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CoDet: A novel deep learning pipeline for cotton plant detection and disease identification

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ABSTRACT

Cotton detection is a crucial component of the agricultural sector because it enables farmers to correctly identify and keep track of the development of cotton crops. Systems for automatically detecting cotton could boost output and efficiency while decreasing costs and waste in cotton growing operations. New cotton detection systems have been developed as a result of recent developments in machine learning and computer vision. These devices can precisely identify and monitor cotton plants using images and sensor data. These systems assess and categorize cotton plants according to their many spectral signatures using convolutional neural networks (CNNs), deep learning algorithms, and hyperspectral imaging, among other methods. The use of cotton detection technologies can help with problems related to crop diseases, pests, and environmental factors in addition to enhancing crop management and production optimization. Farmers and researchers may spot possible issues early and take corrective action to decrease risks and promote healthy crop growth by offering real-time monitoring and data analytics. As cotton detecting technologies have the potential to alter the cotton farming sector and improve environmentally friendly farming techniques, they represent a promising area for research and development. The proposed pipeline demonstrates how cotton may be recognized quickly and reliably.

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KEYWORDS
Computer vision; catmull rom; convolutional networks; feature maps

Introduction

Cotton, one of the most widely grown commodities in the world, is a crucial supply of fibre for the apparel sector. If farmers and researchers want to maximize crop yields, control pests and diseases, and support sustainable agricultural methods, accurate monitoring and detection of cotton growth is essential [1–4]. Recent years have seen the development of a large number of automated cotton identification systems thanks to advancements in computer vision and machine learning technologies. These systems use a variety of methods to evaluate and categorize cotton plants based on their distinctive spectral fingerprints.

Traditional cotton detection techniques rely on physical crop sampling and manual observation, which can be labor- and time-intensive and may not yield real-time data. A backup strategy should be in place in case the first one fails. These systems examine the specific spectral features of cotton plants to ascertain their location, stage of development, and state of health. They do this by using a variety of technologies, including hyperspectral imaging, convolutional neural networks, and deep learning algorithms. Automated cotton detection systems have the potential to revolutionize the cotton farming industry by giving farmers and researchers access to far more precise and timely data on crop growth and development. As a result, increasing crop yields, decreasing waste, and promoting sustainable farming practices may be possible [2].

Detecting cotton is important for a number of reasons. To begin with, cotton is an important crop for the textile industry and is farmed by numerous farmers all over the world as a significant source of income [3]. Accurate identification and monitoring of cotton growth are essential for the efficient and sustainable production of cotton fibre. Second, a range of ailments, pests, and environmental factors can harm the development and output of cotton crops. Early detection and management of these issues are necessary to maintain the health and productivity of cotton fields as well as to prevent crop damage and losses. Last but not least, conventional methods of cotton identification may be labor- and time-intensive and may not provide real-time information on crop growth and development.

Contrarily, automated cotton detection systems can provide farmers and researchers with more accurate and timely data, enabling them to make more informed decisions on the management and optimization of their crops. Overall, cotton detection is crucial for managing crop health and productivity, providing an effective and sustainable production of cotton fibre, and reducing

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waste and losses. The creation of new automated detecting technologies, which would also support more ecologically friendly farming practices, could revolutionize the cotton-growing sector [5, 6].

Recent advancements in technology have attracted a number of academics who study the identification and classification of pests and diseases of cotton leaves. Several constraints reduce the yield and quality of the product in India. Traditional methods are used to find likely diseases or pests, especially when it comes to cotton. The development of cotton crops has not received much attention, despite the fact that there is a sizable quantity of farmland that is suited for cotton plantations. If cotton is not quickly identified, it may result in a variety of adverse effects, depending on the situation.

Cotton plants (as shown in the Figure 1) can cause a number of issues if they are not identified in time, which could have a big impact on the harvest. Cotton plants, like other plants, require a few key elements for optimum growth and production. These elements include adequate space, adequate sunlight, a consistent supply of water, and an abundance of nutrients. Cotton plants cannot grow and produce to their full potential without any one of these essential elements. One of the most crucial factors in the growth of cotton plants is adequate space. To spread out and develop their root systems, which allow them to more effectively absorb water and nutrients from the soil, cotton plants require a specified amount of space. If cotton plants are packed or grown too closely together, they may not have enough room for their root systems to develop completely [7, 8]. This could lead to stunted growth and poor productivity. Another critical element for the development of cotton plants is the capacity to receive adequate sunlight. Sunlight is necessary for photosynthesis, the process by which plants convert light energy into chemical energy to support their growth and development. Cotton plants grown in shaded areas may not receive sufficient sunlight to adequately photosynthesize, which could result in slowed growth, brittle stems, and decreased yields [17].

Delayed detection of pests and diseases in cotton plants can have a major influence on crop output and quality. Pests and diseases can injure plants, which prevents them from developing and growing as they should. If the issue is not identified quickly, it might quickly spread across the entire crop, causing far more significant injury. For cotton plants, pests can be a severe problem and do them harm in a variety of ways. For instance, cotton bollworms can severely damage cotton bolls, which has an impact on cotton quality and yields. In a manner similar to this, aphids can reduce the amount of sap that is accessible to the plants, limiting their capacity to grow and produce [18].

Diseases can also pose a serious threat to cotton plants. For instance, the vascular system of a plant may suffer severe damage from verticillium wilt, which would reduce the plant's ability to transmit nutrients and water. Similar to leaf spots and stem rot, bacterial blight can reduce a plant's overall health and productivity. If insect or disease infestations are not stopped in their tracks, they can quickly spread throughout the crop and cause much more damage. For example, if a farmer misses a bollworm infestation, the bugs could spread throughout the entire crop, severely destroying the cotton bolls [9]. The farmer's bottom line could suffer as a result of decreased cotton yields and quality. To prevent insect infestations and disease outbreaks from damaging the crop, farmers must be cautious and keep a close eye on their cotton plants [10]. This means inspecting the plants for signs of injury or infestation and responding immediately to any issues that are

Figure 1. A collection of various cotton plants.

discovered. Early detection and management of pests and diseases are crucial for ensuring that cotton plants grow and develop properly, leading to higher yields and better-quality cotton [19].

The quality of cotton fibre has a big impact on how much it is worth in the market. The best fibres are produced when cotton plants are harvested at the proper moment. Having a backup plan in place in the event that you need to relocate your company is a wise decision. When cotton plants develop and grow, the quality of the fibres they produce could decline. This is because the fibres may lose their appeal for use in the production of textiles as they become thicker, shorter, and less flexible. If they are not found in time, cotton plants may continue to grow and develop, generating fibres that are less appropriate for use in textiles. If cotton plants are harvested too late, debris may also build up in cotton fibres [11, 12].

Trash is any non-cotton materials that are mixed in with the fibres, such as leaves, branches, or seeds. If the crop is not harvested in a timely manner, cotton plants may start to shed their leaves and produce more waste, which could reduce the quality of the fibres. In addition to debris buildup, late harvesting can cause fibre discoloration. The fibres may no longer be suitable for use in textiles when they begin to turn yellow or brown. Cotton plants may be exposed to moisture for a prolonged period of time if they are kept in the field for an excessively long time, which may cause the fibres to become discolored [20, 21]. Farmers must keep an eye on the plants' growth and development and determine when to harvest based on factors like the weather and consumer demand. The fibres from cotton plants will be of the highest quality when they are picked at the right time, enhancing their market value and the farmer's income.

Water is a vital resource for the growth and development of cotton plants. Cotton plants require regular and adequate watering in order to grow healthily and produce high-quality fibre. Delays in identifying cotton plants could lead to insufficient water availability, which could lead to water stress and hinder growth and production. Water stress occurs when plants do not receive the necessary amount of water to meet their needs. When cotton plants experience water stress, they may show signs of withering, which can hinder growth and output. Water-stressed cotton plants may be more susceptible to pests and diseases, which could further impede their development and productivity [22].

Water stress may be brought on in a number of different ways by delayed cotton plant identification. Cotton plants may not receive adequate water if they are not periodically inspected, for example, during droughts or when irrigation systems fail. Water stress could result, which could stop them from developing and functioning. If cotton plants are not planted in the right soil or if the soil cannot hold enough water, water stress may also arise. If cotton plants are cultivated on sandy soil, which does not properly hold water, they may experience water stress if they are not routinely watered [23].

In order to prevent water stress in cotton plants, farmers must monitor their crops and ensure that they receive adequate water. This necessitates evaluating irrigation systems and the moisture content of the soil in order to ensure that the plants are receiving the required amount of water. Also, it's essential to adjust watering schedules based on the weather and the stage of plant growth and to plant cotton in soil types that retain water well.

100% cotton biodegrades at least 50% to 77% within three months in a large-scale compost, adding carbon to the soil and boosting its fertility. You can recycle cotton. The minute fibres that naturally fall off after use and wash into our waterways are not produced by it. India generated 4.6 billion dollars in revenue in 2016 and controls 24% of the world's cotton-growing territory. Unfortunately, 18% of the cotton crop production was routinely lost each year due to various illnesses that attacked the cotton plants, costing over 900,000 Indian rupees. The biggest challenges keeping cotton production from fulfilling global demands for quality and quantity are diseases and pests. As a result, the farmers as well as the nation's economy suffer.

Textiles are usually made of cotton, a natural material. While being a robust and diversified crop, its processing and production can have a significant detrimental impact on the environment. The delayed discovery of cotton plants may lead to the adoption of alternative materials, which could have its own environmental impacts. Polyester and nylon are two common substitutes for cotton. They are less expensive and more readily available, but they are not biodegradable and can take a very long time to break down in the environment. Synthetic fibre production also requires a significant amount of resources, including fossil fuels, which could contribute to an increase in greenhouse gas emissions and climate change. Contrarily, cotton does not have a long-term negative impact on the environment and can naturally disintegrate.

When implemented right, cotton cultivation can also improve soil health and reduce erosion, which are both good things for the environment. Cotton production can have a negative impact on the environment if done improperly. In order to grow cotton, for instance, farmers typically use a lot of pesticides and fertilizers, which can harm wildlife and contaminate the soil and water sources. The production of cotton can also result in significant amounts of effluent, which may contain harmful chemicals and pollutants. Farmers can limit the harmful impacts of cotton production on the environment by using ecologically friendly growing methods that reduce the use of toxic pesticides and boost biodiversity.

Moreover, in order to reduce waste and maximize resource consumption, textile companies might employ resource-efficient production methods. Early cotton plant detection and the promotion of sustainable practices across the supply chain can help to mitigate the damaging environmental effects of cotton production.

Contributions in this paper

- Because the existing literature failed to consider the distinctive qualities of cotton plants, like how they are distributed and where they grow, the present methods for recognizing cotton plants are not very effective.
- To solve the above mentioned issue, this study suggests a novel strategy dubbed CoDet (Refer Figure 2), which employs a variety of cutting-edge mathematical methods to more precisely identify cotton plants.
- CoDet is taught to recognize cotton plants and has been specifically created to comprehend the growth patterns and patterns of cotton plants.
- The CoDet architecture's layers are each built to evaluate the input photos and produce maps and results that can aid in the identification of many aspects relating to cotton plants.

The organization of the paper is as follows: Section II describes and elaborates the state of the art literature. Section III showcases the proposed CoDet pipeline where it exhibits the model architecture. Section IV discusses about the results and discusses more on the training and testing accuracy and loss part. Finally, the paper is concluded in the Section V.

Prior research: the state of the art literature

In earlier studies on cotton identification, a range of techniques, such as spectral imaging, machine vision, and remote sensing, were emphasized. Remote sensing methods have been extensively used in cotton detection. These techniques monitor the growth and health of cotton crops using aerial or satellite imagery. For instance, cotton crops were identified and their expected output was computed using satellite imagery in a study by Rahman et al. (2018). Remote sensing techniques, like satellite pictures or aerial photography, are widely employed to find cotton.. These methods can give a thorough picture of cotton crops and track their development and well-being over a sizable area. By examining vegetation indices like the normalized difference vegetation index, remote sensing can also be utilized to predict the yield potential of cotton fields (NDVI) [13].

Machine vision systems employ cameras and image processing techniques to recognise cotton plants. In a study by Kumar et al., a machine vision system was developed to recognise cotton plants in a field (2019). The system employed strategies for colour-based segmentation to separate cotton plants from the backdrop. Machine vision techniques can also be used to construct 3D models of the cotton plants, providing valuable information about the development and structure of the plants. Growers can find areas where plants are either too close together or too far apart, which may affect yield potential, by employing these models. These techniques can provide more precise information on particular cotton plants and their characteristics, such as plant height, leaf area, and plant spacing. Machine vision systems can be mounted to drones or ground-based vehicles, making them ideal for real-time and confined area cotton crop monitoring.

To identify the spectral signature of cotton plants, spectral imaging techniques employ hyperspectral sensors. In a study published in 2019, Kundu et al. used hyperspectral imaging to locate cotton plants in a field. The study found that hyperspectral imaging could accurately identify cotton plants even in difficult situations like mixed crops.

To find specific spectral fingerprints linked to diverse cotton plant parts, such as leaves, stems, and flowers, hyperspectral imaging can be used in cotton detection. These spectral characteristics can be used to distinguish cotton plants from other forms of flora in the field and to identify diseases, nutrient deficiencies, and stress in plants.

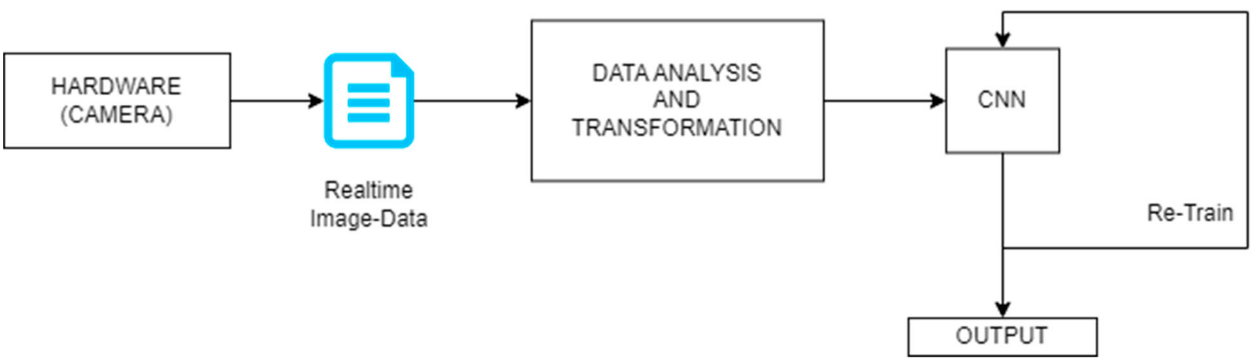

Figure 2. The proposed pipeline of CoDet.

Moreover, hyperspectral imaging has the capacity to detect changes in cotton plants' reflectance over time, which can be used to monitor plant growth and potential for output. The ability to capture information about the physical and chemical properties of the cotton plant that is either invisible to the human eye or undetected by standard imaging techniques is one advantage of hyperspectral imaging.

For instance, variations in the amount of chlorophyll can signal a healthy plant and active photosynthetic activity, and can be detected by hyperspectral imaging. Hyperspectral imaging can also be used to detect changes in the water content and other chemical components of the plant, which can provide crucial information about plant stress and nutrient shortages [14].

Even if each methodology has benefits and drawbacks of its own, using multiple approaches can result in a more comprehensive understanding of cotton crops. For instance, although remote sensing can be used to determine general patterns in cotton growth and health, computer vision can be utilized to provide specific information about specific plants.

Farmers can identify potential problems early on with the help of spectral imaging, which can provide additional information on the chemical and physical features of the plant. These techniques provide farmers with more accurate and fast information about their crops, which can help with agricultural yield optimization, cost reduction, and increased profitability [15, 16].

CoDet: the proposed DL pipeline architecture

The primary objective of this research project is to analyze a big dataset of images collected from various online sources. The dataset consists of around 30,000 photos in total, with a training batch of 25,000 images and a validation set of 5,000 images.

The suggested methodology for the dataset analysis consists of a number of steps. The first step involves employing a high resolution technology to enhance the image pixels. More specifically, the Catmull–rom interpolation method is used to upscale the photographs and improve their visual quality. This step is essential since it may reduce noise and improve the accuracy of subsequent analysis.

The process of t-distributed stochastic neighbor embedding is used to reduce the number of dimensions (t-SNE). This method allows the high-dimensional data to be reduced to a lower-dimensional space while maintaining its similarity structure. This enables a clearer visualization of the data, which can aid in understanding the underlying relationships and patterns in the data.

After dimensionality reduction, point cloud processing is used to handle the dataset. No topological representation is required in this approach; instead, geometric operations and algorithms are directly applied to the data points. Next, a nearest neighbor method is used to identify the dataset's closest neighbors and build a graph that connects them. Using this graph, the dataset's geometric structure and relationships are then depicted in a point cloud form.

Convolutional layers composed of dropout, max pooling, and kernel layers are ultimately employed for detection. These layers enable the model to find characteristics that are crucial for locating certain objects or patterns in the images. These layers give the model the ability to correctly classify the images and identify the presence of specific traits or interesting patterns.

Ultimately, this study endeavor demonstrates how effectively various approaches and procedures may be applied to evaluate huge image databases. By applying methods like super-resolution, dimensionality reduction, and point cloud processing, the researchers are better able to comprehend the underlying patterns and correlations in the data. This has important ramifications for numerous computer vision and image analysis applications.

Catmull–rom interpolation

Catmull–Rom interpolation is a powerful method used in image processing to interpolate data points and create smooth curves. It is especially useful in the context of cotton identification since it may be used to enhance cotton images' quality and reduce the appearance of artifacts and pixelation.

One of Catmull–Rom interpolation's key benefits is its ability to create smooth transitions between pixels. For instance, when resizing an image, the pixels are interpolated to get the new picture size. Catmull–Rom interpolation can make it simpler to identify cotton in an image by ensuring that these transitions are smooth and by eliminating rough edges and other imperfections.

The formula for the Catmull–Rom interpolation of an RGB image is:

$$\begin{aligned} \mathrm{P(t)} = 0.5^*[(2^*\mathrm{P1}) + (-\mathrm{P0} + \mathrm{P2})^*\mathrm{t} \\ + (2^*\mathrm{P0} - 5^*\mathrm{P1} + 4^*\mathrm{P2} - \mathrm{P3})^*\mathrm{t}^2 \\ + (-\mathrm{P0} + 3^*\mathrm{P1} - 3^*\mathrm{P2} + \mathrm{P3})^*\mathrm{t}^3] \end{aligned}$$

where P0, P1, P2, and P3 are the four control points that define the curve, and t is the interpolation parameter that varies between 0 and 1. The output of the function is a new RGB value that represents the interpolated colour at a given point along the curve.

Calculating a curve that goes across the four control points and neatly connects them is how the Catmull–Rom interpolation operates. The curve is generated by the function using a cubic polynomial equation, which makes sure it is smooth and continuous. Because

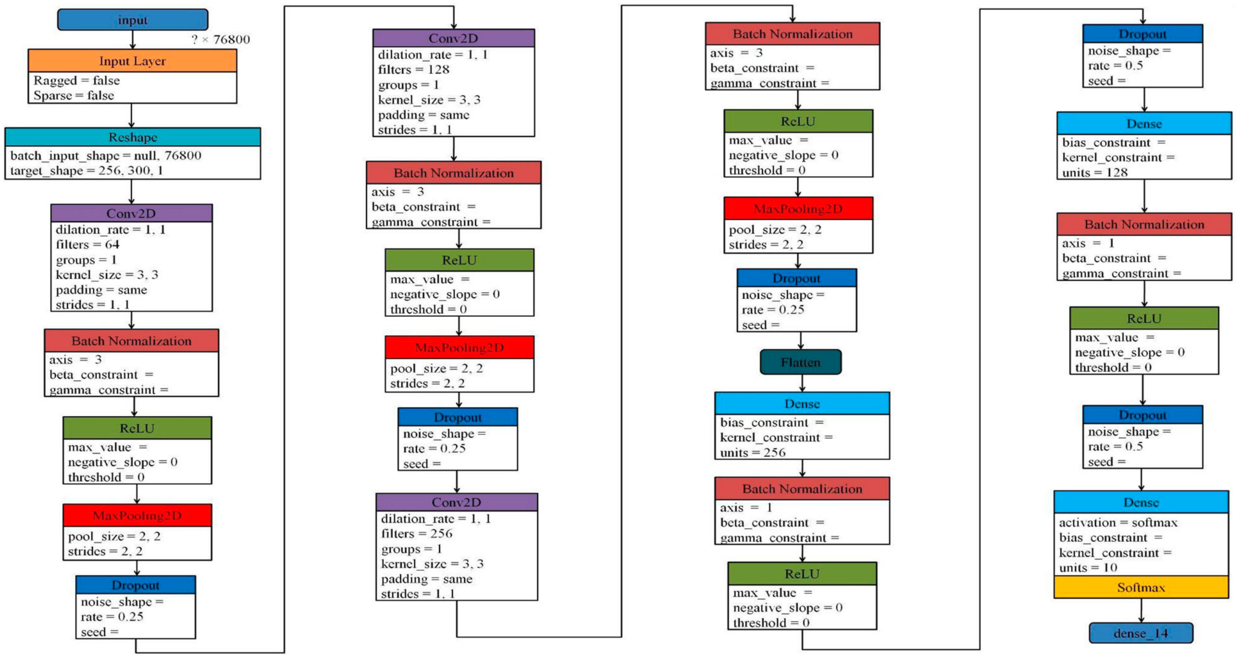

Figure 3. The convolutional layers of the proposed network.

there are no abrupt corners or discontinuities, the resulting curve is perfect for usage in image processing applications. Figure 3 shows the proposed model and its connected layers for deeper insight.

Model architecture

We intend to employ convolutions to create feature maps using convolutional training after data viewing and analysis. Model architecture for CoDet is composed of a number of convolutions. The model architecture is created for problems involving picture categorization. Convolutional layers in a CNN are in charge of identifying patterns and characteristics in the input images. Each convolutional layer creates feature maps by applying a group of teachable filters, sometimes referred to as kernels, on the input image. Each filter moves over the input image and multiplies the matching input image pixel values by the filter weights element-by-element. The feature map's location corresponding to the centre of the filter receives the resultant values' totals and stores them there. The CNN can extract significant information from the input image, including edges, textures, and forms, by learning the proper filter weights.

The first layer in the model architecture given is a Reshape layer, which reshapes the input shape tensor (76800) into a shape tensor (256, 300, 1). This is so because the input images are 256 × 300 pixel grayscale images. The 1 at the end denotes the input image's single channel (grayscale), as opposed to the three channels present in a colour image (RGB).

Three convolutional layers follow the Reshape layer, and each is followed by a BatchNormalization layer and a ReLU activation function. Padding is used in the first convolutional layer, which has 64 filters of size (3, 3), to preserve the feature maps' spatial dimensions. There are 256 filters in the third convolutional layer and 128 filters of size (3, 3) in the second convolutional layer (3, 3). Each layer's filters pick up distinct characteristics and patterns from the input image, and the BatchNormalization layer serves to stabilize and speed up training by normalizing the activations in the feature maps. The network's non-linearity is introduced by the ReLU activation function, which also aids in simulating intricate interactions between input and output.

The MaxPooling layer, which comes after each convolutional layer, decreases the feature maps' spatial dimensions by taking the highest value available in each pooling window. By lowering the number of parameters, this helps to downsample the feature maps and improve the network's efficiency.

The feature maps are flattened into a one-dimensional vector after the third MaxPooling layer and then passed through two fully linked layers, each of which is followed by a Batch Normalization layer, a ReLU activation function, and a Dropout layer with a dropout rate of 0.5. To avoid overfitting, the Dropout layer randomly removes units from the fully connected layers during training. There are 256 units in the top completely connected layer and 128 units in the bottom fully connected layer. A softmax activation function is used in the output layer's 10 units to create a probability distribution over the 10 potential classes.

The overall goal of this model architecture is to identify patterns and features in the input photos that are important for the task of cotton recognition. Convolutional layers pick up on crucial visual cues including edges, textures, and forms whereas fully linked layers pick up on how to combine these cues to determine the final categorization. To train the algorithm to recognise cotton in fresh images or to create bounding boxes around cotton regions, a sizable collection of annotated cotton images can be used.

The loss functions

The box loss and the objectness loss are the two primary loss functions utilized in the CoDet to train the network (or "obj" loss). The box loss gauges how accurately the network can identify an object's bounding box coordinates in an image. In particular, it determines the difference between anticipated and actual ground-truth bounding box coordinates and penalizes the model for any errors. Just the grid cells that house the object's centre are subject to the box loss.

On the other hand, the obj loss quantifies how well the network can recognise an object in an image. It determines the discrepancy between the predicted and actual objectness score, which represents the likelihood that an object will be found in a grid cell, and penalizes the model for any mistakes. Regardless of whether a grid cell contains an object or not, the obj loss is applied to all grid cells.

The optimized loss functions used in CoDet for cotton detection are expressed as follows:

1. Box loss:

$$\mathrm{box\_oss} = \lambda \mathrm{coord}^{*}\Sigma[\mathrm{i,j,k}](1\mathrm{objijk})^{*} \times (\delta \mathrm{x}^2 + \delta \mathrm{y}^2 + \delta \mathrm{sqrt(w)}^2 + \delta \mathrm{sqrt(h)}^2)$$

where λcoord is a hyperparameter that balances the importance of the box coordinates in the loss, δx, δy, δsqrt(w), and δsqrt(h) are the differences between the predicted and ground-truth bounding box coordinates, and the hat symbol ($\wedge$) denotes the ground-truth bounding box coordinates.

2. Objectness loss:

$$\mathrm{obj\_oss} = \Sigma[\mathrm{i,j,k}](1\mathrm{objijk})^{*}(\delta \mathrm{obj}^2) + \lambda \mathrm{noobj}^{*}\Sigma[\mathrm{i,j,k}](1 - \mathrm{objijk})^{*}(\delta \mathrm{obj}^2)$$

where δobj is the difference between the predicted and ground-truth objectness score for the grid cell, λnoobj is a hyperparameter that balances the importance of the objectness score in empty grid cells, and the first term applies to grid cells containing objects, while the second term applies to empty grid cells.

3. Class Loss:

Class loss is the loss function that is employed to penalize inaccurate object classification. It combines confidence loss and localization loss. We use a method known as "label smoothing," which substitutes soft labels with values between 0 and 1 for the hard 0/1 labels. This enhances the generalization of the model and prevents overfitting. The modified formula for class loss with label smoothing is:

$$\mathrm{Class\_oss} = \lambda \mathrm{cls}^{*}\Sigma[\mathrm{obji} = 1 \text{ to } \mathrm{S}^2]\Sigma[\mathrm{cj} = 1 \text{ to } \mathrm{C}] \times [\mathrm{y\,i,j} - ((1-\varepsilon)\mathrm{P\,c(i,j)} + \varepsilon/\mathrm{C})]^2$$

where C is the number of classes, ε is the label smoothing parameter (typically set to 0.1), and P c (i,j) is the predicted probability of cell i belonging to class j. The term $(1 - \varepsilon)$P c (i,j) + ε/C represents the soft label for class j in cell i. By using label smoothing, the model learns to be more robust to noise in the ground truth labels and is less likely to overfit to the training data.

Results and discussion

The suggested structure for identifying cotton plants was developed using Python 3.8 and the Pytorch framework, version 1.13.1. An NVIDIA TITAN Xp GPU, with an inference time of 1000 ms, was used to train the model and execute clustering. An automated script was used to gather the dataset, retrieving images of cotton from Google using Katalon. The proposed architecture is intended to be compact and computation-optimized, which makes it perfect for usage in IoT- and mobile-based applications. This demonstrates that CoDet may be used on hardware with little computing power without sacrificing performance. As a result, CoDet provides a flexible method of identifying cotton plants that is simple to include into a variety of software and hardware. Figure 4 shows the training and testing results.

In CoDet (Cotton Detection), mAP, precision and recall are all important metrics used to evaluate the performance of an object detection model alongside all the loss functions used.

Recall: Recall (refer Figure 5) quantifies the portion of the model's accurate positive predictions that correspond to actual positives in the ground truth. It is calculated by dividing the total of true positives and false negatives by the number of true positives. Good recall indicates that the model has successfully identified the majority of the image's real positives.

mAP (mean Average Precision): The mAP measure (Refer Figure 6), which is frequently used in object recognition tasks, assesses a model's accuracy by calculating the average precision across all object classes. A

	Training	Validation
Accuracy	0.97	0.96
Loss	0.08	0.10

Figure 4. The training and validation results performed on various splits of datasets.

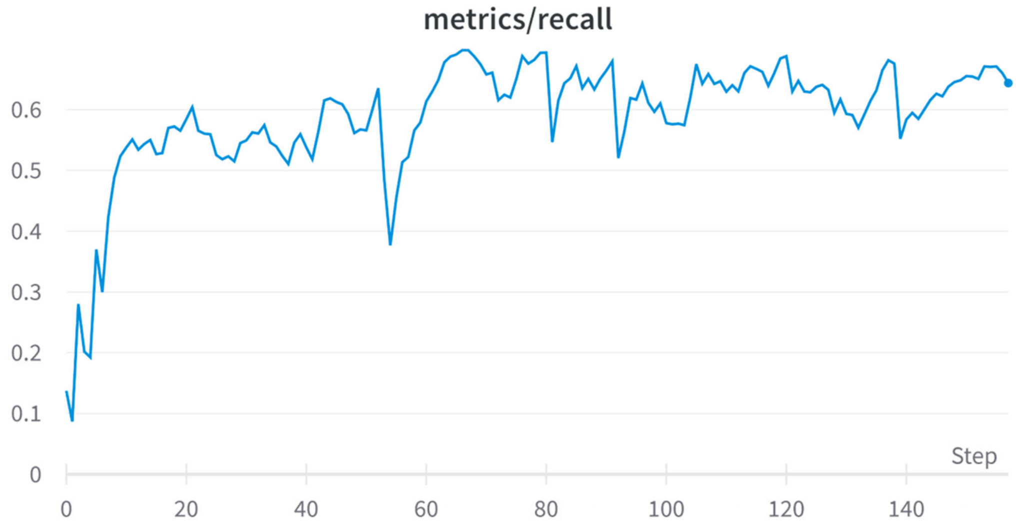

Figure 5. The graph depicts the recall metric.

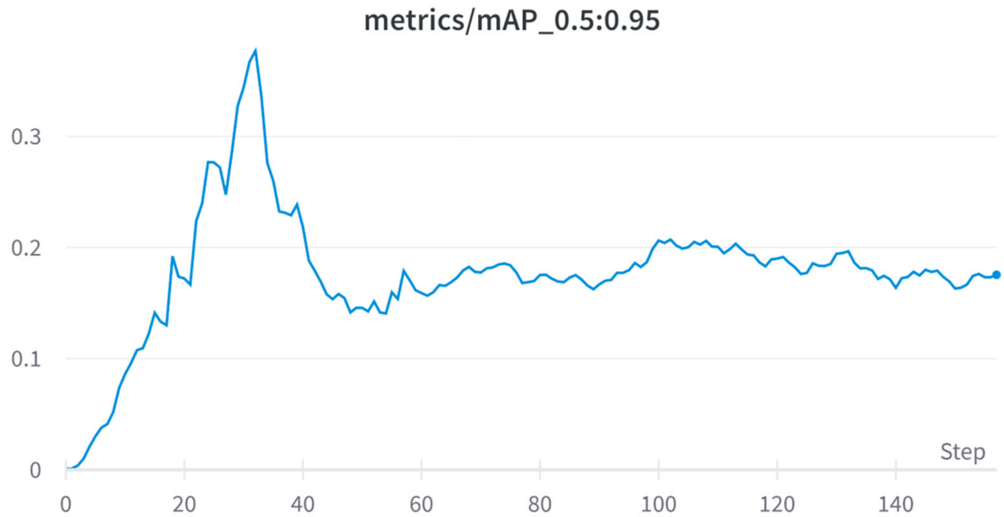

Figure 6. The graph depicts the mAP metric.

greater mAP suggests better detection performance as it measures the area under the precision-recall curve.

Precision: The percentage of valid positive predictions made by the model out of all positive predictions is known as precision. It is calculated by dividing the total of genuine positives and false positives by the number of true positives. A model with high precision has produced fewer false positive detections. Figure 7 depicts the Precision metric.

Figure 8–13 depict the loss metric estimated for the proposed DL pipeline. Figure 14 shows the mosaics of output results generated while testing CoDet on a custom dataset. Figure 15 shows a graph of the training error rate vs maximum features. Figure 16 shows a graph of the training error rate vs. minimum sample. Figure 17 shows the results of evaluation of the proposed CoDet. It has the images predicted using the proposed CoDet.

Future research and conclusion

The accuracy and speed of cotton detection can be increased through the creation of more sophisticated machine learning algorithms, such deep learning. The proposed architecture pipelined as the algorithms are capable of learning intricate features and patterns from big datasets, leading to more precise and trustworthy detection outcomes. A more thorough understanding of cotton fields can be achieved by integrating various sensor types, such as hyperspectral imaging, thermal imaging, and LiDAR. This method can increase the precision of cotton recognition, particularly in challenging contexts like fields of mixed crops or in a variety of lighting and weather situations. Creating mobile, real-time cotton detecting technologies can aid farmers in more efficient crop monitoring.

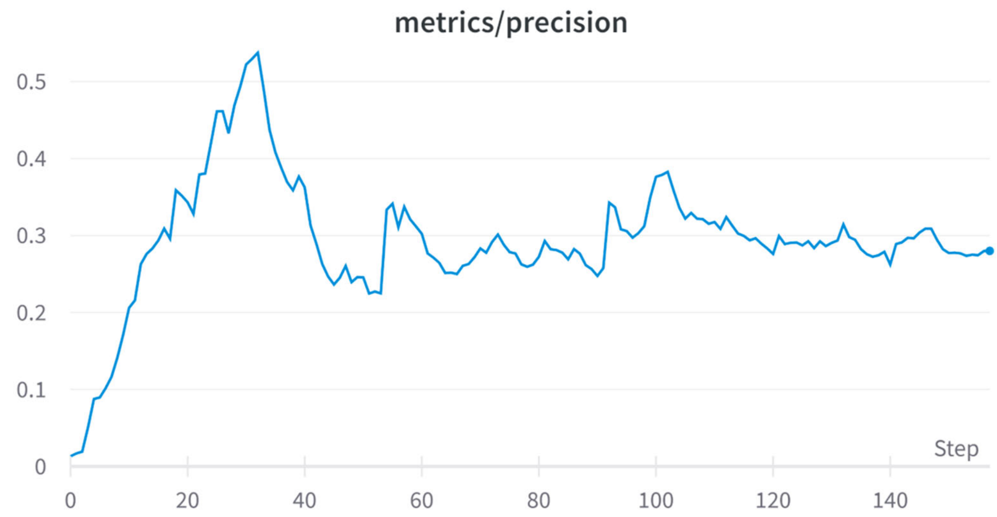

Figure 7. The graph depicts the Precision metric.

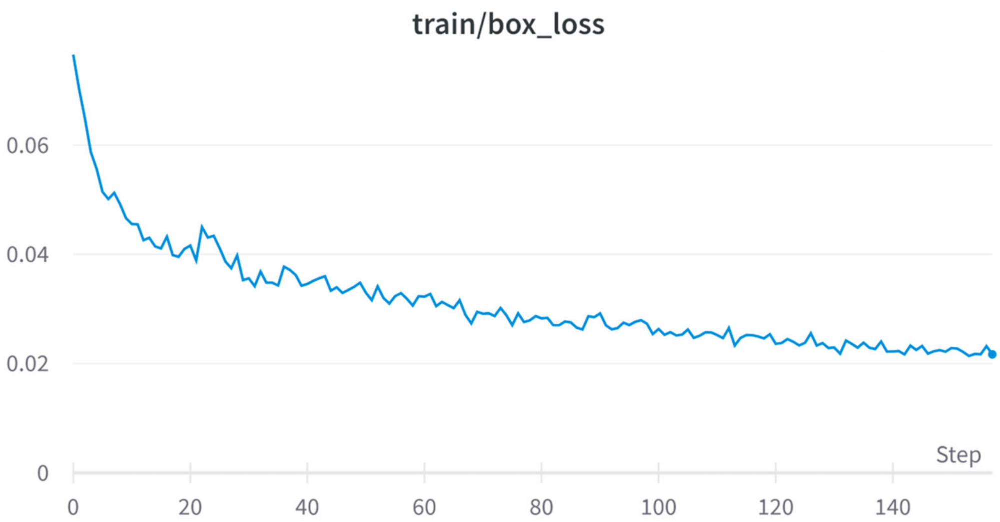

Figure 8. The graph depicts the training box loss for cotton detection of CoDet.

Figure 9. Graph depicting the training object loss for cotton detection of CoDet.

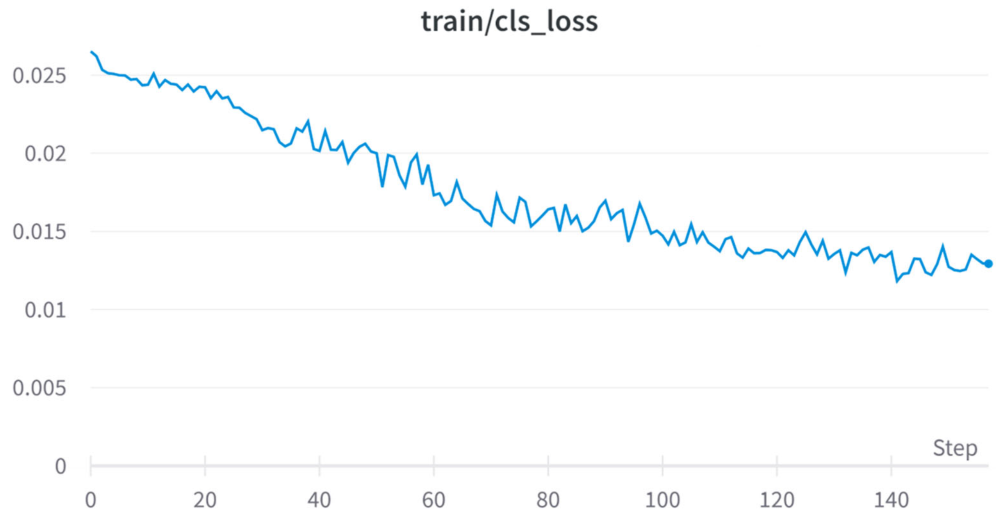

Figure 10. The graph depicts the training class loss for cotton detection of CoDet.

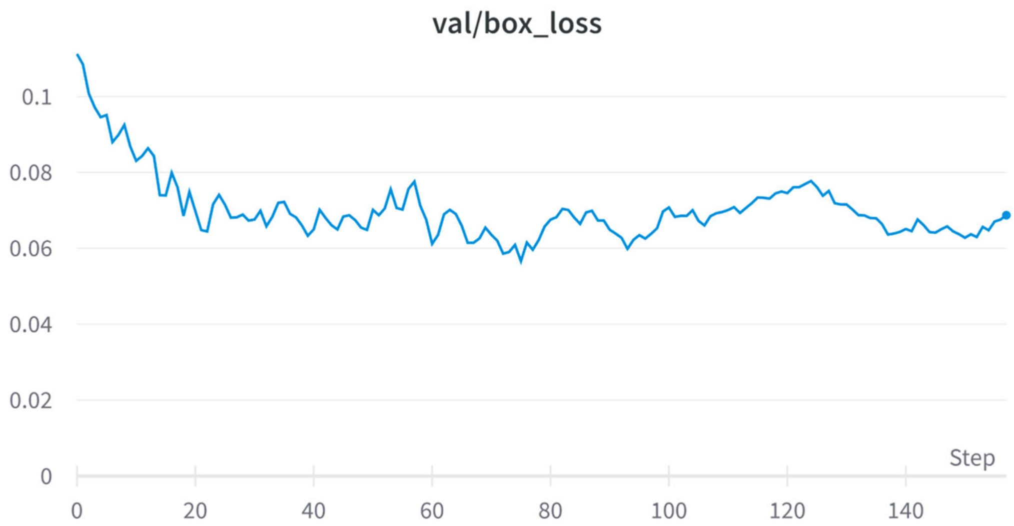

Figure 11. The graph depicts the validation box loss for cotton detection of CoDet.

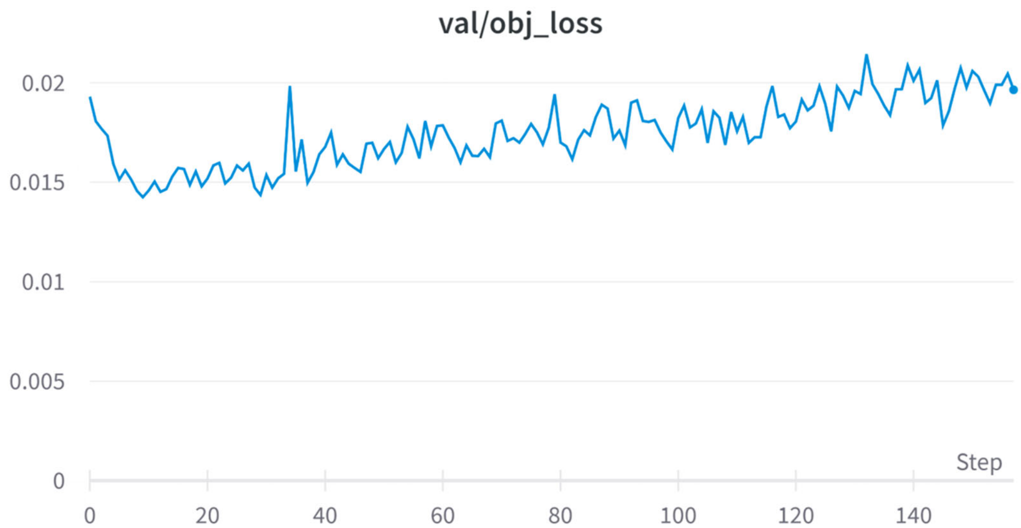

Figure 12. The graph depicts the validation objectness loss for cotton detection of CoDet.

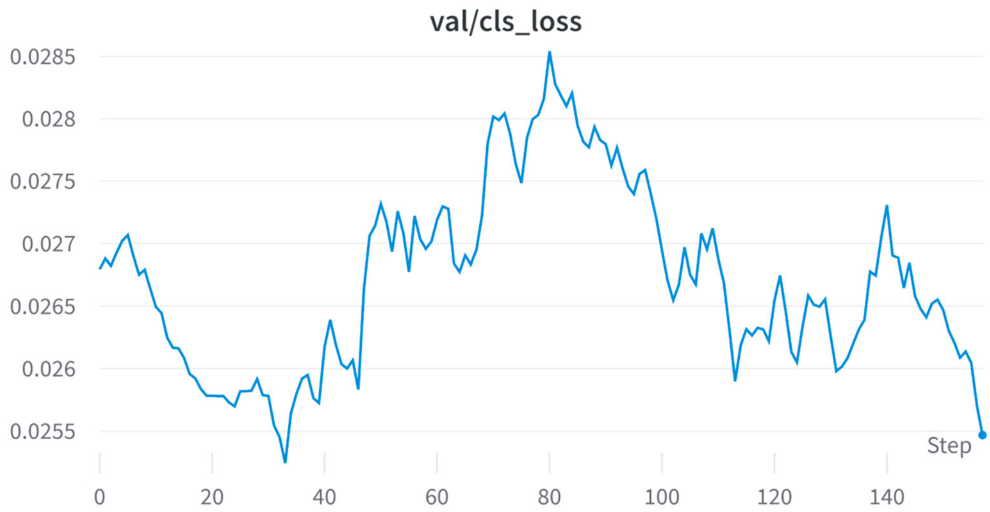

Figure 13. The graph depicts the Validation class loss for cotton detection of CoDet.

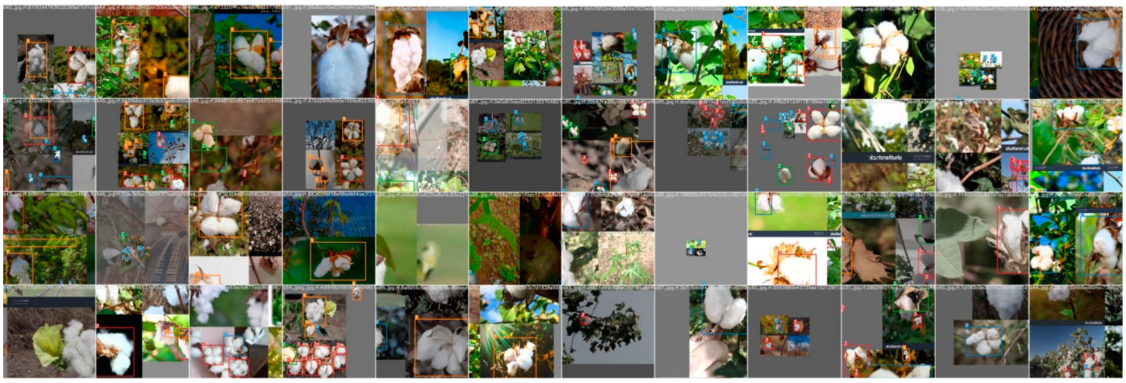

Figure 14. The mosaics of output results generated while testing CoDet on a custom dataset.

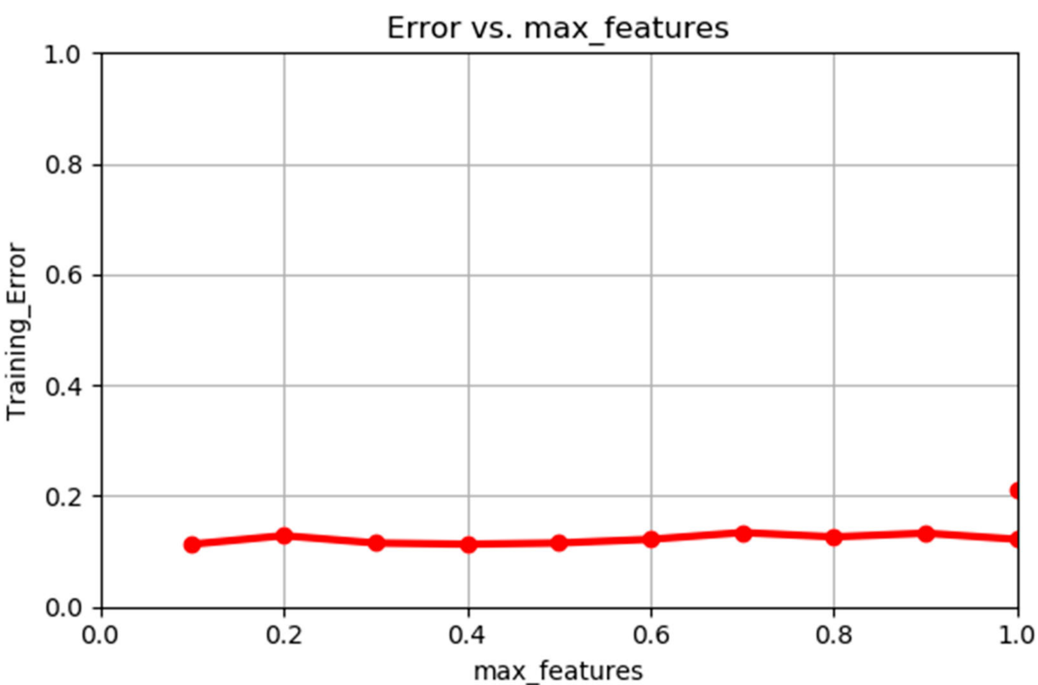

Figure 15. Training error rate vs Maximum features.

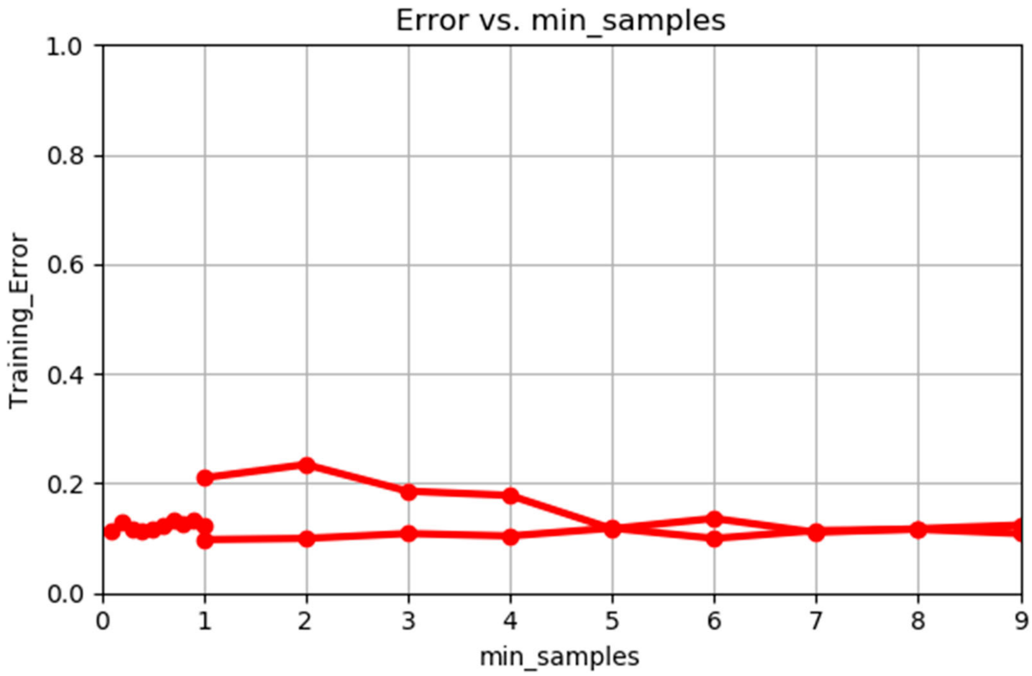

Figure 16. Shows the training error rate vs. minimum sample.

Figure 17. Images predicted using the proposed CoDet.

These devices can be coupled with tablets or smartphones and can give farmers immediate feedback on the health of their crops and their future yield. Farmers may make more informed judgements regarding their crops, resulting in improved yields and more profitability, by creating more sophisticated cotton detecting systems. With the help of these gadgets, which may be connected to tablets or smartphones, farmers can receive quick feedback on the condition of their crops and their potential output. By developing more complex cotton detection systems, farmers may be able to make better decisions regarding their crops, leading to increased yields and profitability.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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