RESEARCH ARTICLE Indian Journal of Agricultural Research, Volume 59 Issue 11: 1743-1751 (November 2025)

Leveraging Inception-V3 and Transfer Learning for Early Detection and Classification of Cotton Crop Diseases

Samuel Chepuri[1], Y. Ramadevi[2]

10.18805/IJARe.A-6391

ABSTRACT

Background: Cotton is an important crop globally and early detection of plant diseases is crucial for maintaining yields. Traditional methods for disease detection are manual and inefficient, highlighting the need for advanced technology like AI to enhance productivity.

Methods: The study utilized the Inception-v3 deep learning model along with techniques such as transfer learning and hyper-parameter tuning. These approaches helped design an efficient system to classify whether a cotton plant is healthy or diseased. Comparisons were made with other pre-trained models like VGG16, ResNet50 and ResNet152V2.

Result: The Inception-v3 model showed exceptional performance:

· Achieved 87.52% accuracy without tuning.

· Achieved 98.85% accuracy after hyper-parameter tuning, marking an improvement of ~11%. This approach also demonstrated faster and more precise predictions for diseases like bacterial blight, army worms and aphids. It supports sustainable farming by reducing chemical usage while maintaining crop quality and yield.

Key words: Convolutional neural network (CNN), Cotton disease detection, Deep learning, Hyperparameter tuning, Inception-V3 model, Transfer learning.

INTRODUCTION

Cotton is a significant crop in India, vital for both its economy and agricultural sector. However, farmers often face challenges in diagnosing diseases in cotton leaves due to a lack of in-depth information. This leads to excessive use of fertilizers, impacting the environment and crop quality.

To address this, advancements in image processing, neural networks and machine learning are being applied. A mobile image processing system is being developed to help farmers identify cotton leaf diseases. This system processes leaf images, compares them with reference data and classifies them as diseased or healthy based on similarities. Machine learning enhances the system's accuracy over time, improving with each iteration. By detecting infected leaves early, farmers can remove them to safeguard the harvest and reduce pest-related damage. This approach aims to protect both the cotton yield and the farming community, promoting sustainable agricultural practices.

Cotton diseases

Cotton plants are highly susceptible to fungal, bacterial and viral infections. These diseases typically manifest on the leaves, showing visible spots or lesions. However, the pathogens are not limited to foliage and can affect bolls and roots as well. Such infections can significantly reduce crop quality and yield if not managed properly. Early detection and precise classification are essential for effective disease control. To be familiar with the fertilizers that need to be given we have to make sure that the detection of the disease must be correct. The diseases that frequently occur on cotton leaves are: Aphids, Army Worm, Bacterial Blight, Powdery Mildew and Target spot.

[1]Department of Computer Science and Engineering, Osmania University, Hyderabad-500 007, Telangana, India.
[2]Department of Computer Science and Engineering Artificial Intelligence and Machine Learning, CBIT, Hyderabad-500 075, Telangana, India.

Corresponding Author: Samuel Chepuri, Department of Computer Science and Engineering, Osmania University, Hyderabad-500 007, Telangana, India. Email: drsamuelchepuri@gmail.com

How to cite this article: Chepuri, S. and Ramadevi, Y. (2025). Leveraging Inception-V3 and Transfer Learning for Early Detection and Classification of Cotton Crop Diseases. *Indian Journal of Agricultural Research*. **59(11):** 1743-1751. doi: 10.18805/IJARe.A-6391.

Submitted: 26-03-2025 **Accepted:** 09-07-2025 **Online:** 11-08-2025

Meta model in deep learning

The 'cotton plant disease' dataset contains 10673 images of various cotton leaves considered from 'Kaggle' is categorized into 6 classes, among them the data split training and testing is 80:20 respectively (Training: 7246 images and Testing: 3427 images). There are various models where we can predict that a leaf is either diseased leaf or an healthy leaf. Fig 1 shows the implementation flow of our model.

Model selection

There are multiple methodologies to predict whether a cotton leaf is a disease or not. Table 1 mentioned below depicts the review of different models:

Architecture of inception-v3

The Inception-v3 is an architecture of a deep convolutional neural network, which combines inception modules for multi-scale feature extraction, as demonstrated in Fig 2.

The inception modules use parallel convolution pathways including filters of different sizes to capture diverse spatial information. Due to its deep structure, Inception-v3 is, however, still computationally effective and can provide a good result in tasks of image classification.

Literature review

The health of cotton crops plays a critical role in global agricultural economies, especially in regions that rely on cotton production for economic growth and stability. With the advent of precision agriculture, leveraging machine learning (ML) and deep learning (DL) models has become essential in automating and improving disease detection and classification in cotton plants. One of the most promising approaches in this domain is the application of the Inception-v3 classifier, coupled with transfer learning (TL), to enhance the accuracy and efficiency of disease detection. This literature review synthesizes key research in cotton disease detection, focusing on Inception-V3 and TL methods to understand their contributions, challenges and future potential.

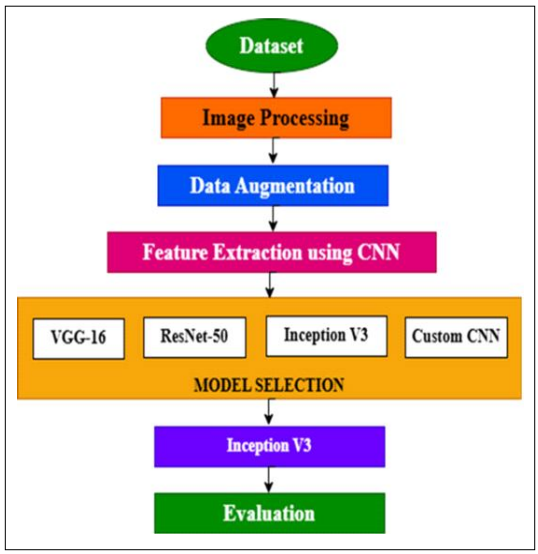


Fig 1: Implementation flow.

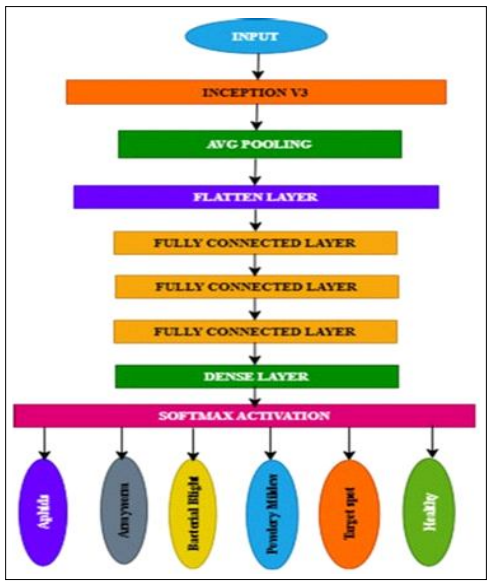


Fig 2: Architecture of implementation.

Deep learning in cotton disease detection

Deep learning models have significantly advanced the automation and optimization of cotton crop disease detection. Numerous studies highlight the role of convolutional neural networks (CNNs) and hybrid architectures in identifying and categorizing diseases in cotton plants. A landmark study by Tao *et al.* (2022) employed a CNN-based approach leveraging the ConvNeXt architecture, which combines transformers for enhanced feature extraction. This method achieved exceptional accuracy rates of 97.2%, 99.7% and 100% across various datasets while maintaining low inference times. However, the study mainly focuses on CNNs, with limited exploration of transfer learning (TL) and alternative algorithms like SVM, KNN, Random Forest and Decision Tree for classification. In contrast, Shaikh *et al.* (2023) implemented the Inception-V3 architecture as a classifier using TL to identify three cotton diseases: bacterial blight, curl virus and fusarium wilt. Their model, trained on a dataset of 950 images sourced from Kaggle and pre-processed with Gabor filters, achieved 97% accuracy. The use of TL improved feature extraction and the model effectively utilized supervised learning techniques. This study underscores the advantages of Inception-V3 and TL in accelerating training and achieving high accuracy for cotton disease detection.

Transfer learning for enhanced accuracy

Transfer learning (TL) is a pivotal method for enhancing disease detection models, especially in agriculture, by utilizing pre-trained models to streamline training. Islam *et al.* (2023) demonstrated the effectiveness of TL using models like VGG-16, Xception and Inception-v3 for cotton disease classification. Among these, Xception excelled with an impressive accuracy of 98.70%. This approach not only boosts model efficiency but also addresses challenges posed by limited datasets in real-world agricultural scenarios. Shaikh *et al.* (2023) expanded on this by incorporating Inception-V3 alongside TL and techniques like Gabor filtering for data augmentation. This combination significantly improves edge detection and texture classification, enabling early disease identification. These methods highlight the practicality of TL in achieving high accuracy with smaller datasets. Other researchers, including Noon *et al.* (2022), explored CNN-based ConvNeXt architecture with transformers, yielding promising results. However, TL-centric models, such as Inception-v3, offer faster training and adaptability across diverse datasets, making them ideal for practical applications. In summary, TL emerges as an invaluable tool in agricultural disease detection, delivering remarkable accuracy and efficiency while addressing the challenges of limited labelled data availability. Its adaptability and scalability make it indispensable for modern agricultural practices.

Meta-learning and hybrid approaches

Hybrid architectures and meta-learning approaches are pivotal in advancing model performance for agricultural applications. Memon *et al.* (2022) introduced a meta-deep learning framework that integrated Custom CNN, VGG-16 and ResNet50, achieving an impressive 98.53% accuracy in identifying cotton diseases like leaf spot and bacterial blight. This innovative approach leveraged the combined strengths of multiple models, enhancing generalization capabilities and minimizing overfitting risks. Although the study did not involve Inception-V3, its findings highlight the effectiveness of hybrid models in improving disease detection for cotton crops. Similarly, Aggarwal *et al.* (2023) investigated pre-trained deep neural networks for rice disease classification, yielding encouraging results with potential applicability to cotton crop health assessment. Their research emphasized the cri,tical role of feature selection in transfer learning (TL) models, further advocating for the use of architectures like Inception-v3. This model excels in extracting high-level features, making it highly suitable for disease classification tasks. Together, these studies underscore the importance of exploring integrated architectures and transfer learning techniques to enhance agricultural disease detection systems. Similar hybrid approaches were also supported by Ahmed (2021), Moyazzoma *et al.* (2021) and Reddy *et al.* (2023), who demonstrated the advantages of CNNs and TL for leaf disease recognition. Additionally, Arathi and Dulhare (2023) employed DenseNet-121 for cotton leaf classification, while Patil and Burkpalli (2021) explored WEKA-based ML pipelines for cotton disease detection, further validating the value of hybrid frameworks in this domain.

Challenges and limitations in cotton disease detection

Despite the successes of these methods, challenges remain in optimizing DL models for real-time, large-scale deployment in agricultural settings. The need for high-quality, large-scale datasets continues to be a limitation for many DL-based models. Hassan *et al.* (2022) addressed this issue by developing a custom CNN model on a dataset of 500 images from local fields in Multan, Pakistan, achieving an accuracy of 85%. However, their results highlight the gap between model performance on small, local datasets and the more generalized, large-scale applications of models like Inception-v3. Another challenge is the computational cost and complexity of deploying these models in real-time field conditions. Alotaibi and Rassam (2023) discussed the importance of leveraging high-performance computing resources to optimize ML models in cloud environments. Applying such principles to cotton disease detection would require efficient resource management to ensure the models remain feasible for use in the field, where computational power may be limited. Furthermore, Alsarhan *et al.* (2021) discussed ML-driven optimization in vehicular networks, principles of which can be extended to resource-constrained agricultural deployments.

Looking forward, integrating Inception-v3 with TL and other advanced architectures holds significant potential for improving cotton disease detection. Mobile applications, as proposed by Rajasekar *et al.* (2021), could make these models more accessible to farmers, providing real-time disease detection tools. This would democratize access to precision agriculture, allowing farmers in remote areas to benefit from advanced DL techniques. The use of cloud-based platforms, as suggested by Alotaibi and Rassam (2023), could further enhance the scalability of these models. By offloading computationally intensive tasks to the cloud, these systems could handle larger datasets and offer real-time insights to farmers. Furthermore, meta-learning approaches, like those explored by Memon *et al.* (2022), could lead to more adaptive models capable of generalizing to new datasets and environmental conditions, further enhancing the robustness of these systems. The interpretability and scalability shown in IoT-driven approaches such as that by Kundu *et al.* (2021) also align with this direction, promising practical implementations for future agricultural decision-making tools.

In recent years, there's been a growing interest in using machine learning and deep learning techniques to detect and classify plant leaf diseases, especially in crops like cotton.

Table 1: Model review.

Model	Merits	Drawbacks
Inception V3	Enhanced ability in terms of the accuracy and the speed of the convergence process. It makes it possible to train various deep neural networks faster.	Training Inception-v3 from scratch on large datasets is time-consuming process, it might takes from days to weeks just to get to adequate level of performance.
ResNet-50	Balance between model simplicity and capacity, Applies to both spatial domain and channel-wise domain.	Deeper architecture may result in a vanishing gradient or overfitting. It is both memory and computation-bound, especially for multiple layers.
VGG 16	The affordability to understand and policy for implementation expedite the process and is easy to handle.	Many parameters are involved which may require high memory and Requirement and performance consistency on the various image datasets.
MobileNet V2	This cross-platform compatibility, combined with the light weight architecture which can handle such devices as smartphones and edge devices.	Lower accuracy compared to the deeper models like VGG-16 or ResNet. May fail to achieve the details caused by its light weight.

For instance, Patil and Burkpalli (2021) took a practical approach by using traditional machine learning algorithms in the WEKA platform to classify cotton leaf images, showing how models like decision trees can still hold value in agricultural applications. On the other hand, researchers like Reddy *et al.* (2023) have shifted towards deep learning, specifically convolutional neural networks (CNNs), to predict cotton leaf diseases with impressive accuracy. Adding to this, Moyazzoma *et al.* (2021) used a transfer learning approach with MobileNetV2, showing that pre-trained models can be powerful tools for plant disease detection, especially when resources or data are limited. While these studies mainly focus on disease detection, Bansal *et al.* (2024) looked at the broader picture of crop productivity by examining how different pigeonpea varieties and spacing patterns impact yield. Together, these studies reflect how AI and data-driven methods are shaping the future of smart farming and plant health management.

The application of the Inception-v3 classifier, using TL, represents a significant advancement in cotton crop disease detection. By leveraging pre-trained models and fine-tuning them for specific agricultural tasks, researchers have demonstrated that high accuracy and efficiency can be achieved, even with relatively small datasets. Hybrid models and meta-learning approaches offer further opportunities for enhancing disease detection and classification, while cloud-based solutions and mobile applications could ensure these technologies reach the field, helping farmers protect their crops in real-time. Continued research in this area promises to refine these methods, making cotton crop disease detection more accessible, accurate and scalable.

MATERIALS AND METHODS

Pre trained models such as Inception-v3 has the potential to identify diseases at the early stages while the pictorial symptoms might not be clear to the natural eye. This kind of detection in advance facilitates to the timely treatment. These Pre trained models can be deployed on varied platforms including drones and edge devices for remote monitoring and scalable of large fields of cotton. The methodology we proposed initiated with a step of pre-processing and data augmentation at University College of Engineering (A), Osmania University, Hyderabad, Telangana during the year 2023 as discussed below.

Data-augmentation

The process of data augmentation retained in this model enclosed a considerably wide shuffle of transformations in order to improve the robustness and diverseness of our dataset.The input image is taken to a size of 224*224 and processed. The practised transformations include shear range of 0.2, zoom range of 0.2, rotation range specified as 80, width_shift_range as 0.2, height_shift_range being 0.2, brightness range from 0.5 to 1.5 and horizontal vertical flips set to true. These measures help the model generalize better and prevent over-fitting. A pre-processing function is employed which is labelled “re-scale” set to ‘1.0/255’ to process the images into a desired format before being sent to be augmented. The validation split used in our model is a 10% split that is integrated into the process to access model performance during training. Fig 3 shows the Augmentation.

Feature extraction using inception-v3

Inception-v3 is a pre-trained CNN model with 17 layers, including convolution layers, Inception blocks and a fully connected layer. It is used for feature extraction by removing the last classification layer and using the activation inputs from this layer for describing features. Inception-v3 integrates techniques like factorized convolutions, regularization, dimension reduction and parallelized computations to optimize network performance. It is known for its computational efficiency, reduced complexity and versatility in feature extraction across various domains. The extracted features can be used to build a classification model with components like LSTM layers, dense layers and dropout layers, trained using the Adam optimization algorithm and specific hyper-parameter values. The Inception-v3 architecture is used for feature extraction in Model 1 of a study, which helps to build a NN model with greater stability and consistency in the year 2024.

Proposed model design

The features that have been extracted are used in the proposed method Inception V3 transfer learning model. Inception-v3 is from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 × 7 convolutions and the use of an auxiliary classifer to propagate label information lower down the network.

Hyper tuning inception-v3

Hyper-parameter tuning for the Inception-v3 model in cotton plant disease detection involves optimizing hyper-parameters like learning rate, batch size, optimizer settings, activation functions and regularization techniques to enhance model

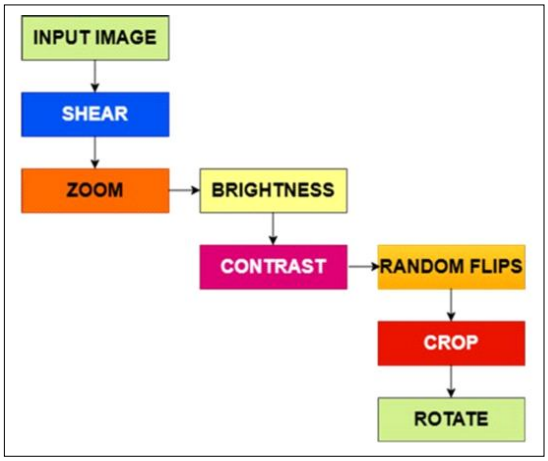


Fig 3: Data augmentation.

performance. By systematically adjusting these hyper-parameters using techniques like grid search or random search, researchers can fine-tune the model for improved accuracy, convergence speed and generalization to unseen data. The learning rate controls how quickly the model learns, epochs determine training frequency, batch size specifies data samples used for parameter updates and dropout rate influences neuron dropout during training. This tuning process is crucial for achieving optimal model effectiveness in identifying and classifying diseases affecting cotton plants. Table 2 determines the metrics for tuning.

Proposed model customized parameters

In the context of the Inception-v3 model, the hyper-parameter tuning process using Grid Search aims to find the best combination of learning rate, dropout rate and optimizer settings that maximize the model's disease detection accuracy. By exploring various hyper-parameter configurations and evaluating their impact on the model's performance, researchers can identify the most effective settings for these parameters. This systematic approach ensures that the Inception-v3 model is fine-tuned to achieve optimal results in classifying cotton plant diseases based on extracted features. Table 3 discover the metrics that are customizing the model proposed is Inception-v3.

RESULTS AND DISCUSSION

A hyper-parameteris known as "epochs" describes that the number of iterations will be performed the learning method over the totaldataset given to training. For every epoch completion, the parameters of the model have been modified for the data collection in training dataset. A portion of the dataset is considered to train the neural network in a couple of lot that makesevery epoch. We can say the epoch is "iteration" as the process of transfering a bunch of training data. The accuracy is very low before tweaking settings Fig 4 depict the loss and accuracy on traditional approaches respectively.

The built-in dataset determines the indecent number in epochs. By using the entire training data, a neural network taking care of training for every cycle throughout the epoch. All the way each portion of knowledge is precisely used. If anepoch moves both the directions backward and forward, it measures as a pass. The proposed methodlogy Inception-v3 adjusts the parameters, so accuracy has increesed. It rises to 98.85%. Minute values also considered and workable to the loss. Completed the training by consideration of 20 epochs. Fig 5 show the loss at 4.27% and accuracy at 98.85% attained by our proposed model after the tuning process respectively.

Table 2: Parameters for tuning the inceptionV3.

Parameter	Description
Dropout	The dropout regularization uses the neural dropping of neurons during training with random while having a fraction within a range to prevent the overfitting that promotes the robustness of the features learned by the models.
Number of epochs	One way to achieve this is to increase the amount of epochs through which the model is trained, allowing the model to undergo more data iterations that could incrementally improve the performance by the model learning the complex relationships in the data.
Optimizer	Optimizers like Adam and RMSprop are effective in the updating process of parameters during training, resulting to fast speeds of training, which invariably facilitate better result.
Weight decay	The relationship between the weight decay parameter and neural network performance is complex. On the one hand, too large values might impede the utility of the model for solving complicated problems. On the other hand, too small values may equally render the regularization effects redundant.
Early stopping	Frequent validation tests the training decay on an external validation set what worse performance so the training is halted when performance degrades and stops using valuable computing resources.
Batch size	Bigger batch sizes enhance training operations by moving more samples for the reason that parallel and capitalizing on the power of current hardware.
Learning rate	Learning rate increases the learning speed by moving in the parameter space at a higher pace but it brings increased probability of hyper-parameter convergence and going off track.
L2 regularization	In contrast, L1 regularization is more conservative and chooses to activate only one strong node rather than many weak nodes through the addition of the squared absolute value of weights into the loss function which promotes less complex and smoother decision boundaries.
Data augmentation	Data augmentation consists of the application of transformations like rotation, flipping and cropping to make samples more neat and increase the intensity of the learning process, thus, allowing the model to be robust and generalize to unseen and new data.
Model architecture	Generating Inception networks, especially if we are talking about unprecedented tasks, includes factor adjusting the quantity and scale of inception modules and changing the size of the kernels, down to the mentioning of the number of filters in convolutional layers depending on the complexity of the task.

Table 3: Tuning metrics of parameters.

Parameter name	Importance	Need of tuning	Possible values
Learning rate	Determining of the learning rate comes in the process of learning whereby its step size during the optimization influences the stable and the speed in convergence of the training process hence, its importance of finding the best parameters for the model.	Exceeding the high learning rate, the model might move around and there is a chance of settling on an unsatisfactory solution. On the contrary, if it is too small the progress may be minimal and it could result to the model hang up in the suboptimal points.	0.0001-0.001
Dropout rate	Dropout probability controls the rate of neuron dropout that reduces over shifting of neurons toward particular features of training input but leads to generalization and the ability to tolerate unseen data.	If the dropout rate is too small, then the model may struggle to prevent dropout-effect effectively, allowing over-fitting to occur.	0.4
Optimizer	By setting the guidelines to update the model's weights, the optimizer algorithm will be able to adjust them based on the gradients of the loss function, thereby steering the process of training to a possible design that would help to attain a minimization associated with the loss and also improve model process.	Concern the practicality of optimizer will lead to the speed of model learning, how accurately it reaches the optimal solution; such as AdamW which could improve training with adaptive learning rates.	AdamW

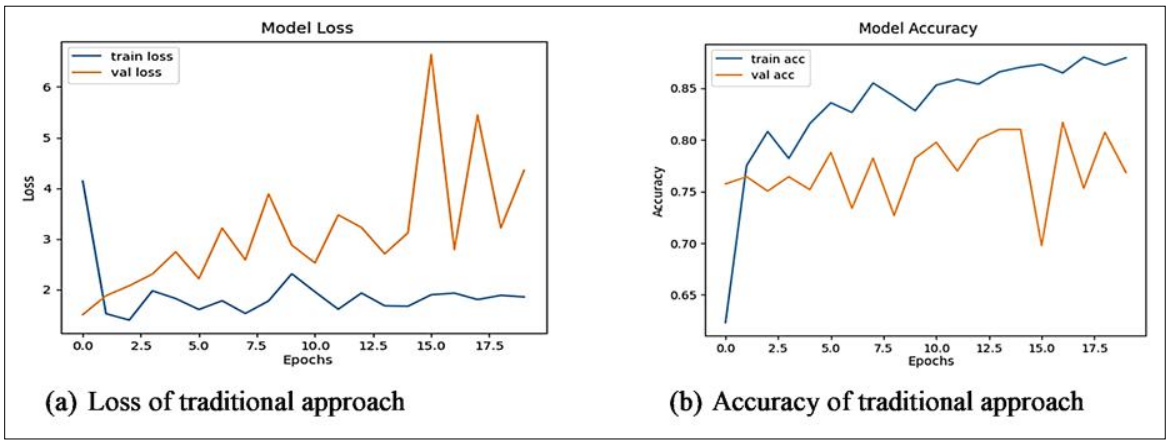


Fig 4: Traditional approach loss and accuracy of traditional approach.

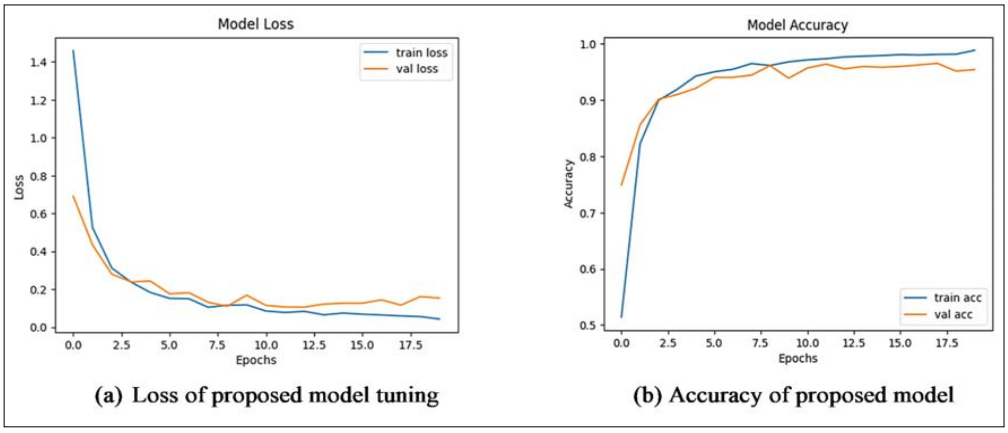


Fig 5: Loss and accuracy of proposed model approach.

The curve of learning derived from the dataset given to training provides how effectively the model is able to picking up the new data. The curve of learning validation derived from a holds out validation dataset, it shows how well the model applies what it has learned to new, unseen data. The training loss drops sharply and it continues to rise till the last epoch. The curve in the proposed model of Fig 6 shows in the form of confusion matrix for the labels as diseases and healthy explains that the loss is low.

In the above Table 4 mentioned the standard evaluation metrics for each disease class including healthy class and

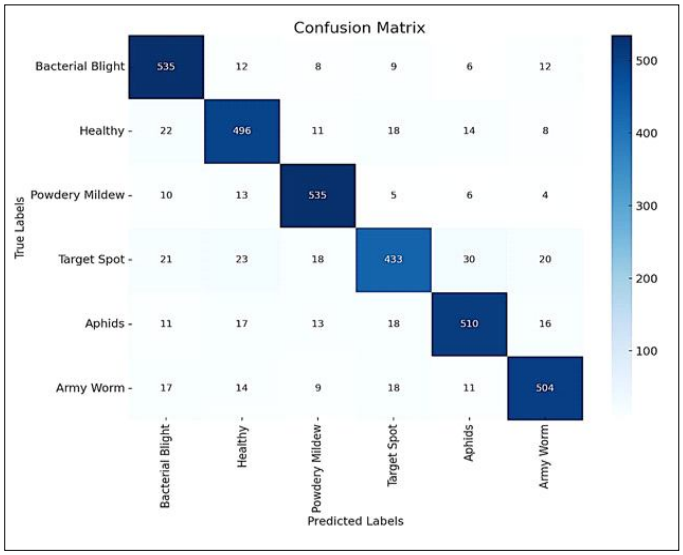


Fig 6: Confusion matrix.

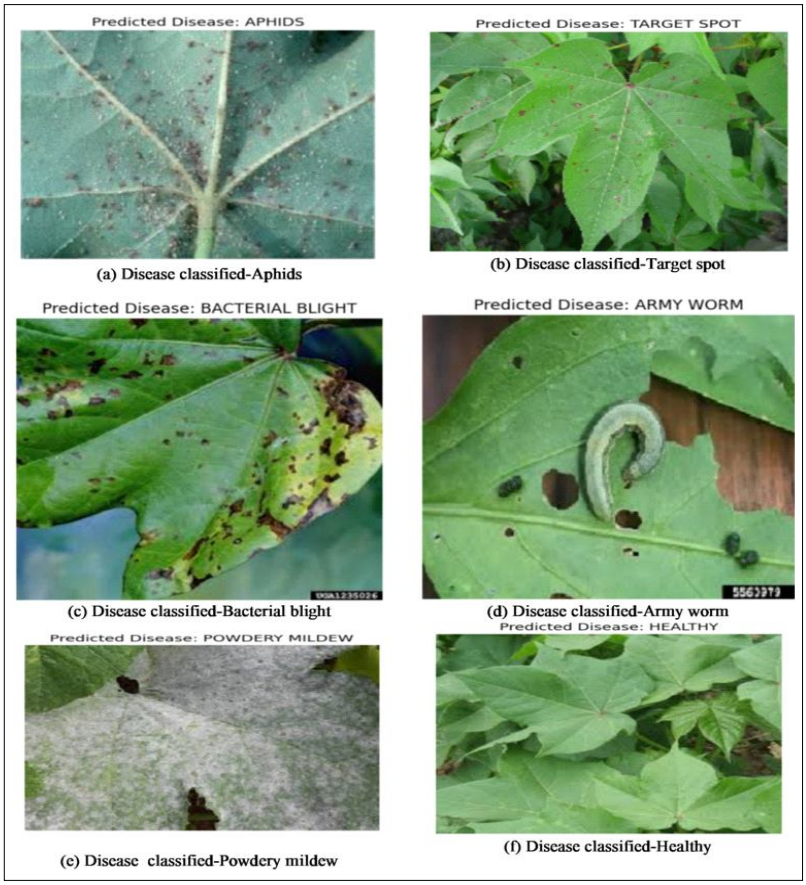


Fig 7: Overview of predicted diseases.

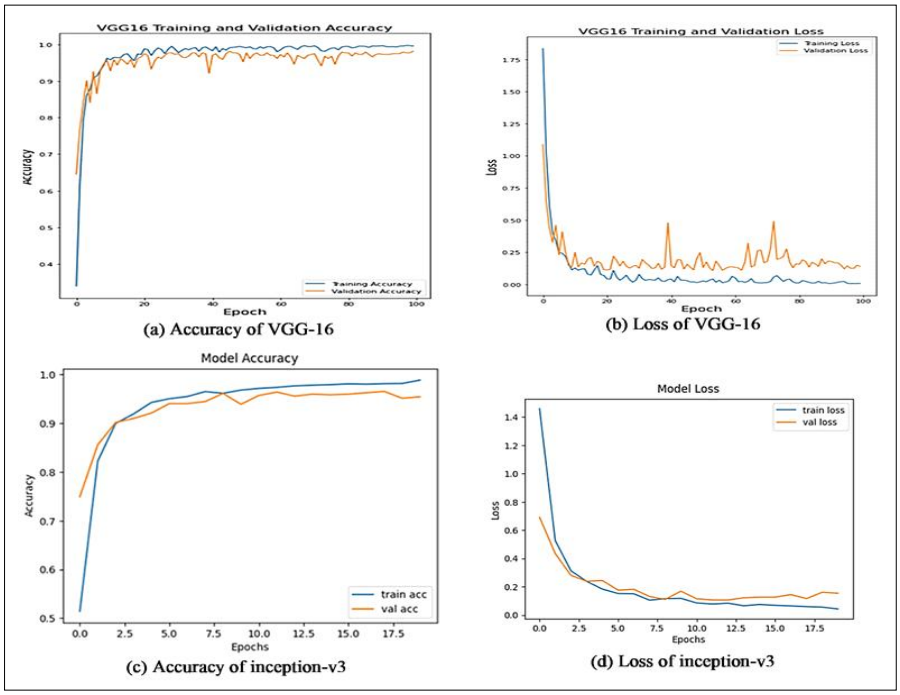


Fig 8: Training and validation.

Table 4: Summary of the classification accuracy of each model evaluated.

Class	Precision	Recall	F1-score
Bacterial blight	0.98	0.97	0.98
Healthy	0.97	0.98	0.97
Powdery mildew	0.98	0.97	0.97
Target spot	0.96	0.97	0.97
Aphids	0.98	0.97	0.97
Army worm	0.97	0.97	0.97

Table 5: Summary of the classification accuracy of each model evaluated.

Method	Accuracy
YOLOX	73.13%
ResNet 50, Xception	95%
CNN	86.72%
Inception V3	97%
Custom CNN, VGG16	98.53%
Proposed model inception V3	98.85

ensuring with Macro F1-score ≈ 97.17% and overall accuracy ≈ 98.03%.

The results and findings of the proposed model Inception-v3 are shown in Fig 8 and Fig 7(a). The model is successfully classify the class of diseased leaf with better accuracy and the the healthy leaf. Diseased leaves shown in Fig 7(a) to 7(e) and healthy leaves are classified as healthy shown in the Fig 7(f). Here the approach is able to analyse the image disease characteristics and identifies the leaf and its particular disease. The designation of disease class is exact. Summary of the classification accuracy of each model is shown in Table 5.

Comparison with VGG-16

We observed the comparison between VGG-16 and showed them in the Fig 8(a) and 8(b) having accuracy and loss 96.69% and 35.47% to the proposed model, Inception-v3 shown in Fig 8(c) and 8(d) having accuracy and loss as 98.85% and 4.27% respectively showing that our model has achieved better results.

CONCLUSION

In conclusion, the application of Inception-v3 for detecting cotton leaf diseases has proven to be a promising advancement in agricultural practices. By utilizing image-based illness classification methods, meta-learning strategies and pre-trained models, the system achieved a remarkable accuracy of 98.85% by the 20th epoch. This precision not only aids in identifying a wide range of diseases, such as bacterial blight, army worms and aphids, but also contributes to more sustainable farming by reducing the overuse of chemicals. The model's ability to maintain crop yield and fibre quality, while minimizing environmental impact, highlights its potential in revolutionizing crop management.

Future efforts should focus on enhancing the robustness of the model through more diverse datasets and refining transfer learning strategies. By tailoring the model to detect diseases in their early stages, farmers could act proactively to prevent outbreaks, leading to higher crop yields and improved plant health. Ultimately, this research lays the groundwork for more efficient, eco-friendly agricultural practices that can drive significant improvements in cotton farming.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not acceptany liability for any direct or indirect losses resulting from the use of this content.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, datacollection, analysis, decision to publish, or preparation of the manuscript.

REFERENCES

Aggarwal, M., Khullar, V., Goyal, N., Singh, A., Tolba, A., Thompson, E.B. and Kumar, S. (2023). Pre-trained deep neural network-based feature selection supported machine learning for rice leaf disease classification. *Agriculture*. **13(5):** 936. https://doi.org/10.3390/agriculture13050936.

Ahmed, M.R. (2021). Leveraging convolutional neural networks and transfer learning for cotton plant and leaf disease recognition. *International Journal of Image, Graphics and Signal Processing*. **4:** 12-19. https://doi.org/10.5815/ijigsp.2021.04.02.

Alotaibi, A. and Rassam, M.A. (2023). Leveraging high-performance computing resources for intrusion detection in cloud environments. *Journal of Cloud Computing*. **12(3):** 295-310. https://doi.org/10.1007/s10291-023-0120-5.

Alsarhan, H., Boulkroune, R. and Elmasry, F. (2021). Machine learning-driven optimization techniques for resource management in vehicular ad hoc networks (VANETs). *Wireless Networks*. **27(6):** 451-469. https://doi.org/10.1007/s11276-021-02563-4.

Arathi, B. and Dulhare, U.N. (2023). Classification of Cotton Leaf Diseases Using Transfer Learning-densenet-121. In [K.E. Rajan and R. Valluru (Eds.)] Proceedings of Third International Conference on Advances in Computer Engineering and Communication Systems: ICACECS 2022 Springer. pp: 393-405. https://doi.org/10.1007/978-981-19-9455-2_36.

Bansal, K.K., Sandhu, K.S., Bharti, V. *et al.* (2024). Influence of varieties and spacings on growth, yield attributes and productivity of pigeonpea. *Indian Journal of Agricultural Research*. **58(6):** 1181-1186. doi: 10.18805/IJARe.A-5748.

Hassan, J., Malik, K., Irtaza, G., Ghulam, A. and Ahmad, A. (2022). Disease identification using deep learning in agriculture: A case study of cotton plant. VFAST Transactions on Software Engineering. **10:** 104-115.10.21015/vtse.v10i4.1224 https://vfast.org/journals/index.php/VTSE/article/view/1224.

Islam, M., Talukder, M.A., Sarker, M.R.A. and Uddin, M.A. (2023). A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture. *Intelligent Systems with Applications*. **20(5):** 200278. 10.1016/j.iswa.2023.200278. 10.48084/etasr.6187.

Kundu, N., Rani, G., Dhaka, V.S., Gupta, K., Nayak, S.C., Verma, S., Ijaz, M.F. and Woźniak, M. (2021). IoT and interpretable machine learning based framework for disease prediction in pearl millet. *Sensors*. **21(16):** 5386. https://doi.org/10.3390/s21165386.

Moyazzoma, R., Hossain, M.A.A., Anuz, M.H. and Sattar, A. (2021). Transfer Learning Approach for Plant Leaf Disease Detection using CNN with Pre-trained Feature Extraction Method Mobilenetv2. In: 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) IEEE. pp: 1-6. https://ieeexplore.ieee.org/document/9331214.

Memon, M.S., Kumar, P., Iqbal, R. (2022). Meta deep learn leaf disease identification model for cotton crop. *Computers 2022*. **11:** 102. https://doi.org/10.3390/computers11070102.

Noon, S.K., Amjad, M., Qureshi, M.A. and Mannan, A. (2022). Handling severity levels of multiple co-occurring cotton plant diseases using improved YOLOX .odel, in IEEE access. **10:** 134811-134825. doi: 10.1109/ACCESS.2022.3232751.

Patil, B.M. and Burkpalli, V. (2021). A perspective view of cotton leaf image classification using machine learning algorithms using WEKA. Advances in Human-Computer Interaction. https://doi.org/10.1155/2021/3617195.

Rajasekar, V., Venu, K., Jena, S., Varthini, R. and Ishwarya, S. (2021). Detection of cotton plant diseases using deep transfer learning. *Journal of Mobile Multimedia*. 10.13052/jmm1550-4646.1828. https://www.researchgate.net/publication/356327612_Detection_ of_Cotton_Plant_Diseases_Using_Deep_Transfer_Learning.

Reddy, S.R.J., Daswanth, N.M.V.S., Pusuluri, S.K., Komalchowdary, D., Rambabu, P.S. and Gopi, A. (2023). Predicting the Cotton leaf Disease using Convolution Neural Networks. In 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS) IEEE. pp: 452-455. https://doi.org/10.1109/ICSCDS56672.2023.10111957.

Shaikh, Pancholi, P. (2023). Cotton leaf disease detection using machine learning approach. *International Journal of Emerging Technologies and Innovative Research*. **10(6):** e69-e78. Available at: http://www.jetir.org/papers/JETIR2306441.pdf.(www.jetir.org | UGC and issn Approved), ISSN: 2349-5162.

Tao, Y., Chang, F., Huang, Y., Ma, L., Xie, L. and Su, H. (2022). Cotton disease detection based on convNeXt and attention mechanisms, in IEEE. *Journal of Radio Frequency Identification*. **6:** 805-809. doi: 10.1109/JRFID.2022.3206841.