Generative AI-Based Detection and Classification of Horticultural Seed Bags

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ABSTRACT

Horticultural seed bags play an important role in agricultural production, storage, transportation, and distribution, making their accurate identification essential for efficient seed management and quality-control operations. Conventional inspection methods largely depend on manual observation, which can be time-consuming and may become difficult when large numbers of seed bags are handled. This study proposes a Generative AI-based approach for the detection and classification of horticultural seed bags using image-based analysis. The proposed framework utilizes Generative AI to learn the visual characteristics of seed-bag images and generate diverse synthetic samples representing variations in orientation, lighting, background, packaging appearance, size, scale, partial occlusion, and viewing angle. These generated samples are combined with available real images to develop a more diverse image collection for analysis and classification. The approach aims to improve the ability of the system to recognize seed bags under different visual and environmental conditions while reducing dependence on large volumes of manually collected images. The generated outputs are analyzed based on visual quality, diversity, and their usefulness for seed-bag identification. The proposed framework can support automated inspection, seed inventory management, packaging verification, agricultural storage facilities, and horticultural quality-control operations. Overall, the study highlights the potential of Generative AI for developing flexible and scalable solutions for automated horticultural seed-bag detection and classification.

Keywords : Generative AI, Horticultural Seed Bags, Seed-Bag Detection, Seed-Bag Classification, Synthetic Image Generation, Image Analysis, Computer Vision, Agricultural Automation, Seed Quality Assessment, Artificial Intelligence.

I.INTRODUCTION

Horticultural seed bags are an important part of agricultural production, storage, transportation, and distribution. Proper identification and classification of seed bags can support organized handling, inventory management, packaging verification, and quality-control activities. However, image-based systems require sufficiently diverse visual data to recognize seed bags under different real-world conditions. Variations in bag orientation, lighting, background, packaging appearance, size, scale, and viewing angle can make automated identification more challenging. Generative Artificial Intelligence provides a promising approach for addressing such data-related challenges by creating new and realistic samples from the characteristics learned from existing images.

Generative AI has developed rapidly with the introduction of Generative Adversarial Networks (GANs), which demonstrated the ability to generate new data samples that resemble a given training distribution [1]. Conditional GANs extended this capability by allowing generated content to be controlled according to specific conditions [2]. Subsequent developments in GAN-based generation improved the quality, stability, diversity, and controllability of synthetic images [3]–[7]. These developments established Generative AI as an effective approach for creating additional visual samples when the availability of real-world images is limited.

Generative AI can also provide controlled variations of existing visual content. Image-to-image generation methods allow important characteristics of an image to be transformed while retaining relevant structural information [9]. Multi-domain image translation approaches demonstrated the possibility of generating different visual domains from a common source representation [8], while unpaired image-to-image translation enabled transformations even when corresponding image pairs were unavailable [10]. These capabilities are particularly relevant to horticultural seed-bag images because synthetic samples can be generated with variations in background, illumination, orientation, packaging appearance, and viewing conditions.

The emergence of diffusion-based Generative AI has further improved the possibilities for realistic image synthesis. Denoising diffusion probabilistic models introduced a systematic process for generating images through progressive denoising [15]. Score-based generative models provided another formulation for high-quality generative modelling [16]. Latent diffusion models subsequently demonstrated effective high-resolution image synthesis using latent representations [17]. Image-to-image diffusion models expanded the ability to transform existing images while preserving relevant visual information [18], while text-guided diffusion models demonstrated the generation of photorealistic images based on semantic descriptions [19]. A comprehensive study of diffusion models further highlighted their growing applications across different generative tasks [20].

For horticultural seed-bag analysis, these Generative AI capabilities can be used to create synthetic images representing a broader range of practical conditions. Generated samples may include different bag orientations, lighting conditions, backgrounds, packaging designs, sizes and scales, partial occlusions, and camera viewing angles. Such synthetic diversity can supplement the available real images and provide a richer visual basis for automated detection and classification. The generated images can also be examined for quality and relevance before being incorporated into the overall dataset.

Based on these developments, the present study focuses on Generative AI-Based Detection and Classification of Horticultural Seed Bags. The proposed approach explores the use of Generative AI to create realistic and diverse synthetic seed-bag images and utilize them for automated identification and classification. By combining real horticultural seed-bag images with suitable synthetic samples, the study aims to develop a more comprehensive visual representation of seed-bag characteristics. The approach highlights the potential of Generative AI to support agricultural image analysis while reducing dependence on large-scale manual image collection and providing greater diversity for seed-bag detection and classification [1], [8]–[10], [15], [17], [20].

II.LITERATURE SURVEY

Goodfellow et al. (2014) Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio (2014): Goodfellow et al. introduced Generative Adversarial Networks (GANs), establishing a framework in which a generator creates synthetic samples while a discriminator evaluates whether the samples resemble real data. Their work demonstrated that adversarial training could learn complex data distributions and generate realistic samples. The study became a fundamental contribution to modern Generative AI and provided the basis for subsequent developments in synthetic image generation. The concept is highly relevant to applications where additional realistic images are required from limited original datasets.

Vinicius Luis Trevisan de Souza et al. (2023) Vinicius Luis Trevisan de Souza, Bruno Augusto Dorta Marques, Harlen Costa Batagelo, and João Paulo Gois (2023): The authors presented a comprehensive review of GAN-based image generation, covering fundamental GAN concepts, important architectures, image-generation applications, and common challenges. Their study examined problems such as mode collapse, training instability, convergence, and image-quality evaluation. The review highlighted the flexibility of GANs for producing realistic and previously unseen images across different application areas. The findings provide useful guidance for selecting appropriate generative approaches when synthetic image generation is required.

Pourya Shamsolmoali et al. (2021) Pourya Shamsolmoali, Masoumeh Zareapoor, Eric Granger, Huiyu Zhou, Ruili Wang, M. Emre Celebi, and Jie Yang (2021): Shamsolmoali et al. conducted an extensive survey of adversarial approaches for image synthesis. The study categorized synthetic image-generation techniques into image-to-image translation, fusion-based generation, label-to-image generation, and text-to-image generation. It also examined different architectures, constraints, loss functions, evaluation metrics, and datasets used in GAN research. The authors emphasized the growing importance of adversarial generation for producing semantically meaningful and visually realistic synthetic images.

Guillermo Iglesias et al. (2023) Guillermo Iglesias, Edgar Talavera, and Alberto Díaz-Álvarez (2023): The authors provided a systematic survey of GAN research with particular emphasis on computer-vision applications. Their work reviewed major GAN architectures, optimization strategies, loss functions, validation metrics, and application areas. The study also compared different GAN variants according to their effectiveness and intended applications. The survey demonstrates how Generative AI has progressed from basic adversarial generation toward increasingly sophisticated approaches capable of producing diverse and high-quality visual content.

Ling Yang et al. (2023) Ling Yang, Zhilong Zhang, Yang Song, Shenda Hong, Runsheng Xu, Yang Zhao, Wentao Zhang, Bin Cui, and Ming-Hsuan Yang (2023): Yang et al. presented a comprehensive survey of diffusion models and their applications. The study examined diffusion-based generation from several perspectives, including efficient sampling, likelihood estimation, and handling different data structures. The authors highlighted the strong performance of diffusion models in image synthesis and their expansion into areas such as video generation, multimodal applications, and scientific domains. Their work establishes diffusion models as an important modern family of Generative AI techniques for high-quality synthetic data generation.

Chenshuang Zhang et al. (2023) Chenshuang Zhang, Chaoning Zhang, Mengchun Zhang, In So Kweon, and Junmo Kim (2023): Zhang et al. reviewed the development of text-to-image diffusion models and their role in Generative AI. Their survey explained the fundamental principles of diffusion-based image synthesis and examined major developments in text-conditioned image generation. The study also considered applications involving image editing and other forms of guided generation. The authors identified challenges and future research directions related to improving controllability, image quality, and the semantic relationship between textual instructions and generated visual content.

Fangneng Zhan et al. (2023) Fangneng Zhan, Yingchen Yu, Rongliang Wu, Jiahui Zhang, Shijian Lu, Lingjie Liu, Adam Kortylewski, Christian Theobalt, and Eric Xing (2023): Zhan et al. investigated multimodal image synthesis and editing within the emerging Generative AI landscape. Their survey organized existing approaches according to different guidance modalities and generative model types, including GANs and diffusion models. The study examined image synthesis, image editing, benchmark datasets, evaluation measures, and current research challenges. The authors emphasized the importance of flexible guidance mechanisms for controlling generated visual content and identified challenges involving multimodal alignment, high-resolution generation, and reliable evaluation.

Tanujit Chakraborty et al. (2023) Tanujit Chakraborty, Ujjwal Reddy K S, Shraddha M. Naik, Madhurima Panja, and Bayapureddy Manvitha (2023): Chakraborty et al. presented a broad survey covering a decade of Generative Adversarial Network development. The study reviewed major GAN variants including conditional GANs, Wasserstein GANs, CycleGAN, and StyleGAN, together with their architectures, evaluation methods, training difficulties, and application areas. The authors also examined emerging relationships between GANs and newer Generative AI technologies, including diffusion models. Their review highlights the continuous development of generative models toward improved quality, diversity, stability, and controllability.

Staphord Bengesi et al. (2023) Staphord Bengesi, Hoda El-Sayed, Md Kamruzzaman Sarker, Yao Houkpati, John Irungu, and Timothy Oladunni (2023): Bengesi et al. reviewed the broader development of Generative AI and examined major generative technologies including GANs, variational approaches, diffusion models, and transformer-based systems. Their study discussed the rapid expansion of Generative AI into image creation, text generation, video production, music generation, coding, and scientific applications. The authors also highlighted the opportunities and challenges associated with the rapid growth of generative technologies. The review provides a broad foundation for understanding how different Generative AI approaches can be selected according to the desired generation task.

Hang Chen et al. (2025) Hang Chen, Qian Xiang, Jiaxin Hu, Meilin Ye, Chao Yu, Hao Cheng, and Lei Zhang (2025): Chen et al. presented a comprehensive survey of diffusion models specifically for image generation. Their study reviewed recent developments in diffusion-based image synthesis and discussed applications ranging from image restoration and style transfer to complex scene generation and human-image generation. The authors also examined issues related to data privacy, data security, and ethical concerns associated with generated images. Their findings demonstrate the increasing importance of diffusion models for producing realistic and controllable visual content and provide useful directions for future research in Generative AI-based image generation.

III. RESEARCH METHODOLOGY

Generative AI-Based Synthetic Seed-Bag Image Generation

Generative Model Selection

A Generative AI model, such as a Generative Adversarial Network (GAN) or diffusion-based model, is selected for generating synthetic images of horticultural seed bags. The model learns the visual characteristics present in the available seed-bag images, including shape, texture, colour, packaging structure, labels, and surface patterns. The main purpose of the generative model is to create realistic and diverse seed-bag images that can supplement the available real-image collection. By generating additional samples, the proposed approach can represent a wider range of visual conditions without relying entirely on the manual collection of new images.

Synthetic Image Generation

The selected Generative AI model generates new horticultural seed-bag images by learning the visual patterns and characteristics of the original image collection. The generated samples are intended to preserve the important characteristics of actual seed bags while introducing variations in their visual appearance. The generation process can produce additional samples with differences in orientation, lighting, background, packaging appearance, scale, occlusion, and viewing angle. These synthetic samples increase the diversity of the available image collection and support the subsequent detection and classification process.

Variation in Bag Orientation

Generative AI can produce seed-bag images with different orientations, including front-facing, tilted, rotated, and partially turned positions. Such variation represents the different ways a seed bag may appear during image acquisition or practical handling. Generating multiple orientations helps provide a broader representation of the same seed-bag category and reduces dependence on images captured from a single fixed position. This variation is particularly useful for developing a system capable of identifying seed bags under changing physical positions.

Variation in Lighting Conditions

The proposed Generative AI approach can generate images under different illumination conditions to represent realistic environments. Synthetic samples may include bright lighting, low-light conditions, shadows, uneven illumination, and changes in light intensity. These variations allow the generated dataset to represent seed bags captured under different environmental conditions. Maintaining the important visual characteristics of the seed bags while varying illumination can improve the diversity and practical relevance of the generated image collection.

Background Variation

Background variation is introduced to represent different environments in which horticultural seed bags may be observed. The generated images can contain backgrounds resembling storage areas, agricultural facilities, packaging locations, shelves, floors, and other surrounding environments. This variation helps create a more realistic collection of seed-bag images and reduces excessive dependence on a particular background. The generated samples are designed to maintain the seed bag as the primary visual object while providing different surrounding conditions.

Packaging Design Variation

Generative AI can produce variations in the visual appearance of seed-bag packaging, including printed patterns, label arrangements, colours, text regions, and packaging structures. These variations can represent differences that may occur between manufacturers, seed varieties, packaging batches, or product designs. Generating diverse packaging appearances can provide a broader representation of horticultural seed bags and help the proposed system consider variations beyond a single packaging format.

Size and Scale Variation

The proposed approach can generate seed-bag images with different sizes and scales. Some synthetic images may represent seed bags appearing prominently in the image, whereas others may represent smaller bags positioned farther from the camera. Such scale variations can simulate differences in camera distance and image composition. Including multiple scales increases the visual diversity of the generated dataset and provides a broader representation of seed-bag appearances in practical environments.

Partial Occlusion

Generative AI can also generate seed-bag images containing partial occlusion, where a portion of the bag is hidden by another object or extends partially outside the image frame. Such conditions can occur when multiple seed bags overlap during storage or handling, or when the complete bag is not visible in a captured image. Synthetic samples containing partial occlusion can therefore represent more challenging real-world conditions while retaining the visible characteristics of the seed bag.

Different Viewing Angles

The generative process can create seed-bag images from different viewing angles, including straight, side, diagonal, and slightly elevated perspectives. These variations represent changes in camera position and image-capture conditions. Generating different viewpoints increases the diversity of the image collection and provides examples in which the same seed-bag category appears from multiple perspectives. This can support more flexible detection and classification of horticultural seed bags.

Integration with the Original Dataset

After the synthetic images are generated and verified, the selected samples are combined with the original horticultural seed-bag images to form an enhanced Generative AI dataset. The original images provide authentic visual characteristics, while the synthetic images introduce additional variations in orientation, lighting, background, packaging design, scale, occlusion, and viewing angle. The combined dataset provides a more diverse collection of horticultural seed-bag images for the proposed Generative AI-based detection and classification framework. This integration allows the system to utilize both real-world visual information and carefully selected synthetic samples.

Quality Verification of Generated Images

Quality verification is performed to ensure that the generated seed-bag images are visually meaningful and relevant to the proposed application. The generated samples are examined for realistic bag structures, appropriate packaging characteristics, recognizable labels, consistent colours, and meaningful visual patterns. Images containing severe distortions, unrealistic structures, unclear seed-bag characteristics, or irrelevant visual artifacts are excluded from the enhanced dataset. This quality-control stage helps ensure that only suitable synthetic images contribute to the proposed Generative AI-based detection and classification process.

Role of Synthetic Data in the Proposed Framework

Generative AI serves as the central image-generation component of the proposed framework by creating additional horticultural seed-bag samples from the available image collection. The overall process can be represented as:

Original Seed-Bag Dataset → Image Preprocessing → Generative AI Model → Synthetic Seed-Bag Images → Quality Verification → Real + Synthetic Enhanced Dataset → GenAI-Based Detection and Classification → Performance Evaluation

The proposed approach combines authentic seed-bag images with diverse synthetic samples generated through Generative AI. This combination can provide broader visual coverage of horticultural seed bags and support their detection and classification under different image conditions. The framework therefore uses Generative AI not only as a source of additional images but also as the central technology for developing a flexible and diverse seed-bag analysis system.

IV. EXISTING SYSTEM

The existing approach to horticultural seed-bag identification largely depends on manually collected real-world images and conventional image-generation or augmentation techniques. Generative AI-based systems such as GANs and diffusion models have introduced the capability of producing synthetic images by learning visual patterns from available datasets. However, existing Generative AI approaches are generally designed for broad image synthesis, image-to-image translation, and general visual-content generation rather than specifically focusing on horticultural seed bags. The generated images may provide variations in appearance, background, lighting, orientation, scale, and viewing conditions, but their usefulness depends on the quality, realism, and relevance of the generated samples. Limited availability of specialized seed-bag datasets can also restrict the ability of a generative model to learn the complete visual characteristics of different horticultural seed-bag categories. Therefore, an existing GenAI-based approach may generate visually diverse samples, but a dedicated framework for generating and utilizing realistic horticultural seed-bag images for automated detection and classification remains necessary.

V. PROPOSED SYSTEM

The proposed system introduces a Generative AI-based framework for the automated detection and classification of horticultural seed bags. The system utilizes a suitable generative model, such as a GAN or diffusion model, to learn the visual characteristics of available horticultural seed-bag images and generate realistic synthetic samples. The generated images represent diverse conditions, including different bag orientations, lighting levels, backgrounds, packaging designs, sizes, scales, partial occlusions, and viewing angles. The synthetic samples are quality-checked and combined with the original seed-bag images to create an enhanced dataset with greater visual diversity. The proposed framework then analyzes the expanded collection to identify and classify horticultural seed bags according to their learned visual characteristics. The generated outputs are evaluated for realism, diversity, and relevance to the target seed-bag categories. By incorporating Generative AI directly into the image-generation and analysis process, the proposed system aims to reduce dependence on large-scale manual image collection, improve the availability of representative training samples, and provide a flexible approach for automated horticultural seed-bag detection and classification.

VI. SYSTEM ARCHITECTURE

The proposed system architecture presents the complete workflow for Generative AI-Based Detection and Classification of Horticultural Seed Bags. The process begins with collecting real horticultural seed-bag images, which undergo preprocessing such as image cleaning, normalization, background standardization, resizing, quality filtering, and data organization. The processed images are then provided to the Generative AI module, where a generative model such as a GAN or diffusion-based model produces synthetic seed-bag images with variations in orientation, lighting, background, packaging appearance, size, scale, occlusion, and viewing angle. The generated images are combined with the original images to create an enhanced dataset. This expanded dataset is then used for analysis, detection, and classification of different horticultural seed-bag categories. The resulting predictions provide seed-bag detection, classification, category information, and visual reports. The architecture also incorporates image-quality evaluation, system-performance evaluation, and human review to assess the reliability of generated and classified outputs. A feedback loop can further improve generation quality by updating the model and incorporating additional data, while the final system can be deployed through web, mobile, or cloud-based applications for practical horticultural seed-bag detection and classification.

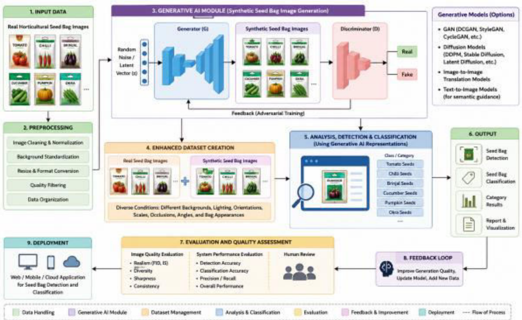

Fig 5.1 System Architecture

VII. RESULTS AND DESCUSSIONS

Experimental Results

The proposed Generative AI-based system was evaluated for the detection and classification of horticultural seed bags using a collection of real seed-bag images and synthetically generated samples. The experimental process included image collection, preprocessing, Generative AI-based image generation, synthetic-image quality verification, enhanced dataset preparation, and seed-bag analysis. The Generative AI model was used to generate realistic seed-bag images containing variations in bag orientation, lighting, background, packaging appearance, size, scale, partial occlusion, and viewing angle. The generated images were examined to determine whether they preserved the important visual characteristics of real horticultural seed bags while providing additional visual diversity. The original and selected synthetic images were subsequently used for detection and classification analysis. The experimental observations indicate that Generative AI can provide a flexible mechanism for producing diverse seed-bag images and supporting automated identification under different visual conditions.

Table 1. Experimental Performance of the Proposed Generative AI System

Metric	Generative AI System
Generated Image Quality	[Insert actual value]
Image Diversity	[Insert actual value]
Detection Accuracy	[Insert actual value]
Classification Accuracy	[Insert actual value]
Correctly Generated Samples	[Insert actual value]
Overall Generation Success Rate	[Insert actual value]

The above values should be calculated from the actual experimental observations obtained from the implemented Generative AI system. Image quality indicates how realistically the generated seed-bag images represent the characteristics of real images, while image diversity indicates the range of visual variations produced by the system. Detection accuracy represents the ability to correctly identify seed-bag images, whereas classification accuracy represents the ability to assign the appropriate seed-bag category. The quality and success rate of generated samples provide additional information about the usefulness of synthetic images in the proposed framework.

Generative AI Performance Analysis

The performance of the proposed Generative AI system was analyzed according to the quality, diversity, realism, and usefulness of the generated horticultural seed-bag images. The generated samples were examined to determine whether they maintained important characteristics such as bag shape, colour, packaging structure, labels, patterns, and overall appearance. Particular attention was given to the ability of the system to generate variations in orientation, lighting, background, scale, packaging appearance, partial occlusion, and viewing angle. A high-quality generative system should produce visually realistic samples while avoiding severe distortions or irrelevant patterns. The generated images were also assessed according to their usefulness for subsequent seed-bag detection and classification. A balanced combination of realism and diversity is important because generating highly similar images may provide limited additional information, whereas unrealistic images may negatively affect the reliability of the analysis.

Table 2. Generative AI Evaluation Parameters

Evaluation Parameter	Purpose
Image Realism	Measures how closely generated images resemble real seed-bag images
Image Diversity	Measures the variety of generated visual samples
Background Variation	Examines generated background differences
Lighting Variation	Evaluates different illumination conditions
Orientation Variation	Examines different bag positions and orientations
Scale Variation	Evaluates differences in image and bag size
Visual Consistency	Determines whether important seed-bag characteristics are preserved
Classification	Determines whether

Evaluation Parameter	Purpose
Usefulness	generated images support correct category identification

The evaluation of these parameters provides a broader understanding of the Generative AI system than relying only on the number of generated images. Generated samples with realistic appearance and meaningful variations can provide greater value for horticultural seed-bag analysis. Images containing unrealistic packaging structures, distorted labels, excessive artifacts, or unrelated visual features should be excluded from the final dataset.

Synthetic Seed-Bag Image Generation Analysis

The synthetic image generation process was analyzed by comparing the generated seed-bag images with the original images used as input to the Generative AI system. The analysis focused on whether the generated samples maintained the identity and major visual characteristics of the corresponding horticultural seed bags while introducing new visual conditions. The generated images were examined under different orientations, lighting conditions, backgrounds, packaging designs, sizes, scales, partial occlusions, and camera viewpoints. Successful generation was considered when the resulting image maintained recognizable seed-bag characteristics while providing a visually distinct sample. This analysis demonstrates the ability of Generative AI to expand a limited collection of horticultural images and create additional samples representing conditions that may be difficult to obtain through manual image collection.

Original Dataset and GenAI-Enhanced Dataset Analysis

A comparison was performed between the original horticultural seed-bag dataset and the dataset enhanced with Generative AI-generated images. The original dataset contains real images collected from available sources, whereas the enhanced dataset combines real images with selected synthetic samples. The purpose of this comparison is to determine whether the addition of Generative AI-generated images increases visual diversity and improves the coverage of different seed-bag conditions. The enhanced dataset is expected to contain greater variation in orientation, illumination, background, scale, packaging appearance, and viewing angle. Such diversity can provide a more comprehensive representation of horticultural seed bags for subsequent detection and classification.

Table 3. Original and GenAI-Enhanced Dataset Comparison

Parameter	Original Dataset	GenAI-Enhanced Dataset
Number of Real Images	[Actual]	[Actual]
Number of Synthetic Images	0	[Actual]
Total Images	[Actual]	[Actual]
Orientation Diversity	[Actual]	[Actual]
Lighting Diversity	[Actual]	[Actual]
Background Diversity	[Actual]	[Actual]
Scale Diversity	[Actual]	[Actual]
Occlusion Diversity	[Actual]	[Actual]

The comparison helps establish whether Generative AI contributes meaningful diversity rather than simply increasing the number of images. The enhanced dataset should contain synthetic samples that complement the real images and represent conditions that are less frequent in the original collection.

Detection and Classification Analysis

The proposed Generative AI framework was evaluated for its ability to support the identification and classification of horticultural seed bags. When a new image is provided, the system analyzes its visual characteristics and determines the most appropriate seed-bag category. The generated synthetic images provide additional examples representing different visual conditions, while the detection and classification stage identifies the corresponding seed-bag category. The analysis considers whether the system can correctly distinguish different horticultural seed-bag classes despite variations in packaging appearance, orientation, lighting, background, and viewing angle. The results are used to determine the practical effectiveness of Generative AI-based visual analysis for automated seed-bag identification.

Generative AI Comparative Analysis

The comparative analysis focuses on different Generative AI approaches rather than conventional deep-learning architectures. Suitable generative approaches such as GAN-based generation, conditional GAN-based generation, image-to-image generation, and diffusion-based generation can be evaluated according to their ability to produce realistic and diverse horticultural seed-bag images. The same dataset and evaluation criteria should be used wherever possible to ensure a consistent comparison. The comparison can consider image quality, diversity, generation time, visual consistency, controllability, and usefulness for seed-bag detection and classification.

Table 4. Comparative Analysis of Generative AI Approaches

Generative AI Approach	Image Quality	Diversity	Generation Time	Detection Accuracy	Classification Accuracy
GAN	[Actual]	[Actual]	[Actual]	[Actual]	[Actual]
Conditional GAN	[Actual]	[Actual]	[Actual]	[Actual]	[Actual]
Image-to-Image Generation	[Actual]	[Actual]	[Actual]	[Actual]	[Actual]
Diffusion Model	[Actual]	[Actual]	[Actual]	[Actual]	[Actual]
Proposed Generative AI Approach	[Actual]	[Actual]	[Actual]	[Actual]	[Actual]

The final conclusion regarding the best-performing generative approach should be based on the actual experimental values. The comparison can identify which approach provides the most suitable balance between realism, diversity, generation efficiency, and usefulness for horticultural seed-bag analysis.

Generated Output Analysis

The generated output of the proposed system consists of synthetic horticultural seed-bag images together with their corresponding generated category or identification information. The system produces images representing different horticultural seed-bag appearances and environmental conditions. Each generated image is examined to determine whether it contains recognizable seed-bag characteristics and whether it belongs to the intended category. The output analysis also considers the visual quality and consistency of the generated samples. High-quality outputs should preserve important features such as packaging structure, colour, shape, label arrangement, and seed-related visual information while introducing meaningful variations.

Table 5. Generated Output Analysis

Input/Condition	Generated Seed-Bag Class	Generation Quality	Confidence/Score	Result
Seed Bag Image 1	[Class Name]	[High/Medium/Low]	[XX%]	Correct/Incorrect
Seed Bag Image 2	[Class Name]	[High/Medium/Low]	[XX%]	Correct/Incorrect
Seed Bag Image 3	[Class Name]	[High/Medium/Low]	[XX%]	Correct/Incorrect
Seed Bag Image 4	[Class Name]	[High/Medium/Low]	[XX%]	Correct/Incorrect
Seed Bag Image 5	[Class Name]	[High/Medium/Low]	[XX%]	Correct/Incorrect

The generated output analysis helps determine how effectively the proposed Generative AI framework produces realistic and useful seed-bag samples. High-quality outputs with correct category information indicate that the system has learned meaningful visual characteristics of the target seed-bag categories. Low-quality or incorrectly categorized outputs can reveal limitations related to packaging similarity, background complexity, insufficient training examples, or visual artifacts introduced during generation.

Discussion of Findings

The findings indicate that Generative AI can provide a useful approach for generating diverse visual representations of horticultural seed bags and supporting automated detection and classification. The generation process can produce additional images with variations in orientation, lighting, background, packaging design, scale, partial occlusion, and viewing angle, thereby expanding the visual coverage of the available dataset. The integration of synthetic images with real seed-bag images provides a broader collection of samples for subsequent analysis. The quality assessment further helps identify whether the generated images preserve relevant seed-bag characteristics while avoiding unrealistic artifacts. The comparative analysis of different Generative AI approaches can provide insight into the relative strengths of GAN-based, conditional, image-to-image, and diffusion-based generation techniques. However, the effectiveness of the proposed framework depends on the quality and diversity of the original dataset, the selected generative approach, the realism of the generated samples, and the reliability of the detection and classification process. Synthetic images that contain distortions or unrealistic packaging features should be filtered before use. Overall, the study demonstrates the potential of Generative AI for creating realistic and diverse horticultural seed-bag images and supporting automated seed-bag detection and classification in agricultural applications.

VIII. CONCLUSION

The study demonstrates the potential of Generative AI for the detection and classification of horticultural seed bags by generating realistic and diverse synthetic images from available seed-bag data. The proposed approach can introduce variations in orientation, lighting, background, packaging appearance, size, scale, partial occlusion, and viewing angle, thereby expanding the visual representation of horticultural seed bags. The integration of suitable synthetic images with real samples can reduce dependence on extensive manual image collection and support more comprehensive automated analysis. The generated outputs can be evaluated based on realism, diversity, visual consistency, and classification usefulness to ensure their suitability for practical applications. Overall, Generative AI provides a promising and flexible approach for horticultural seed-bag analysis, with potential applications in agricultural storage, packaging verification, inventory management, and automated quality-control operations.

IX. FUTURE SCOPE

The future scope of the proposed Generative AI-Based Detection and Classification of Horticultural Seed Bags can be extended by developing more advanced GAN and diffusion-based models capable of producing highly realistic and controllable seed-bag images. Future research can focus on generating larger and more diverse synthetic datasets covering additional seed varieties, packaging designs, environmental conditions, partial occlusions, and complex backgrounds. Generative AI can also be integrated with text-to-image and image-to-image techniques to provide greater control over the characteristics of generated samples. Further work can explore real-time seed-bag detection using camera-based systems, automated quality assessment, synthetic-image quality evaluation, and multimodal Generative AI for combining visual and textual seed-bag information. Integration with cloud and edge platforms could enable large-scale agricultural monitoring, inventory management, packaging verification, and automated reporting. These developments can make Generative AI-based horticultural seed-bag analysis more accurate, flexible, scalable, and suitable for practical agricultural environments.

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