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Extensive Analysis of Field Adapting Strategies for Smart Farming's Farming Processing of Images

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Abstract
Precision agriculture has led to the incorporation of computer vision and machine learning that has made it possible to achieve successful improvements in crop management, disease identification, and output estimation. Nevertheless, its applicability to model generalization on alternative farming conditions is limited because of the lack of large labelled agricultural data. Domain adaptation has proven to be a strong tool to address the performance gap between the source domain and the target domain, making it robust in analyzing the images regardless of the changing climatic, geographical and crop dependent conditions. This review gives in-depth analysis of the recent methods of domain adaptation used in agricultural image analysis like transfer learning, adversarial learning, feature alignment, and self-supervised methods. We divide methods into categories explained by the strategy they utilize, point out their strengths in terms of performing weed detection, counting fruits, and classifying diseases, and mention the most important problems such as data heterogeneity, domain shift, and computational complexity. Lastly, the future research vectors are presented, and the researchers focus on the multimodal fusion of information, the possibility of using lightweight architectures in real-time and the role of foundation models in smart farming systems.

Keywords: ***Precision agriculture, domain adaptation, agricultural image analysis, transfer learning, adversarial learning, crop disease detection, weed recognition, feature alignment, smart farming, computer vision.***

1.Introduction

Artificial intelligence integration into an agricultural environment has provided new opportunities to enhance management over crops, detect diseases and predict yields. Central to this development is the use of agricultural image analysis, which is highly dependent on the machine learning and computer vision algorithms to help comprehend various forms of visual information that has been captured with the help of satellites, drones, and land-based sensors. However, whereas, such models tend to work excellently in controlled settings, they fail relatively badly when implemented in new or changing sets. This is a challenge caused by the issue of domain shift in the sense of the statistical distribution of training data is not the same as that of application data. The effect of domain shift is intensified in farmlands because agricultural land always faces unstable weather conditions, diverse crops, geographical diversity, and discrepancy in image sensors. Consequently, models that are trained using a particular dataset-e.g., tomato disease images of a given experimental farm, will not only be prone to fail when transferred to a different region or season but also experience diminished accuracy and low generalizability of smart farming solutions(1).

Domain adaptation (DA) has consequently appeared as a crucial mechanism towards achieving the resilience and robustness of agricultural image analysis systems. Being a specific type of transfer learning, DA seeks to align feature representations in source and target domains such that algorithms could achieve good performance irrespective of having to deal with previously unseen environments. In contrast to the common transfer learning, which can include variations in both tasks and domains, the problem of domain adaptation supposes the common task and minimizes differences between data distributions. That is why it is especially appropriate in the area of agriculture where dominant activities, like the identification of diseases, mapping of weeds, and agricultural scouting crop surveillance, are the same, yet the observed physical conditions differ exponentially depending on the environment.

Farm scenes are a subject of many variations. RGB cameras can detect normal, near-IR devise can be used to measure physiological characteristics such as chlorophyll content and hyperspectral cameras can detect hundreds of spectral bands used to distinguish between subtle plant stress conditions. Moreover, environmental influences like altering amount of light over a day or change in weather conditions with seasons and equipment put into background diversity of soils further adds to the even-handedness of visual knowledge. Such differences cause challenging domain incongruities that derail a direct transfer of off-the-shelf computer vision models, particularly ones that are initially trained on general use datasets such as ImageNet. Therefore, classical computer vision pipelines are not sufficient in regards to agricultural applications, which have to adopt adaptive frameworks that can accommodate domain discrepancies and bases its performance on few labeled data.

FIGURE 1 Domain Adaptation in Agricultural Image Analysis

The difficulty is compounded by a lack of annotations. Identifying the agricultural images usually demands the skills of agronomists or plant pathologists and is time consuming, expensive and usually impractical when handled in large proportions. As an illustration, disease detection on wheat rust at different growth phases or annotation of aerial images on weed infestation area involves thorough knowledge of the domain as well as careful annotation. Unlike in other fields like natural image classification where millions of annotated images are available, agricultural datasets are still very small and lack diversities. This bottleneck can be mitigated with domain adaptation techniques that can be used to generalize a model so that it can transfer the knowledge it has learned onto a new domain, with few or even no labels. By means of methods such as adversarial training, feature alignment, and self-supervised learning, DA methods help to decrease the required amount of meticulous yourself labeling albeit rise in generalization(2).

In the past ten years studies have been conducted that demonstrate the potential of transformation of the DA in agricultural setting. The uses include crop disease and pest identification, counting of fruits and monitoring their growth as well as the identification of livestock among others. As an example, techniques that are based on the adversarial domain adaptation strategy are able to effectively transfer pest detection models between seasons, as well as between geographic regions, and the approaches of feature alignment have contributed to the recognition of crop varieties addressed in different soil and light contexts. Also, the flexibility of DA is not limited to the plant-oriented applications; it has also been used on animal farm, like re-identifying cows over different barns with different camera layouts. The achievements of these successes demonstrate that domain adaptation is more than a technical solution to the challenges of precision agriculture but an enabler of scalable precision agriculture.

At present, DA use in agriculture is in its infancy compared to other more advanced fields such as natural image recognition. Although many surveys in the field of general computer vision are available, there are still a limited number of systematic reviews that are specifically adjusted to situations within agriculture. Such a gap indicates the significance of synthesis of knowledge in this area, i.e., the summarization of methodologies, classification of approaches, and estimation of the performance over sample datasets. An adequate taxonomy is necessary that can not only help with academic research but also give a proper taxonomy that could be used in industry. Generally speaking, there are two paradigms of DA methods in agriculture; shallow paradigm based on handcrafted features and conventional machine learning, and deep learning paradigm based on neural networks to enable automated feature extraction. Shallow approaches provide approaches like classifier adjustment, subspace learning, and sample reweighting, and can be effectively computational, which makes them appropriate in resource-scarce conditions. By contrast, recent advances have focused on deep methods, which propose adversarial networks, discrepancy-based training and self-supervised adaptation rules, which discover more powerful representations.

2.Background

The key concept that needs to be addressed when analyzing the role of domain adaptation in agricultural image analysis is the challenges caused by the domain shift itself and the principles that distinguish the concept of domain adaptation with other similar aspects, such as the concept of transfer learning. Image based models used in farming do not get created in a vacuum, and they have to operate within an environment that varies unfathomably in bright lights, climatic differences, crop type, soil background, and types of sensors used. The causes lead to data distributions which differ during training and deployment, leading to a state, where models trained over a source dataset struggle to generalize to other target domains. Domain shift is a common phenomenon that is especially significant in the agricultural field due to the fact that it relies on the outdoor environment which is by its nature dynamic and heterogeneous(3). To illustrate, a crop disease model that is trained in the maize fields, of one region, may not work in a different country in which maize replaces the phenotypic properties, or the imagery is collected using various cameras. These inconsistencies illuminate the need to use domain adaptation to make efficient and transferable smart farming systems even more robust.

Domain adaptation has a different concept which needs to be understood individually so as to have a clear understanding of what it encompasses with respect to transfer learning. Knowledge in transfer learning refers to a situation that involves reusing knowledge learned in some task or domain to solve another task, the task and domain can vary. Domain adaptation, in turn, comprises a more specific (yet highly practical) subdivision of transfer learning. In this case, the task is the same, such as classification of diseases or the likelihood of detecting weeds, but the nature of the data distribution varies within fields. This minor difference has huge consequences: whereas transfer learning is focused on flexibility throughout the various tasks, domain adaptation is concerned with the minimisation of the statistical distance between the target and source distributions. In agriculture, this has usually consisted of training models on well-annotated lab or benchmark data to work on fields in the real world, where there are limited or no labeled data.

The standard domain adaptation issue in the farming industry can be characterized in 3-dimensions, which include the variability in space, time and modality. Spatial variability is a factor that is caused by the fact that pictures of the same crop type can be different when they are taken in the different geographic regions. Temporal variability defines how the visual properties of plants develop with the process of growth stages or seasons. Lastly, there is modality variability where agricultural images are recorded with the help of various sensors, including RGB camera, drones carrying multispectral sensors, or even satellite carrying hyperspectral images. Such differences imply that although these underlying biological characteristics might resemble in some aspects, the visual manifestation of an underlying data is extremely variable in depictions across realms. Unadjusted, a model trained to work under one condition will not work well or at all given new conditions.

Traditionally, very early methods of domain adaptation in agriculture have been based on what can be referred to as shallow methods. These were of three broad categories: (1) instance-based adaptation in which samples of the source domain get reweighted based on how similar they are to the target domain; (2) feature transformation in which features in both domains are transformed into a common space of representations; and (3) classifier adaptation in which adapters to target domain variations are elaborated or fine-tuned. Such limited techniques had the benefit of computation efficiency and interpretability, which made it appropriate in situations where the computational resource accessibility is limited, like in edge devices that are positioned directly in the field. As an example, instance-based reweighting enabled models trained based on crop images in a single farm to assign greater significance to samples that were found to be contrasting to the target farm conditions and thus filled the realm of the gap. Likewise, by use of feature transformation techniques, data on drones and satellites could be transformed into a common subspace which enhanced reliability in classification.

The introduction of deep learning, nonetheless, changed the course of the domain adaptation research studies. Through convolutional neural networks (CNNs) and their descendants, one could learn, automatically, powerful and flexible hierarchical representations. To exemplify this behavior of learning complicated patterns, deep domain adaptation approaches take advantage by making domain alignment considerations part and parcel of neural architectures. As an example, a technique called adversarial learning consists of employing a discriminator to facilitate the learning process so that the source and target domain features are indistinguishable, which leads to implicit alignment(4). This has been used in segments like fruit identification, crop pest identification and crop growth in agriculture. Advances in applying the models such as Faster R-CNN to agriculture applications showed that domain adaptation could often show great improvements in tasks in the challenging field setting compared to that of shallow models that drastically underperform on high dimensional non linear data.

Reliable availability of labeled data is another factor that has been found to be crucial in adoption approaches to domains in agriculture. Subsequently, DA techniques can be generically described as either; supervised, semi-supervised, and unsupervised. Supervised DA takes advantage of a few labeled examples in the target domain; therefore, it becomes feasible to polish the adaptation mechanism with a bit of direct supervision. Semi-supervised DA is an integrated approach to DA effective alignment, which synthesizes labeled and unlabeled data to minimize annotation costs and still provides information needed to help orient the model. Unsupervised DA: the most common in agriculture: which presumes that none of the items in the target domain are labeled. This is especially applicable in precision farming where it is too expensive to map plant diseases or label down to weeds. Unsupervised DA allows scalable and practicable ways of addressing real-world farming systems, only through unlabeled target data.

The domain adaptation in agriculture is very significant. Since climate change is not only changing growing conditions but also due to the fact that farms now exist across different ecosystems, adaptability has become not only a necessity but also a luxury. An example is a pest recognition model developed in Asia which upon application, in Europe, it might face entirely new phenotypic expression of this same pest. Barring the use of DA, retraining these types of models, without their prior training, would be requiring huge amounts of labeled data to do so, which would be impractical to carry out. However, with DA, one can transfer and align the knowledge of the original model owing to which the requirement to create new marks is greatly reduced. Moreover, DA allows multimodal fusion, with different sensors (e.g., drones and satellites) being able to aggregate data in the case of different domains, which allows enriching agricultural decision-making systems(5).

To conclude, the rationale behind domain adaptation in agriculture is based on three foundations i.e. on the unavoidability of domain shift based on environmental and technological variability, the ineffectiveness of traditional shallow learning, and the disruptive power of deep learning based adaptation. Domain adaptation, by harmonizing source and target domains, reweighting, feature projection, adversarial learning, and other self-supervised methods, brings agricultural image analysis models closer to the ultimate goal of real applicability. Since farms are still in the process of digitalization and precision agriculture becomes increasingly dependent on visual intelligence, the use of DA will grow as a supplementary tool to a bedrock of valuable and scale-able agricultural technologies.

3.Agricultural Image Analysis Using Shallow Domain Adaptation

In the agricultural applications of the domain adaptation, the classical machine learning techniques were heavily used until the times of deep neural networks. Such methods, which are usually called shallow domain adaptation techniques, addressed domain shift by applying statistical domain models, linear transformations, and manually crafted features. Shallow methodologies were important in establishing the fact that it was possible to perform cross-domain transfer using fewer amounts of data and computing power, albeit, they were not as potent as modern deep learning methods. Their efficiency and interpretability mean that they are of interest today wherever expressive models need to be avoided, e.g., mobile phones or edge-based farming monitoring solutions. Generally, shallow DA can be categorized in three broad categories as instance-based adaptation, feature-based transformation and classifier-oriented adaptation.

Instance-Based Adaptation

It is based on the idea that not every training sample in the source domain serves equally in target domain performance by instance-based DA strategies. They weigh samples to distributions more reflecting target domains, instead of requiring equal importance of all source data. The mismatch in domains is minimised by this selective weighting so that domain-irrelevant training examples get a low weight. Within the subject of agriculture this method is especially useful in the process of conveying knowledge between geographically proximate areas or between similar crop breeds. Instances of this could be such as crop imagery obtained in any given farm may be more alike to those of other farms than areas farther away, and weighting such samples accordingly would significantly increase the transferability of the model.

Several algorithms have been identified to operationalize this key idea with reweighting mechanisms based on density ratios, active transfer learning, and partial ones that combine domain-invariant features. This has been used in agricultural remote sensing where instance reweighting has been used in the¬ coregionalization of hyperspectral image classification enabling the model to accommodate changes in spectral reflectance that occur seasonally. On the same note, instance-based frameworks have incorporated data augmentation techniques that mimic changes in lighting conditions or soil conditions to assist models generalization to novel conditions never witnessed during data collection. Although very useful in most scenarios, the drawbacks of these methods are based on precision of estimation of the probability distributions which is often computationally expensive to high-dimensional agricultural data.

Approaches to the feature transformation

The second pillar of shallow DA is the feature transformation techniques. What is meant here is a projection of source and target data transformed into a mutual representation space that is non-domain invariant. This targeted alignment of distributions in this space would allow models trained on the source distribution to generalize better to target environment. In this regard, subspace alignment methods, canonical correlation analysis, and kernel-based algorithms have been very popular.

In the purposes of agriculture, feature transformation has resolved inter-domain mismatch of seasons, sensors and growth phases. As an example, subspace alignment methods have been used to make crop classification models developed with early-season satellite imagery robust to later-season imagery. Kernel-based transformations have found particular application in hyperspectral data, in which plants encode tiny stressed-plant signals that the nonlinear nature of the feature relationships enhance. A subsequent new trend has been the development of generative solutions to changing the visual appearance of agricultural imagery across multiple fields e.g. mapping RGB imaging taking drone images to match the spectral signature of satellite imagery. Not only do these transformations decrease the distribution gaps, allowing distributions to be very sparse, but they make it easier to perform multi-sensor fusion, also becoming a more critical need in precision agriculture(6).

Although successful, transformation-based strategies yield some problems. They are prone to the critical choice of feature spaces and kernel functions, and uncertainty coping with nonlinear and complicated relationships TV the genuine world of agricultural information. Still, they offer computationally compact solution to attaining domain alignment without incurring hefty expenses of deep neural networks.

TABLE 1 Shallow Domain Adaptation Methods in Agricultural Image Analysis

Approach	Key Idea	Agricultural Applications	Strengths	Limitations
Instance-Based Adaptation	Assigns higher weights to source samples similar to target distribution	Cross-regional crop monitoring, hyperspectral crop stress analysis	Simple, interpretable, reduces domain gap effectively	Sensitive to density estimation errors; struggles with very high-dimensional data
Feature Transformation	Projects source & target into a common subspace or feature space	Seasonal crop classification, sensor fusion (UAV–satellite), disease detection	Captures shared patterns, enables multi-sensor fusion	Needs careful kernel/space design; less effective for nonlinear complexity
Classifier-Based Adaptation	Updates classifiers using unlabeled or few labeled target samples	Cross-season crop recognition, weed detection, yield prediction	Reduces annotation cost, can integrate ensembles for robustness	Dependent on classifier choice; limited for highly complex tasks

Classifier-Oriented Adaptation

The third group of shallow DA is aimed at improving classifiers instead of reweighting observations or feature transformation. In this case, the source domain trained model is directly alleviated using a small or unlabeled target data. Techniques also vary considerably, including methods of updating decision boundaries using target domain distributions, to methods of combining several classifiers in ways known as ensemble learning.

Classifier adaption in agriculture has been used in applications like cross-season crop recognition where the classifier is updated iteratively in accordance with new spectral and phenotypic situations. Particularly, ensemble methods have been found to work well with heterogeneity. Ensemble frameworks can greatly reduce a lack of robustness and decrease bias by synthesizing output of multiple base classifiers, trained on various domains. The methods based on Random Forest, e.g., have been further developed to use cross-domain weighting, allowing a better detection of the disease under investigation across regions. Likewise, adaptation layers of support vector machines have been utilized in determining whether to weed or to identify the type of crop, using different imaging conditions(7).

There have also been supplements of semi-supervised and active learning techniques to DA based on classifiers. Active learning also reduces the cost of annotation since the most informative data is chosen that makes the classification model learn more about the target domain; hence better generalization. This is particularly useful in the agricultural industry where the professional labeling is not only expensive, but also time costly. To give an illustrative example, in one application, hyperspectral crop monitoring, active multi-kernel approaches have allowed reducing the necessity to use extensive labeled data by considering only a limited number of samples of strategic choices.

Strengths, Weaknesses of Shallow DA

The great asset of shallow DA techniques is their interpretability and simplicity. Observably, they can be easily used in remote or limited resources settings, drones, edge, and mobile devices because they do not need a lot of computing power as deep networks. Additionally, since they are anchored on the basis of traditional statistical learning, their decision-making processes are less complex to understand making them more useful when the stakeholders in agriculture insist on transparency.

Nonetheless, shallow approaches have severe limitations as well. They regularly have trouble with high-dimensional data including hyperspectral imageries or video recorded by UAVs, where complicated nonlinear correlations overpower. They are also less flexible in their dependence on hand-crafted properties than more automated approaches to deep learning, which learn the hierarchical representations. Consequently, during the last stage, despite the fact that shallow DA techniques allowed to set the initial foundations of domain adaptation in agriculture, nowadays, their contribution is more likely countercyclical, offering lightweight options in certain situations as deep DA methods spearhead most state-of-the-art achievements.

4.Deep Domain Adaptation in farming

The blistering speed of the development of deep learning has transformed the sphere of domain adaptation drastically. In contrast to shallow-based solutions which use manual feature design and alignment via statistics, the deep model automatically learns hierarchical, domain independent representations using a multi-layer neural framework. This has been revolutionary in regard to agriculture. Besides addressing the nonlinear and high-dimensional agricultural data, deep DA also provides sound strategies that can deal with variations in sensors, climates, and crop phenotypes. Such techniques usually fall into the sets of supervised, semi-supervised, and unsupervised, which relate to the presence of target domain labels or lack.

Understropped Deep Domain Adaptation

Supervised DA presumes a small collection of labeled data present in the target environment. This tiny labeled set can convert the model to introduce straight away the ground-truth knowledge about the target environment, that will power the alignment process in a more efficient manner(8). The training goal typically includes two tasks: (1) the binary cross-entropy loss to the labeled source data, and (2) the loss of alignments that minimize gaps or mismatches in distributions of source and target features. The alignment can be through statistical measures like the Maximum Mean Discrepancy (MMD), adversarial discriminators or the covariance matching methods.

Supervised deep DA has been applied in agriculture to cross-sensor data fusion and monitoring crops in various growth stages. As a case in point, pretrained convolutional neural networks that recognize objects in drone images can be re-trained on several annotated satellite images so that the model can transfer learning easily among sensing platforms. In a related fashion, there has been some work on supervised DA frameworks to detect farmland boundaries, with small amounts of ground-truth data in an area of interest sufficient to finetune a model already trained more widely on publicly available datasets. This setting is preferable to other more extreme modes in that it balances the trade off between the effectiveness of deep feature learning and target supervision, but still uses enough supervision to guarantee a solid alignment.

Semi-Supervised Deep Domain Adaptation

Semi-supervised DA goes one step further using a combination of target labeled and unlabeled data. Practically, it is of great importance in the field of agriculture when it is possible to acquire several labels but impossible to mark thousands of images. Semi-supervised techniques commonly use pseudo labeling: the model will identify labels on unlabelled target samples, and then update the labelling in a series of iterations. This is also enforced by techniques like co-training and consistency regularization to force stable predictions across domains.

More recent contributions have even managed to incorporate generative models and meta-learning into semi-supervised DA, allowing good results on few annotations. As an example, the detection of wheat diseases in the

wheat disease detection scenario, researchers have managed to train segmentation models on just a few manually labeled images supported by large amounts of unlabeled video frames. The cross-domain generalization has also been improved with pseudo-labeled datasets created using deep diffusion models. YOLO semi-supervised based frameworks have been used in vegetable detection, and adapted to difficult settings with dense planting and variable lighting, demonstrating that even complex object detection pipelines can be scaled to low-label environments(9).
The advantage of semi-supervised DA consists of the fact that it is trying to find a compromise between high cost of annotations and substantial improvements in comparison to the unsupervised ones. Practically, this renders it very useful in crop monitoring systems since farmers may only need to give a few examples labeled in their farm field so that models may generalize well using the large, unlabeled data.

Deep Domain Adaptation without supervision

Unsupervised deep DA is the most popular and perhaps the most powerful method of image analysis in agriculture. Only labeled source, and unlabeled target data can be available in such a situation. The models are thus constrained to make use of solely domain alignment methods having no access to labeled data of the target environment. The agricultural annotation owing to its high cost has led to the dominance of the unsupervised DA in the smart use of farming in real world situations.
Adversarial training, discrepancy-based approaches and self-supervised learning strategies are three general directions in unsupervised DA research.

- Adversarial Training: motivated by generative adversarial networks (GANs), adversarial DA algorithms set up a feature extractor in an adversarial relationship with a domain discriminator. This is because the extractor gains experience in studying how to make representations that deceive the discriminator by tying source and the target features in a process called alignment. Adversarial DA in agriculture has been applied to sensor-to-sensor style transfer (i.e. matching aerial imagery to satellite data), disease identification across lighting conditions, and predicting yield across regions with diverse climates. Such hybrid systems, in which GAN-based methods of translating or otherwise converting images are coupled with adversarial feature alignment methods have been the most promising, with the ability to enable not only model feature adaptation but also create synthetic target-style imagery to use in training.
- Discrepancy-Based Methods These methods simply act to directly reduce statistical differences between domains (often measured using MMD, Wasserstein distance, or correlation alignment). As an example, domain adaptation networks used with plant disease datasets have already made a considerable contribution to the recognition of cross-crop in the alignments of the distributions of features across heterogeneous settings. Discrepancy-based frameworks have as well adapted the use of the vision transformers, which improved complex row-detection under heterogeneous field settings compared to CNNs(10).
- Self-Supervised Learning (SSL): SSL has found relatively more recent applications in domain adaptation to accommodate large collections of unlabeled data in the agricultural context. Using domain-invariant features Expanding on alternative ways to obtain domain-invariant features, we can train encoders on auxiliary tasks, including contrastive learning or image reconstruction. After pre training, some models are fine-tuned with source labels and adjusted to target domains using light-weight alignment layers. As an example, leaf disease recognition has been tackled using SSL-driven DA, which was shown to substantially enhance label-scarce classification using contrastive pretraining.

Pros and Cons

A paradigm shift has been made by Deep DA methods over shallow approaches. They are absolutely necessary in the modern precision farming since they can process non-linear complex and high dimension agricultural data. These enable the transfer of knowledge gained in one region to other areas so that models trained in a specific area do not rely on expensive labels and a swiftness in rolling out smart agricultural solutions on a large scale.
Nevertheless, these approaches have their problems as well. They are computationally intensive and therefore, hard to implement in resource-starved environments like the rural farms with fewer computers. Adversarial models are difficult to train, which can stabilize through fine-tuning to avoid problems such as mode collapse. Also, deep networks are considered as a black-box which decreases the observability which might be an issue with agricultural stakeholders who usually need transparency in decision making systems.

5.Conclusion

The evolution of domain adaptation has opened new possibilities for advancing agricultural image analysis, transforming it from a largely experimental pursuit into a practical foundation for precision farming. Across this review, it becomes clear that the fundamental challenge in agricultural computer vision is not merely learning effective models but ensuring that those models generalize across the diverse and ever-changing realities of real-world farming. Environmental heterogeneity, seasonal cycles, soil and crop variability, and sensor differences make agricultural data uniquely dynamic. Without domain adaptation, intelligent models trained in one context are unlikely to succeed elsewhere. Thus, DA emerges as an essential bridge between research environments and operational agricultural systems.

Shallow domain adaptation methods, grounded in traditional machine learning, demonstrated the feasibility of addressing domain shifts with lightweight and interpretable approaches. Techniques such as instance reweighting, feature subspace alignment, and classifier adjustment provided early solutions to cross-regional and cross-seasonal variations. While limited in their ability to capture nonlinear and high-dimensional data patterns, they remain useful for applications requiring transparency, efficiency, and deployment in resource-constrained contexts such as small farms or mobile devices.

The rise of deep learning fundamentally changed the landscape of DA in agriculture. Deep DA methods, through adversarial training, discrepancy minimization, and self-supervised learning, have shown remarkable capacity to align domains even when labels are absent. These approaches have powered breakthroughs in plant disease detection, crop yield forecasting, land-use classification, and weed mapping. By extracting domain-invariant features and leveraging large pools of unlabeled data, deep DA enables scalable and robust agricultural intelligence. The taxonomy of supervised, semi-supervised, and unsupervised approaches provides flexibility to match real-world constraints, from scenarios with minimal labels to those where none are available.

Despite this progress, several challenges persist. High computational costs limit the deployment of deep DA models in remote or resource-poor farming regions. Training stability, particularly in adversarial frameworks, remains a significant obstacle. Moreover, interpretability continues to be a major concern agricultural stakeholders such as farmers and agronomists often require not just predictions but understandable reasoning behind those predictions. The gap between research benchmarks and real-world deployment also highlights the need for standardized agricultural datasets and evaluation protocols that reflect practical farming conditions rather than controlled environments alone.

Looking forward, three promising directions stand out. First, the integration of multimodal data sources such as combining satellite, drone, and ground-level images can provide richer inputs and greater resilience against domain shifts. Second, the development of lightweight and efficient architectures will enable real-time deployment of DA-powered systems in the field, bringing benefits directly to farmers. Finally, the application of foundation models and self-supervised pretraining offers a pathway to universal agricultural representations that can adapt to diverse tasks with minimal fine-tuning, further reducing reliance on costly annotations.

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Conflicts of interest

The authors have no conflicts of interest to declare

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