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Methods Based on Machine Learning for Large-Scale Classification of Crop Leaf Diseases

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Abstract

Worldwide productivity of crops is seriously threatened by crop leaf diseases, which can result in large crop losses and negative economic effects. Effective disease management and crop protection depend on the early and precise detection and classification of these illnesses. Machine learning approaches have gained popularity recently due to their ability to automate procedures related to illness diagnosis and classification. An overview of the several machine learning–based methods used for crop leaf disease diagnosis and classification is provided in this review paper. We go over the basic ideas and methods of the machine learning algorithms that are applied here, as well as their advantages and disadvantages. Additionally, we examine and contrast the results of several machine learning approaches published in the literature, emphasizing the critical elements affecting their efficacy. Ultimately, we pinpoint the present obstacles and forthcoming research avenues to promote progress in this domain.

Keywords: Machine learning, convolutional neural network (CNN), transfer learning, support vector machine (SVM), random forest, deep learning

INTRODUCTION

New peaks and achievements have been established in the healthcare, transportation, business analytics, and agricultural fields as a result of the current surge in advancements in computer vision, neural networks, and machine learning [1]. India's economy relies heavily on agriculture. To stay alive in this ever-changing climate and surroundings, automation and improvements to traditional techniques of disease detection are essential. To address the crop's supply and demand problems, the agricultural sector requires radical improvements. Maximum agricultural output may be achieved by regular crop monitoring and rapid disease diagnosis if a crop is contaminated. In India, cotton farmers frequently face difficulties due to leaf diseases. Common ailments include those caused by bacteria (grey mildew), fungi (leaf spot, reddening), and viruses (leaf curl). The end product is lower in quality and quantity because of this [2]. Within the food production industry, continuous monitoring helps boost output by identifying problems early and implementing fixes accordingly. Plant diseases can be identified in several ways. In the absence of visible symptoms, a thorough examination may be necessary to diagnose some disorders. This study aims to compare and evaluate several machine learning-based methods for cotton disease identification. Traditional plant disease diagnosis relied on the trained eyes of professionals [3]. They were time-consuming and prone to errors in judgement, though. Early detection of a disease in crop leaves using a dependable and cost-effective method is critical for preventing the illness's spread. One viable method to quickly and cheaply reach this aim has been shown by the recent development of deep learning technology and the massive quantity of collected information.

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Problem Statement

Diseases affecting crop leaves have become an issue because they reduce yield and quality. In order to monitor vast agricultural fields, it is critical to find ways to identify and categorize agricultural leaf diseases automatically as they show up on the leaves. We comparatively study classical ML algorithms, deep learning” in this thesis [4]. A model for the accurate diagnosis of leaf diseases in agricultural crops was developed using learning based on convolutional neural network (CNN) architecture and CNN algorithm. The crop scenario in India dates as far back as the Indus Valley Civilization. India’s agricultural heritage runs deep. Agriculture in India is in a state of disarray. This region relies more heavily on precipitation from the sky. In an effort to increase crop yields, several agricultural sector development plans have been drafted. Diversifying crop yields is essential in today’s agricultural sector since it allows for more flexibility and variety in crop output. Agriculture in India varies by region, with different regions focusing on different crops with similar requirements. The advent of new agricultural technology, especially during the time of the Green Revolution, has caused significant shifts in Indian crop culture. Even though changes have been made in agriculture, optimal agricultural productivity has not yet been achieved to maximize yield, farmers must employ both crop rotation and modern farming techniques [5].

PROBLEM FORMULATION

The research paper approach for studying crop leaf disease detection and classification is presented in this section. Careful planning went into the study’s approach to ensure a high level of relevance to the subject [6]. Researchers explain their study’s methodology and why they chose it for this particular investigation. You can find all the information about the study’s methodology and the data-gathering tool here. This study evaluates and contrasts two approaches to leaf disease classification [7]. Deep learning and more traditional approaches to machine learning algorithms are both utilized by us. Deep learning also makes use of transfer learning techniques. Tables and other graphical representations of data are common for machine learning algorithm output. Last but not least, we discuss a few of the ethical issues [8]. Detailed machine learning approaches for crop leaf disease detection and ~~categorization are illustrated in the image below.~~

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Data Preprocessing

When preparing an image for analysis, preprocessing involves applying several changes to the raw data. Intensity discrepancies in the cotton pictures may have been caused by weather conditions, camera variances, or other causes. It shows that the brightness is not evenly distributed throughout the image. Consequently, the noise will be seen in the images [9]. Even when shooting the same leaf many times with the same camera, the results could seem quite different. To make sure that every leaf looked the same vivid green, intensity normalization was used. The dimensionality constraints of the models employed in practice need a consistent scaling of the images. Then, we give each disease category a name using the Label Encoder Python module [10].

Process and Evaluation Method

As the research is focused on classification, accuracy is one of the criteria used to evaluate True positive (TP): The event’s anticipated and actual values are both positive. When an event’s observed value conflicts with a negative forecast, it is called a false positive (FP) [11]. When an occurrence is seen and anticipated to have a negative value, it is said to be a true negative (TN). An example of a false negative (FN) would be an observed event value that is negative despite a positive predicted value. Tuples that the classifier successfully labeled as negative are known as true negatives (TN), whereas tuples that the classifier correctly labeled as positive are known as true positives (TP) [12].

The discriminator true positives are those that accurately identify positive tuples while false positives are known as FP. The same is true for false negatives (FN), which are positive tuples that have been incorrectly categorized [13]. The method by which the reliability ratings are determined in Table 1 is as follows.

Table 1. Confusion matrix.

		Predicted	
		Positive	***Negative***
Observed	Positive	TP (of TPs)	FN (of FNs)
	Negative	FP (of FPs)	TN (of TNs)

Accuracy: The number of samples used to determine the accuracy of a classification model is proportional to the number of correct predictions made by the model. It shows how well the model classified the test data. To achieve the aforementioned research objectives, it is an essential indication [14].

RESULTS

Classical Machine Learning Algorithms

Random Forest Results

A random forest classification approach was used to identify and classify cotton leaf diseases. In order to train and evaluate the classification model, the data was utilized in stratified fivefold cross-validations. All three-color spaces—RGB (red, green, blue), Lab, and HSV (hue, saturation, value)—are used independently throughout the research [15]. The general success rate of HSV testing in terms of categorization accuracy compares favorably to results obtained using Lab or RGB images. Table 2 shows that compared to RGB images, Lab or HSV color transformations produce better classification accuracy and F1 score. Four performance measures are used to determine the experiment's final outcome [16]. Table 3 displays performance data including correct predictions, correct recall rates, and F1 score. The accuracy of the random forest model was estimated to be 86.5%.

The dataset consists of four distinct kinds of cotton leaves, and a support vector machine (SVM) classification model is trained using stratified K-fold cross-validation [17]. Before feeding it into the classification model, the data is divided into a training set and a testing set using stratified K-fold cross-validation. Throughout the investigation, RGB images, the Lab color space, and the HSV color space are all utilized independently. The efficiency of the output is evaluated in four dimensions [18]. Table 4 presents the F1 score, recall, accuracy, and precision as performance metrics. The overall classification accuracy achieved with HSV testing is greater than that achieved using Lab or RGB pictures. Table 5 demonstrates that the use of Lab and HSV color conversions, as opposed to RGB images, improves classification accuracy and F1 score.

The validation results show that SVM outperforms random forest in terms of prediction accuracy, with a score of 90% compared to 86% for random forest.

Table 2. Results of random forest model.

	Accuracy	Precision	Recall	F1 Score
RGB values	88.3%	88.8%	90.4%	81.3%
Lab	90.2%	90.6%	91.5%	85.3%
HSV	88.5%	90.2%	87.1%	86.7%

Table 3. Results of random forest using HSV color space support vector machine (SVM) results.

	Accuracy	Precision	Recall
Split 1	86.1%	86.2%	86%
Split 2	83.4%	83.2%	83.8%
Split 3	87.2%	88.3%	87.6%
Split 4	88.6%	90%	87.7%
Split 5	87.5%	88.8%	85.4%
Average	86.5%	87.3%	86.1%

Table 4. Results of support vector machine model.

	Accuracy	Precision	Recall	F1 Score
RGB values	88.3%	88.8%	90.4%	81.3%
Lab	90.2%	90.6%	91.5%	85.3%
HSV	88.5%	90.2%	87.1%	86.7%

Table 5. Results of support vector machine using HSV color space.

	Accuracy	Precision	Recall
Split 1	88.3%	88.8%	90.4%
Split 2	90.2%	90.6%	91.5%
Split 3	88.5%	90.2%	87.1%
Split 4	92.3%	93%	91.5%
Split 5	91.2%	91.4%	88.6%
Average	90.1%	90.8%	89.7%

Deep Learning Algorithms

First, we built a basic CNN using the Keras package for deep learning networks. This CNN has predefined layers for typical tasks such as max pooling, convolution, and more. An accurate custom-made CNN with many layers was created and tested. This model undergoes extensive training using 25, 64, 128-, and 256-size filters, as well as 11 convolution layers [19]. It is possible to find the sweet spot for learning rate and batch size by conducting a series of trials to adjust the hyper parameters. The model underwent 25 rounds of refinement during which achieved an accuracy of 85.31% with a 32-batch size and a learning rate of 0.0001. It was also determined that the F1-score was 83.75. Additionally, the confusion matrix of the generated model is displayed, which contrasts the actual and predicted class counts. Both the accuracy and loss of the CNN model during training and validation are shown in Figures 1–4 and Table 6.

Transfer Learning Using Inception v3, VGG 16, and ResNet 50

Applying a model that has already been trained to a new, unrelated task is called transfer learning. By utilizing the transfer learning approach, the training process may be finished more quickly and with less computer resources. With ResNet 50, Inception v3, and VGG 16, three transfer learning models are pre-installed. This architecture's default size for running models is 224 × 224 pixels. We do this by computing a small number of additional dense layers on top of the previously trained network and then freezing the remaining layers. With Inception v3, the prediction accuracy was 91% to 94%, with VGG 16 it was 93% to 94%, and ResNet 50 it was 91% to 91%.

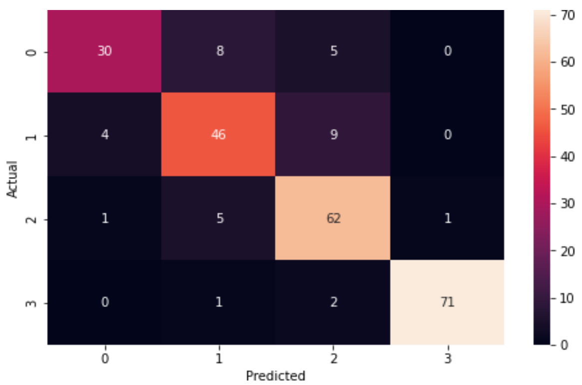

Figure 1. Confusion matrix of convolutional neural network (CNN).

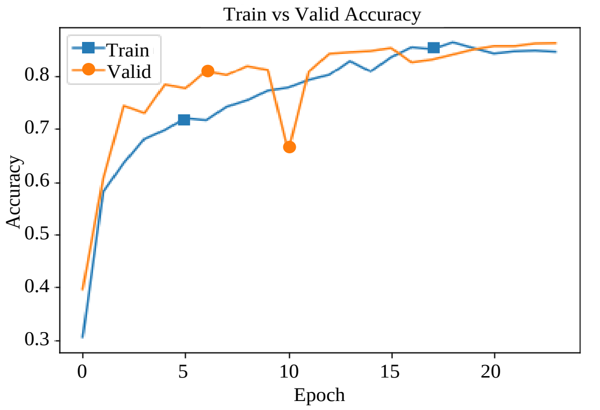

Figure 2. Training and validation accuracy of convolutional neural network (CNN) model.

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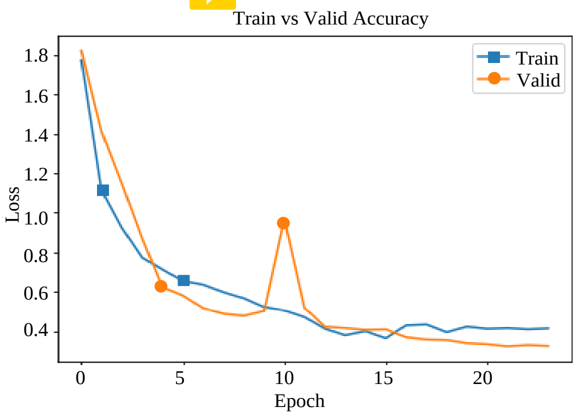

Figure 3. Training and validation loss of convolutional neural network (CNN) model.

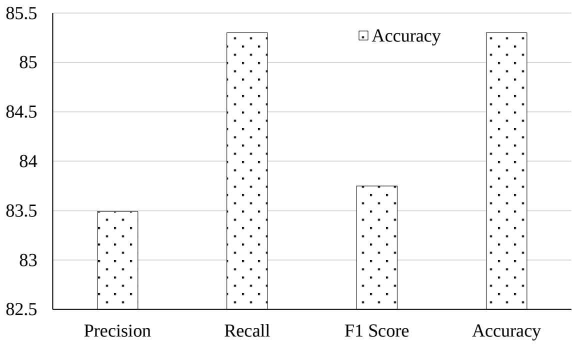

Figure 4. Results of convolutional network (CNN) model.

Table 6. Results of convolutional neural network (CNN) model.

Precision	83.5%
Recall	85.25%
F1-score	83.75%
Accuracy	85.31%

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Inception v3

With a score of 94%, Inception v3 obtained the best prediction accuracy. All three metrics—precision, recall, and F1 score—recognized by the model were 92.5%. Figure 5 displays the confusion matrix of the generated model, which contrasts the actual and predicted class numbers [20]. In Figure 6, we can see the Inception v3 model's training and validation accuracy, as well as its training and validation loss in Figures 7 and 8, and Table 7.

VGG16

VGG 16 has shown a 93% success rate in making predictions. With a recall accuracy of 91.75% and a precision of 92.25%, the model obtained an F1 score of 92.25%. Figure 9 (VGG1) shows the model's confusion matrix, which contrasts the expected and actual number of classes [21]. Figures 10–12 (VGG2 and VGG3) display the accuracy and loss, respectively, of the VGG16 model during training and validation (Table 8).

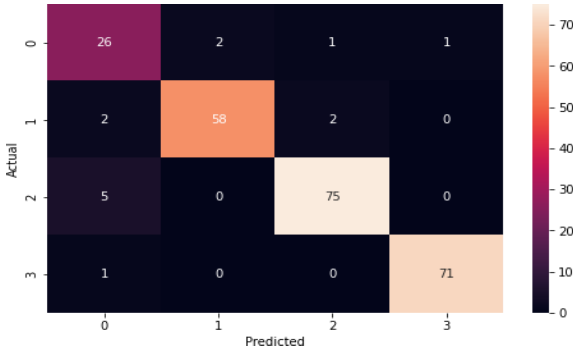

Figure 5. Confusion matrix of Inception v3.

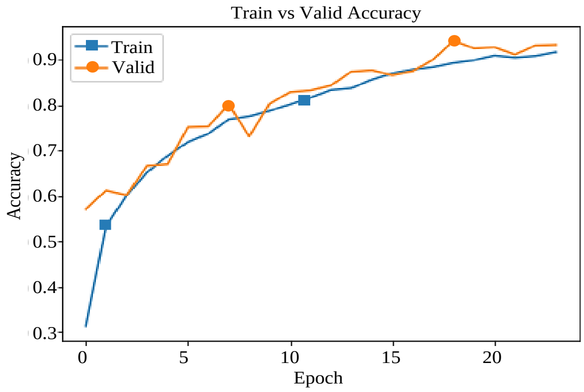

Figure 6. Training and validation accuracy of Inception v3.

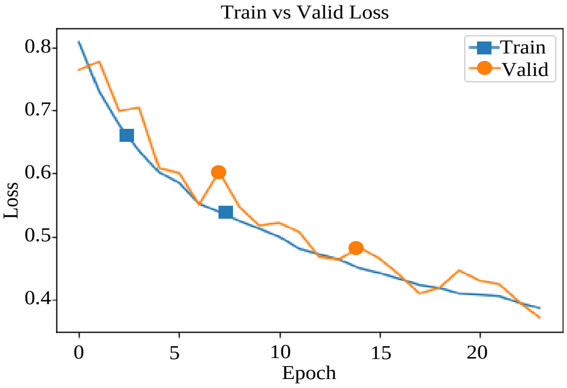

Figure 7. Training and validation loss of Inception v3.

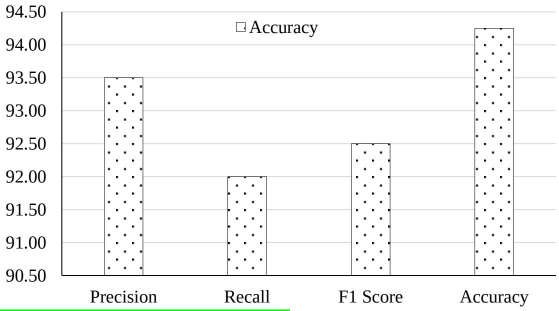

Figure 8. Results of Inception v3.

Table 7. Results of Inception v3.

Precision	93.5%
Recall	92%
F1 score	92.5%
Accuracy	94.26%

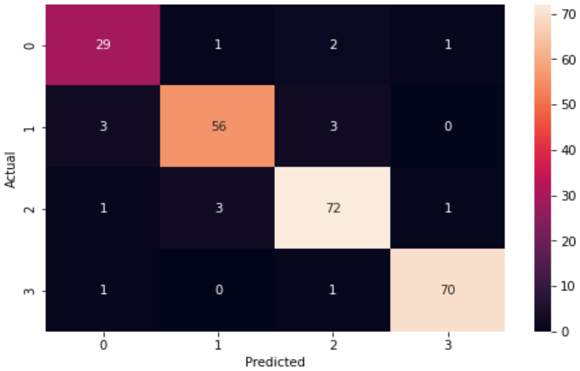

Figure 9. Confusion matrix of VGG 16.

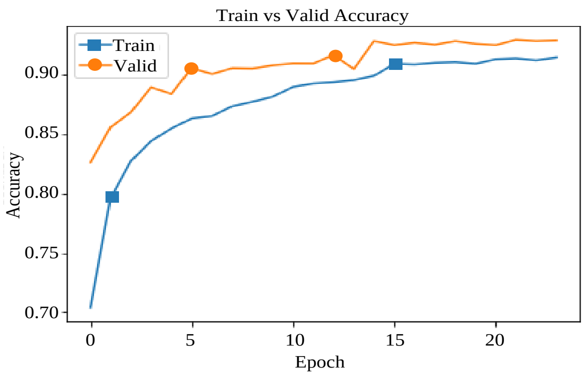

Figure 10. Training and validation accuracy of VGG 16.

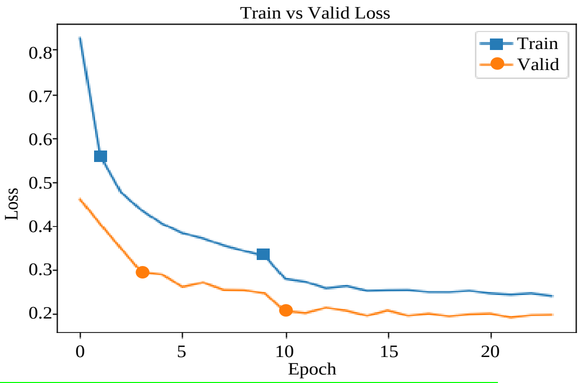

Figure 11. Training loss and validation loss of VGG 16.

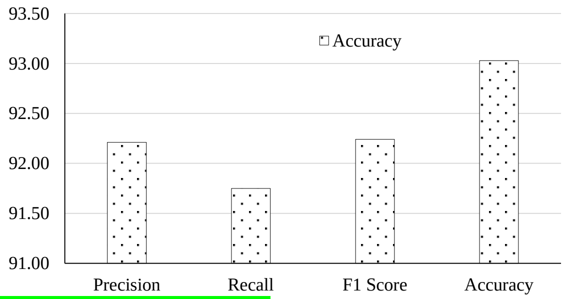

Figure 12. Results of VGG 16.

Table 8. Results of VGG 16.

Precision	93.5%
Recall	92%
F1 score	92.5%
Accuracy	94.26%

ResNet 50

The prediction accuracy of ResNet 50 was 91%. The model achieved an F1 score of 90% and a recall and accuracy of within 0.5%, respectively. The confusion matrix of the final model, depicted in Figure 13 (ResNet 1), displays the discrepancy between the actual and predicted number of classes [22]. Figure 14 (ResNet 2) and Table 9 display the ResNet 50 model's training and validation accuracy, whereas Figures 15 and 16 (ResNet 13) display the model's training and validation loss.

Model Comparison

According to Table 10, when it comes to cotton leaf disease classification, the Inception v3 transfer learning architecture performs better than other models in terms of recall, precision, and accuracy (Figure 17).

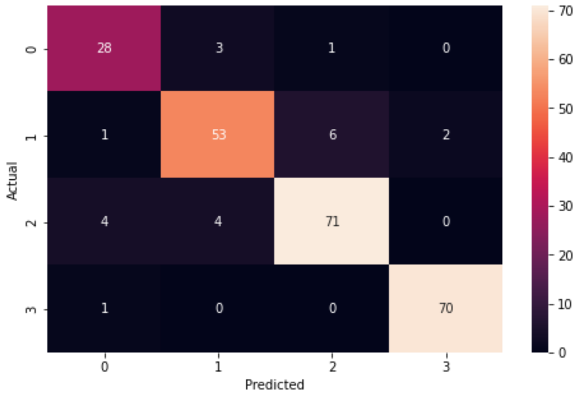

Figure 13. Confusion matrix of ResNet 50.

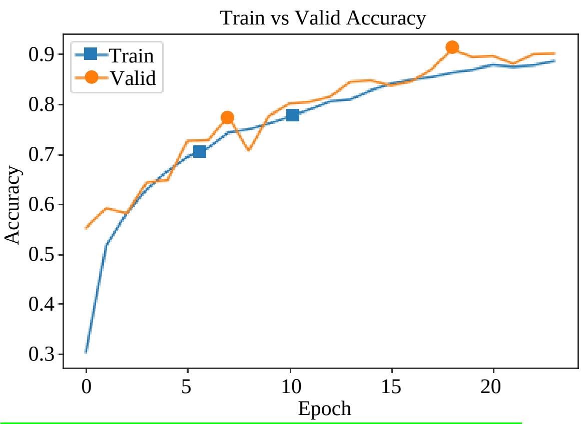

Figure 14. Training and validation accuracy of ResNet 50.

Table 9. Results of ResNet 50.

Precision	90.5%
Recall	89.05%
F1Score	90%
Accuracy	91%

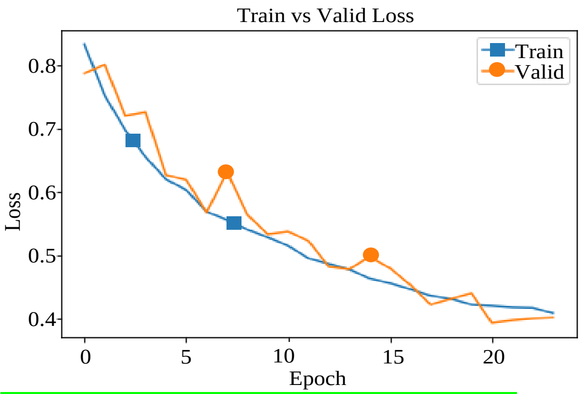

Figure 15. Training loss and validation loss of ResNet 50.

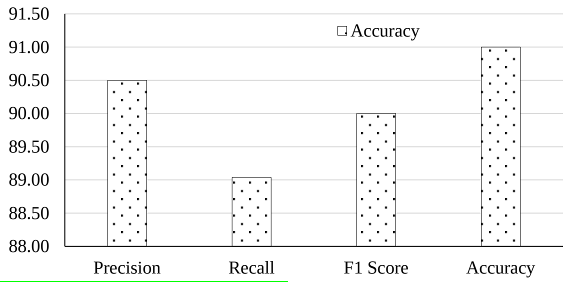

Figure 16. Results of ResNet 50.

Table 10. Results.

Algorithm	Accuracy	Precision	Recall
Inception v3	94%	93.5%	92%
VGG 16	93%	92.25%	91.75%
ResNet 50	91%	90.5%	89.05%
Support vector machine	90.1%	90.8%	89.7%
Random forest	86.5%	87.3%	86.1%
Convolutional neural network (CNN)	85%	83.5%	85.25%

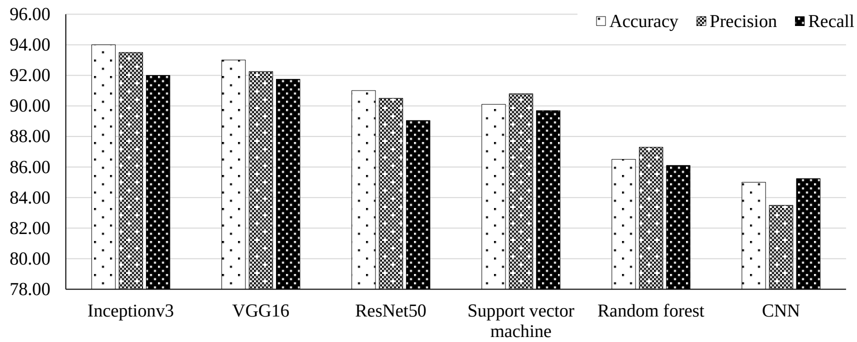

Figure 17. Accuracy of different algorithms.

At 94% accuracy, it lagged behind VGG 16 by a whisker. In comparison to more traditional models, these results offer credence to our theory that disease detection and classification in cotton leaves may be better accomplished using CNN-based transfer learning techniques. Metric values like accuracy prove that the training data had improved images, which improved the model's performance [23].

CONCLUSION AND FUTURE SCOPE

The purpose of our research was to compare and contrast how well pre-existing connected limited device configuration (CLDC) models handled the dataset and the challenge of cotton disease identification. When it came to cotton disease classification, we tested a proprietary CNN, two machine learning algorithms (RF and SVM), and three deep learning algorithms (VGG 16, ResNet 50, and Inception v3).

Image processing, color transformation, segmentation, feature extraction, and classification are utilized for the purpose of illness symptom categorization. This study analyzed a dataset consisting of 1225 high-quality RGB pictures. The dataset covered four disease categories: Alternia leaf, grey mildew, leaf reddening, and healthy leaves. In all, 170 pictures of healthy leaves, 301 pictures of grey mildew, 388 pictures of leaf reddening, and 365 pictures of Alternia leaves were used to extract characteristics and classify diseases. There were separate experiments on the plant disease classification using RGB, Lab, and HSV processed pictures. We classified data in the research using SVM and RF models. Stratified fivefold cross-validation is used for training and testing feature vectors in this experiment. When looking at the two classification models side by side, SVM comes out on top. When we compared the evaluated deep learning networks to the machine learning algorithms across all metrics, we discovered that the former consistently performed better. We determined the monetary worth of all transferable skills.

A minimum score of 90% is required in order to be considered for the evaluation of machine learning algorithms. The Inception v3 network outperformed the competition on our dataset and in our classification test with accurate results (94%), precise results (93.50%), recall (92%), and an F1 score (92.50%), all of which are sufficient for illness classification.

The study accomplished its aims; however, it encountered several constraints and challenges. One big problem was that there was not enough data from diverse demographics and areas to test and improve the model. Furthermore, four separate disease categories were used to train the created models. Because of this, models might not be able to predict when newly discovered cotton diseases would appear. Classification of images with numerous diseased leaves or many leaves in general presents extra hurdles, and these classifications have not been tested to their full potential. In addition, training the algorithms' final few layers of transfer learning might have been costly and time-consuming.

Future Scope

By comparing the dataset and the cotton infection localization issue, our review aimed to evaluate the performance of existing CLDC models. For the purpose of cotton disease ranking, we examined three deep learning computations (VGG 16, ResNet 50, Inception v3), one unique CNN, and two artificial intelligence methods (RF and SVM). The side effects of sicknesses are ordered utilizing picture handling, variety change, division, highlight extraction, and grouping. Alternia leaf, dark mold, leaf blushing, and sound leaves are the four illness classifications addressed in the dataset examined in this review, which aggregates 1225 great RGB photographs. Qualities were removed and diseases were ordered from a sum of 170 photos of Alternia leaves, 301 pictures of dark mold, 388 pictures of leaf blushing, and 365 pictures of solid leaves. RGB-, Lab-, and HSV-handled photographs were undeniably tried autonomously in their own examinations of plant disease arrangement. In the review, we utilized SVM and RF models to classifications information. Highlight vectors are prepared and tried involving separated 5-overlap cross-approval in this examination. SVM performs better compared to RF does while looking at the two arrangement models.

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