

# Towards Sustainable Cotton Farming: A Survey of Deep Learning Techniques for Disease Detection

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Abstract This paper surveys the current state of research on cotton disease detection leveraging deep learning techniques. Cotton, a vital crop globally, faces various diseases that impact yield and quality. Traditional detection methods are laborious, prompting the exploration of automated approaches. Deep learning offers promise in this domain, warranting a thorough examination of methodologies, datasets, performance metrics, challenges, and future prospects. Cotton disease detection traditionally relies on manual observation, which is time-consuming and prone to errors. In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a potent tool in automating this process. Transfer learning, recurrent neural networks (RNNs), attention mechanisms, and generative adversarial networks (GANs) augment the capabilities of CNNs in disease classification tasks. Publicly available datasets play a crucial role in training and evaluating deep learning models for cotton disease detection. These datasets vary in size, annotation quality, and representativeness of real-world scenarios. Researchers employ various preprocessing techniques to enhance the quality of input images, followed by training strategies and optimization techniques to improve model performance. Performance evaluation of deep learning models involves the selection of appropriate metrics and comparative analysis with baseline methods. Challenges persist, including the scarcity of labeled datasets, generalization across environmental conditions, and real-world deployment complexities. Future directions encompass the integration of multispectral and hyperspectral imaging, leveraging unmanned aerial vehicles (UAVs), and addressing economic implications for stakeholders. In conclusion, deep learning holds significant promise in revolutionizing cotton disease detection, offering benefits in precision agriculture and crop management practices. However, addressing existing challenges and embracing emerging technologies will be pivotal in realizing the full potential of these advancements.

Keywords-Cotton, disease detection, deep learning, convolutional neural networks, agricultural automation.

# I. INTRODUCTION

Cotton holds a prominent position in India's agricultural landscape, being one of the nation's most vital cash crops. Its cultivation not only contributes significantly to the economy but also plays a crucial role in providing livelihoods to millions of farmers across the country [1]. However, the cotton industry faces persistent challenges, particularly concerning the detrimental impact of diseases on yield and quality [1].

In India, where cotton cultivation spans vast regions, diseases pose a significant threat to crop productivity. Fusarium wilt, bacterial blight, cotton leaf curl virus (CLCuV) [2], and Alternaria leaf spot are among the primary diseases that afflict cotton plants, leading to substantial yield losses if left unchecked. These diseases

not only reduce crop yield but also diminish fiber quality, affecting the marketability of cotton produce [2].

The need for effective disease management strategies is paramount in India's cotton sector. Traditional methods of disease detection, reliant on manual observation, are timeconsuming, labor-intensive, and often subjective. With the ever-growing demand for cotton and the pressure to enhance agricultural productivity sustainably, there is a pressing need for automated disease detection methods that can accurately and efficiently identify diseased plants, enabling timely intervention and mitigation measures [2].

Against this backdrop, leveraging advanced technologies such as deep learning offers a promising avenue for revolutionizing disease detection in cotton cultivation. By harnessing the power of deep learning algorithms, specifically convolutional neural networks (CNNs), it

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becomes feasible to automate the detection process, thereby augmenting the efficiency and precision of disease management practices in Indian cotton farming [2].

## 1.1. Objectives of Research

The objectives of the paper on cotton disease detection using deep learning:

- To Provide a Comprehensive Overview: The primary objective of this paper is to offer a thorough and comprehensive overview of the current state-of-the-art techniques and methodologies employed in using deep learning for cotton disease detection.
- To Survey Existing Literature: The paper aims to survey and analyze existing literature, including research papers, articles, and studies, related to the application of deep learning in cotton disease detection. By synthesizing this literature, the paper aims to identify key trends, challenges, and advancements in the field.
- To Explore Methodologies and Techniques: Another objective is to explore the various methodologies, techniques, and deep learning architectures used in cotton disease detection. This includes examining the use of convolutional neural networks (CNNs), transfer learning, recurrent neural networks (RNNs), and other advanced deep learning models.
- To Evaluate Performance and Challenges: The paper seeks to evaluate the performance of deep learning models in cotton disease detection tasks. This involves assessing the accuracy, precision, recall, and other performance metrics of these models across different datasets and scenarios. Additionally, the paper aims to identify and discuss the challenges and limitations associated with current approaches.
- To Discuss Future Directions and Opportunities: Finally, the paper aims to discuss future directions and opportunities for research in the field of cotton disease detection using deep learning. This includes identifying potential areas for improvement, such as the development of novel algorithms, the creation of larger and more diverse datasets, and the integration of emerging technologies like multispectral imaging and unmanned aerial vehicles (UAVs).

#### **II. TRADITIONAL METHODS**

Traditional methods of cotton disease detection [4] have relied heavily on manual observation and symptom recognition by agricultural experts. Farmers and field workers visually inspect plants for signs of disease, such as discoloration, lesions, wilting, or abnormal growth patterns. Additionally, laboratory-based techniques may involve sample collection and analysis under microscopes or through biochemical assays. While these methods have been effective to some extent, they are often timeconsuming, labor-intensive, and subjective, leading to potential inaccuracies and delays in disease diagnosis and management.

Traditional methods of cotton disease detection involve a variety of techniques, each with its own advantages and limitations. Here's a more detailed explanation of some common traditional methods [4]:

- Visual Inspection: Visual inspection [5] involves trained agronomists, farmers, or field workers visually examining cotton plants for symptoms of disease. These symptoms may include discoloration of leaves, lesions, wilting, stunted growth, or abnormal patterns of leaf or fruit development. Visual inspection is often the first line of defense against diseases in cotton fields due to its simplicity and low cost. However, it relies heavily on the expertise of the observer and may not always be accurate, especially for early-stage or asymptomatic infections.
- Symptomatology and Field Surveys: Agronomists and plant pathologists often conduct field surveys to assess the prevalence and severity of diseases in cotton crops. These surveys involve systematically examining multiple plants across different locations within a field or region [5]. Researchers record the presence and severity of disease symptoms, such as leaf spots, blights, wilting, or necrosis. Field surveys provide valuable data for assessing disease incidence and distribution patterns but can be time-consuming and labor-intensive, particularly in large-scale agricultural settings [5].
- Laboratory-based Techniques: In cases where visual symptoms are inconclusive or when accurate identification of pathogens is required, laboratory-

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based techniques may be employed. These techniques involve collecting plant samples, such as leaves, stems, or fruits, and conducting various tests to identify pathogens or disease-causing agents. Common laboratory techniques include microscopy, culturing pathogens on agar plates, polymerase chain reaction (PCR) [5] assays for DNA-based pathogen identification, and enzyme-linked immunosorbent assays (ELISA) [5] for detecting specific proteins or antigens. While laboratory-based techniques offer high specificity and accuracy, they are often timeconsuming, require specialized equipment and expertise, and may not be feasible for rapid diagnosis in the field.

• **Remote Sensing and Imaging:** Remote sensing technologies, such as satellite imagery, aerial photography, and unmanned aerial vehicles (UAVs) [5], are increasingly being used for monitoring crop health and detecting diseases in cotton fields. These technologies capture multispectral or hyperspectral images of crops, allowing for the detection of subtle changes in plant physiology and health indicators associated with disease. Remote sensing-based approaches can provide large-scale, non-invasive monitoring of cotton crops but may require sophisticated image processing algorithms and expertise for accurate interpretation of data.

Overall, traditional methods of cotton disease detection play a crucial role in disease surveillance and management. However, they have limitations in terms of accuracy, scalability, and timeliness, highlighting the need for more automated and efficient approaches, such as those enabled by deep learning and other advanced technologies..

# **III. DEEP LEARNING CONCEPT**

Deep learning [6] is a subset of machine learning that focuses on algorithms inspired by the structure and function of the human brain's neural networks. It involves training deep neural networks, which are composed of multiple layers of interconnected nodes (neurons), to learn hierarchical representations of data. Deep learning algorithms excel at automatically extracting features and patterns from large volumes of raw data, making them well-suited for a wide range of tasks, including image recognition, natural language processing, speech recognition, and more [6].

Key components of deep learning include:

- 1. **Neural Networks:** Neural networks [7] are the fundamental building blocks of deep learning algorithms. They consist of interconnected layers of artificial neurons, each performing simple mathematical operations on input data and passing the results to the next layer. The layers are typically organized into an input layer, one or more hidden layers, and an output layer. Deep neural networks [7] contain multiple hidden layers, allowing them to learn complex representations of data.
- 2. Activation Functions: Activation functions [7] introduce non-linearity into neural networks, enabling them to learn and represent complex patterns in data. Common activation functions include sigmoid, tanh, ReLU (Rectified Linear Unit), and softmax. These functions introduce non-linearities into the network, enabling it to model complex relationships between input and output variables.
- 3. **Backpropagation**: Backpropagation [8] is an optimization algorithm used to train deep neural networks by adjusting the weights and biases of the network based on the error between predicted and actual outputs. It involves iteratively propagating the error backward through the network, updating the network parameters using gradient descent or its variants to minimize the error.
- 4. **Convolutional Neural Networks (CNNs)**: [8] CNNs are a specialized type of neural network designed for processing grid-like data, such as images. They consist of convolutional layers that apply filters to input data, pooling layers that downsample feature maps, and fully connected layers that perform classification. CNNs are widely used in computer vision tasks, including object recognition, image classification, and object detection.
- 5. **Recurrent Neural Networks (RNNs)**: RNNs [8] are neural networks designed to handle sequential data, such as time-series data or natural language sequences. Unlike feedforward neural networks, RNNs have connections that loop back on themselves, allowing them to retain information about previous time steps. This enables RNNs to model temporal dependencies in sequential data and

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is commonly used in tasks such as speech recognition, language translation, and time-series prediction.

6. Generative Adversarial Networks (GANs): GANs [9] are a class of deep learning models composed of two neural networks, a generator and a discriminator, trained simultaneously in a competitive manner. GANs are used to generate new data samples that closely resemble the training data distribution. They have applications in image synthesis, data augmentation, and generative modeling.

Overall, deep learning has revolutionized the field of artificial intelligence by enabling the development of highly complex and powerful models capable of learning from large and diverse datasets. Its applications span across various domains, including healthcare, finance, automotive, agriculture, and more, and continue to drive advancements in artificial intelligence research and technology.

# IV. DEEP LEARNING AND DISEASE DETECTION

Deep learning has emerged as a promising tool for cotton disease detection, offering potential solutions to the challenges faced by traditional methods. Here's how deep learning is applied in cotton disease detection:

- Automated Image Analysis: Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), can analyze images of cotton plants to automatically detect disease symptoms. Researchers train CNNs on large datasets of labeled images, where each image is annotated with the presence or absence of specific diseases. The CNN learns to recognize patterns and features indicative of disease, enabling it to accurately classify new images [9].
- **Improved Accuracy:** Deep learning models can achieve high levels of accuracy in disease detection, often surpassing human performance [9]. By leveraging large datasets and sophisticated neural network architectures, deep learning algorithms can learn subtle patterns and variations in cotton plant images that may not be discernible to the human eye. This leads to more reliable and consistent disease diagnosis, even in early stages of infection.
- Efficiency and Scalability: Deep learning enables the automation of disease detection processes,

reducing the need for manual labor and expertise [10]. Once trained, deep learning models can analyze images rapidly and at scale, making them well-suited for large agricultural operations. This efficiency allows for timely intervention and management of disease outbreaks, helping to minimize crop losses.

- **Transfer Learning:** Transfer learning techniques can further improve the performance of deep learning models for cotton disease detection, especially in scenarios where labeled data is limited. Researchers can leverage pre-trained CNN models on large image datasets and fine-tune them for specific disease detection tasks in cotton plants. This approach accelerates the training process and enhances the generalization ability of the models [10].
- Integration with Other Technologies: Deep learning can be integrated with other technologies such as remote sensing, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) devices for comprehensive monitoring of cotton fields. By combining image data with environmental and geospatial information, deep learning models can provide holistic insights into crop health and disease dynamics, facilitating more informed decision-making for farmers and agronomists.

Overall, deep learning holds great promise for revolutionizing cotton disease detection by providing accurate, efficient, and scalable solutions. Continued research and development in this field are essential for further advancing the application of deep learning in agriculture and improving crop productivity and sustainability.

# V. RELATED WORKS

Several studies focus on leveraging deep learning (DL) techniques to enhance agricultural practices, particularly in cotton farming. **Stephen, A., et al. (2024) [11]** emphasize the importance of plant monitoring throughout the growth stages, aiming to improve yield. They develop a big data-driven system using mobile app-collected images to monitor cotton plants' health, with MobileNetV3Large showing high accuracy.

**Kukadiya, H.,et al. (2024) [12]** concentrate on early detection of cotton leaf diseases, proposing an ensemble model based on VGG16 and InceptionV3. Through exhaustive experimentation, they determine optimal

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hyperparameters, achieving higher accuracies than individual pretrained models.

Thivya Lakshmi, R. T., et al. (2024) [13] highlight the significance of automated cotton detection systems, employing CNNs and deep learning to precisely identify and monitor cotton plants. These systems offer real-time monitoring, aiding in disease and pest management while enhancing production optimization.

**Islam, M. M., et al. (2023)** [14] stress the impact of AIbased systems in detecting cotton diseases early, proposing a DL-based approach using transfer learning algorithms. Their model, particularly Xception, exhibits high accuracy, facilitating real-life disease prediction and increasing cotton production.

**Naeem, A. B., et al. (2023)** [15] address cotton leaf diseases in Pakistan, employing DL to recognize various diseases. They train CNNs to distinguish between healthy and diseased leaves, achieving 98% accuracy overall.

**Singh, P., et al. (2023)** [16] focus on India's cotton production, highlighting the challenges posed by pests and diseases. They develop a DL-based approach capable of detecting 22 types of cotton leaf diseases, achieving high accuracy and demonstrating potential for real-time implementation in disease detection systems.

**Memon, M. S., et al. (2022)** [17] emphasize the importance of early disease detection in cotton plants to mitigate significant crop damage. They propose a meta deep learning model for accurately identifying various cotton leaf diseases, achieving an impressive accuracy of 98.53% through training on a dataset of 2385 images augmented for increased diversity.

**Rajasekar, V., et al. (2022)** [18] address the challenges faced by cotton farmers in India due to diseases affecting crop yield. They develop a deep learning network combining ResNet pre-trained on ImageNet and the Xception component, achieving superior performance in detecting cotton diseases compared to other techniques, with training and validation accuracies of 0.95 and 0.98 respectively for ResNet-50.

Zambare, R., et al. (2022) [19] propose a CNN-based approach for efficient disease management and prediction in cotton plants. Their system preprocesses input images,

segments leaves, extracts features, and classifies diseases, achieving a remarkable classification accuracy of 99.38% through model optimization and training with over three layers and three hundred epochs.

Harshitha, G., et al. (2021, November) [20] address the decline in cotton production in India due to diseases, proposing a deep learning model to accurately classify healthy and diseased cotton leaves based on infected patterns. Achieving a classification accuracy of 97.13% on the Cotton Disease Dataset Kaggle, their method outperforms existing state-of-the-art techniques.

**Zekiwos, M., & Bruck, A. (2021) [21]** focus on Ethiopia's cotton production, aiming to enhance disease and pest detection using CNNs. Their model achieves an impressive accuracy of 96.4% in identifying various leaf diseases and pests, demonstrating its potential for real-time applications.

**Caldeira, R. F., et al. (2021) [22]** propose using deep learning models to identify lesions on cotton leaves, crucial for monitoring crop health. Their research achieves precision rates of 86.6% and 89.2% using GoogleNet and ResNet50, respectively, outperforming traditional image processing approaches and suggesting improved plant inspection capabilities.

Table 1. Literature Findings

Autho	Main	Key Factors	Findings
r	Concept		
Name			
(Year)			
Stephe	Plant	Utilization of	Emphasizes
n, A.,	monitorin	mobile app-	continuous
et al.	g using	collected	monitoring
(2024)	big data-	images,	throughout
[11]	driven	application of	growth stages
	system	MobileNetV3L	to enhance
		arge for high	yield through
		accuracy	precise plant
			health
			assessment
Kukadi	Early	Ensemble	Achieves
ya,	detection	model	higher
H.,et	of cotton	combining	accuracies
al.	leaf	VGG16 and	than
(2024)	diseases	InceptionV3,	individual
[12]		optimization of	models,

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hyperparameter suggesting efficient S disease detection at early stages Utilization of Offers real-Thivya Automate Laksh d cotton CNNs and deep time mi, R. detection learning for monitoring T., et systems precise aiding in al. identification, disease and (2024)real-time pest [13] monitoring management, contributing to production optimization Islam, AI-based Employing Facilitates M. M., systems transfer real-life et al. for early learning disease (2023)disease algorithms. prediction [14] detection particularly and enhances Xception for cotton high accuracy production through early detection Naeem DL for Training CNNs Achieves , A. B., recognizin for high overall et al. g various distinguishing accuracy of (2023)cotton leaf healthy and 98% in [15] diseases diseased leaves disease recognition Singh, DL-based Focus on India's Demonstrates P., et high accuracy approach cotton al. for production, and potential (2023)detecting detection of 22 for real-time [16] cotton leaf types of implementati diseases diseases on Memo Meta deep Training on Emphasizes n, M. learning augmented the S., et model for dataset, importance of early achieving early al. (2022)detection, disease 98.53% offering a [17] detection accuracy highly accurate solution Rajase Deep Combination of Achieves kar, V., learning ResNet prehigh training et al. network trained on and (2022)for disease ImageNet and validation [18] detection Xception, accuracies, superior outperformin

		performance in	g other
		disease	techniques
		detection	-
Zamba	CNN-	Model	Remarkable
re, R.,	based	optimization,	classification
et al.	approach	training with	accuracy of
(2022)	for disease	over three	99.38% in
[19]	managem	layers and three	disease
	ent	hundred epochs	management
			and
			prediction
Harshit	Deep	Classification	Achieves
ha, G.,	learning	based on	high
et al.	model for	infected	classification
(2021,	classifyin	patterns,	accuracy on
Novem	g cotton	outperforming	the Cotton
ber)	leaves	existing	Disease
[20]		techniques	Dataset
			Kaggle
Zekiwo	CNNs for	Focus on	Demonstrates
s, M.,	enhancing	Ethiopia's	potential for
&	disease	cotton	real-time
Bruck,	and pest	production,	applications
А.	detection	achieving high	in disease and
(2021)		accuracy	pest detection
[21]			
Caldeir	Deep	Precision rates	Suggests
a, R.	learning	using	improved
F., et	models for	GoogleNet and	plant
al.	identifyin	ResNet50,	inspection
(2021)	g lesions	surpassing	capabilities
[22]		traditional	through
		methods	accurate
			lesion
			identification

#### VI. DISCUSSION AND FINDINGS

In the realm of cotton plant health management, recent years have witnessed significant advancements driven by deep learning (DL) and convolutional neural networks (CNNs). The discussion centers on the findings extracted from a series of studies addressing various aspects of cotton disease detection, plant monitoring, and automated systems for yield optimization.

#### Enhanced Disease Detection:

Authors such as Islam et al. (2023) and Memon et al. (2022) underscore the pivotal role of AI-

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based systems in early disease detection. Their research emphasizes the efficacy of DL models, particularly Xception and meta deep learning models, in accurately identifying and predicting cotton diseases. These findings suggest a substantial potential for mitigating crop damage and increasing production through timely interventions.

## \* Real-time Monitoring and Management:

Thivya Lakshmi et al. (2024) and Singh et al. (2023) introduce automated systems leveraging CNNs and DL for real-time monitoring of cotton plants. Their studies showcase the capability of these systems in aiding disease and pest management while optimizing production. The emphasis on continuous monitoring throughout growth stages, as highlighted by Stephen et al. (2024), underscores the significance of proactive strategies in ensuring optimal yield.

## Model Performance and Optimization:

Research by Zambare et al. (2022) and Rajasekar et al. (2022) focuses on model optimization and performance enhancement. Their utilization of advanced CNN architectures and ensemble models demonstrates superior classification accuracy and performance in disease management and prediction. These findings emphasize the importance of robust model architectures and optimization techniques in achieving high-quality results.

# ✤ Geographical Context and Application:

Studies such as those by Naeem et al. (2023) and Zekiwos & Bruck (2021) address the specific challenges faced by cotton farmers in different geographical regions. By tailoring DL approaches to local contexts, these studies achieve impressive accuracies in disease and pest detection, showcasing the adaptability and potential for real-time application of such technologies across diverse agricultural landscapes.

# \* Comparative Analysis:

Comparative studies, such as that by Kukadiya et al. (2024), highlight the importance of ensemble models and hyperparameter optimization in achieving higher accuracies compared to individual pretrained models. Such analyses contribute to the ongoing refinement and advancement of DL-based approaches in cotton disease detection and plant health management.

In summary, the findings from these studies collectively underscore the transformative potential of DL and CNNs in revolutionizing cotton plant health management. From early disease detection to real-time monitoring and optimized yield, these advancements offer promising solutions to address the challenges faced by cotton farmers globally, ultimately contributing to sustainable agricultural practices and food security.

## **VII.** CONCLUSION

In conclusion, the application of deep learning techniques for cotton disease detection represents a significant advancement in agricultural technology with the potential to revolutionize crop management practices. This paper has highlighted the effectiveness of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), in automating the process of disease detection from images of cotton plants. By leveraging large datasets of labeled images, deep learning models can learn to recognize subtle patterns and features indicative of disease, achieving levels of accuracy and efficiency that surpass traditional methods. The scalability of deep learning enables rapid analysis of images at scale, facilitating timely intervention and management of disease outbreaks to minimize crop losses and ensure food security. Transfer learning techniques further enhance the performance of deep learning models, especially in scenarios with limited labeled data, while integration with other technologies such as remote sensing and UAVs provides comprehensive monitoring of crop health and disease dynamics. Despite these advancements, challenges remain, including the scarcity of labeled datasets, the need for robust models that generalize across diverse environmental conditions, and the integration of deep learning solutions into real-world agricultural settings. Addressing these challenges will require interdisciplinary collaboration between researchers, farmers, industry stakeholders, and policymakers to develop and deploy effective solutions. Looking ahead, the future of cotton disease detection lies in continued research and innovation in deep learning and its integration with emerging technologies. By harnessing the power of artificial intelligence, we can empower farmers with the tools and insights needed to ensure sustainable cotton production and mitigate the impact of diseases on global agriculture.

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In conclusion, deep learning offers immense potential to transform cotton disease detection, paving the way for a more resilient and productive agricultural sector.

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