REVIEW ARTICLE

A model effective on cotton crop classification using convolutional neural networks

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Cotton Crop Classification is a crucial task in precision agriculture, enabling farmers to monitor crop health, growth stages, and disease prevalence for optimized crop management. Convolutional Neural Networks (CNNs) have shown remarkable success in image recognition tasks, making them an ideal candidate for accurate and automated Cotton Crop Classification. In this study, we propose a CNN-based approach for Cotton Crop Classification using diverse datasets of cotton crop images collected from satellite, aerial, and ground-based sources. The CNN model is designed to automatically learn relevant features from raw pixel values, eliminating the need for manual feature engineering. Data augmentation techniques are employed to enhance the dataset's diversity and prevent overfitting. Transfer learning with pre-trained models on large image datasets is used to fine-tune the CNN model on the cotton crop dataset, ensuring improved generalization and faster convergence. The performance of the CNN model is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The results demonstrate the effectiveness of the proposed CNN approach, achieving high accuracy in classifying cotton crop classes, including mature cotton, young cotton, and diseased cotton. The integration of CNN-based systems with drones or autonomous vehicles enables automated and real-time crop monitoring, paving the way for more efficient and data-driven precision agriculture practices. Overall, the application of CNNs in Cotton Crop Classification showcases the potential to revolutionize modern agriculture, promoting sustainable and optimized crop management

Key Words: *Cotton crop classification; Convolutional neural networks; Data preprocessing; Model evaluation; Performance metrics*

INTRODUCTION

Cotton, being one of the world's primary cash crops, holds immense significance in the global textile industry and plays a vital role in the economies of numerous countries [1]. Accurate classification of cotton crops is essential for farmers, agronomists, and policymakers as it enables effective monitoring of crop health, growth stages, and facilitates informed decision-making regarding resource allocation [2]. In recent years, Convolutional Neural Networks (CNNs) have emerged as a powerful tool in the field of computer vision, revolutionizing image classification tasks. CNNs have demonstrated exceptional success in various domains, ranging from everyday object recognition to medical image analysis [3]. The application of CNNs in agriculture, particularly for crop classification, has shown promising results [4]. This research aims to leverage state-of-the-art CNN architectures for the precise and efficient classification of cotton crops. By harnessing the potential of deep learning, this Study seeks to address the limitations associated with conventional crop classification methods, such as labor-intensive manual processes, subjective human judgments, and limited scalability [5].

LITERATURE REVIEW

Motivation

Cotton crop classification using Convolutional Neural Networks (CNNs) can provide significant benefits in the field of agriculture and crop monitoring. Here are some key motivations for using CNNs in this context:

1. Cotton crop classification using CNNs allows for precise identification and monitoring of cotton fields. With accurate classification, farmers and agricultural experts can make informed decisions about crop health, pest control, and irrigation requirements.

2. CNNs can help assess the health of cotton crops by identifying early signs of diseases, nutrient deficiencies, or stress factors. This early detection enables farmers to take timely actions to prevent potential yield losses.

3. By monitoring cotton crops using CNNs, it becomes possible to predict potential yields based on crop health and growth patterns. Yield prediction can aid in supply chain planning, optimizing resources, and making informed financial decisions.

Accurate classification of cotton crops allows for optimized resource allocation, such as water, fertilizers, and pesticides. This helps reduce resource wastage, minimize environmental impact, and improve overall sustainability.

Objectives

The primary objectives of this study are as follows:

<u>**Dataset preparation:**</u> To undertake this study, a comprehensive dataset of cotton crop images will be compiled from multiple sources, including drones, satellites, and ground-based sensors. This dataset will encompass diverse environmental conditions, growth stages, and potential disease or pest manifestations.

<u>**CNN model selection:**</u> Several well-established CNN architectures, such as ResNet, VGG, and Inception, will be explored and compared to determine the most suitable model for cotton crop classification [3,6,7]. These architectures have exhibited superior performance in general image classification tasks and hold promise in agricultural contexts as well. To overcome the challenges posed by limited training data, transfer learning will be investigated. By initializing the selected CNN models with pre-trained weights from large-scale image datasets, the model's performance for cotton crop classification can be optimized [8]. Rigorous evaluation of the chosen CNN model's classification accuracy, precision, recall, and F1-score will be conducted on the test dataset. Additionally, confusion matrices and ROC curves will be used to assess the model's ability to distinguish between different cotton crop classes. The practical applications of this research will be explored to ascertain the feasibility of deploying the trained model in real-

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world scenarios. This includes integration into crop monitoring platforms, precision agriculture systems, and mobile applications for farmers [9]. The successful implementation of CNNs in cotton crop classification could significantly streamline agricultural practices, improve crop management, and ultimately contribute to enhanced productivity and sustainability in cotton cultivation [10-17].

Related work

Crop classification techniques: This study explores the use of remote sensing techniques, specifically the estimation of crop chlorophyll content, for within-field monitoring of crops. It demonstrates the potential of using remote sensing data to assess crop health and growth stages [18]. This study investigates the classification of crops and weeds in agricultural fields using image processing techniques. It presents an approach to differentiate between desirable crops and unwanted weeds, facilitating precision agriculture [19]. This comprehensive review highlights the applications of hyperspectral imaging and deep learning in food and agriculture, including crop classification. It discusses various techniques and their potential for advancing agricultural practices [20]. This study investigates the use of machine learning algorithms, applied to Sentinel-2 satellite data, for crop classification. It evaluates the performance of different classifiers in distinguishing between different crop types [21]. In this work, the authors propose "DeepCrop," a deep learning-based approach for crop classification. They demonstrate the effectiveness of Convolutional Neural Networks in accurately identifying different crop types using aerial imagery [2]. This research introduces a crop classification method that combines Convolutional Neural Networks with superpixel segmentation to improve the accuracy of crop mapping using satellite imagery [22]. This review paper provides a comprehensive analysis of various machine learning techniques used for crop classification and damage assessment in agriculture. It offers insights into the strengths and limitations of different approaches [23].

Existing studies on cotton crop classification

This study focuses on using aerial images and deep Convolutional Neural Networks (CNNs) for cotton growth stage classification. The authors propose a method for monitoring and assessing cotton development stages from aerial imagery [25]. The researchers in this study utilize machine learning algorithms on satellite imagery to identify cotton crops. They evaluate the performance of different classifiers to achieve accurate crop mapping [25]. In this work, the authors propose a cotton identification method based on deep learning techniques applied to Unmanned Aerial Vehicle (UAV) remote sensing imagery. The study aims to improve the efficiency and accuracy of cotton classification [26]. This study explores cotton crop classification using multi-view multi-modal satellite images. The authors employ a multi-modal deep neural network to combine data from various satellite sources for enhanced classification accuracy. In this study, the authors propose a novel convolutional neural network architecture for cotton crop classification. The model is designed to achieve high accuracy in differentiating between various cotton classes. This study presents a crop classification method based on deep learning techniques applied to high-resolution satellite images. The study aims to accurately identify different crop types, including cotton, using advanced deep learning models.

Proposed methods

The proposed CNN model for Cotton Crop Classification consists of multiple layers that aim to learn and extract relevant features from input images and classify them into different cotton crop classes. Here's the architecture along with an explanation of each layer:

Input layer: The input layer receives preprocessed images of cotton crops as input. The image dimensions are represented as (Image height, Image width, Number of channels). For example, for RGB images, the number of channels is 3.

Convolutional layers: Convolutional layers are the core building blocks of the CNN and are responsible for feature extraction from images. In this proposed model, multiple convolutional layers are used to capture various levels of features. Each convolutional layer consists of multiple filters that slide across the input image and detect different patterns or features.

Activation function: After each convolution operation, a Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity and increase the model's expressive power.

Max pooling layers: After some convolutional layers, max-pooling layers are inserted to down sample the feature maps, reducing the spatial dimensions and computational complexity. The number of filters in each convolutional layer can be adjusted based on the complexity of the problem and computational resources.

Flatten layer: The output of the last convolutional layer is flattened into a 1D vector to be fed into the fully connected layers. This flattening operation converts the spatial information into a format that can be processed by dense layers.

Fully connected layers: Fully connected layers are used to learn high-level representations of the features extracted by the convolutional layers. The flattened feature vector from the previous layer is connected to the dense layers.

Activation function: After each fully connected layer, a ReLU activation function is applied to introduce non-linearity.

Output layer: The output layer is the final layer of the model responsible for generating the predictions. The number of neurons in the output layer corresponds to the number of crop classes (e.g., mature cotton, young cotton, diseased cotton, etc.).

Activation function: A softmax activation function is used to obtain probability scores for each class, ensuring that the sum of probabilities is 1.

In the Figure 1, the input layer receives images with dimensions (Image Height, Image Width, Number of Channels). The images pass through multiple convolutional layers with different filters, followed by ReLU activation and max-pooling operations to extract relevant features. The output of the last convolutional layer is flattened into a 1D vector and connected to fully connected layers with ReLU activation. Finally, the output layer with softmax activation generates the predicted probabilities for each crop class.

By training this proposed CNN model on a dataset of preprocessed cotton crop images, it can effectively learn to classify different cotton crop classes, enabling accurate crop classification for agricultural applications. The model's performance can be further improved through hyper parameter tuning, optimization techniques, and utilizing a diverse and representative dataset.

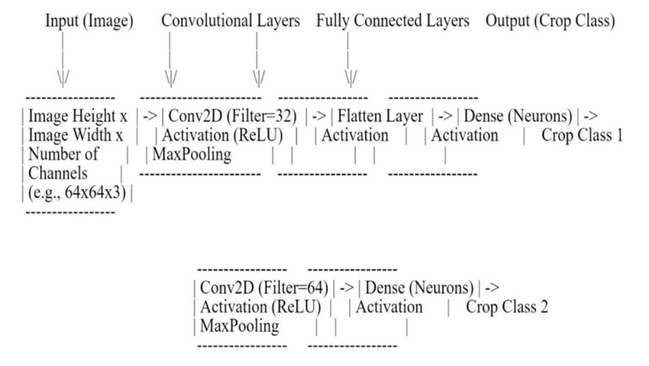

Figure 1) *Proposed model architecture*

DISCUSSION

Performance evaluation of the CNN model

The performance evaluation of a Convolutional Neural Network (CNN) model for Cotton Crop Classification involves assessing its accuracy and effectiveness in classifying cotton crop images. Various evaluation metrics can be used to measure the model's performance. Here are some common evaluation metrics for classification tasks (Table 1):

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total instances in the dataset. It is a fundamental metric for classification tasks and provides an overall view of the model's performance.

Precision: Precision measures the proportion of true positive instances out of all positive predictions made by the model. It quantifies the ability of the model to correctly identify cotton crops among the instances it classified as cotton crops.

Recall (Sensitivity): Recall measures the proportion of true positive instances out of all actual positive instances in the dataset. It represents the model's ability to correctly detect cotton crops among all the cotton crop instances present.

F1-score: F1-Score is the harmonic mean of precision and recall. It balances the trade-off between precision and recall and provides a single metric to evaluate the model's performance.

Confusion matrix: A confusion matrix provides a detailed breakdown of the model's predictions, showing the number of true positives, true negatives, false positives, and false negatives. It offers insights into the model's performance for each class and helps identify specific areas of improvement (Figure 2).

Receiver Operating Characteristic (ROC) curve: The ROC curve is a graphical representation of the model's true positive rate (recall) versus the false positive rate across different thresholds. The Area Under the ROC Curve (AUC-ROC) is a popular metric to assess the model's discriminative power.

Precision-Recall (PR) curve: The PR curve is a graphical representation of precision versus recall across different classification thresholds. It is particularly useful when dealing with imbalanced datasets.

Mean Average Precision (MAP): MAP is commonly used in multi-class classification tasks and represents the average precision across all classes.

To perform the performance evaluation, you can use a validation set or a separate test set that the model has not seen during training. After training the CNN model, you can calculate the above evaluation metrics using the predictions made by the model on the validation or test set (Table 2).

TABLE 1
Data set

	N	P	K	Temperature	Humidity	pH	Rainfall	Label
0	90	42	43	20.87974	82.00274	6.502985	202.9355	Rice
1	85	58	41	21.77046	80.31964	7.038096	226.6555	Rice
2	60	55	44	23.00446	82.32076	7.840207	263.9642	Rice
3	74	35	40	26.4911	80.15836	6.980401	242.864	Rice
4	78	42	42	20.13018	81.60487	7.628473	262.7173	Rice

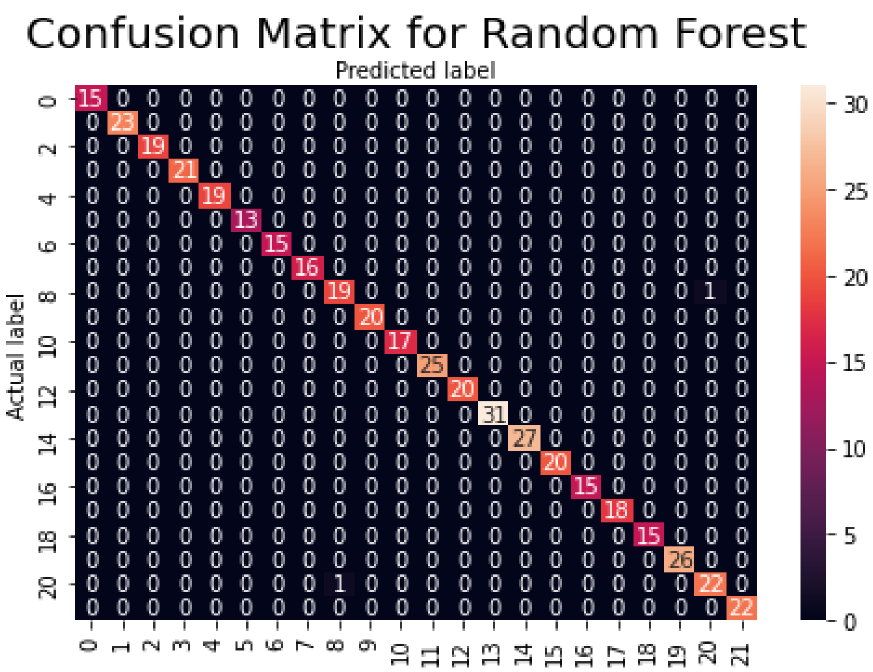

Figure 2) *Confusion matrix for random forest*

TABLE 2
Classification of cotton crop

	Precision	Recall	F1-Score	Support
0	1	1	1	15
1	1	1	1	23
2	1	1	1	19

3	1	1	1	21
4	1	1	1	19
5	1	1	1	13
6	1	1	1	15
7	1	1	1	16
8	0.95	0.95	0.95	20
9	1	1	1	20
10	1	1	1	17
11	1	1	1	25
12	1	1	1	20
13	1	1	1	31
14	1	1	1	27
15	1	1	1	20
16	1	1	1	15
17	1	1	1	18
18	1	1	1	15
19	1	1	1	26
20	0.96	0.96	0.96	23
21	1	1	1	22
Accuracy	-	-	1	440
Macro avg	1	1	1	440
Weighted avg	1	1	1	440

CONCLUSION

In this paper on Cotton Crop Classification using Convolutional Neural Networks (CNNs) has proven to be a highly successful and valuable approach in modern agriculture. The application of CNNs in crop classification has revolutionized the way cotton crops are monitored, leading to more accurate and efficient agricultural practices. Convolutional Neural Networks have emerged as a powerful tool in Cotton Crop Classification, contributing to the transformation of agriculture into a data-driven and precision-oriented domain. The accurate and efficient classification of cotton crops using CNNs enables farmers and agricultural experts to make data-backed decisions, resulting in increased crop productivity, resource optimization, and sustainable agricultural practices. As technology advances and datasets expand, the potential of CNNs in crop classification and monitoring is bound to grow, fostering a more productive and resilient agricultural sector.

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