RESEARCH ARTICLE

Unsupervised domain adaptation for highlight detection and removal in agricultural robot vision system

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Assessment of the cotton boll health is essential for field oversight and maturity rating. Typical methods for agricultural image acquiring are unsuitable for cotton boll images due to the possibility of distribution mismatch that resulted from environmental variables such as duration, climate, farming activities, and regions. Adapting a domain can solve this problem. This study applied a domain-adversarial neural network-driven unsupervised domain adaptation (DANN-UDA) approach to gather the cotton bolls datasets, which involved multiple steps of target label inference and dense inherent ConvNet-based feature extraction. The proposed approach was executed in the agricultural robot with Ubuntu and Robot Operating System (ROS) environment and verified using an agricultural robot captured cotton boll image. The efficiency of proposed DANN-UDA method in cotton boll identification was evaluated and demonstrated better results. The performance of the cotton boll stage detection of proposed DANN-UDA was compared using Visual Geometry Group (VGG) and You Only Look Once version 5 (YOLOv5) networks in agricultural robot vision system. The results demonstrated that the proposed approach obtained the best identification outcomes in a variety of scenarios. Additionally, the proposed model could serve as a helpful substitute for human observation and conventional categorization techniques.

Keywords: unsupervised domain adaptation (UDA); agriculture; cotton boll; domain-adversarial neural network (DANN); robot.

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Introduction

Cotton is a significant cash crop and a key source of natural feed, food, and fiber source. Harvesting robots may replace human labor and lower the cost of harvesting since hand preference is time-consuming and expensive [1]. Consequently, plucking cotton bolls can be effectively substituted by using harvesting robots. The growing environment of cotton bolls is an important variable in determining the output and quality of harvest. The separation phase, boll opening, and growth cessation are three of the most crucial phases in the growth of a cotton boll from formation to full cracking [2]. Effective field harvest management could significantly lower the possibility of premature cracking or boll rotting. A second opportunity for cotton boll growth can be internally after the boll's initial growth has slowed or stopped, possibly during the boll opening phase. This time frame has a significant influence on the surface clothes, prevention of boll rotting, and accelerating maturity. Different varieties of cotton bolls have diverse stages of development including the beginning, developing, partly cracked, and completely opened states [3]. Cotton boll health must be accurately assessed to handle the field efficiently and determine crop maturity. Conventional techniques of assessing cotton bolls frequently require manual inspection and image capture, both of which are susceptible to inaccuracies caused by environmental variability like time, climate, and geography. These problems highlight the requirement for sophisticated methods to increase the accuracy of boll evaluation.

Recent development in agricultural technology has introduced advanced methods. Machine learning and computer vision have emerged as potential approaches to enhancing cotton boll detection precision. Convolutional neural networks (CNNs) have been used to identify cotton growth stages and evaluate boll health more precisely [4]. However, conventional image processing techniques and CNN-based methods still encounter substantial domain adaptation problems. A mismatch between training data and real-world circumstances can result in decreased model efficiency, emphasizing the requirement for enhanced methods [5, 6]. In recent studies, different methods such as integrating support vector machines with image processing for boll counting and yield estimation have shown promised results [7]. Furthermore, deep learning methods have been investigated for identifying diseases in cotton plants, showing their versatility and efficacy in agricultural settings [8, 9]. Despite these advances, the issue of domain shift, where model efficiency degrades because of changes in environmental conditions, is still an important obstacle [10, 11].

This study aimed to develop and assess a new domain-adversarial neural network-driven unsupervised domain adaptation (DANN-UDA) method to tackle the domain shift challenge in cotton boll evaluation and improve the precision of boll detection by adapting to different environmental circumstances and mitigating the effect of distribution mismatch. By using a dataset of cotton boll images, this study proposed an extensive strategy that incorporated target label inference and dense intrinsic ConvNet-based feature extraction [1, 12]. The proposed DANN-UDA method combined numerous sophisticated techniques including You Only Look Once version 5 (YOLOv5) network for real-time object identification and the Visual Geometry Group (VGG) network for feature extraction and classification to attain high efficiency [13, 14]. The system was deployed in Ubuntu and the Robot Operating System (ROS) settings, enabling real-time image processing by agricultural robots. The DANN-UDA model's efficiency was assessed by comparing its efficacy against conventional classification techniques and evaluating its capacity to adapt to various environmental circumstances [15, 16]. This study enhanced the accuracy of boll identification and decreased dependence on manual inspection, which was usually labor-intensive and susceptible to errors by automating the assessment procedure and using cutting-edge machine learning methods [17, 18]. The proposed DANN-UDA model was a strong substitute for conventional techniques with possible uses in other aspects of precision agriculture and might result in more effective field management and superior crop yield prediction, contributing to the total innovation of agricultural technology [19].

Materials and methods

Development of an agricultural robot vision system

The agricultural robot was operated by two personal computers (PCs) running Ubuntu and Robot Operating System (ROS). Ubuntu was dedicated to visual highlight identification and removal methods, while the ROS hosted nodes for navigation, vehicle control, and localization. The two PCs interacted using the ethernet through a specialized switch and router with one PC running the ROS master. The router nodes on either PC could find one another and communicate immediately. An agricultural robot with a high-resolution camera captured detailed photographs of agricultural fields including cotton bolls at various development phases was employed to explore the cotton field and detect

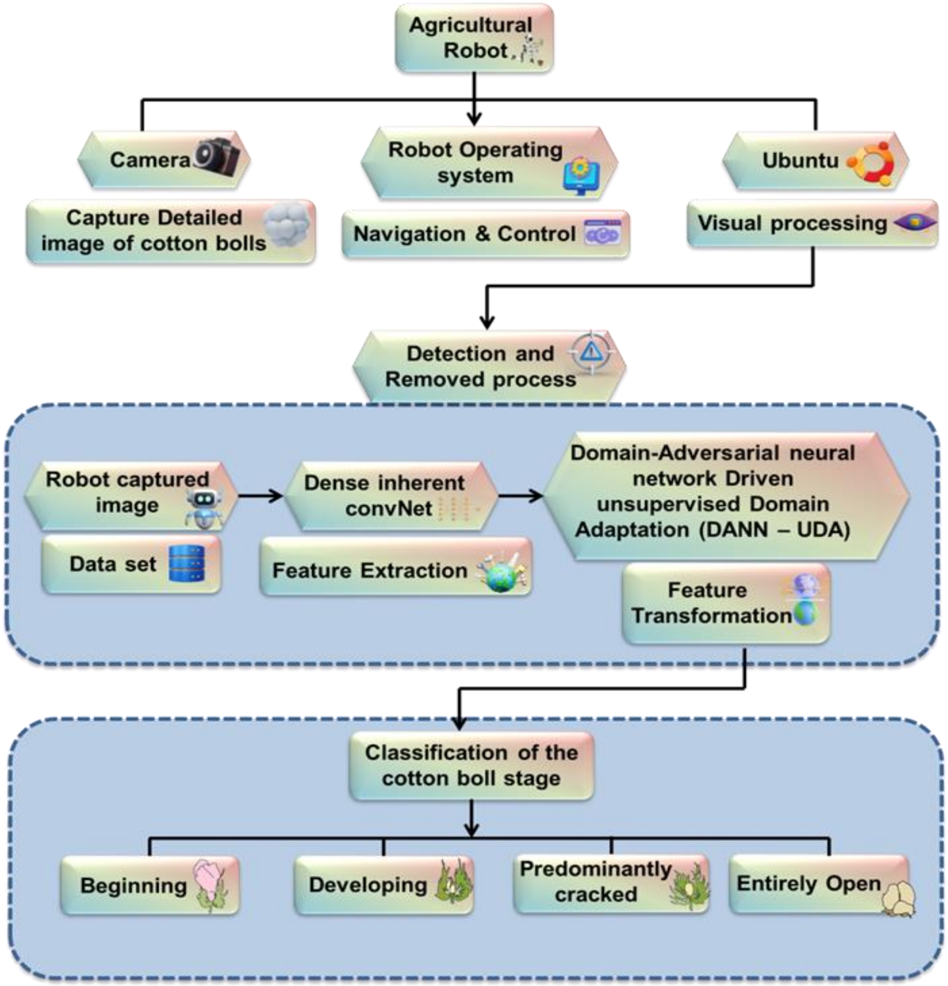

Figure 1. Overview of the proposed agricultural robot vision system.

the cotton boll stage under varying environmental conditions. The images were analyzed in real-time to identify the highlights and eliminate the uneven lighting images with a pulsed illuminating system. Cameras were calibrated using the automatic multi-camera calibration in the MATLAB calibration toolbox. Ubuntu classified cotton bolls into development stages using a dense inherent ConvNet-based feature extraction of the image. The DANN-UDA approach was then detecting patterns and characteristics that were important to each stage. The output comprised cotton boll phases as beginning, developing, predominantly cracked, and entirely open. The image detection and removal in the agricultural robot vision system were depicted in Figure 1.

Agricultural robot captured image

The images taken by an DJI P4 Multispectral agricultural robot camera (DJI, Shihezi, Xinjiang, China) were obtained at 44.3069° N and 86.0299° E, which included 250 cotton bolls, encompassing four growth phases with 60 images of each stage and containing features of size, shape, color, texture, and surrounding land. Cotton field images were cropped to demonstrate cotton bolls in many developmental stages including the starting stage, growing stage, primarily cracked stage, and completely open stage. The effects of various cotton growth variables such as the plant years and the plant region were also considered when assessing the suggested approach for cotton boll stage identification. All images in the cotton boll image dataset were acquired by field observations throughout a five-year period from 2019 to 2023. The dataset contained five separate sequences, each depicting a different year, capturing seasonal fluctuations and growth trends over numerous years. Each sequence contained photos from distinct plant locations and depicted varied environmental conditions. This temporal and spatial variability made the dataset more resilient for training and testing the model. The photos were chosen randomly within each stage to eliminate bias and offer a representative sample of each growth phase, which ensured that the dataset included a wide range of boll appearances and circumstances, making it ideal for training machine learning models to recognize and categorize cotton bolls at different stages of development.

Feature extraction using dense inherent ConvNet

Dense inherent ConvNet was used to recognize and extract elements from images that were relevant to the stages of cotton boll growth. The dense inherent ConvNet model was fed with images of cotton bolls at different phases and was trained to identify patterns and characteristics that corresponded to each step of cotton bolls. It was possible to extract pertinent characteristics including boll size, shape, color, texture, and surrounding land by using the convolutional layers and hierarchical structure of the dense inherent ConvNet. Features for agricultural applications including plant monitoring, yield estimation, and classification were also extracted. Dense inherent ConvNet employed hand-crafted features on a wide range of visual tasks to achieve the capacity to learn intricate input changes with comparatively domain-invariant and linearly separable results. The forward feature extraction procedure consisted of three primary layers, which were convolution, pooling, and full connected layers. The convolution layer was a weighted accumulation procedure that the template convolution kernel moved to the convolution layer in the input image and generated the complicated image through multiplying and combining the components that crossed the input image and template's established domains at each time traveling to a cotton boll stage by obtaining a point in the target image of cotton bolls. Pooling was the process of combining samples from different bolls in a field to get accurate information for cotton boll stage identification, which facilitated the evaluation of maturity and uniformity and were important for wise management choices and harvest scheduling optimizations. The pooling function took advantage of the general probabilistic properties of nearby outputs at a specific place. The fully connected layer was used to analyze characteristics that were obtained from images and assist in dividing different stages of bolls. By connecting each of the neurons from the preceding layer using Deep Learning (DL) methods, this layer facilitated pattern recognition, which was essential for accurately differentiating between the various developmental phases of cotton bolls. In addition, features relevant to the growth stages of cotton bolls including boll size, shape, color, texture, and surrounding land characteristics were extracted and used for the DANN-UDA model accurate identification and differentiation of cotton boll growing stages.

Domain-adversarial neural network (DANN) for feature transformation

DANN was used to improve model robustness in cotton boll stage detection by matching information across many domains such as backdrops or lighting conditions. To identify the stage of a cotton boll in a variety of agricultural circumstances, DANNs was used to develop domain-invariant representations, which allowed for proper classification independent of environmental variables (Figure 2). The typical DANN design had one hidden layer to classify $e(w)$ in the natural classification equations (1) and (2), where each determined conditional probability of DANN ($g(w)$) was assigned to w.

$$g(w) = sign\ (a + Xw) \quad (1)$$

$$e(w) = softmax(d + Ug(w)) \quad (2)$$

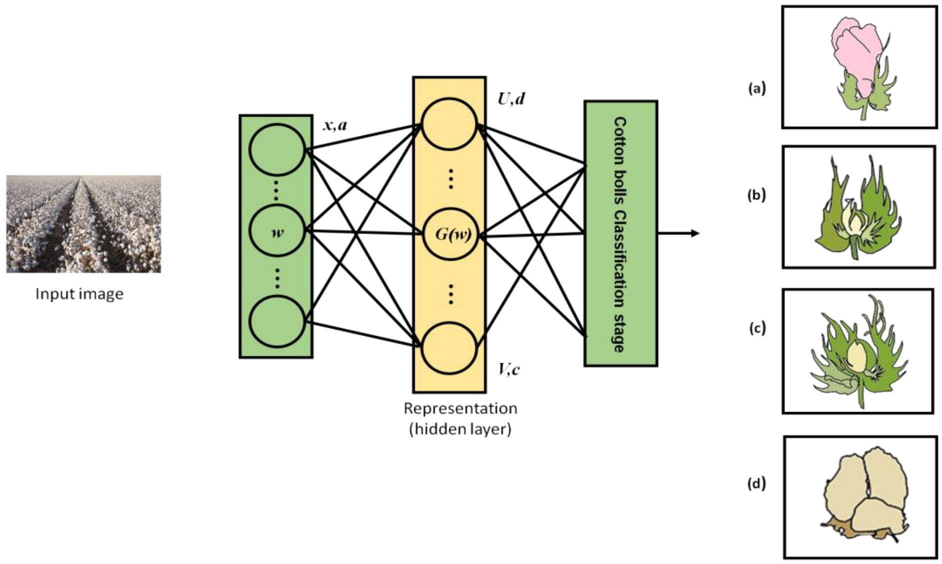

Figure 2. Structure of DANN. (a) beginning, (b) developing, (c) predominantly cracked, (d) entirely open.

The agricultural robot vision system was developed using equations (3) and (4).

$$Sign(b) \overset{def}{=} [\frac{1}{1+exp(-b_j}]_{j=1}^{|b|} \quad (3)$$

$$softmax(b) \overset{def}{=} [\frac{exp(b_j)}{\sum_{i=1}^{|b|} exp(b_j)}]_{j=1}^{|b|} \quad (4)$$

The sigmoid function ($Sign(b)$) of each element $|b|$ in the vector b_j valued among 0 and 1 for cotton boll stage reorganization. The variable of $K(e(w), z)$ was the target domain of the starting stage in cotton bolls and represented the maturity of cotton given environmental variables x, u, a, d using equations (5) and (6).

$$K(e(w), z) \overset{def}{=} log \frac{1}{e_z(w)} \quad (5)$$

$$\underset{x,u,a,d}{min} [\frac{1}{n} \sum_{j=1}^{n} K(e(w_j^t), z_j^t)] \quad (6)$$

Moreover, the growing of cotton is significantly affected by the climate. Temperature, humidity, and rainfall are among the factors that impact cotton growth and quality, which, in turn, affects harvesting production.

Unsupervised domain adaptation (UDA)

The UDA model started with unlabeled target domain of cotton boll image data, and then utilized predictions to produce pseudo-labels for target domain of cotton boll image data. Further, the model was fine-tuned with both labeled source domain and pseudo-labeled target domain of cotton boll image data. UDA in cotton referred to the identification of phases including growing, blooming, maturity, boll development, and seedling to facilitate strong model transfer across various habitats and growth circumstances. Source domain observations could reliably determine the required domain's labels. Consequently, an iterative making loop approach was used to estimate counterfeit labels of the intended domain of sample as below.

$$\mathrm{f_j(x_s) = v_j^s\ y + c_j} \quad (7)$$

where $\mathrm{f_j(x_s)}$ was the score obtained using k-nearest neighbor (KNN). The target domain ($\mathrm{U = \{y_s', x_s'\}}$) could be determined by the score $\mathrm{f_j(x_s)}$. To establish a threshold for categories, $\partial = \{\partial \mathrm{j} = 1,2,3 \ldots \mathrm{c}d_j$ and v_j were the weight and bias coefficients of the j th class of KNN attained from *M*. $S^{(1)}$ was the subsequent transition matrix $V^{(1)}$ using the measure learning approach. $S^{(2)}$ was the efficient with cotton bolls. It was possible to use reliability on the source sector with knowing actual labels as an indicator to monitor the intended sector's label prediction outcome and created a pattern classification model that had high generalization performance.

Domain-Adversarial Neural Network-driven Unsupervised Domain Adaptation (DANN-UDA) was a method for improving machine learning models' capacity to generalize across domains by resolving domain shifts. It combined a DANN with UDA, in which a feature extractor learned to generate domain-invariant features by training against a classifier that used these traits to complete tasks such as cotton boll classification. UDA refined the model using unlabeled target domain data and often creating pseudo-labels, which improved resilience and accuracy in real-world scenarios. Cotton bolls were classified into developmental phases by the suggested agricultural robot system, which employed a Dense Inherent Convolutional Neural Network and DANN-UDA. The system detected and removed visual highlights from high-resolution photos collected with a calibrated camera system, ensuring reliable analysis in a variety of environments.

Evaluation of proposed DANN-UDA

The proposed DANN-UDA was evaluated and compared with several recognized methods. The accuracy of DANN-UDA was estimated using KNN by selecting the closest data points in the feature space. The conventional methods were employed for comparison studies, which included No Adaptation (NA), a baseline technique with no domain adaptation being used; Geodesic flow kernel (GFK), a method using geodesic flow to connect the source and target domains for adaptation; Transfer joint matching (TJM) method that aligned the distributions of the source and target domains; 7-layer VGG-M model, a deeper CNN model being tested for its efficiency in classification tasks; Convolution neural network fully connected (CNN-FC), the standard CNN model with fully connected layers; Convolution neural network spatial pyramid pooling (CNN-SPP), a CNN model with spatial pyramid pooling to deal with various image sizes; Local binary pattern (LBP), a handcrafted feature approach that defined textures in the image. Gabor, a handcrafted feature approach for capturing texture and spatial frequency data; Sparse codes (SC) that encoded data as sparse mixtures of basic functions; Locality-constrained linear coding (LLC) that improved SC by integrating location limitations; CNN-fully vectorized (CNN-FV), a CNN variation in which characteristics were vectorized; CNN-conventional learning pipeline (CNN-CLP), a normal CNN model with a traditional learning pipeline; and Joint distribution adaptation (JDA) that aligned the joint distributions of source and target domains for improved adaptation. Through the comparison, the most effective methodologies for cotton boll stage detection would be determined, which guaranteed dependable and accurate results across various settings.

Results and discussion

KNN was used to estimate the accuracy of the proposed DANN-UDA method. KEL, AEL, and T00 denoted the plant types, while the numbers 05 and 01 were apparatus numbers, accordingly, which were assigned by the agrometeorological analysts. UDA methods used for this study were NA, GFK, TJM. Additionally, certain traditional CNN-based, end-to-end prediction techniques were examined with the goal of determining an appropriate encoding strategy for the column characteristics, which included 7-layer VGG-M, CNN-FC, CNN-CLP, and CNN-SPP.

Estimation of DANN-UDA accuracy

Table 1 showed the accuracies in classification of the cotton bolls using different hand-crafted methods. The plant groups AEL01, KEL01, and T0005 (2019-2023) indicated various sets of cotton boll images categorized by specific plant kinds or apparatus numbers allocated by agrometeorological analysts. These groups

Table 1. Numerical outcomes of accuracy.

Methods	AEL01	KEL01	T0005-2019	T0005-2020	T0005-2021	T0005-2022	T0005-2023
LBP	65.6	60.9	49.5	51.6	51.0	44.0	53.2
Gabor	67.4	76.2	72.7	68.8	69.9	75.9	73.3
SC	41.8	59.6	61.1	51.0	48.4	45.4	56.3
LLC	56.7	52.8	49.6	42.0	42.6	40.0	51.4
DANN-UDA	70.4	80.8	79.3	75.7	79.3	83.1	80.4

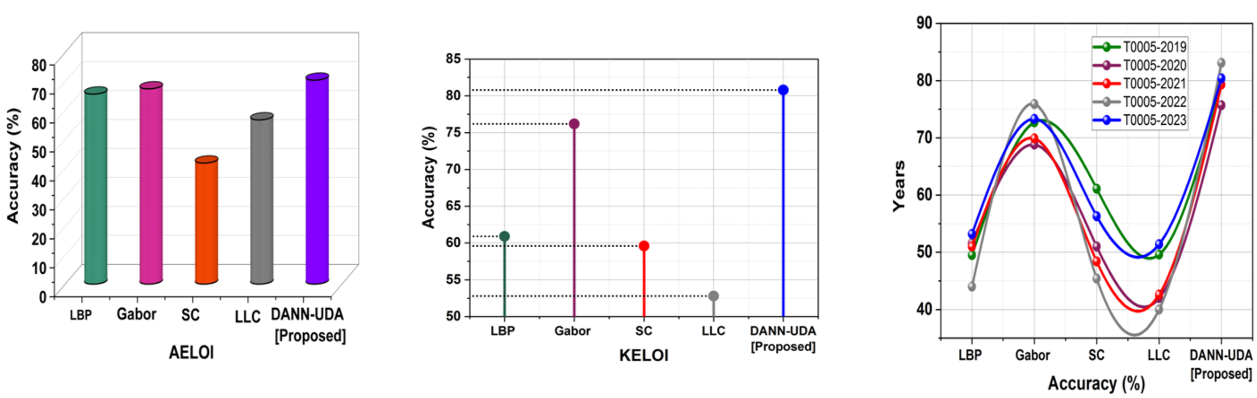

Figure 3. Result of Cotton bolls identification using different hand-crafted methods.

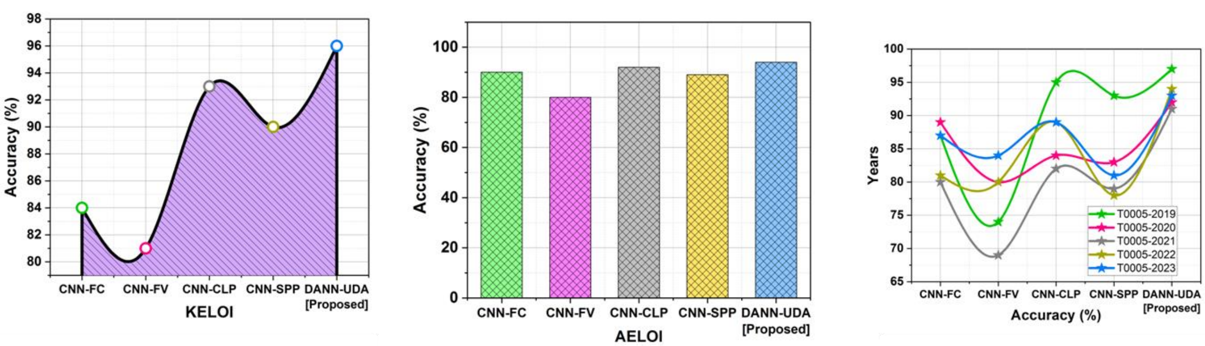

Figure 4. Result of cotton bolls classification using different CNN-based methods with VGG-M.

spanned a wide range of climatic circumstances and cotton boll growth phases and guaranteed thorough evaluation. The proposed DANN-UDA method was thoroughly tested across these varied plant groups to determine its robustness and efficacy in comparison to standard hand-crafted methods of LBP, Gabor, SC, and LLC. The results showed that DANN-UDA had the highest accuracy among all tested methods.

Comparison of DANN-UDA with other methods

The results of cotton boll identification using different existing hand-crafted methods and proposed DANN-UDA method showed that the proposed DANN-UDA achieved 70.4%, 80.8%, 79.3%, 75.7%, 79.3%, 83.1%, and 80.4% in AEL01, KEL01, T0005-2019, T0005-2020, T0005-2021, T0005-2022, T0005-2023 groups, respectively, which were better than that of other methods (Figure 3). However, when using different CNN-based methods with VGG-M, cotton boll identification using the proposed DANN-UDA achieved 94%, 96%, 97%, 92%, 91%, 94%, and

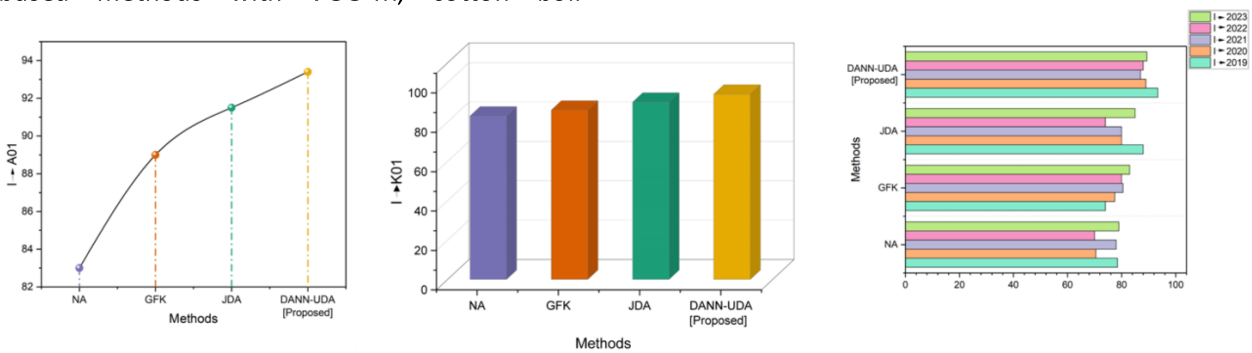

Figure 5. Cotton bolls identification using UDA methods.

93% in AEL01, KEL01, T0005-2019, T0005-2020, T0005-2021, T0005-2022, and T0005-2023, respectively, which was better than the other existing methods (Figure 4). The cotton boll identification using UDA methods showed that the proposed DANN-UDA method achieved 94%, 96%, 93.4%, 94.1%, 93.4%, 89%, 87%, 88%, and 89.4% in A01, K01, T2019, T2020, T2021, T2022, and T2023, respectively, comparing to the existing methods, which was better than other methods (Figure 5). The results demonstrated that the proposed DANN-UDA method achieved the best results because it effectively addressed the challenges of domain shifts caused by environmental factors like time, climate, and location, which traditional methods struggled to handle. By using a domain-adversarial neural network (DANN), the method adapted to different conditions and ensured accurate feature extraction and classification across various settings. This adaptability allowed the model to consistently outperform other techniques in identifying cotton boll stages, making it more reliable and precise in diverse agricultural environments.

Testing the proposed method in the field

The proposed DANN-UDA method was tested in field conditions to ensure its practical applicability. High-resolution images of cotton bolls at various developmental stages were collected from multiple fields over the years 2019 to 2023. These images were annotated by experts and preprocessed through cropping, resizing, and normalization. The DANN-UDA model was then applied to identify the stages of the cotton bolls with performance assessed using metrics of accuracy, sensitivity, specificity, and confidence intervals to ensure precision and consistency. Comparative analysis with traditional hand-crafted features of LBP, Gabor, SC, LLC and other CNN-based methods demonstrated the superior performance of the DANN-UDA approach. Additionally, the method was integrated into an agricultural robot vision system and successfully provided real-time feedback on cotton boll stages, thus validating its robustness and practical utility in real-world agricultural monitoring. A YOLO-based learning system with YOLO-VGG has been used for immediate object recognition and manipulation by agricultural robots, specifically for recognizing and navigating fruit trees in complicated environments through YOLOv5 network. In this study, the agricultural robot identified the cotton boll stage through a vision system, which used existing YOLOv5, YOLO-VGG, and the proposed DANN-UDA novel approaches for the vision detection to identify the cotton boll stage. The performances of three vision detection classification algorithms were evaluated using four metrics including accuracy, precision, recall, and F1 score. Accuracy was the ratio of accurate predictions to total predictions, indicating the classification model's overall success in correctly recognizing cotton boll stages throughout the dataset. Precision quantified the accuracy of the model's positive predictions, guaranteeing that identified cotton bolls were in the correct stage without misclassifying of other items or phases.

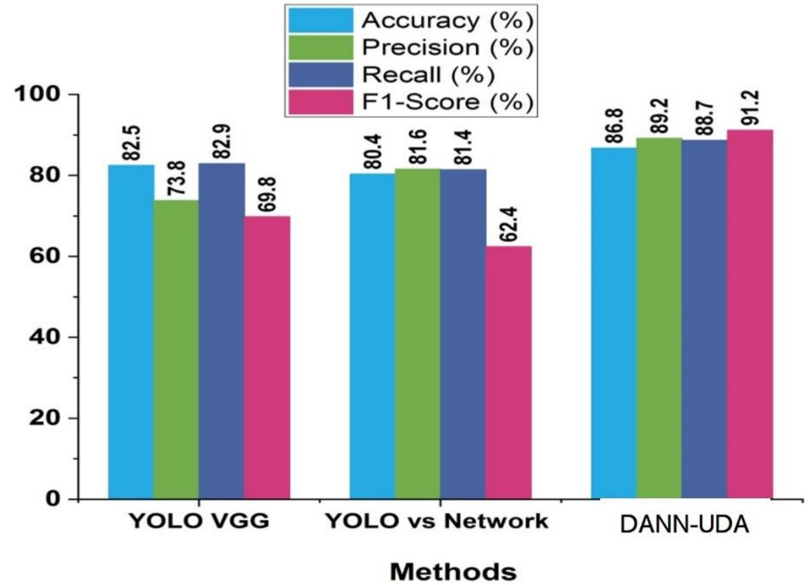

Figure 6. Cotton boll identification analysis.

Recall assessed the model's ability to capture all important instances within a dataset, providing complete monitoring and analysis in agricultural contexts. The F1 score was the harmonious average of both recall and precision and was a balanced measure of the effectiveness of a model that considered both accuracy and recall, showing strong and dependable accuracy and recall in practical farming scenarios applications. The results showed that YoLO VGG had a greater accuracy percentage of 82.5% than YOLO v5 network's 80.4%, while proposed DANN-UDA had the best accuracy percentage of 86.8% (Figure 6). The overall performance of DANN-UDA was higher than that of the other two YOLO based systems.

The agricultural robot vision system tended to classify the growth stages of cotton bolls and assisted in exactitude agriculture by identifying cotton boll maturity accurately, which could enable prompt actions and optimize potential yield. The cotton boll phase occurs throughout the late growth stages, where the bolls enhance the fibers. The potential pest damage, labor-intensive harvest requirements, and weather sensitivity are all the issues to affect the yield. The proposed DANN-UDA method was used to assess the cotton boll health in the field, which was essential for field oversight and maturity rating, and achieved superior results in cotton boll identification comparing to the other existing methods. The results of this study suggested the potentials for improving cotton boll stage identification using robots, machine learning algorithms, and sophisticated imaging technologies in the future and would provide accurate and effective tool for agricultural management and monitoring.

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