MobileNetV3** offer a practical balance between accuracy and computational efficiency, making them suitable for **real-time applications in precision agriculture**. However, challenges such as inter-species similarity, dataset imbalance, and environmental variations still hinder model robustness, emphasizing the need for **domain adaptation and advanced attention-based architectures** in future studies.

5. Challenges and Limitations

Despite significant advancements in deep learning-based seed classification, several challenges persist that hinder large-scale implementation and real-world applicability. Addressing these limitations is crucial for improving model accuracy, reliability, and deployment feasibility in agricultural environments.

1. **Dataset Diversity:** The performance of deep learning models heavily depends on the availability of large and diverse datasets. However, most existing datasets contain limited seed species captured under controlled laboratory conditions. The absence of comprehensive datasets encompassing multiple crop varieties, growth stages, and environmental conditions restricts model generalization. Developing open-access, multi-species datasets with standardized imaging protocols can significantly enhance robustness and cross-domain adaptability.
2. **Lighting and Background Variations:** Variations in illumination, shadow, and background textures can substantially affect image quality and, consequently, model performance. Seeds captured under uncontrolled

field conditions often exhibit inconsistent visual properties. Incorporating domain adaptation techniques, image normalization strategies, and data augmentation methods can help mitigate these variations and improve model resilience to real-world conditions.

3. **Intra-Class Similarity:** Seeds belonging to morphologically similar species, such as different varieties of wheat or barley, exhibit minimal visual differences, making classification highly challenging. Advanced feature extraction mechanisms, attention-based architectures, and multimodal learning approaches integrating spectral or morphological data could provide improved discriminative capability in such cases.
4. **Model Interpretability:** Deep learning models are often criticized for their "black-box" nature, where the decision-making process remains opaque. This lack of interpretability reduces user trust and limits acceptance in regulatory or certification contexts. Future research should emphasize explainable AI (XAI) techniques to visualize and interpret feature importance, enabling domain experts to understand and validate model decisions.
5. **Hardware Constraints:** Training and deploying deep neural networks typically require high-performance GPUs and substantial memory resources. This poses a challenge for small-scale agricultural research institutions and developing regions with limited computational infrastructure. The adoption of lightweight architectures, model compression, pruning, and edge computing can facilitate the use of deep learning in resource-constrained environments.

In summary, future research should focus on building **generalizable, interpretable, and resource-efficient models** through advancements in dataset standardization, domain adaptation, and model optimization. Integrating multimodal data sources such as hyperspectral imaging and environmental metadata—may further enhance the precision and scalability of seed classification systems in practical agricultural applications.

6. Future Research Directions

1. **Explainable AI (XAI):** Implementing interpretable models to visualize and justify classification outcomes.
2. **Multimodal Learning:** Combining visual, spectral, and morphological data for more accurate classification.
3. **Edge AI and IoT Integration:** Deploying lightweight models on embedded systems for on-field real-time classification.
4. **Few-Shot and Semi-Supervised Learning:** Utilizing limited labeled data to expand recognition capability.
5. **Federated Learning:** Enabling distributed model training across agricultural institutions without sharing raw data.
6. **3D Seed Imaging:** Employing 3D imaging and volumetric CNNs for enhanced shape-based analysis.

7. Conclusion

Deep learning-based models have revolutionized the domain of plant seed classification by surpassing traditional handcrafted feature-engineering approaches in terms of accuracy, automation, and adaptability. Convolutional Neural Networks (CNNs), along with transfer learning frameworks such as ResNet and DenseNet, have demonstrated exceptional capabilities in extracting discriminative visual features from seed images, even under challenging imaging conditions. These models have enabled the development of robust and efficient classification systems that facilitate automated quality control, species identification, and variety recognition within modern agricultural practices.

However, despite these remarkable advancements, persistent challenges related to **dataset diversity**, **model interpretability**, and **computational efficiency** continue to limit the widespread deployment of such systems in real-world agricultural environments. The integration of **explainable AI (XAI)** techniques can enhance transparency and trust in model predictions, while **multimodal fusion** combining visual, spectral, and morphological data can strengthen discriminative performance. Furthermore, advancements in **edge computing** and **lightweight neural architectures** hold promise for enabling real-time, on-device inference, making deep learning solutions accessible to small-scale farmers and research institutions.

In conclusion, the continued evolution of deep learning, supported by interdisciplinary research in computer vision and agricultural science, is expected to make automated seed classification a vital tool in precision agriculture—promoting efficiency, sustainability, and scalability in global food production systems.

References

1. Kumar, S., Sripathy, K. V., Bhaskar, K. U., & Vinesh, B. (2023). Principles of quality seed production. Malavika Dadlani, 109.
2. Jadhav, S., Patil, A., & Deshmukh, P. (2023). *Seed Classification using Deep Learning Techniques.* Computers and Electronics in Agriculture, 209, 107894.
3. Zhang, Y., Chen, L., & Wang, F. (2022). *CNN-Based Plant Seed Recognition and Classification.* IEEE Access, 10, 67845–67855.
4. Xu, P., Tan, Q., Zhang, Y., Zha, X., Yang, S., & Yang, R. (2022). Research on maize seed classification and recognition based on machine vision and deep learning. Agriculture, 12(2), 232.
5. Singh, S. K., Jha, R., Pandey, S., Mohan, C., Ghosh, S., Singh, S. K., ... & Singh, A. (2025). Artificial intelligence-based tools for next-generation seed quality analysis. Crop Design, 100094.
6. Wu, H., Liu, T., & Zhao, J. (2022). *Hybrid CNN-ViT Architecture for Agricultural Image Classification.* Sensors, 22(15), 5642.
7. Sood, A., Sharma, R. K., & Bhardwaj, A. K. (2022). Artificial intelligence research in agriculture: A review. Online Information Review, 46(6), 1054-1075.
8. Trigka, M., & Dritsas, E. (2025). A comprehensive survey of deep learning approaches in image processing. Sensors, 25(2), 531.
9. Ramesh, M., & Singh, R. (2024). *Transfer Learning for Seed Image Classification using ResNet and EfficientNet.* Agricultural Informatics, 12(2), 145–158.
10. Alsajri, A., & Hacimahmud, A. V. (2023). Review of deep learning: Convolutional neural network algorithm. Babylonian Journal of Machine Learning, 2023, 19-25.
11. Srikar, M., & Malathi, K. (2022). A Supervised Stable Object Detection with Image Feature Extraction using Image Segmentation by Comparing Histogram of Oriented Gradients (HOG) Algorithm over Scale Invariant Feature Transform (SIFT) Algorithm Model. Journal of Pharmaceutical Negative Results, 13.
12. Shen, J., Yuan, M., Dong, Y., Lu, F., Zhan, K., & Ren, D. (2022, November). Classification of seeds based on a novel multiple feature combination descriptor. In 2022 China Automation Congress (CAC) (pp. 1869-1873). IEEE.
13. Eryigit, R., & Tugrul, B. (2021). Performance of Various Deep-Learning Networks in the Seed Classification Problem. Symmetry, 13(10), 1892. https://doi.org/10.3390/sym13101892
14. Jin, C., Zhou, L., Pu, Y. et al. Application of deep learning for high-throughput phenotyping of seed: a review. Artif Intell Rev 58, 76 (2025). https://doi.org/10.1007/s10462-024-11079-5
15. Rybacki P, Niemann J, Bahcevandziev K, Durczak K. Convolutional Neural Network Model for Variety Classification and Seed Quality Assessment of Winter Rapeseed. Sensors. 2023; 23(5):2486. https://doi.org/10.3390/s23052486.
16. Rybacki P, Niemann J, Bahcevandziev K, Durczak K. Convolutional Neural Network Model for Variety Classification and Seed Quality Assessment of Winter Rapeseed. Sensors. 2023; 23(5):2486. https://doi.org/10.3390/s23052486.
17. Deepali Koppad, K. V. Suma, and Nethra Nagarajappa. 2024. Automated Seed Classification Using State-of-the-Art Techniques. SN Comput. Sci. 5, 5 (May 2024). https://doi.org/10.1007/s42979-024-02759-8
18. Li, Q., & Zhou, Y. (2023). *Explainable Deep Learning for Agricultural Image Analysis.* Computers in Industry, 152, 104090.

Author Declaration:
The author declares no conflict of interest. This work serves as a comprehensive literature review to support further experimental research in agricultural deep learning systems.