A Deep Learning Solution for Early Detection of Cotton Nutrient Deficiencies

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Abstract

Cotton, the purest form of cellulose, is indispensable in various industries, including textiles and paper production. Enhancing the health of cotton crops is pivotal for an industry that sustains millions of jobs globally. This study aims to advance the early detection of nutrient deficiencies in cotton foliage. A novel transfer learning approach was employed to develop a predictive model. Comparative analysis with established pre-trained Convolutional Neural Networks (CNNs) was conducted, evaluating metrics such as accuracy, loss, and computational efficiency during the training and validation phases. The Proposed Model demonstrated a commendable validation accuracy of 96.38%, indicating its potential for practical application in agronomy.

Keywords: **Cotton, Nutrient Deficiency, Transfer Learning, Convolutional Neural Networks, Precision Agriculture**

1. Introduction

Cotton, often referred to as "White Gold," is a cornerstone of India's economy. It is cultivated in more than 80 countries for its versatile applications, including thread production, fiber blending, and oil extraction from seeds [1]. The oil content in cotton seeds varies between 15-20%, serving as a valuable organic resource. Cotton seed cake, a byproduct, is a rich organic fertilizer containing approximately 6% nitrogen, 3% phosphorus, and 2% potash. In contrast, cotton seeds, linters, and pulp are utilized as concentrated cattle feed [2,3]. Environmental factors such as temperature, humidity, and soil moisture influence the fiber's properties, with suboptimal irrigation and nutrient deficiencies notably diminishing yields [4].

Macronutrient scarcity manifests in stunted plant growth, poor flowering, and reduced yield, with symptoms in leaf discoloration and stunted foliage development [5]. Specific symptoms include interveinal chlorosis, marginal chlorosis, uniform chlorosis, necrosis, distorted leaf edges, and diminished leaf size [6]. Phosphorous deficits notably alter leaf physiology, impacting chlorophyll content, photosynthesis, adenosine triphosphate (ATP), and nonstructural carbohydrate levels [7]. Similarly, sulfur shortages can compromise yield and fiber quality [8]. Micronutrient deficiencies—boron, copper, iron, manganese, and zinc—exacerbate issues, leading to subpar crop production and seed quality [9]. Various diagnostic techniques, such as spatial FCM clustering [10] and deep learning-based image processing [11], have been employed to detect these deficiencies. Effective nutrient management is thus critical for the optimal growth and development of cotton plants [12].

2. Related works

The detection of foliar diseases in cotton plants has been the subject of extensive research, employing various image-processing techniques for disease identification. Image filtering, segmentation, and feature extraction have been pivotal in discerning diseased areas on leaves. Transfer learning, a prominent method in computer vision, facilitates model generation by leveraging pre-learned patterns, thus reducing computational costs and time [13, 14].

Support Vector Machine (SVM)-based regression systems have been utilized to classify cotton leaf diseases such as Bacterial Blight, Alternaria, Grey Mildew, Cereospra, and Fusarium Wilt, achieving a classification accuracy of 83.26% [15]. Otsu's global thresholding method, coupled with a Multi SVM classifier, has been reported to detect diseases with an accuracy of 87.5% [16].

K-means nearest neighbor (KNN) algorithms have classified diseases like grey mildew, Bacterial blight, Leaf curl virus, Gemini virus, and Alternaria leaf spot with an accuracy of 92%. However, this was not the highest accuracy achieved among the methods reviewed [17]. A study employing KNN classification on a dataset of 150 training images and 40 validation images, each with a resolution of 1024 × 1024 pixels, reported an accuracy of 82.5% for grey mildew classification [18].

Integrating K-means clustering with Artificial Neural Networks (ANN) has resulted in a classification accuracy of 92.5%. However, the specific metrics for KNN were not disclosed [19]. Principal Component Analysis (PCA) combined with KNN, using a sample size of 110, has been applied to classify diseases such as Blight, Narcosis, Alternaria, Grey mildew, and Magnesium deficiency [20]. Decision tree Random Forest algorithms have been employed for cotton disease prediction, yielding an accuracy of 96.73% and a sensitivity of 82.21% [21].

Furthermore, the adaptive neuro-fuzzy inference system and Graph cut method have been used to detect diseases like Bacterial blight, Myrothecium, and Alternaria, achieving an accuracy of 90% [22]. Rough set fuzzy C-means clustering has been applied to segment Cotton aphids in 20 images, attaining a segmentation accuracy of 85% [23]. SVM classifiers have also been used to distinguish between Bacterial blight and Magnesium deficiency, with a classification accuracy of 98.46% for a dataset comprising 100 infected and 30 noninfected images [24].

3. Methodology

The dataset for model training was generated by artificially inducing nutrient deficiencies in cotton plants via hydroponics. Approximately five plants were cultivated in each of the 39 hydroponic containers. These were categorized into six groups representing macronutrient deficiencies, six for micronutrient deficiencies, and one control group with a standard nutrient solution. For each nutrient deficiency, three replicate containers were used. The leaves exhibiting deficiency symptoms were manually harvested and digitized using a high-resolution HP Scanjet G3110 scanner. The original dataset images were resized to 224×224 pixels to facilitate the training process. The final dataset comprised 13 categories, each containing 100 images. It was partitioned into a 70:30 ratio for training and network testing/validation.

The proposed transfer learning model is structured with nine inception net modules, encompassing twenty-two layers and twenty-seven levels, including pooling layers, as shown in Figure 1. The input layer is defined with dimensions of 224×224 pixels. The inception modules employ convolution filters of sizes 1×1, 3×3, and 5×5. The initial convolution layer utilizes a 7×7 filter size to reduce the input dimensionality while retaining spatial information. Subsequent convolution layers compress the image dimensions by factors of four and eight before reaching the first inception module, thereby reducing computational load. A 1×1 convolution block with two-layer depth is implemented to minimize operations. Maximum pooling layers interspersed between inception modules down sample the input. In contrast, average pooling layers compute the mean of the feature maps from preceding modules. Dropout layers are incorporated to mitigate overfitting.

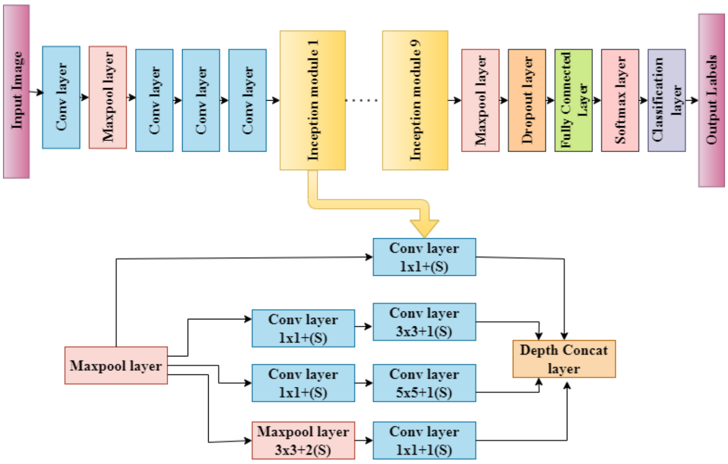


Figure 1. Proposed Transfer Learning Model

The network culminates in a SoftMax layer, an activation function to compute the probability distribution across an input vector, representing class likelihoods. Auxiliary classifiers are utilized during training—though not during inference—to contribute to the overall loss estimation. These classifiers consist of an average pool layer, a convolution layer, two fully connected layers, a 70% dropout layer, and a linear layer with a SoftMax activation function, processing activations from earlier inception modules.

We employed several key performance metrics to evaluate our model, each defined by a specific formula. The network underwent multiple training iterations with refined parameters, evaluated based on Accuracy (Acc), Precision (Pre), Recall, F1-score (Score), and Specificity (Spe). The iteration yielding the most favorable results was preserved. Alongside the performance metrics, the Confusion Matrix is a vital tool for evaluating the classification model's performance. It is a table used to describe the performance of a classification model on a set of test data for which the true values are known. The matrix itself is composed of four elements:

True Positives (TP): Correctly predicted positive observations.
True Negatives (TN): Correctly predicted negative observations.
False Positives (FP): Incorrectly predicted positive observations (Type I error).
False Negatives (FN): Incorrectly predicted negative observations (Type II error).

The formulas for the metrics based on the confusion matrix are as follows:

Accuracy (Acc) is the proportion of true results among the total number of cases examined, calculated as

$$\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision (Pre), also known as the positive predictive value, is the ratio of true positives to all positive predictions given by

$$\text{Pre} = \frac{TP}{TP + FP} \tag{2}$$

Recall, also referred to as sensitivity, measures the proportion of actual positives correctly identified and is calculated as

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

The F1-score (Score) is the harmonic mean of precision and recall, providing a balance between the two, and is defined as ("Evaluation Metrics in Machine Learning | by Tania Afzal - Medium")

$$\text{Score} = 2 \times \frac{\text{Pre} \times \text{Recall}}{\text{Pre} + \text{Recall}} \tag{4}$$

Lastly, Specificity (Spe) quantifies the proportion of actual negatives correctly identified, which is the complement of the false positive rate and is calculated as

$$\text{Spe} = \frac{TN}{TN + FP} \tag{5}$$

These formulas collectively offer a comprehensive assessment of the model's performance. Comparative analysis with existing pre-trained models focused on training and validation accuracy. The training was executed on a desktop with an AMD Ryzen Threadripper CPU, NVIDIA A5000 GPU, and 96GB of RAM. The trained network was archived for subsequent application.

4. Result and Discussion

This study evaluated three distinct training methodologies. Initially, a high-accuracy pre-trained network was selected, and a transfer learning model was constructed and subsequently fine-tuned. The original dataset comprised images with resolutions of approximately 3000×3000 pixels, each with a file size of around 20 megabytes, cumulatively amounting to 26 gigabytes—a volume too substantial for efficient network training. To address this, image dimensions were reduced to 100×100 pixels, significantly accelerating training speed and reducing dataset size. However, this resolution reduction led to the loss of critical spatial information, resulting in misclassification. The nutrient-deficient leaf images from the dataset are shown in Figure 2.

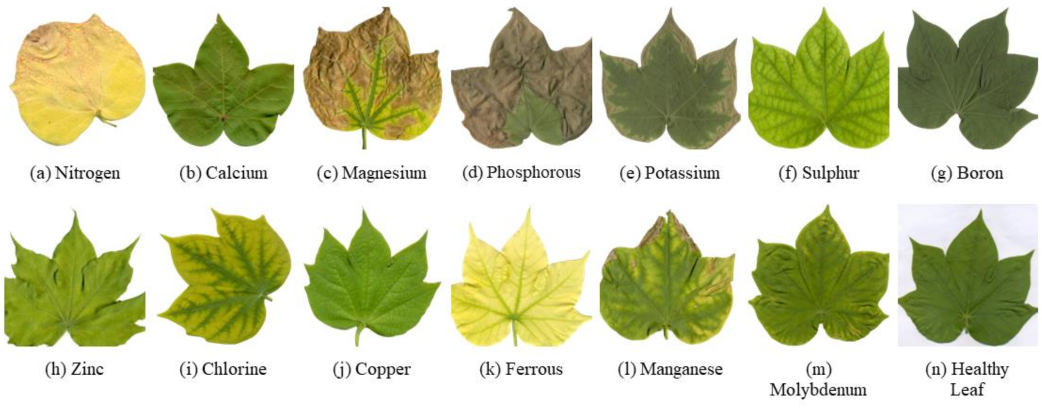


Figure 2. Cotton leaves with nutrient deficiencies.

Ultimately, images were resized to 224×224 pixels, a compromise that preserved essential details while maintaining manageable memory requirements. The study utilized over 1200 images of cotton leaves exhibiting various nutrient deficiencies. Eighty percent of these images were allocated for training, with the remaining twenty percent reserved for testing. The Stochastic Gradient Descent with Momentum (SGDM) optimizer was employed, and varying epoch counts and learning rates were used to optimize training. A batch size of 25 images per iteration was fixed to ensure comprehensive training coverage. Performance metrics such as Accuracy, Precision, Recall, F1-score, and Specificity were utilized to refine and evaluate the network throughout the training and validation phases, as shown in Table 1.

Table 1. Evaluation Metrics of Fine-Tuned Network

S. No	Model	Epoch	Learning Rate	Acc	Pre	Recall	Score	Spe
1	Trial 1	100	0.001	89.44%	92.41%	89.44%	89.31%	99.04%
2	Trial 2	50	0.01	90.00%	86.67%	86.67%	86.67%	98.79%
3	Trial 3	10	0.01	91.94%	93.72%	91.94%	91.69%	99.27%
4	Tuned Model	10	0.001	95.56%	96.51%	95.56%	95.62%	99.60%
5	Fine-tuned	10	0.0001	96.11%	96.70%	96.11%	96.14%	99.65%

The training process underwent several iterations:

First Trial: The epoch count was set to 100, and the learning rate was set to 0.001, achieving an accuracy of 89.44%.

Second Trial: The Epoch count was reduced to 50, and the learning rate increased to 0.01, resulting in an accuracy of 90%.

Third Trial: Further reduction of epoch counts to 10 with a learning rate of 0.01, leading to an improved accuracy of 91.94% and better specificity.

Fourth Trial (Tuned model): Maintained 10 epochs with a learning rate 0.001, yielding a superior accuracy of 95.56%.

Final Tuning: Epoch count fixed at ten and learning rate fine-tuned to 0.0001, culminating in the best performance across all parameters with an accuracy of 96.11%. The graph in Figure 3 shows that the fine-tuned network performs better in all metrics.

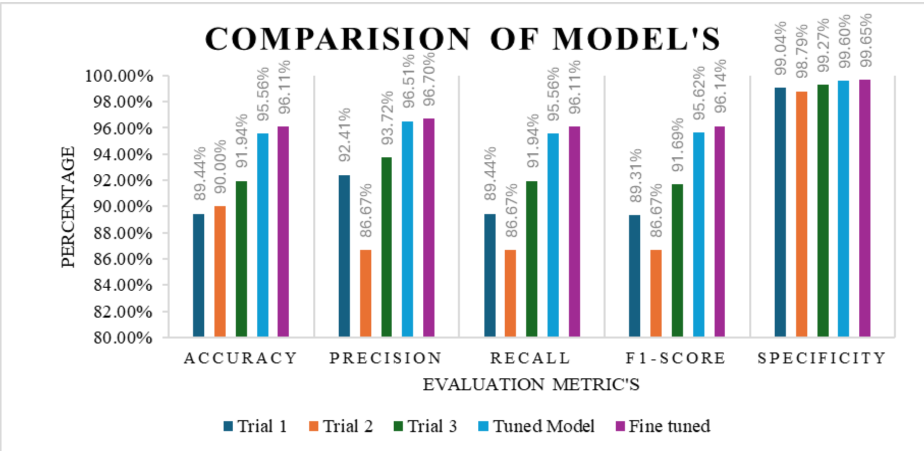


Figure 3. Comparison Graph of Tuning Models

The proposed model's performance was benchmarked against other pre-trained networks, as shown in Table 2, assessing both the training duration and classification accuracy of new data. Derived from GoogleNet and InceptionNet architectures, the proposed model required only 46 seconds for training—a shorter duration than InceptionNet's. Moreover, it outperformed other pre-trained models' accuracy, attributable to the meticulously fine-tuned parameters. The validation accuracy of the proposed network reached 96.38%, surpassing GoogleNet's 93.33% and InceptionNet's 89.44%.

Table 2. Performance of Pre-trained Network v/s Proposed Network

Trial	Elapsed Time	Network Name	Training Accuracy %	Training Loss %	Validation Accuracy %	Validation Loss %
1	46sec	Proposed Network	100	0.0008	96.3889	0.0671
2	1min 17sec	vgg16	100	0.0026	87.7778	0.4122
3	28sec	googlenet	99.2188	0.0459	93.3333	0.1412
4	16sec	squeezenet	98.4375	0.0688	84.4444	0.6712
5	58sec	mobilenetv2	100	0.0205	89.1667	0.3937
6	23sec	resnet18	100	0.0181	86.1111	0.2920
7	1min 3sec	resnet50	100	0.0140	89.4444	0.2474
8	1min 50sec	resnet101	100	0.0092	93.8889	0.1873
9	1min 54sec	inceptionv3	100	0.0846	89.4444	0.4977
10	6min 39sec	inceptionresnetv2	99.2188	0.4754	78.0556	0.8727

A confusion matrix was plotted to compare the true and predicted classes across the entire dataset, revealing no misclassifications among the 70 images per category. This indicates a robust dataset for model training. The confusion matrix for training data is shown in Figure 4.

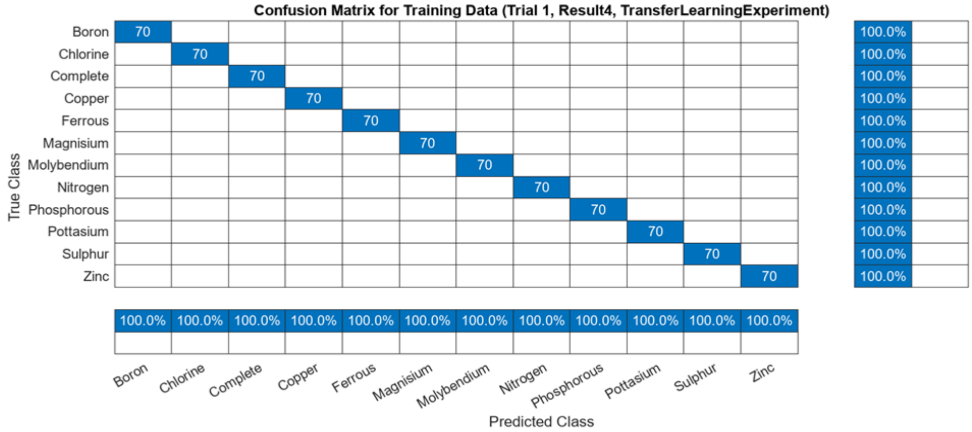


Figure 4. Confusion matrix for the training of the fine-tuned network

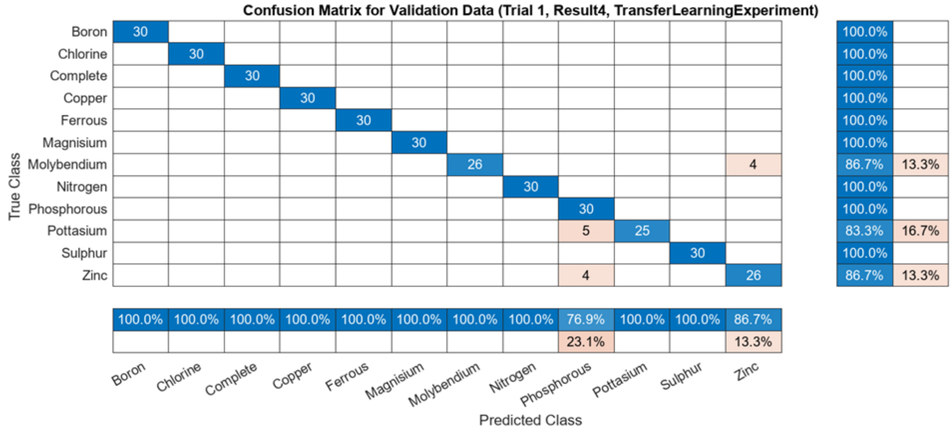


Figure 5. Confusion matrix for the validating of the fine-tuned network

The proposed model exhibited a misclassification rate during validation, with 13 out of 30 test samples incorrectly identified, as shown in Figure 5. Misclassifications occurred primarily with zinc and potassium deficiencies mistaken for phosphorus and molybdenum for zinc. Consequently, the classification accuracies for zinc, potassium, and molybdenum deficiencies were 86.7%, 83.3%, and 86.7%, respectively. Nevertheless, the overall accuracy between true and predicted classes was 96.38%.

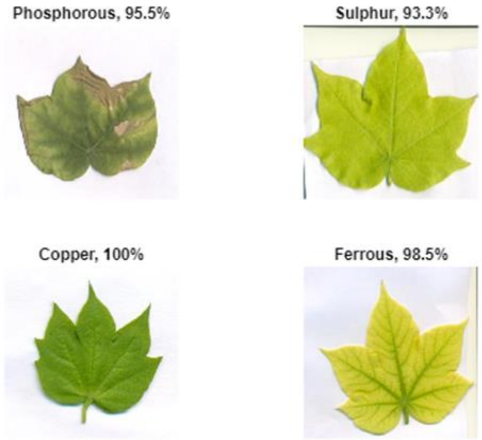
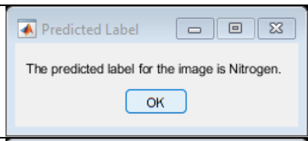
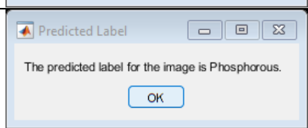
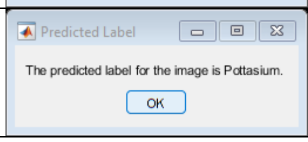
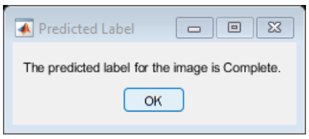


Figure 6. Predicted class for random validation images from the dataset.

The model's efficacy was further demonstrated by its prediction accuracy for unknown leaf deficiencies, consistently exceeding 95% accuracy, as shown in Fig 6. Additionally, the model's practicality was validated by testing known deficiency images, which, upon classification, triggered a dialog box displaying the identified deficiency. The average prediction time was approximately 1.5 seconds, underscoring the model's efficiency, as shown in Table 3.

Table 3. TESTING PROPOSED MODEL

S: No	Deficiency	Classified Image	Predicted Class	Elapsed Time
1	Nitrogen			1.489955 seconds
2	Phosphorous			1.466716 seconds
3	Potassium			1.457844 seconds
4	Complete			1.456076 seconds
5	Ferrous			1.497839 seconds

5. Conclusion

Nutrient deficiency poses a significant challenge to agricultural productivity. Precise identification and remediation of such deficiencies are crucial for preventing further detriment to cotton crops. This paper introduces a deep learning model tailored for this purpose. A comprehensive dataset was curated to facilitate the training of various pre-existing networks as well as the proposed model. The research focused on classifying diverse nutrient deficiencies, with the proposed model demonstrating robust performance on the cotton leaf dataset.

A comparative analysis with other pre-trained Convolutional Neural Network (CNN) models revealed that the proposed transfer learning model attained a validation accuracy of 96.38%, surpassing its counterparts. The findings highlight the potential of machine learning methodologies in combating nutrient deficiency issues in cotton cultivation. By integrating such advanced diagnostic tools, farmers can enhance crop yields and maximize profitability, thereby contributing to sustainable agricultural practices.

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