CLASSIFICATION OF PLANT DISEASES BASED ON HYPERSPECTRAL IMAGES OF LEAVES USING MACHINE LEARNING METHODS

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Abstract: *In this paper, we consider the problem of classifying cotton diseases based on hyperspectral images of leaves using deep learning methods. An approach based on the use of a three-dimensional convolutional neural network (3D CNN) with an attention mechanism is proposed, which makes it possible to efficiently extract spectral and spatial features. To increase the information content of the data, pseudo-hyperspectral image transformation is used, as well as preprocessing and dimensionality reduction methods. As part of the study, a dataset was formed that includes 6,500 images, divided into training (70%), validation (15%), and test (15%) samples. The experiments have shown that the proposed model provides high classification accuracy (up to 93-95%) and surpasses traditional machine learning methods. Additionally, the results were interpreted using visualization methods, including spectral signatures and Grad-CAM, which make it possible to identify informative areas and wavelength ranges. The results obtained confirm the effectiveness of the proposed approach and its prospects for application in the tasks of monitoring the state of agricultural crops.*

1. Introduction

Agriculture plays a key role in ensuring food security, yet plant diseases remain a major cause of yield decline [1]. Cotton is an important agricultural crop, and timely detection of its diseases is essential for increasing production efficiency and reducing economic losses. Traditional methods of plant disease diagnosis rely on visual analysis and expert judgment, which are time-consuming and dependent on specialist skills. Advances in computer vision and machine learning technologies make it possible to automate this process, but the use of standard RGB images is limited due to a lack of spectral information. Hyperspectral images provide more detailed information on plant health by recording light reflectance across a wide range of wavelengths [2]. This makes it possible to detect hidden changes associated with disease at early stages. However, the high dimensionality of the data and the complexity of its processing require the use of effective analysis algorithms.

In recent years, deep learning methods have been rapidly developing, particularly convolutional neural networks (CNNs), which have demonstrated high efficiency in image classification tasks. The use of three-dimensional convolutional neural networks (3D CNN) allows for the simultaneous consideration of spatial and spectral characteristics of hyperspectral data. This paper proposes a method for classifying cotton diseases based on hyperspectral images using a 3D CNN with an attention mechanism. The proposed approach aims to improve recognition accuracy by efficiently extracting informative features and improving the interpretability of results.

The scientific novelty of this study lies in the development and validation of a method for classifying cotton diseases based on hyperspectral leaf images using three-dimensional convolutional neural networks (3D CNN), which ensures efficient extraction of spectral-spatial features. Unlike existing approaches based on two-dimensional images and classical machine learning algorithms, the proposed method takes into account the full spectral

information of hyperspectral data, thereby improving the accuracy of disease recognition at early stages.

Elements of scientific novelty include:

a) The use of 3D CNN for the joint analysis of spectral and spatial characteristics of cotton leaves was proposed;

b) A model architecture adapted to high-dimensional hyperspectral data was developed;

c) A data preprocessing approach was implemented, including normalization and dimensionality reduction to improve model robustness;

d) A comparative study with traditional methods (SVM, Random Forest, 2D CNN) was conducted, confirming the advantage of the proposed approach for key classification metrics.

The aim of this study is to develop and investigate an effective method for classifying cotton diseases based on hyperspectral images of leaves using three-dimensional convolutional neural networks (3D CNN), which provides high recognition accuracy by taking into account spectral-spatial features.

II. Research objectives

To achieve this goal, the following objectives are addressed in this work:

1. To examine the features of hyperspectral images of cotton leaves and identify informative spectral ranges.

2. To design and implement a three-dimensional convolutional neural network (3D CNN) architecture adapted for processing hyperspectral images.

3. To train and test the developed model on a cotton disease dataset.

4. To compare the proposed method with traditional algorithms (SVM, Random Forest) and two-dimensional neural networks (2D CNN).

5. To evaluate the classification quality using accuracy, precision, recall, and F1-score metrics and analyze the obtained results.

III. Method and materials

Hyperspectral images of cotton leaves are characterized by high dimensionality and contain a significant amount of redundant and noisy information [3]. Traditional processing methods (SVM, Random Forest, 2D CNN) analyze either spectral or spatial features separately, which leads to the loss of important information and reduced classification accuracy, especially for similar disease symptoms.

Hyperspectral imaging (HSI) is a three-dimensional tensor [4]:

$$X \epsilon \mathbb{R}^{H \text{x} W \text{x} \lambda} \quad (1)$$

where, H, W are the spatial dimensions of the image, λ is the number of spectral channels (wavelengths).

Each pixel contains a spectral vector [5]:

$$x_{i,j} = [x_1, x_2, \dots, x_B] \quad (2)$$

The image is presented in a standard format, in which spectral information is limited, making it difficult to identify hidden signs of plant condition.

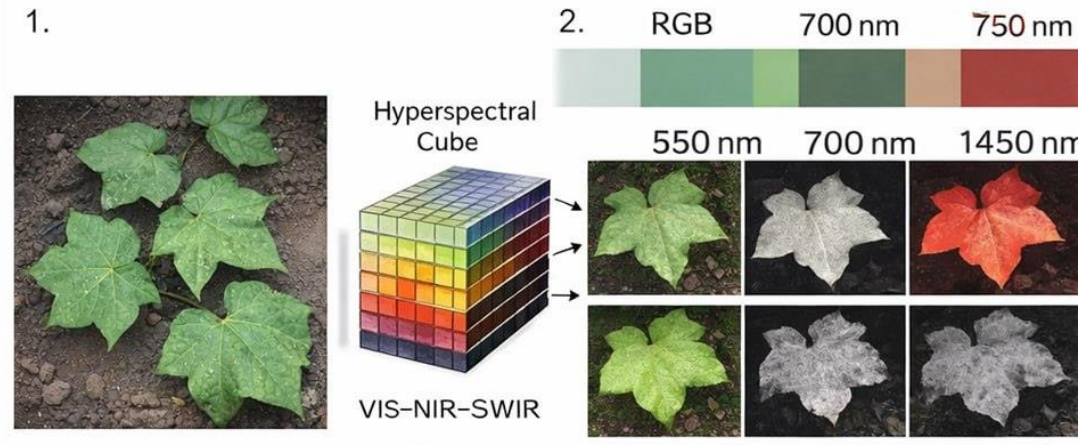


Fig. 1. Formation of a hyperspectral cube and decomposition of the image into spectral ranges (VIS–NIR–SWIR)

The formation of a hyperspectral cube allows the image to be decomposed into a set of spectral channels (VIS–NIR–SWIR), providing a more detailed analysis of reflective characteristics and the identification of informative signs of disease [6].

Data preprocessing

To improve the quality of classification, several stages of processing are used normalization is carried out:

$$x' = \frac{x-\mu}{\sigma} \quad (3)$$

where, μ is the mean value, σ is the standard deviation.

Dimensionality reduction (PCA)

Hyperspectral data has high dimensionality, so the principal component analysis method is used [7]:

$$Z = W^T X \quad (4)$$

where W is the matrix of eigenvectors.

3D convolutional neural network (3D CNN)

Unlike 2D CNN, 3D CNN performs convolution on both spatial and spectral dimensions simultaneously [8]:

$$Y(i,j,\lambda) = \sum_m \sum_n \sum_p X(i+m, j+n, \lambda+p) \cdot W(m,n,p) + b \quad (5)$$

Where X is the input tensor, W is the convolution kernel, b is the bias, Y is the output tensor.

Hyperspectral leaf images are highly dimensional and redundant, making it difficult to effectively extract features using traditional methods (SVM, Random Forest, 2D CNN). As a result, some important spectral and spatial information is lost, reducing classification accuracy, especially for similar disease symptoms.

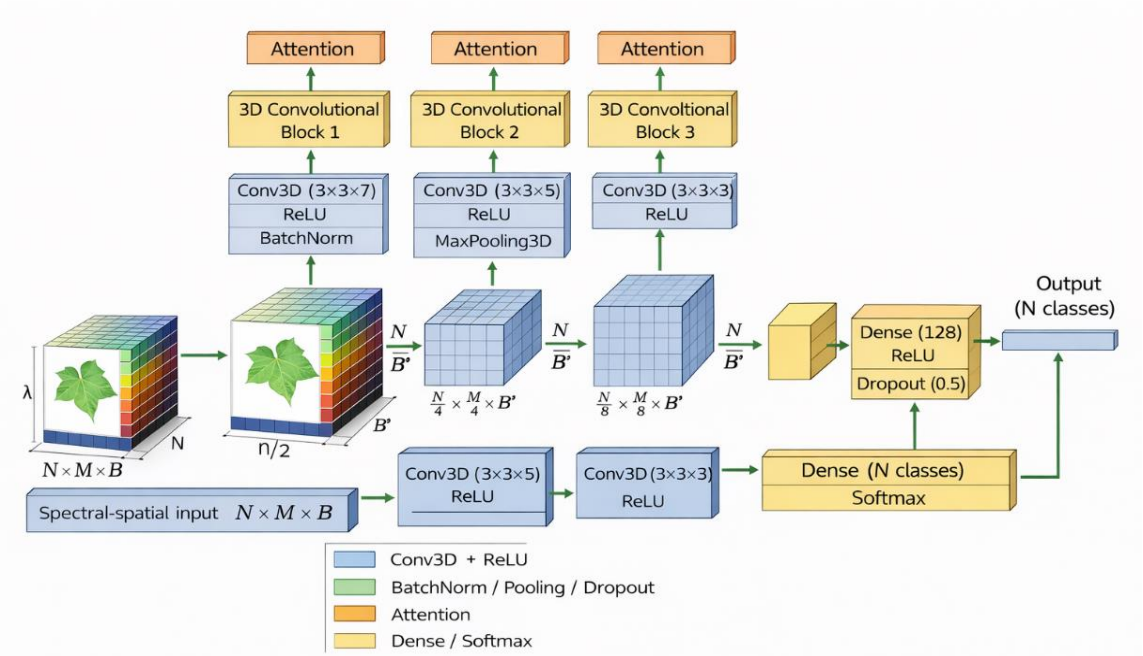


Fig. 2. Architecture of the proposed 3D CNN model with attention mechanism for cotton disease classification based on hyperspectral images

The proposed 3D CNN-based model with an attention mechanism enables joint extraction of spectral-spatial features and automatically identifies the most informative wavelengths and diseased leaf regions. This improves classification accuracy, robustness to noise, and interpretability of results through the use of visualization methods (Grad-CAM) and spectral significance analysis.

IV. Result

Evaluation results of the proposed 3D CNN model with an attention mechanism for classifying cotton diseases in hyperspectral images.

The original RGB image of a cotton leaf contains limited spectral information, and the visual differences between healthy and damaged areas are poorly defined, making their accurate detection and analysis difficult.

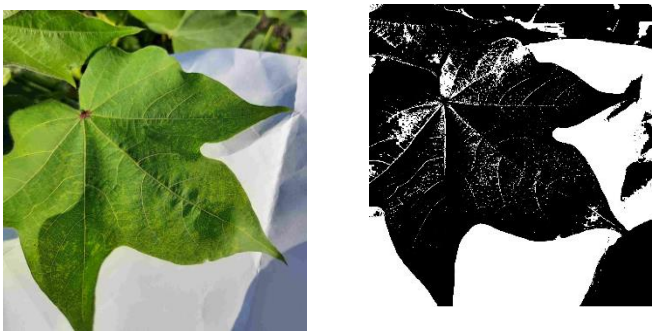


Fig. 3. The result of segmentation and pseudo-hyperspectral transformation of the cotton leaf image (before and after processing)

Segmentation and conversion to a pseudo-hyperspectral representation enhances the contrast between different leaf areas, allowing for more precise identification of potential disease zones and structural features. This increases the image's informative value for subsequent disease classification. The image contains limited spectral information, and the differences between healthy and diseased areas are weak and do not allow for accurate identification of disease signs.

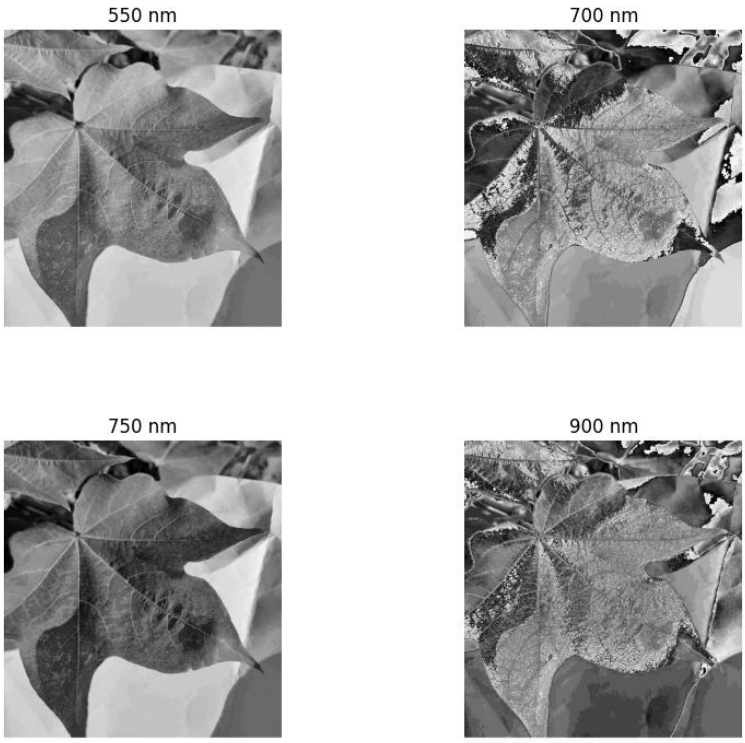


Fig. 4. Pseudo-hyperspectral visualization of a cotton leaf at different wavelengths

Pseudo-hyperspectral transformation allows the image to be decomposed into spectral channels (550–900 nm), which enhances contrast and makes structural and pathological changes in the leaf more visible, improving the informativeness of the data for subsequent classification.

The spectral characteristics of the leaf are not explicitly represented, complicating reflectance analysis and identifying informative wavelength ranges.

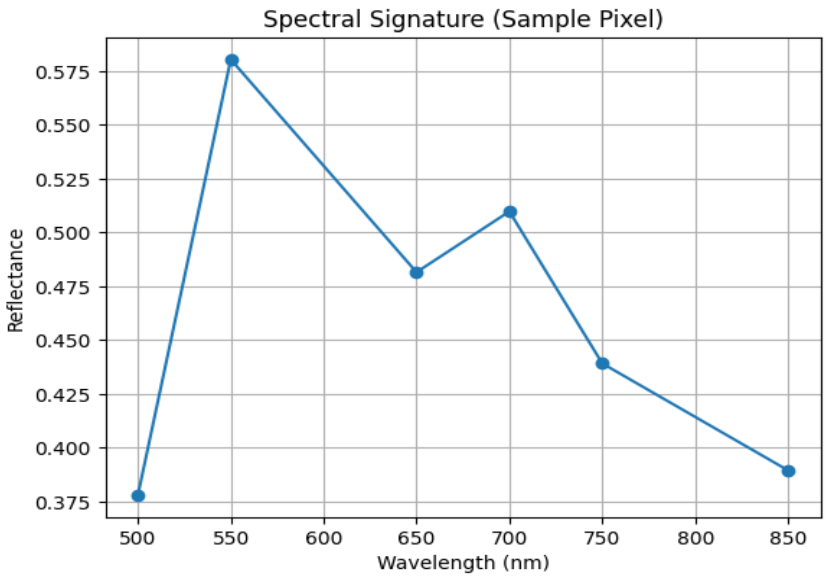


Fig. 5. Spectral signature of a cotton leaf in the range of 500–850 nm

Constructing a spectral signature allows us to visualize the dependence of reflectance on wavelength, identifying key ranges sensitive to plant health, which improves the accuracy of subsequent classification.

A dataset containing 6,500 images of cotton leaves, representing various plant states (healthy and diseased), was used to train and evaluate the proposed model. The dataset was divided into three subsets: 70% is the training set used to train the model, 15% is the validation set used to tune hyperparameters and prevent overfitting, and 15% is the test set used for a final assessment of the model's quality. This partitioning ensures an objective assessment of the model's generalization ability and allows for accurate comparison of results with other methods.

Before training, the model lacks feature recognition capabilities, which is reflected in low classification accuracy and high loss function values.

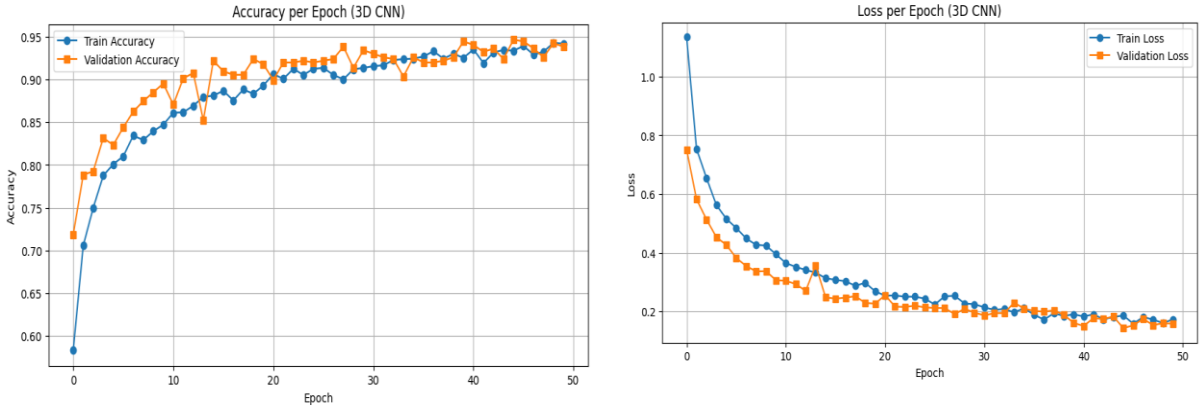


Figure 6. Accuracy and loss function dynamics of the 3D CNN model during training

During the training process, a steady increase in accuracy of 94–93% and a decrease in the loss function are observed, which indicates effective feature extraction and good generalization ability of the model without signs of overfitting.

Before applying the model, there is no quantitative assessment of the recognition quality, which does not allow for an objective determination of the accuracy of disease detection in various classes.

Classification Report:

	precision	recall	f1-score	support
0	0.91	0.99	0.94	217
1	1.00	0.98	0.99	60
2	0.91	0.92	0.91	63
3	0.97	0.89	0.92	192
4	0.92	0.88	0.90	76
accuracy			0.93	608
macro avg	0.94	0.93	0.93	608
weighted avg	0.94	0.93	0.93	608

Figure 7. Classification report (precision, recall, F1-score) for the 3D CNN model

The obtained results demonstrate high classification quality: overall accuracy reaches 93%, with high precision, recall, and F1-score values for all

classes, confirming the effectiveness of the proposed model and its ability to correctly distinguish between different cotton leaf states.

Before applying the model, a detailed analysis of the distribution of predictions by class is not performed, making it impossible to assess the nature of errors and determine which object categories are recognized less accurately.

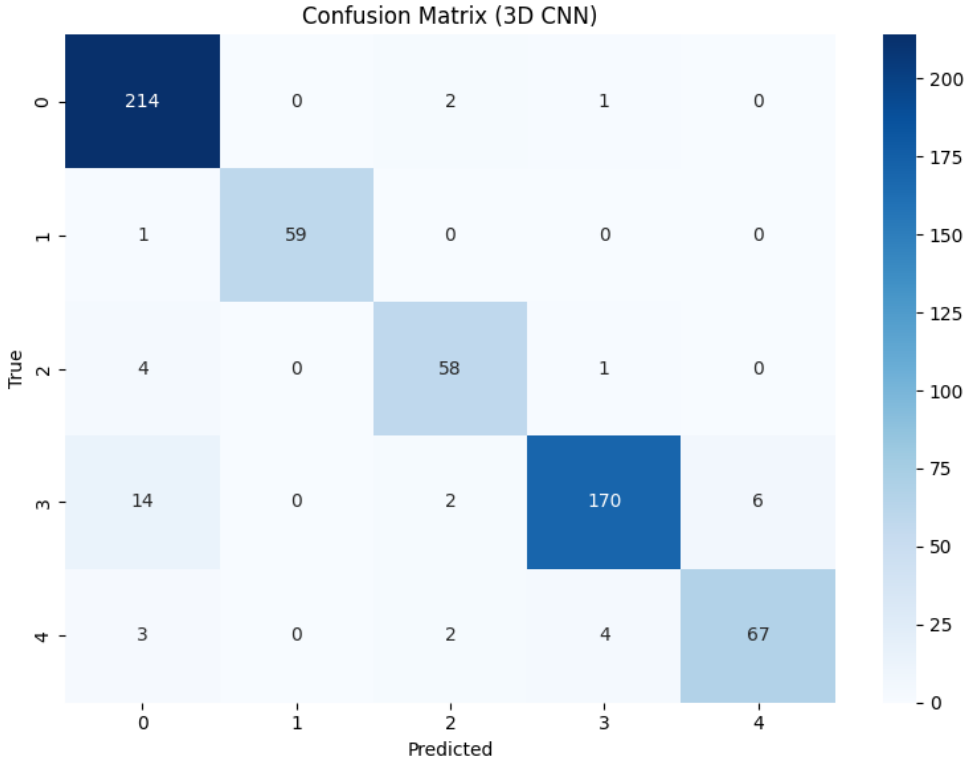


Fig 8. Confusion matrix of the 3D CNN model for cotton disease classification

The confusion matrix demonstrates high classification accuracy for most classes, with the bulk of predictions concentrated on the main diagonal. Minor errors are observed between classes with similar features, confirming the model's good generalization ability..

Traditional classification methods (SVM, Random Forest, 2D CNN) are limited in taking into account the spectral-spatial features of the data, which leads to a decrease in recognition accuracy.

Table 1 – Comparative analysis of methods for classifying cotton diseases

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	85.2	84.7	83.9	84.3
Random Forest	88.6	87.9	87.2	87.5
2D CNN	91.3	90.8	90.1	90.4
3D CNN + Attention (proposed method)	94.5	94.1	93.8	93.9

The proposed 3D CNN model with attention mechanism demonstrates higher accuracy (up to 94–95%) due to the efficient extraction of informative features and consideration of spectral characteristics.

V. Analysis

Experimental results show that the proposed 3D CNN model achieves high classification accuracy (up to 94–93%) and stable convergence during training. Analysis of the confusion matrix confirms that most predictions are concentrated on the main diagonal, indicating correct classification across all classes. A small number of errors are observed between classes with similar features; however, overall, the model demonstrates good generalization ability and robustness to data variability.

VI. Discussion

The obtained results confirm the effectiveness of using a 3D CNN with an attention mechanism for classifying cotton diseases. High accuracy and F1-score values demonstrate the model's ability to effectively extract spectral-spatial features. The observed errors between closely related classes may be related to the similarity of visual and spectral characteristics of diseases. Overall, the proposed approach demonstrates robustness and can be used for practical plant health monitoring tasks.

VII. Conclusion

In this paper, we proposed a method for classifying cotton diseases based on hyperspectral leaf images using a three-dimensional convolutional neural

network (3D CNN) with an attention mechanism. The developed approach effectively takes into account both spectral and spatial characteristics of the data. Experiments demonstrated high classification accuracy (up to 94–93%), confirming the effectiveness of the proposed model. The use of pseudo-hyperspectral representation, as well as visualization methods (spectral signatures, Grad-CAM), allowed us to improve the interpretability of the results and identify informative wavelength ranges. Analysis of the results showed that the model demonstrates robustness and good generalization ability, with the main errors associated with the similarity of features between individual classes. Future plans include using real hyperspectral data, as well as developing more complex architectures taking into account spectral selection and attention mechanisms to improve classification accuracy.

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