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Prediction and detection of harvesting stage in cotton fields using deep adversarial networks

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Abstract

Cotton is a crucial crop that has a significant impact on the global economy, and the timing of the harvest is crucial for maximizing the yield and quality of cotton fiber. However, predicting and detecting the harvesting stage of cotton plants is a complex task that requires analyzing various factors such as plant growth, leaf senescence, and boll maturity. Traditional methods for harvesting prediction are labor intensive and time consuming, making it essential to develop efficient and accurate methods. In this paper, we present a novel deep adversarial network (DAN) called CropCycleNet, which combines the features of both convolutional neural networks and generative adversarial networks. The proposed DAN can identify different stages of cotton plant growth, detect diseases, and affect plants to ensure proper removal. We propose Histogram base Gradients Feature Orientation Transform method influences feature descriptors and allows feature-level fusion to improve object recognition accuracy. Experimental validation of CropCycleNet was performed to evaluate the accuracy, precision, recall, and F1 performance metrics at various stages of cotton plant growth. The proposed DAN identified the harvesting stage in cotton fields with 93.27% prediction accuracy, outperforming other existing state-of-the-art methods.

Keywords Cotton plant · Deep adversarial network (DAN) · Harvesting stage · CropCycleNet · H-GFOT · Diseases recognition

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1 Introduction

The cotton industry is a leading commercial crop yield worldwide. The cotton bud, available in the perennial cotton plant, is an essential raw material utilized for product enhancement in various industries, such as edible oil extraction, paper manufacturing, textiles, medicinal products, and livestock feed (Maghsoudi et al. 2015). Cotton fiber must have essential characteristic features, such as retention in color, absorbency, strength, and comfort. After harvesting, the increased production of cotton fiber undergoes the ginning process, which generates a considerable amount of cotton waste that poses a significant challenge (Chen et al. 2012; Mohammed and Al-Janabi 2022; Salcedo et al. 2020). The non-cotton fiber produced during processing, such as post-harvest field thrash (PHT), cotton gin trash (CGT), and crushed seeds, is efficiently used for extracting edible oil. CGT comprises cotton plant sticks, calyx, soil, and leaves (Al-Gaadi et al. 2016). These by-products are used as soil composts and provide supplemental nutritional content for livestock feed (Xu et al. 2018; Syah et al. 2022; Hacking et al. 2020). The cotton by-product, mainly obtained from CGT, is also used in commercial bioenergy applications. The cotton plant contains several nutrients, such as phenolics, fatty acids, proteins, lipids, terpenes, and carbohydrates, distributed throughout the entire plant. The cotton and by-products generated as organic waste are non-toxic to the environment and can be exploited as helpful energy (Wang et al. 2020; Kadhuim and Al-Janabi 2023).

The developmental phases for cotton can be divided into five main growth stages: diseased, diseased, fresh, fresh, and maturation. It is essential to monitor the growth stages to ensure a standardized quality of the cotton fiber. Proper monitoring can help optimize the harvesting process to ensure the maximum yield and quality of the cotton fiber. The cotton industry relies heavily on the timely harvesting of quality cotton fiber to increase production rates. Proper harvesting techniques are crucial to avoid significant losses in the industrial sector. Defoliated cotton bolls in an open stage are picked separately before the cotton is harvested (Al-Gaadi et al. 2016; Xu et al. 2018; Syah et al. 2022; Hacking et al. 2020). Cotton is typically harvested when the moisture content is equal to or less than 12%, but the cotton can suffer during the picking and ginning. Extended harvesting times can lead to exploitation of the standardized quality of the cotton plant due to harsh exposure to open bolls. Cotton harvesting typically involves either a stripper or spindle pickers.

Commercial cotton production involves several stages: planting, weeding, spraying, and harvesting. Adopting active cropping technologies, such as seeding transplantation, plastic mulching, and plant training, is essential in increasing cotton lint yield (Septiarini et al. 2020; Al-Janabi and Alkaim 2022; Sun et al. 2019; Shi et al. 2022; Syazwani et al. 2021). During the harvesting stage, many farmers are required to increase cotton production. Optimizing the harvesting process is crucial to ensure the cotton fiber's maximum yield and quality. Cotton farmers must be aware of the proper techniques for harvesting to avoid losses in the industrial sector. In addition to the traditional harvesting methods, new technologies and techniques can be implemented to improve cotton production rates. The use of active cropping technologies can significantly increase the yield of cotton lint. In contrast, the timely harvesting of quality cotton fiber can ensure a standardized quality of the cotton plant.

Generative adversarial networks (GANs) are a type of machine learning algorithm that use a generator network and a discriminator network to produce realistic synthetic images. DANs have been increasingly used in agriculture for crop monitoring and prediction, including in the cotton industry. Researchers have employed DANs to predict and detect the harvesting stage of cotton fields by training the network on a dataset of cotton field images captured at different stages of growth and development (Syazwani et al. 2021). Once the DAN is trained, it can be used to produce synthetic images of the same field at different stages of growth and development for predicting and detecting the harvesting stage. However, there are some drawbacks to using DANs in agriculture. One challenge is the need for large amounts of high-quality training data. Another challenge is that the generated images may not be completely accurate or represent the actual field, leading to potential errors in predictions. Additionally, DANs may require significant computational resources and time for training, limiting their scalability and applicability in some settings (Al-Janabi et al. 2021).

Therefore, this paper mainly focused on the prediction and detection of the harvesting stage of cotton fields, which is a crucial task for maximizing the yield and quality of cotton fiber. DANs have shown great potential for this application, as they can learn to generate synthetic images of cotton fields at different stages of growth and development. The use of DANs offers a non-invasive, fast, and efficient method for predicting and detecting the harvesting stage of cotton fields, which can save time and resources for cotton farmers. With further research and development, DANs may become a standard tool for cotton farming operations. The three essential roles of CropCycleNet are as follows:

- *Identifying different stages of cotton plant growth* CropCycleNet is designed to predict and detect the harvesting stage of cotton plants by analyzing various factors such as plant growth, leaf senescence, and boll maturity.

- *Detecting diseases and affected plants* CropCycleNet can also identify if a cotton plant is affected by a disease or is unhealthy. This is important for proper removal as cotton plant by-products are utilized in the commercial world market.
- *Improving object recognition accuracy* The proposed CropCycleNet combines a Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) using feature-level fusion techniques to improve the accuracy of object recognition. This can help in identifying the harvesting stage of cotton fields more accurately.

The rest of the paper is organized as follows: Sect. 2 presents a comprehensive review of the existing literature related to the problem to understand better the progress made in the specific area. Section 3 details the mathematical framework of the proposed model and its operational flow, which is used to identify different stages of cotton plant growth and predict the harvesting period. Section 4 presents the proposed model's performance validation through a comparative analysis with existing state-of-the-art methods. Finally, the conclusion and future scope are discussed in Sect. 5.

2 Related works

Cotton is a significant fiber crop that contributes 35% of the global fiber supply, and China is a leading producer. Precision agriculture techniques are vital for optimizing cotton production, and target perception is a key factor in protecting crops. Cotton has a long growth period, making it highly susceptible to diseases and pests, requiring significant pesticide use. Studying cotton's target perception can help improve pesticide spraying efficiency (Liu et al. 2022). Perception techniques such as laser, ultrasound, and radar can be used in agriculture, and ultrasonic signals can be used to analyze the density of the canopy in vineyards and orchards. The live validation of point quadrats can aid in assessing the density of the canopy in cotton fields.

In order to achieve precision spraying for pistachio trees, ultrasonic sensors are used to sense the canopy and guide low volume spraying (Fu et al. 2019). Radially ranged laser sensors have also been developed for sprayers with variable rates that match the tree's canopy using scanned laser technology (Lai and Tseng 2022). Laser sensors with a wide range have been evaluated for their accuracy in measuring complex shapes and sizes, and for compatibility with different objects, enabling sprayers to be adjusted to different rates (Wu et al. 2020a). The perception of the target is dependent on both laser and radar, and ultrasonic technology is used to estimate the shape and volume of larger plants to guide precision spraying. However, small and scattered fields in China make it difficult for machinery to perform these functionalities (Al-Janabi et al. 2020a).

Predicting crop yield in extensive and unfeasible areas primarily relies on data collection (Ukwuoma et al. 2022). In the cotton field, yield is measured manually by counting and weighing the number of cotton balls and fiber content per UA (unit area) (Wu et al. 2020b). However, with recent advancements in technology, there has been an increase in the use of machines for predicting crop yield (Luo et al. 2022; Apolo-Apolo et al. 2020). Various studies have employed algorithms for counting fruits in the yield, classifying them based on maturity level, and using robots for harvesting (Al-Janabi et al. 2020b; Chen et al. 2022; Harel et al. 2020). These technological innovations are changing the landscape of agriculture, making it more efficient and effective.

Region segmentation in images using pixelation data has become essential for identifying regions based on their location (Al-Janabi and Alkaim 2020). A new approach has also been proposed for detecting the presence of cotton balls using semantic image segmentation on specific regions (Liu et al. 2020), which has addressed previous issues with machinery. Advances in computational vision, mainly using large-scale Graph Processing Units (GPUs) (Al-Janabi 2021; Luo et al. 2021; Wu et al. 2022a, 2022b), have led to the developing of several deep learning algorithms for identifying specific stages of cotton growth. For example, Convolutional Neural Networks (CNNs) have been used for counting and detecting new cotton flowers in aerial images. In contrast, other systems can count and track fully grown cotton balls using moving images. Additionally, algorithms have been developed to estimate cotton yield by analyzing aerial images during harvesting. By utilizing this information, product management in cotton fields can be significantly improved.

3 Materials and methodology

The materials and methods section outlines the experimental design and procedures used in the proposed DAN for identifying the cotton harvesting period based on the classified plant growing stages. It describes the dataset used for training and testing, the architecture of the DAN, and the training process, including hyperparameter settings and evaluation metrics. The section provides a detailed account of the methodology employed to achieve the research objectives.

3.1 Overview

Deep adversarial networks (DANs) have shown great potential in identifying and detecting various objects and features in images, including crops and plants. In the case of cotton plants, DANs can be used to identify the stages of plant growth and the timing of cotton ball maturation, which can help farmers determine the optimal time for harvesting the crop. DANs combine two neural networks, a generator, and a discriminator, to identify and classify different image features. The generator creates synthetic images of the detected feature, such as a cotton ball, while the discriminator evaluates whether the images are real or fake. Through an iterative process of training and adjustment, the generator learns to create more realistic images that can fool the discriminator, leading to more accurate feature detection. In the context of cotton plant harvesting, a DAN could be trained on a dataset of images of cotton plants at different growth stages, focusing on identifying the presence of cotton balls in the images. The generator would create synthetic images of cotton balls at different stages of maturation. At the same time, the discriminator would evaluate whether the images are real or fake based on a ground truth dataset. As the generator improves its ability to create realistic images, the discriminator becomes more accurate in identifying cotton balls, leading to improved detection and identification of mature cotton plants. By accurately identifying the maturation stage of cotton balls, a DAN can help farmers determine the optimal time for harvesting the crop, which can lead to improved crop yield and reduced labor costs. This technology can also enable farmers to monitor their crops more efficiently and effectively, leading to more sustainable and profitable cotton farming practices (Fig. 1).

To predict the harvesting stage of cotton plants in a field, a convolutional neural network (CNN) and generative adversarial network (GAN) are used as a deep adversarial network (DAN). The system collects images of the cotton plants throughout the day using cameras or mobile phones and uses image processing to identify the harvesting stage of the plant. However, environmental light conditions can significantly affect image quality, so the recognition system must be designed to work under ideal conditions. The system requires a fixed recognition system that captures the central part of the cotton plant from a downward, horizontal angle. Images are captured at different times during the cotton plant's growth cycle and labeled based on three scores corresponding to different growth stages: seedling stage, bud stage, boll stage, and boll opening harvesting stage. The amount of data collected during the different growth stages varies, with more data collected during the boll stage. During the training process, a major percentage of the captured images are used to train the system to recognize the different growth stages of the cotton plant. The remaining images are used for validation. The system considers environmental factors such as sunlight exposure, wind flow direction, and shading of plant size to help identify the bolls in a cotton plant, which are essential for harvesting.

The data processing stage is essential to the cotton plant analysis process. Images of the cotton plant undergo size adjustment, data augmentation, and format conversion performed using an enhanced Python script. The size of the captured images is altered to save computing resources and improve the analysis process's speed. The proposed model is more generalized via the adaptation of data augmentation methodologies, mainly to reduce the overfitting of images. The training set includes various data augmentation techniques, such as flip horizontal, brightness regularization, image blurring, adding noise content, and altering color gradation, to make the model more robust. The proposed model uses a Convolutional Neural Network (CNN) with a deep adversarial network to convert image datasets into a recorded format to identify the exact true images at present in the harvesting stage in the agricultural field. The analysis involves identifying the cotton plant in the harvesting stage by analyzing captured images. Defoliation or harvesting time is when the cotton is defoliated to improve boll opening and control the regrowth of the cotton plant, making it essential to enter the harvesting stage. The chemicals produced from the plant at this stage improve the efficiency of cotton harvesting, with a simultaneous reduction in time management. Harvesting performance is affected by various factors, such as temperature, plant condition, product rate, and spray coverage. The temperature is the most critical primary source in determining the cotton plant at the harvesting stage. After defoliation, the cotton plant is suitable for harvesting only under several optimal conditions. In the case of cool temperatures, the defoliation process is extended for a long period, affecting the harvesting stage of the cotton plant. The harvesting stage is categorized into two different modes, herbicidal and hormonal. Herbicidal harvesting affects the cotton plant's leaf due to the production of ethylene, whereas hormonal harvesting increases the ethylene concentration rate without affecting the cotton leaf.

Overall, the Deep Adversarial Network (DAN) based on CNN and GAN provides a practical and accurate method for identifying the harvesting stage of cotton plants in a field. Using image processing and machine learning techniques, the system can help farmers optimize their harvesting operations and increase crop yields.

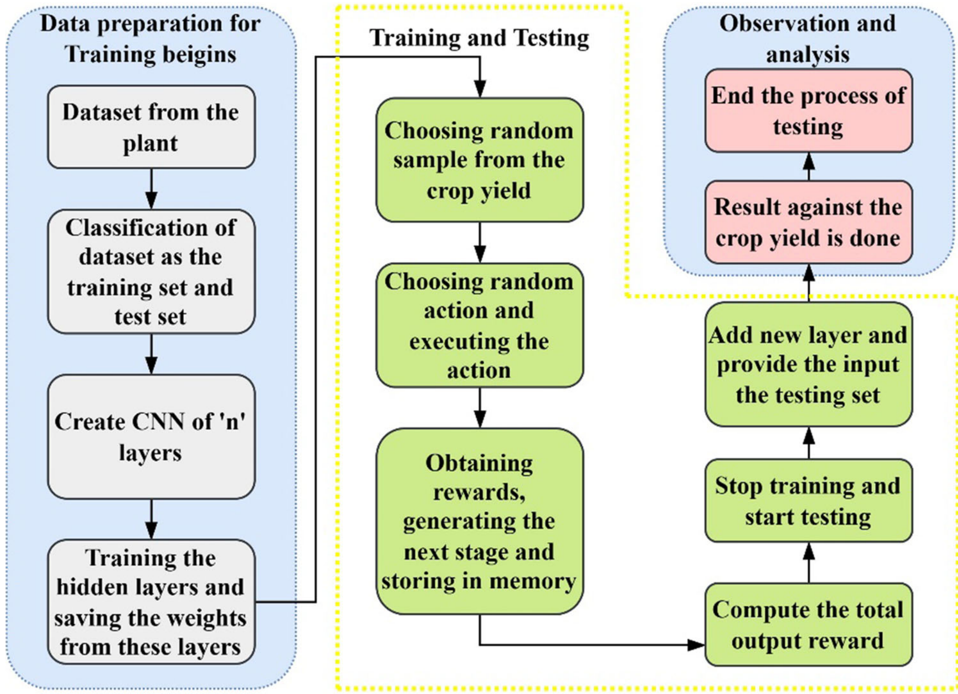


Fig. 1 The proposed DAN operational flow for identifying the cotton harvesting stages

3.2 CropCycleNet architecture

The convolutional neural network (CNN) is a deep learning model that can efficiently recognize and classify images of the various growing stages of the cotton plant. The CNN network model architecture comprises three layers for feature extraction: the convolution layer, the max-pooling layer, and the fully connected layer, as shown in Fig. 2. In the convolution layer, a kernel template is applied to the input images of the cotton plant. Each iteration collects the elements intersecting the domain and is summed to generate a convoluted image. The template is a filter with specific characteristic features to classify cotton images. The pooling function is then performed on the convoluted image based on characteristic statistical features to extract texture information. The max-pooling, average pooling, and L2 pooling are different types of pooling operations. The mean value of the max-pooling layer is generated using the texture information and convolution layer parameters. The features extracted during the convolution and pooling layer are collected in the fully connected layer. In this layer, the nodes are effectively connected with each node of the preceding layers. The CNN sequential model continues to identify the various stages of the cotton plant until the entire input is identified and classified.

This architecture have the same five convolutional layers, followed by three fully connected layers as AlexNet, but with varying numbers and sizes of the kernels.

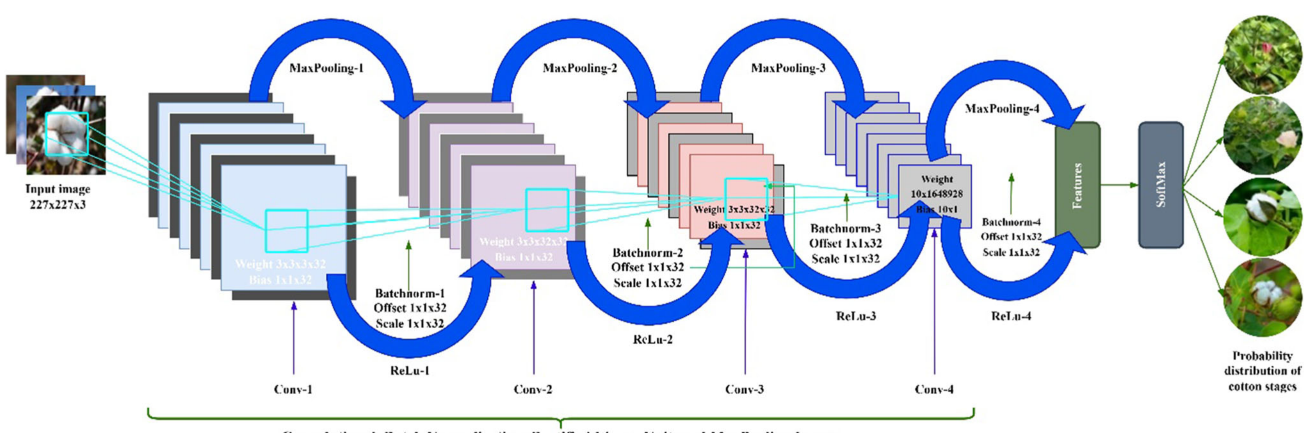


Fig. 2 DAN model for predicting the harvesting period after classifying the cotton growing stages based on the H-GFOT approach

- Convolutional Layer 1: 32 kernels of size 3 × 3 × 3, followed by ReLU activation
- Normalization Layer (LRN—Local Response Normalization)
- Max-Pooling Layer 1: 2 × 2 kernel with stride 2
- Convolutional Layer 2: 256 kernels of size 3 × 3 × 32 × 3, followed by ReLU activation
- Normalization Layer (LRN)
- Max-Pooling Layer 2: 2 × 2 kernel with stride 2
- Convolutional Layer 3: 384 kernels of size 3 × 3 × 3 × 32, followed by ReLU activation
- Convolutional Layer 4: 4096 kernels of appropriate size (to match output of previous layer), followed by ReLU activation
- Convolutional Layer 5: 4096 kernels of appropriate size (to match output of previous layer), followed by ReLU activation
- Max-Pooling Layer 3: 2 × 2 kernel with stride 2
- Fully Connected Layer 1: 4096 neurons
- Fully Connected Layer 2: 4096 neurons
- Fully Connected Layer 3: Number of neurons equivalent to the number of classes in the cotton plant stage classification.

Each convolutional layer would be followed by a ReLU (Rectified Linear Unit) activation function, which introduces non-linearity into the model and aids in learning complex patterns. Also, dropout layers could be used between the fully connected layers to avoid overfitting. Remember, this architecture is based on the provided information and can be further modified based on the problem's specifics, including the size of the input images and the number of output classes. You should also adjust hyperparameters such as the learning rate, batch size, and number of epochs for optimal results.

Thus, the CNN network model efficiently extracts features of the cotton plant and accurately classifies its various stages. Histogram based Gradients Feature Orientation Transform (H-GFOT) approach helps reduce deviation, and the softmax function is utilized as an activation function to regulate the output of the network model. During the training process, the CNN network model identifies the dissimilarities between the predicted and original values. The gradient descent algorithmic approach modifies the weight to reduce the deviation. The cotton image with 16 convolution kernels is forwarded to the max-pooling layer, and the output involved in the prediction is obtained using the softmax function. The softmax function is a generalized logistic function that covers multiple dimensions and is familiarly utilized as an activation function in the neural network to regularize the output of the proposed network model. The softmax function is expressed as follows:

$$S(z) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} = \sigma(\tilde{z})_i, \tag{1}$$

where $\sigma(\tilde{z})_i$ is the probability of the input vector belonging to class j. z_j is the jth element of the input vector $\tilde{z}$. k is the number of classes. e^{z_i} is the standard exponential function applied to the jth element of the input vector. $\sum_{j=1}^{k} e^{z_j}$ is the sum of the standard exponential function applied to all elements of the input vector.

3.2.1 H-GFOT method

Integrating Histogram of Oriented Gradients and Scale-Invariant Feature Transform using feature-level fusion techniques results in an adaptive learning rate method that enhances object recognition accuracy. This method is beneficial for scaling the average moving gradient with momentum. In the H-GFOT method, individual learning rates for different elements are computed, and first- and second-moment gradients are used to estimate the neural network weights. The random variable with the Nth moment is equal to the expected value of the Nth power of the variable, which can be denoted mathematically as

$$m_n = E[x^n], \tag{2}$$

where m_n represents the Nth moment of the random variable X, and $E[x^n]$ represents the expected value of X raised to the power of n. The Nth moment provides information about the shape and distribution of the variable X, and it can be used to calculate various statistical measures such as mean, variance, and skewness. The first moment ($n = 1$) is equivalent to the mean of the distribution, while the second moment ($n = 2$) corresponds to the variance. Higher moments provide more detailed information about the distribution, but they are usually less commonly used in practice. The concept of moments is essential in probability theory and statistics, as it allows for analyzing and modeling random variables and their distributions. The H-GFOT method mentioned in the original text uses the first and second moments of gradients to estimate the learning rates of the neural network weights.

The network model produced synthetic raw data as the generator and discriminator worked against each other. Based on an unsupervised approach and accurate training data, the generator in the adversarial network produced the desired data samples. The generated data samples were then fed as input to the discriminator, which classified them based on the accuracy range and identified the probability value of fake input being generated. The training process was expressed using the following formula:

$$V(D, G) = E_{xP_{\text{data}}(x)}[\log D(x)] + E_{zP_z(z)}[\log(1 - D(G(z)))], \tag{3}$$

where $V(D, G)$ represents the adversarial loss function, $D(x)$ represents the probability that x comes from the real dataset, $G(z)$ represents the generated fake input, and $P_{\text{data}}(x)$ and $P_z(z)$ represent the probability distribution of real data and noise input z, respectively. This training process aims to minimize the adversarial loss function to improve the model's accuracy in recognizing cotton bolls.

3.2.2 GANs

The GAN model is utilized to predict the stage of cotton plant growth during the harvesting stage. The system includes a segmentation mask to improve the accuracy and reliability of the output generated from raw images. The generator network undergoes progressive growth during training to produce reliable results. The network layers are integrated in the training process, allowing the model to convert low-resolution images into high-resolution ones. This approach improves the stability of the generator network during training. Both the generator and discriminator networks are fed with high-resolution images to produce double-resolution image frames. The loss function is an essential metric used in the training and testing process to evaluate the model's performance and prevent overfitting. It is the sum of errors generated during the training, validation, or testing. Using the loss function, the parameter's value is adjusted to minimize the corresponding loss. In the GAN-based algorithm, the loss function is utilized in both the generator and discriminator to optimize the output. The expression for the GAN-based loss function is given below:

$$L_{\mathrm{G}}(\tilde{x}) = -E_{\tilde{x}\ P_g}[D(\tilde{x})], \tag{4}$$

$$L_{\mathrm{D}}(x, \tilde{x}, \hat{x}) = E_{\tilde{x}\ P_g}[D(\tilde{x})] - E_{x\ P_r}[D(x)] + \lambda E_{\hat{x}\ P_{\hat{x}}}\left[[\nabla_{\hat{x}} D(\hat{x})]_2 - 1\right]^2 + \varepsilon E_{x\ P_r}[D(x)]^2, \tag{5}$$

where the loss function of the generator and discriminator networks is represented as L_{G} and L_{D}, respectively. P_r represents the data distribution, and the gradient penalty coefficient is denoted as lambda (λ), while the epsilon penalty coefficient is denoted as epsilon (ε), which is used to prevent drifting in the loss function. The expressions for the output sequence of the generator and the input sequence of the discriminator are as follows:

$$\tilde{x} = G(z) = (\tilde{x}_{t+1}, \ldots, \tilde{x}_{t+t_{\text{out}}}), \tag{6}$$

$$x = (x_{t-t_{\text{in}}+1}, \ldots, x_{t-t_{\text{out}}}). \tag{7}$$

The mean Intersection-Over-Union (mIoU) is used to evaluate the segmentation performance of the proposed system in identifying the plants in the harvesting stage in a cotton field. The mIoU measures the similarity between the predicted and ground truth images. The error rate is calculated by comparing the predicted image with the original image obtained through the training and testing procedures. The pseudocode of the proposed DAN is illustrated as follows:

Input: Pre-processed image data of the cotton field
Output: Predicted cotton harvesting period
Begin

1. Load pre-trained DANs model for plant stage classification.
2. Divide the dataset into training, validation, and testing sets.
3. Train the DANs model using the training set.
4. Evaluate the performance of the model using the validation set.
5. Test the performance of the model using the testing set.
6. Obtain the predicted plant growth stages for the input image.
7. Based on the predicted plant growing stages, classify the cotton harvesting period using a decision tree or a rule-based system.
8. Output the predicted cotton harvesting period.
9. **End module**

4 Results and discussion

This section presents the proposed DAN algorithm's analysis, testing, and validation for identifying the cotton harvesting period based on the classified plant growing stages. The dataset used in this study was obtained by capturing images of the cotton field under various conditions and categorizing them into training, validation, and testing sets. The results show that the proposed method outperforms existing methods in terms of accuracy, precision, recall, and F1-score, as measured by mean Intersection-Over-Union (mIoU) and error rate. We present the results of our proposed DAN and demonstrate its superiority over other existing methods in two ways: (1) feature extraction improvement and (2) detection and classification of different growth stages of cotton plants. To compare our proposed H-GFOT algorithm with other methods, including Histogram of Oriented Gradients (HOG) (Salcedo et al. 2020), Scale-Invariant Feature Transform (SIFT) (Al-Gaadi et al. 2016), and Local Binary Patterns (LBP) (Al-Janabi and Alkaim 2022), we conducted a performance analysis of the feature extraction process.

Similarly, we compared the performance of our proposed CropCycleNet with other existing networks such as Recurrent Neural Networks (RNNs) (Syazwani et al. 2021), Long Short-Term Memory Networks (LSTMs) (Fu et al. 2019), Generative Adversarial Networks (GANs) (Wu et al. 2020b), Deep Belief Networks (DBNs) (Harel et al. 2020), and Self-Organizing Maps (SOMs) (Liu et al. 2020) for detecting and classifying different growth stages of cotton plants. Our proposed DAN outperformed the existing feature extraction and performance comparison methods. These results demonstrate the effectiveness and superiority of our proposed DAN in accurately identifying the harvesting period of cotton plants.

4.1 Evaluation metrics

Various performance metrics were employed to evaluate the accuracy of the proposed model, including key performance indicators such as specificity accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's performance in correctly identifying and classifying the different growth stages of the cotton plant and help determine the overall effectiveness and efficiency of the proposed approach.

The metric accuracy measures the proportion of correctly classified samples and is expressed as

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}), \quad (8)$$

where TP is a true positive, TN is a true negative, FP is a false positive, and FN is a false negative.

Precision is the number of true positives divided by the number of predicted positive values and is expressed as

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}). \quad (9)$$

Recall, also known as sensitivity or true positive rate, is the proportion of true positives to the total number of actual positive samples and is expressed as

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}). \quad (10)$$

The F1-score is a combined measure of precision and recall and is expressed as

$$\text{F1} - \text{Score} = 2 * ((\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})). \quad (11)$$

These metrics are commonly used in evaluating the performance of classification models, including machine learning models for identifying the growth stages of cotton plants. By comparing the performance of the proposed model with existing methods using these metrics, we can determine the superiority of the proposed model in accurately identifying the growth stages of the cotton plant.

4.2 Observations

The experimental results demonstrate that the proposed model is highly effective in identifying the different growth stages of the cotton plant based on unique features trained in the CropCycleNet, enabling accurate detection and classification of the crops. As shown in Fig. 3, the model can accurately identify the different stages in randomly selected frames, enabling precise counting and improved harvesting processes and productivity. The model also enables the prediction of the accurate harvesting period, leading to increased production rates for the cotton industry. According to that, the proposed DAN model is evaluated to identify various growth stages of the cotton plant. The dataset is trained using the proposed method, and the accuracy and loss curves are plotted. The proposed method achieves a high recognition speed and accuracy of up to 93.27% using a high-resolution convolution structure. The confusion matrices are analyzed to evaluate the precision, recall, and F1-score of the proposed method for identifying the seedling stage, bud stage, boll stage, boll opening stage, and harvesting stage of the cotton plant. The results show a 100% prediction accuracy for the seedling and bud stages and 80% accuracy for the other stages. The seedling and bud stages also exhibit a high precision rate, while the boll and boll opening harvesting stages have lower accuracy despite having more data available. The accuracy and loss function of the proposed CropCycleNet are presented in Fig. 4, respectively. These results demonstrate the effectiveness of the proposed DAN for accurately identifying the growth stages of the cotton plant, especially in the seedling and bud stages.

4.3 Discussion

The proposed model's performance was evaluated in two different scenarios: during the forenoon (10.00 am to 1 pm) and the afternoon (2 pm to 6 pm). This evaluation demonstrated a significant improvement in identifying the cotton plant growth stages and analyzing each cotton boll to predict when it will reach the harvesting stage. It is essential to continuously monitor the crop between 6 and 8 months, as this period has the maximum chance of affecting plant diseases that can spoil the productivity of the cotton yield.

A confusion matrix was randomly computed to evaluate the model's accuracy by taking one test frame in both the forenoon and afternoon. The results indicate that the

Fig. 3 The proposed CropCycleNet model detects the different stages in randomly selected frames

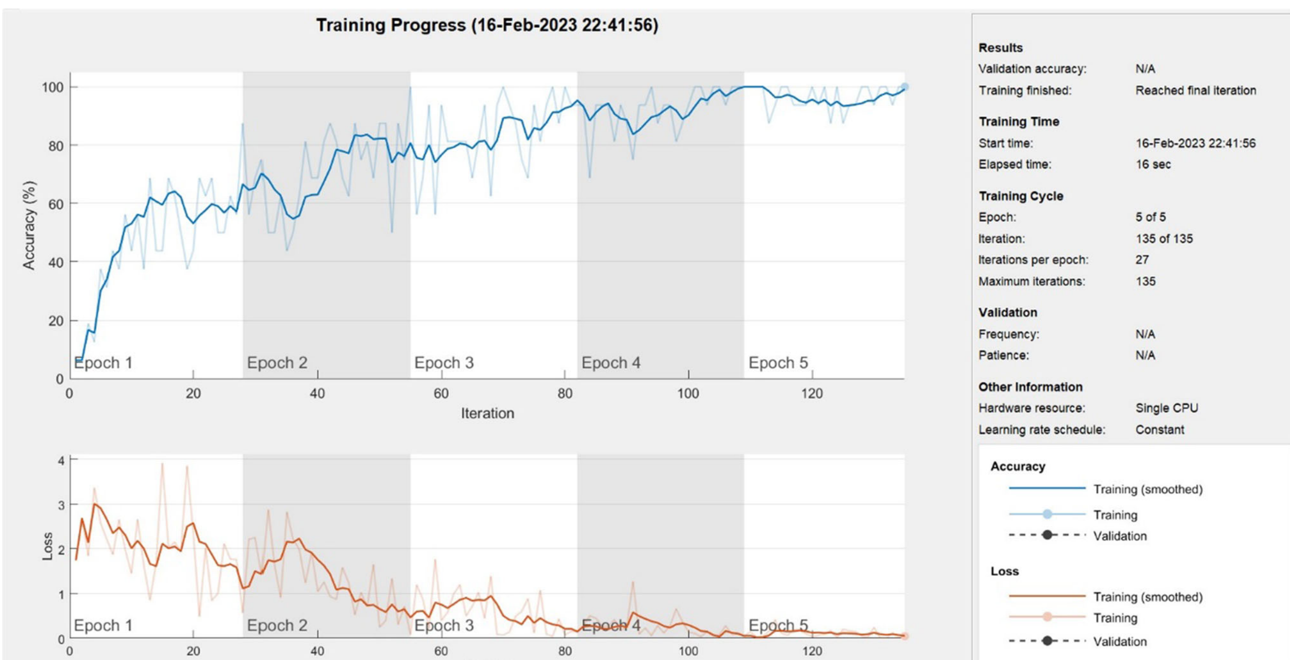


Fig. 4 The proposed model training acquires an accuracy and loss function

maximum accuracy of cotton stage identification occurred in the forenoon frame compared to the afternoon frame.

This difference in accuracy is because the visual quality of the afternoon frame is lost due to reduced light reflection in the evening, which creates some shadows that affect the clarity of the image quality. Therefore, the maximum probability of prediction is not achieved, which is reflected in the confusion metrics shown in Fig. 5. These results highlight the importance of considering the time of day when collecting images for the model's input. The proposed model has the potential to significantly improve the cotton yield by accurately predicting the harvesting period. It can also help detect plant diseases early, which can prevent damage and improve yield. The model's performance in different scenarios can be further improved by developing techniques to address the limitations of image quality in the afternoon frames, such as using image

Fig. 5 Confusion metric. **a** Forenoon identification and **b** afternoon identification

Table 1 Performance of cotton plant growth and classification output during forenoon using proposed CropCycleNet model

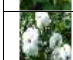
Cotton plant stages	Accuracy	Precision	Recall	F1-score	Overall accuracy (%)
	93.98	93.57	92.42	91.3	**93.8375**
	94.12	93.09	92.79	92.5	
	93.23	93.71	94.1	94.5	
	94.02	91.57	92.58	93.6	

Table 2 Performance of cotton plant growth and classification output during afternoon using proposed CropCycleNet model

Cotton plant stages	Accuracy	Precision	Recall	F1-score	Overall accuracy (%)
	90.98	90.57	89.42	88.3	**90.8375**
	91.12	90.09	89.79	89.5	
	90.23	90.71	91.1	91.5	
	91.02	88.57	89.58	90.6	

processing algorithms to enhance the visual quality of the images.

The proposed model's performance was evaluated in two scenarios: forenoon and afternoon. The aim was to determine the accuracy of identifying the cotton plant growth stages and analyze each cotton boll's harvesting stage. The crop was monitored continuously for 6–8 months because this period had the highest risk of plant diseases that could reduce the cotton yield. Confusion metrics were randomly computed using one test frame in both the forenoon and afternoon.

The results showed that the maximum accuracy of cotton stage identification was achieved during the forenoon frame compared to the afternoon frame. This was because the visual quality of the afternoon frame was lower due to reduced light reflection in the evening, leading to some shadow reflections that affected the image's clarity. As a result, the maximum prediction probability was not achieved in the afternoon frame. Tables 1 and 2 also confirm this observation. Overall, the proposed model's performance was demonstrated to be effective in identifying cotton growth stages and evaluating critical parameters in different scenarios provided valuable insights for improving the model's accuracy. The overall performance of feature extraction and prediction is comparatively analyzed with the other existing state-of-the-art methods, as shown in Figs. 6 and 7.

5 Conclusion

This research work proposed a CropCycleNet model to identify the growth stages of the cotton plant and predict the harvesting period. The proposed model used a deep learning approach and achieved an accuracy range of up to 93.27% (Forenoon) and 90.52% (Afternoon) using a convolution structure with high resolution. Performance metrics such as precision, recall, F1-score, and reliability were considered to evaluate the model's performance. The performance evaluation results show that the proposed model effectively identifies the growth stages of the cotton plant and predicts the harvesting period. The confusion matrix analysis shows that the highest accuracy of identification of

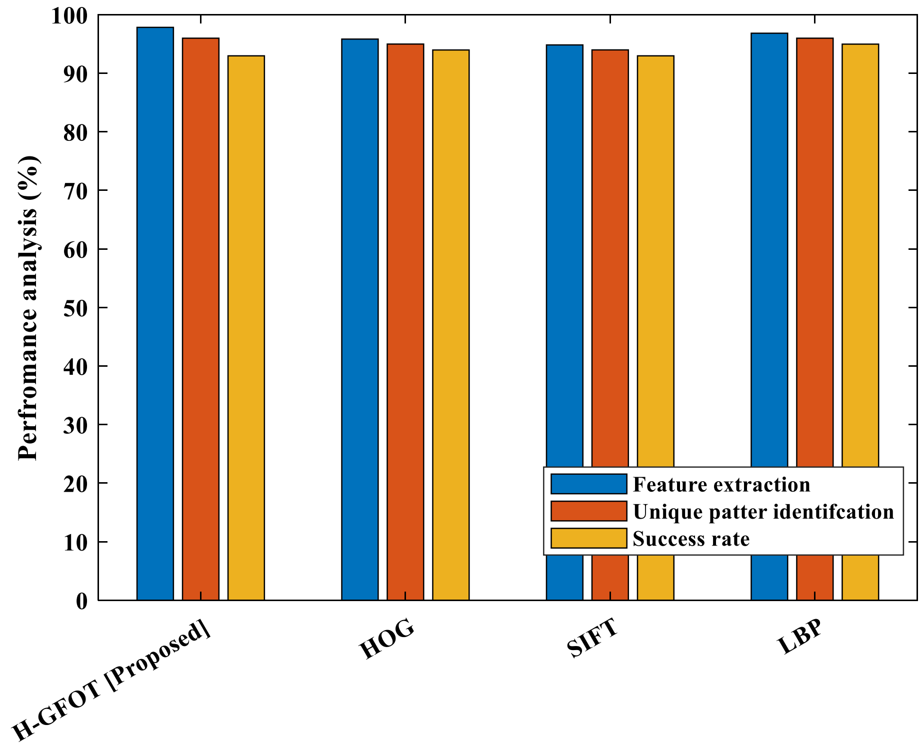


Fig. 6 Performance chart of feature extraction methods

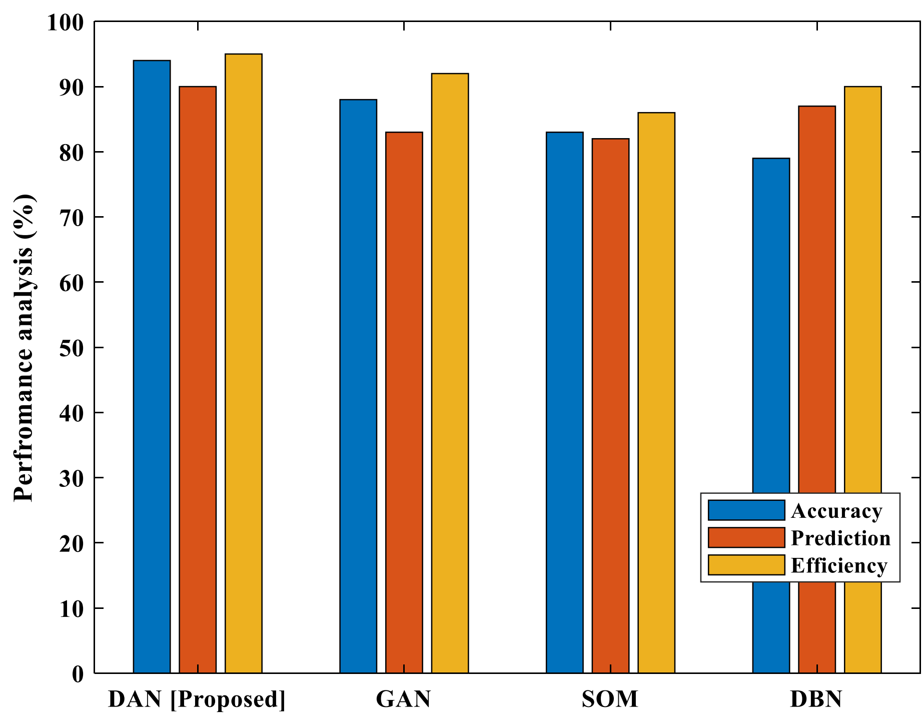


Fig. 7 Comparison performance chart of the prediction and classification functions over different methods

the cotton stage is achieved in the forenoon frame compared to the afternoon frame. However, the proposed model can be further improved by considering the effects of external factors such as weather, soil quality, and diseases that can affect the growth and productivity of the cotton plant. Overall, the proposed model has the potential to improve the efficiency and productivity of the cotton farming industry by enabling farmers to accurately predict the harvesting period and take appropriate measures to ensure optimal growth and yield. Future work can be focused on enhancing the model's accuracy by incorporating additional features and improving its robustness to external factors.

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Declarations

Conflict of interest The authors declare they have no conflicts of interest to report regarding the present study.

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Consent for publication The authors declare that this work has not been published before, that it is not under consideration for publication elsewhere, and that all co-authors have approved its publication.

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