



A COMPREHENSIVE REVIEW ON DEEP LEARNING TECHNIQUES FOR DISEASE DETECTION IN COTTON CROPS

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ABSTRACT

Every nation has its individual strategies towards its economic growth. But the backbone of any nation's economy is agriculture. On the other hand, technology is gearing up to new horizons leaving its impact on all the sectors. Most importantly, Health and agriculture are amongst in which AI based techniques are being used and still there is a lot of scope for advancement. Cotton being called as white gold to be preserved very well in terms of crop yield and at the same time it must not be a burdensome. The scenario is that there are huge losses in this field due to various reasons among which crop or plant diseases being a primary reason. Several researchers proposed Deep learning-based solutions for early identification of the diseases in cotton crops. However, there are gaps left uncovered which are taken up as research interest. In this paper, in addition to the cotton plant diseases explored and presented, various research articles are made as a part of our study and the contributions of respective researchers are cited. The advent of deep learning and its applications have been discussed briefly. Available image Datasets related to cotton crop diseases are also presented in the paper.



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I. INTRODUCTION

In South Asia, agriculture being the prime source of livelihood [1], the malnourished population is more than 50% of that of world's population who are undernourished. These nations are well named for their agricultural exports that account for a significant portion of their GDP. The soil fertility in this region is meant for high crop yields, leading to surplus production as well huge exports for over 50 years. It greatly benefits the farmers and various crops including cotton, thereby strengthening the country's economy resulting in hike of a nation's GDP [2]. Therefore, for achieving a stable economy and optimized crop revenue, high-quality and high-quantity yields are very much necessary [3]. However, there is a threat in achieving better yield due to pests, weeds, and other such attacks. Despite the existing practices, the losses are substantial due to the said factors. Between 2001 and 2003, there were 50% losses for wheat, above 80% for cotton and around 28% for soyabeans reported in 19 regions [2]. The introductory part of this paper first discusses the objectives of this paper, then traditional methods being adopted subsequently cites the importance of Cotton research, and how deep learning is proving its ability in cotton crop research.

The objectives of this paper include:

- (i) Providing a detailed and thorough insights related to Cotton plant research, the need of research, techniques being implemented in cotton research is the primary objective of this paper.
- (ii) The paper intends to explain various types of diseases undergone by the cotton plants.
- (iii) Survey of around 60 articles related to deep learning in cotton plant disease detection is another objective of this paper. Reviewing the literature identifies the current trends, gaps in the existing research and advancements.

- (iv) Discussing various techniques encompassing Deep Learning such as CNN, the networks built on basis of CNN, ensemble techniques, Transfer Learning, Vision Transformers and other such Deep learning networks.
- (v) Providing the details of bench mark datasets in cotton plant disease detection.
- (vi) Providing insights on the performance of various techniques in terms of metrics such as Accuracy, precision, recall, F1 score and so on.
- (vii) Providing future insights for effective research on cotton plant disease detection.

The leading producers of cotton are China, India, America and Brazil. The cotton production over the past decade is shown in Figure 1.

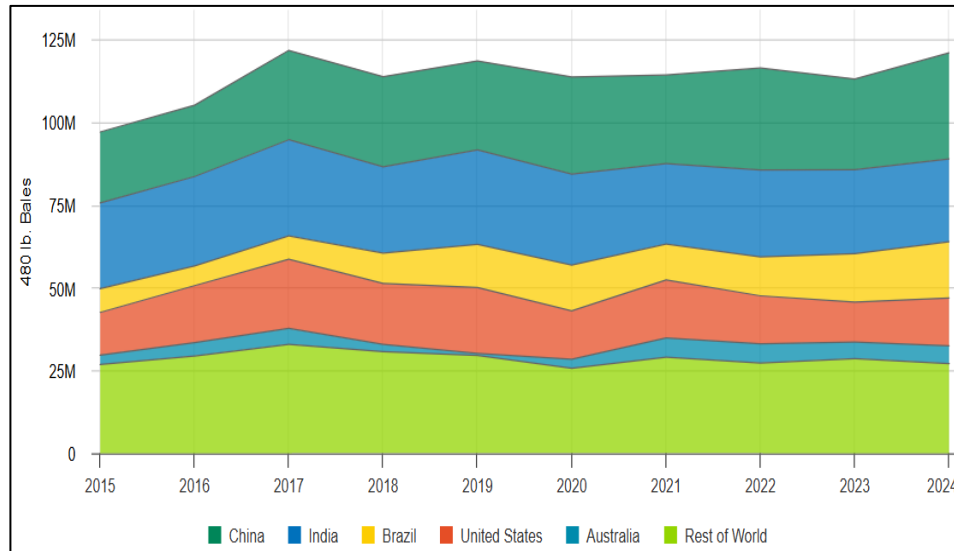


Figure 1: Cotton production over the past decade.

Source: [4].

Depending on various environmental conditions, cultivation areas, plantation times and the yield, the cotton is being produced in 59 varieties [5]. Whichever variety of crop, if proper care is not taken, it results in substantial crop losses due to diseases. The cotton crop is the most vulnerable crop which shall be attacked by pests due to which the quality and yield is affected significantly. Globally the trade value of cotton is about 40 billion USD, which is expected to increase to 60 billion USD by the end of 2030 [6]. The diseases affecting cotton crops include Anthracnose, Wilt, Sore Shin, Minor Boll-Rots, Rust, Thrips, and Mealybug [7]. Diagnosing the crop diseases at an early stage plays a vital role in performing the remedial action due to which the farmers can be benefitted so well. Usually farmers by their experience, examines the cotton leaves with their naked eye and identify the diseases. Here the diagnosis is being done after the crop gets infected. Rather, if it could be investigated and diagnosed early, certain measures could be taken. Moreover, to examine the crops, physical presence of the farmers is required. Yet times, farmers cannot identify the diseases so accurately. Even the plant pathologists do it following a traditional approach, it takes long time and of course sometimes the diagnosis may go wrong. Detecting the diseases at an early stage is highly essential to obtain high quality yield and to do so, implementation of effective management practices is certain. Attaining agricultural sustenance, most importantly in high qualitative and quantitative cotton yield and ensuring the lives of millions of cotton farmers worldwide, is possible only when there is an efficient control due to which the cotton plant diseases mitigate. If the disease management is not apt, the diseases leads to notable economic losses, consequently it raises the risk of employment in both agricultural & textile sectors [8]. The advancement of technology in the fields of image processing and machine learning, has eased the diagnosis of plant diseases including cotton [8-10] that boosted Nation's economy, supporting rural Work as well the national textile industry [9].

1.1 TRADITIONAL TECHNIQUES AND SHIFT TOWARDS DEEP LEARNING BASED TECHNIQUES

Traditional techniques in cotton disease research comprises Onsite inspection, Physical observation, acquiring the details from farmers, field surveys, tests in laboratories, utilizing remote sensing techniques and performing image analysis. Although traditional techniques are having advantages, there are disadvantages namely time consumption, presence of experts physically in the fields, scalability issues, data misinterpretation, yet times suffer from accurate information, labour intensive and incurring high costs. Deep Learning is a subfield of Machine Learning inspired by the structure and function of the human brain. It utilizes artificial neural networks with multiple layers (hence "deep") to analyze and learn from vast amounts of data. Unlike traditional machine learning, deep learning excels at automatically extracting intricate features from raw, unstructured data (like images, audio, and text). Potential features of Deep Learning include Automatic Feature Extraction, Handling Complex Data, Scalability with Data, Achieving State-of-the-Art Results and with such impressive features the technology is into its wide range of applications across various industries among which Computer Vision, Natural Language Processing (NLP), Healthcare, Agriculture, Finance, Recommender Systems and so on. Deep Learning is a powerful and rapidly evolving field within Artificial Intelligence that enables computers to learn complex patterns from data, leading to remarkable advancements in various applications that impact our daily lives. CNN (Convolutional Neural Network) is the foundational deep learning model for most computer vision tasks which is inspired by the visual cortex and excel at processing grid-like data such as images.

Popular CNN architectures are AlexNet, the first deep CNN model introduced in 2012 that achieved breakthrough performance on the ImageNet dataset, popularizing deep learning for computer vision; VGGNet introduced in 2014 explored the effect of network depth, using very small (3x3) convolutional filters stacked together. On the other hand, GoogLeNet (Inception) was introduced in 2014 which presented the "Inception module" that efficiently use computational resources by using parallel convolutional filters of different sizes. In 2015 ResNet was introduced which revolutionized deep network training by introducing "skip connections" (residual connections) that allow for the training of very deep networks (hundreds or even thousands of layers) without the vanishing gradient problem. DenseNet was introduced in 2017 which emphasized feature reuse and EfficientNet in 2019 focused on efficiently scaling network dimensions (depth, width, and resolution) in a balanced way to achieve better performance with fewer parameters. Transfer learning is a powerful technique in deep learning where a model trained on a large, general dataset is repurposed as a starting point for a model on a second, related task. Instead of training a new model from scratch, you leverage the knowledge (features, weights) learned by the pre-trained model. Due to transfer learning, model development becomes faster and the data needs are reduced besides offering better performances. Also transfer learning offers improved performance as well as resource efficiency. Originally designed for natural language processing, Transformers have recently shown great promise in computer vision tasks. They rely on the "attention mechanism," which allows the model to weigh the importance of different parts of the input when making predictions.

The key Components of Transformers comprise Self-Attention modules that enable the model to attend different parts of the input image to capture long-range dependencies; Multi-Head Attention modules that Uses multiple attention mechanisms in parallel to capture different types of relationships and Transformer Blocks which consist of self-attention layers followed by feed-forward neural networks. Vision Transformer (ViT) are the specially designed transformers for computer vision applications. They directly apply the transformer architecture to sequences of image patches. Swin Transformers are one among the vision transformers which introduces a hierarchical Transformer structure with shifted windows, improving efficiency and performance on various vision tasks. Deep learning (DL) has revolutionized numerous fields, showcasing remarkable success in areas such as healthcare for disease diagnosis, autonomous systems for self-driving vehicles, network security, Natural language processing, agriculture, etc. Particularly in the agriculture domain, DL has been applied for tasks such as crop yield prediction, classification using aerial imagery, agricultural field monitoring, stress identification in plants, infected leaf detection, etc. Highlighting the advancements of DL underscores its transformative potential and contextualizes its relevance to the present study. This section introduces the objectives of the paper followed by cotton crop research importance using deep learning methods. In the next section various cotton diseases have been discussed and the subsequent section presents the essence of the literature surveyed and provides insights for the future research. In section four, datasets have been detailed and in final section conclusions are given.

II. OVERVIEW OF COTTON DISEASES

Insects, mites, pathogens, weeds, nematodes, rodents, and birds constitute the pest complex of cotton. Of the biotic stresses, insect pests cause by far, the highest economic losses. The cotton plant is the host of 1326 species of insects. The major types of diseases can be categorized into Viral and Phytoplasma diseases, Soil borne diseases, Bacterial diseases, Fungal foliar diseases, Boll rots, Physiological disorders and diseases due to nutritional deficiency. Under Viral Phytoplasma category, the variety of diseases are Cotton Leaf Curl Virus diseases (CLCuD), Tobacco Streak Virus (TSV), Cotton Leaf Roll Dwarf Virus (CLRdV), Cotton Leaf Crumple Virus (CLCrV) and Cotton virescence – Phytoplasma. The healthy leaf of a cotton plant and the diseased leaf (curl) are as shown in Figure 2.



Figure 2: Healthy cotton leaf, Diseased leaf (downward curl and upward curl).
Source: Authors, (2026).



Figure 3: Plant effected with vein thickening.
Source: Authors, (2026).



Figure 4: Leaf enation.
Source: Authors, (2026).



Figure 5: Plants infected with whitefly & CLCuD.
Source: Authors, (2026).

Other forms of disease effected plants are shown in Figures 3, 4 and 5; while the tobacco streak virus, CLRDV and CLCrV effected plants are shown in Figure 6.



Figure 6: Plants infected with TSV, CLRDV & CLCrV.
Source: Authors, (2026).

Under the soil borne diseases, Root rot and wilt diseases prevail. The root rot, drying of plants and bark shredding are presented in Figure 7.



Figure 7: Root Rot & bark shredded infected Plants.
Source: Authors, (2026).

Root rot of cotton is a worldwide occurrence and has been a major cause of loss in many countries. Different fungi as well as nematodes cause injury to the cotton roots. The disease symptoms occur on the lower part of the stem and roots which leads to the wilting of plant foliage from top to bottom. Bacterial diseases occur at the seedling to boll development stages. Systemic infections show the main veins as black streaks. Bacterial leaf blight diseased leaf and boll are as shown in Figure 8.



Figure 8: Bacterial leaf blight infected leaf and boll.
Source: Authors, (2026).

Bronze wilts a mysterious cotton disease also referred to as copper top, red wilt, sudden wilt, or phloem wilt and is characterized by bronze or red discoloration and wilting of leaves. The infected plant is as shown in Figure 9.



Figure 9: Bronze twilight.
Source: Authors, (2026).



Figure 10: Alternaria & Cercospora leaf spot / blight.
Source: Authors, (2026).

Various leaf spot and leaf blight diseases are due to fungus & bacteria and hence they are categorized under Fungal foliar diseases. Alternaria leaf spot / blight, Cercospora leaf spot / blight, Corynespora, Myrothecium, Colletotrichum, Helminthosporium leaf spot diseases; Ascochyta leaf blight, Ramularia Grey mildew and Phakospora Leaf Rust are few cotton plant diseases. The mentioned leaf spot, leaf blight, mild dew and leaf rust disease infected leaves are shown in Figures 10 and 12. Coming to Boll rots, they are of two types, namely external boll rot and internal boll rot. These rots are also caused due to fungi and bacteria pathogens. The two types of rots are shown in Figure 11.



Figure 11: External and Internal boll rots.
Source: Authors, (2026).

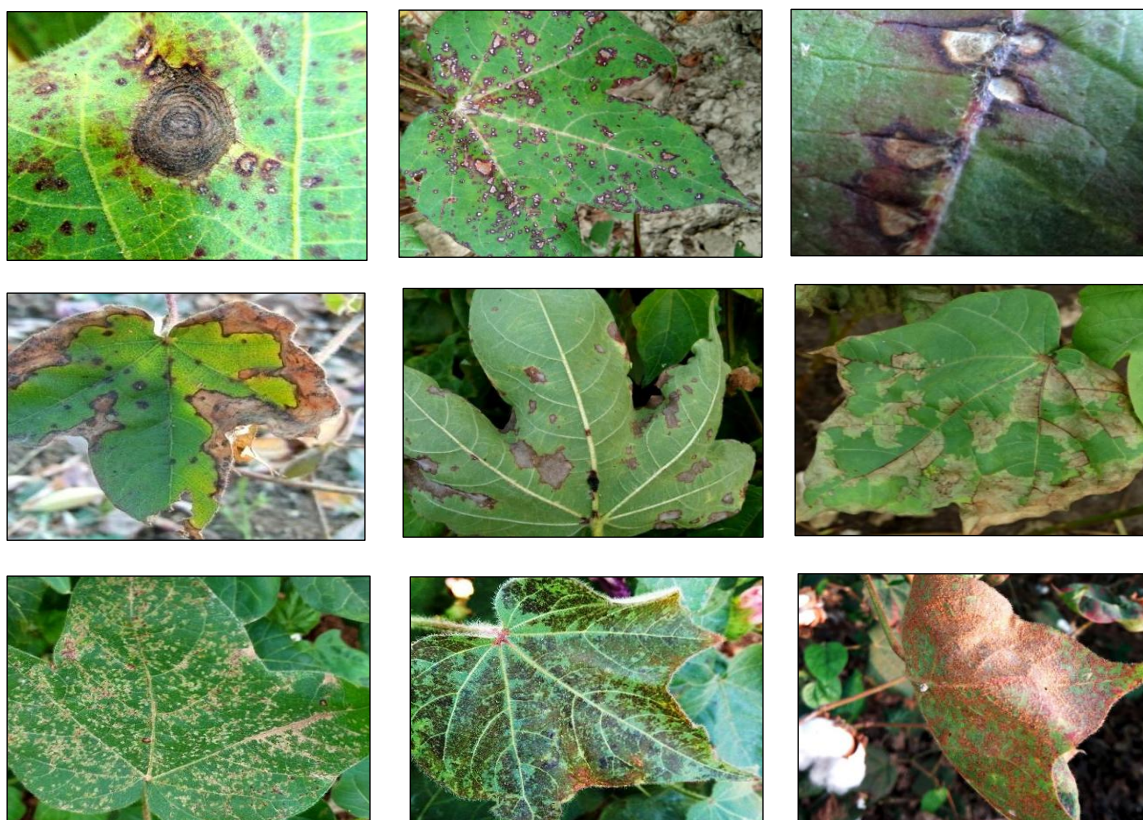


Figure 12: Various leaf spot, leaf blight, grey mild dew and leaf rust diseases.
Source: Authors, (2026).

Deficiency of soil mineral nutrients may be the consequence of low soil mineral contents, extreme temperatures, pH, drought and waterlogging conditions that alter the mineralization and hence availability to plants. Soil nutrients are considered as essential during the critical crop reproductive phases.

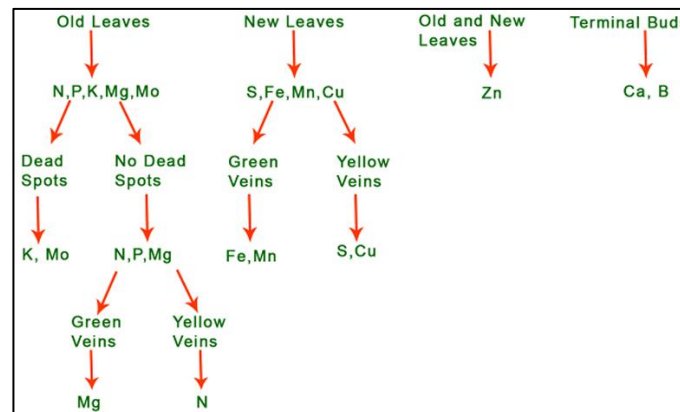


Figure 13: Nutritional deficiency symptoms.

Source: Authors, (2026).

Deficiency in the nutrients must be supplemented with required nutrients for enhanced productivity. In the cotton plant growth cycle the following elements are identified as essential viz., Carbon, Hydrogen, Oxygen, Nitrogen, Phosphorus, Potassium, Calcium, Magnesium, Sulfur, Iron, Manganese, Zinc, Copper, Boron, Molybdenum, Chlorine, Cobalt, Selenium and Sodium. The symptoms in various parts of cotton plants are presented in Figure 13. The diseases quoted above are the compilation in various parts of the world. They are due to various reasons such as climatic conditions, bacteria, fungi, viruses and nutritional deficiencies. Due to these diseases, huge economic losses incur, consequently the nation's economy stands impactful. In reducing the losses various methods are to be implemented and modern computational intelligence methods play a vital role in Effective disease management. Early disease detection, pest management, crop management, soil management and so on comprise the disease management. The research towards cotton crop protection and high yield is open, and questions arise in how machine learning, deep learning and its advancements could be employed in effective disease management. Research could be performed on disease prediction, diagnosing the aptness of the environmental condition, proportion of the nutrients and soil fertility, various deep learning architectures that provide valuable insights towards optimization of cotton yield. Precision Agricultural practices that lead to higher yields to be emphasized. Scalability is another important aspect which the research has to address.

III. LITERATURE SURVEY

Plant leaves or crops are vulnerable to different diseases during agricultural cultivation. The diseases halt the growth of their respective species. Early and precise detection and classification of the diseases may reduce the chance of additional damage to the plants. The detection and classification of these diseases have become serious problems. Farmers that use computerized image processing methods in their fields can reduce losses and increase productivity. Numerous techniques have been adopted and applied in the detection and classification of plant diseases based on images of infected leaves or crops. Researchers have made significant progress in the detection and classification of diseases in the past by exploring various techniques. There are several datasets available related to varieties of crops/plants from various sources in different forms i.e., text, image, video on which the techniques could be applied and make predictions, detection, classification and so on. The usage of Deep Learning in plant/crop disease detection is enormous. However, there is a lot of scope for research in different sub fields in this area of research. Cotton is an important cash crop, and its diseases significantly impact the yield. Detection of diseases at an early stage helps farmers in taking pre-emptive measures to help improve cotton crop yields. DL-based object detection can automate the process, saving time and resources. These are the key factors that encourage researchers to work on these diseases and are the real motivation behind this study as well. This research primarily focuses on the accurate and timely detection of diseases in cotton crops. In this regard, the following are the main contributions of this study. According to [11] presents distinguished deep learning models for disease detection which include VGG16, DenseNet, MobileNet, EfficientNet, NasNet, InceptionV3, MobileNet and ResNet models.

The models are employed on the real cotton disease data collected in the form of images of leaves from fields. Before the data is inputted to the models, preprocessing has been done using well-known techniques. Among all the models, ResNet152 model outperformed other DL models with which the model turned into an efficient approach for cotton disease detection. With this it could be understood that the power of DL could be harnessed and it helps protecting the cotton crop and ensures a promising output. In [12] made an effort in improving crop health monitoring of cotton farming systems as well its management. Their research emphasizes on the importance of utilization of cutting-edge techniques in image processing in agricultural activities. Various techniques namely YOLOv5, VGG16 and ResNet 50 are employed in identifying the cotton plant diseases. In terms of ROC curve metric, YOLOv5 seems to be better than VGG16 and ResNet50. Also it had the highest F1 score, precision and recall, while ResNet50 slightly outperformed VGG16 in terms of true positive rates, F1 score, precision and recall. Also, in terms of accuracy YOLOv5 performed well than ResNet50 while the latter model offered high efficiency and accuracy than VGG16 due to which the models are considered to be more appropriate for those applications that demand high precision and low false positive rates. According to [13] presented a deep learning model incorporating a special module namely Convolutional Block Attention Module (CBAM) with which the cotton leaf diseases could be automatically detected with high accuracy.

To do so, a publicly available dataset was utilized which had 2,137 original images and augmented to 7,000 images categorized into seven classes. Healthy leaf being one category and Leaf Hopper Jassids, Curl virus, Bacterial Blight, Herbicide Growth Damage, Leaf Reddening and Leaf Variegation are the other categories. Although various deep learning models including MobileNet, DenseNet121, EfficientNetB1, DenseNet169, InceptionV3 and XceptionNet are used in disease detection; EfficientNetB1 with CBAM achieved highest accuracy of 99.21%. However, during preprocessing stage, image resizing, normalization and noise reduction are performed so as to improve image quality. Integration of CBAM improved the detection performance. According to [14] introduced mobilenet comprising subset of layers, a novel deep learning framework constituting transfer learning, data augmentation, model check points, decaying learning rate schedule and early stopping mechanisms. The model demonstrated extraordinary performance in classifying cotton disease of seven categories with 98.42% overall accuracy while class-wise precision in the range of 96% to 100%. The model's substantial performance and its lightweight nature well suits the real-world applications in smart farming. In [15] Stephen, A., et al. used different pre-trained CNN architectures InceptionV3, ResNet18, GoogLeNet and MobileNetV3 Large to diagnose the cotton plants. The model focussed on the regions of cotton plant viz., stem, bud, flower, boll, crown, land, unhealthy leaf, young boll, weed, and young leaf.

The images of cotton plants are collected using smartphones. Amongst all the models, MobileNetV3Large offered highest accuracy, precision value and specificity of 93.9%, 97.48% and 96.12% respectively. By [16] proposed a novel ensemble model considering two pretrained networks VGG16 and InceptionV3 as base models for early detection of diseases in cotton leaves. The proposed model offered higher training and testing accuracies of 98% and 95% relative to the base models. The model achieved the accuracy in 20 epochs with other hyper parameters settings, learning rate as 0.0001 and stochastic gradient descent (SGD) optimizer. The pipelined architecture by [17] comprise the algorithms which are capable of learning complex features, patterns from large datasets and can lead to more precise and reliable detection outcomes. The model could well detect, particularly in challenging situations such as fields of mixed crops and in lighting and weather situations. The model could be enhanced by integrating various sensor types namely hyperspectral, thermal imaging, and LiDAR. According to [18] employed seven models for automatic detection of cotton leaf diseases among which five are pre trained models and two are advanced transformer-based architectures. The Vision Transformer (ViT) model achieved highest performance with accuracies of 96.72% and 93.39% in the binary class and multi-class classifications respectively. In addressing the problems such as several model parameters and low detection accuracy in case of SSD-based cotton leaf disease detection mechanisms Guo et.al. [19] proposed a fusion model that combined SE, ECA and CBAM attention mechanisms.

The mechanisms are combined to filter the disease target features and at the same time suppress the information related to jamming targets. According to [20] employed three models ResNet101, Inception v2, and DenseNet121 in cotton crop disease detection. Hyper parameter tuning is performed with the Nesterov accelerated gradient. Among the models DenseNet121 offered high performance accuracy which acts as a powerful tool for farmers in accurate and swift diagnosis. In [21] performed an exhaustive study on various deep transfer learning techniques in cotton plant disease detection. The models employed are variants related to EfficientNet, Xception, ResNet, Inception, VGG, DenseNet, MobileNet, and InceptionResNet on a complete dataset of infected cotton plants with five disease categories namely Bacterial Blight, Powdery Mildew, Target Spot, Army Worm and Aphids in addition to the healthy ones. EfficientNetB3 model outperformed with an accuracy of 99.96% 0.149 loss and root mean square error of 0.386. Intrusion of CLCuD caused due to Curl virus intrigates a substantial threat to the cotton yield. Prompt addressing the challenge of identifying CLCuD is highly essential and deep learning plays a vital role in addressing such issues. According to [22] used two deep learning models, specifically the Convolutional Neural Network (CNN) in two variants on two distinct datasets, one, a public dataset and the other, a proprietary collection. The dataset consists of 1349 cotton leaf images capturing both healthy and diseased ones. When compared to the normal CNN model, the dynamic weight layering CNN model achieved 99% accuracy in the disease detection.

According to [23] used three Transfer learning models DenseNet201, InceptionV3 and Xception on a publicly available cotton dataset. Results demonstrated that among the employed models, DenseNet201 achieved highest accuracy of 94.33%. This research aids in effective crop management and productivity. In the experiments conducted by [24] fine-tuned Transfer Learning (TL) models VGG-16, VGG-19, Xception and InceptionV3 are used on the publicly available cotton dataset for disease detection. Among the models used, Xception model offered highest accuracy of 98.70% In [25] conducted experiments in three configurations using an improved Deep CNN based model. One is using different data split ratios, second is different choices of pooling layer - max-pooling vs. average-pooling, and third epoch sizes. The model used a dataset of 2293 cotton leaf and plant images comprising four classes of leaves, various plant disease combination categories. The model attained an accuracy of 97.98%. According to [26] employed six pre trained networks VGG16, VGG 19, DenseNet121, DenseNet169, ResNet50V2 and MobileNetV2 in detecting the bacterial blight and curl virus in cotton crops. The dataset comprises 1362 images collected from local agricultural fields and another 1292 images collected from online resources on which experiments were conducted. According to [27] employed Deep CNN ensemble by combining Inception Net and VGG16 to diagnose cotton leaf diseases Cotton leaf curl virus, fusarium wilt and bacterial blight.

Weight parameter optimization using RMSProp and Adam optimizers had been explored. In [28] performed research using CNN in detecting 22 leaf diseases that comprise categories related to bacterial, fungal, viral, nutrient deficiency, etc. The proposed model offered 99.39% accuracy with negligible error rate and less computational time. According to [29] performed experimentation using state-of-the-art YOLO DL framework on an indigenous cotton plant image dataset in identifying bacterial blight and curl virus. This resulted in YOLOv5 offering better performance when compared to YOLOv6 and YOLOv7 models. The accuracy is 92% and the inference time is 25 ms which may suit on-field real time applications. By [30], made a study using six CNN architectures experimented on a cotton leaf dataset comprising near about 387 diseased leaves and 519 healthy leaves collected from reliable sources. The pretrained CNN architectures employed were AlexNet, ResNet50, InceptionV3, NASNet, VGG 16, and Xception among which ResNet50 and VGG 16 shown significant performance with 97.56% of accuracy. However, the number of parameters associated with VGG16 are more than ResNet50. The method employed by [31] consists of two core steps, feature extraction and classification. Initially to balance the input data, the data augmentation is performed after which feature extraction is done from a pre-trained VGG-16 model, subsequently the output is passed to 11 fully convolutional layers and finally generate an anomaly map, that define the probability of the lesion region. The proposed model is evaluated on two publicly available datasets which offered 99.99% accuracy.

According to Memon, [32] proposed a meta deep learning model to perform cotton leaf disease detection on a dataset containing 2385 images initially and later augmented. Disease detection was performed and performance in terms of accuracy is compared with transfer learning models CNN, VGG16 and ResNet50. The proposed meta DL model offered noteworthy performance of 98.53% accuracy. According to [33] proposed a CNN based model which is used to detect cotton plant leaf disease considering a dataset from Kaggle. The model attained 97.13% classification accuracy. In [34], to monitor the cotton crop health and for effective disease management, chosen two deep learning models GoogleNet and Resnet50 and they attained a precision of 86.6% and 89.2%, respectively. When compared with traditional approaches namely SVM, KNN, ANN and NFC techniques the DL models proved to be 25% more precise. In [35] as a part of their experimentation, performed segmentation as well classification. They presented a few-shot learning frame work that performs cotton leaf disease spot classification task. Due to this timely control of cotton diseases is possible. As an initial step, segmentation is performed on cotton leaf's disease using various methods. Support Vector Machine (SVM) method and threshold segmentation are used. Next, the segmented disease spot images are compiled as a disease spot dataset and finally the cotton leaf disease spots were classified using two-way parallel CNN. Also the CNN has been used in building the leaf spot feature extractor.

According to [36] used deep transfer learning specifically ResNet trained on the Network combination of ImageNet and XceptionNet to recognize cotton crop leaf diseases and achieved high accuracy in cotton crop disease detection. Cotton plant disease detection is accomplished by Saqib et.al. [37] using deep CNNs. The proposed ResNet50 model achieved training and validation accuracies of 0.95 and 0.98 respectively. According to [38] employed VGG16 transfer learning model to detect cotton leaf diseases on a dataset containing 6,158 samples categorized into seven disease classes and one healthy class. The metric evaluation of pretrained models resulted in an accuracy of 95.02% attained by VGG16. According to [39] developed a CNN-based model which achieved 90% accuracy in cotton leaf disease detection. For iOS integration, the model was converted later to CoreML thereby enabling offline disease identification. This aided farmers in giving real-time recommendations for crop disease management. In [40] implemented Mask R-CNN to detect cotton leaf diseases which attained 94% accuracy. Their study insisted the importance of instance segmentation techniques which could localize the disease affected regions in a precise manner. For [41] performed cotton leaf disease detection using VGG16 on a dataset containing 2,238 images in six categories. Due to Feature selection, the model's ability significantly improved in detecting the diseases at an early-stage. The model achieved 95.52% accuracy and this approach reinforced the effectiveness of feature engineering. In [42] proposed ResNet50-based system to detect bacterial blight and curl virus diseases in cotton leaves.

Experimentation is performed on a dataset, comprising 2,000 images and the model achieved 95% accuracy and it demonstrates the efficiency of transfer learning. According to [43], employed a deep CNN to detect cotton leaf diseases while Kumar et.al. [44] proposed a 2D-CNN model. In [45] adopted transfer learning approaches to detect cotton plant leaf diseases. In [46], modelled CropCycleNet, a deep adversarial network with which we could study the health of cotton plants and analyze factors related to plant growth and maturity. According to [47], employed transfer learning techniques Densenet121 and Cropnet architectures to classify cotton leaf diseases while by [48] made an assessment on the severity of fusarium oxysporum cotton disease using images captured using UAVs. A hybrid domain adaptation DL time series model is employed and this method improved the spatio-temporal transferability of CNN-BiLSTM model which later allowed to leverage historical datasets efficiently. In [49] employed conventional approaches, such as CNNs to classify the diseases associated with cotton leaves. In [50] proposed RESNET algorithms to classify the diseases and predict the labels of the disease to find out the accuracy and the best suitable algorithm. According to [51] proposed a Convolutional Neural Network (CNN)-based approach for the automated detection of rice leaf diseases using deep learning. For [52] proposed a Convolutional Neural Network (CNN)-based approach for the automated detection of tomato leaf diseases using deep learning. Research insights provided from the above literature reviewed:

- In most of the articles various deep learning models are employed and comparisons are drawn with respect to those models.
- There is a need to focus on diagnosing newly emerging cotton diseases.
- Ensemble techniques are not much used. Hence ensemble techniques and in addition, variants of Ensemble techniques could be employed.
- Specific diseases could be focused upon.
- Transformers, especially Vision Transformers could be widely used.
- Hyper parameter tuning and Optimization techniques could be employed.
- Data balancing is a vital factor which is highly essential for better performance.
- Light weight models to be used so that the real time detection and monitoring is possible in mobile devices etc...
- Challenges related to Dataset quality, size, Resolution of images need to be addressed.
- Focus could be made on Datasets related to India (in preparing new datasets)
- Sensor based, IOT based and UAV based Agricultural research data could be made as a part of research.
- Scalability of the dataset which means huge cotton plant disease datasets are to be considered for experimentation due to which model standardization could happen.

IV. A BRIEF NOTE ON DATASETS AVAILABLE

Data plays an important role in the experimentation. Unless qualitative and quantitative data is made available, proper analysis cannot be done. In this section, around 12 bench mark datasets related to cotton crop diseases are presented. The datasets compiled by respective organizations are recent ones. Most of the datasets are compiled by authentic bodies while few datasets are from Kaggle. Dataset particulars are presented in Table 1.

Table 1: Particulars of the datasets.

Dataset Name (Year)	Description	Reference
SAR-CLD-2024 (2024)	Data was collected by visiting the cotton field which is the National Cotton Research Institute field in Gazipur, Dhaka, Bangladesh. Dataset consists of 2137 images and after augmentation the number of images is 7000, Output classes – Seven.	SAR-CLD-2024: A Comprehensive Dataset for Cotton Leaf Disease Detection - Mendeley Data [53]
CoSEV (2023)	Data compiled by Islamia University of Bahawalpur Pakistan Faculty of Science, NFC Institute of Engineering and Technology Training. Dataset comprises 496 images and after augmentation the number of images is 1186. Output classes – Five.	CoSEV: A cotton disease dataset for detection and classification of severity stages and multiple disease occurrence - Mendeley Data [54]
Cotton Leaf Disease Dataset with Severity Levels (2025)	Data collected by Agarwal, Dr D Y Patil Institute of Engineering and Technology. Dataset consists 1016 images and after augmentation the number of images is 3604, Output classes – Four.	Cotton Leaf Disease Dataset with Severity Levels - Mendeley Data [55]
Cotton leaf disease dataset (2021)	Dataset consists of 1710 images and the output classes - Four	cotton leaf disease dataset [56]
A Dataset of Cotton Leaf Images (2024)	Dataset consists of 4000 images and after augmentation the number of images is 8000. the output classes - Four.	A Dataset of Cotton Leaf Images for Disease Classification Using Deep Learning by Azeem Ayaz Mirani, Shahzaman Nizamani, Mehwish Leghari, saima soomro, Qazi Ejaz, Mushtaque Ahmed Rahu :: SSRN [57]
Cotton Disease dataset (2020)	Dataset consists of 2310 images which are into healthy and diseased plants as well healthy and diseased leaves.	Cotton Disease Dataset [58]
CotLeaf-1 (2024)	Cotleaf-1 dataset is a collection of 13,597 images of cotton leaf surfaces acquired with a hand-held microscope to develop deep learning models to classify images based on leaf hairiness and assist Cotton breeders in their variety selection efforts. Remaining datasets are also available.	CSIRO Data Access Portal - CotLeaf-1: Cotton Leaf Surface Images dataset 2019-21 [59]
CotLeaf-2 (2024)	Dataset consists of 810 images	CSIRO Data Access Portal - CotLeaf-2: Cotton Leaf Surface Images dataset 2021-23 [60]
CotLeaf-X (2024)	Dataset consists of 5049 images	CSIRO Data Access Portal - CotLeaf-X: Cotton Leaf Surface Images dataset with eXpert labels [61]
AnnCoT: Annotated Cotton Trichome dataset	1250 images dataset	CSIRO Data Access Portal - AnnCoT: Annotated Cotton Trichome dataset [62]
Cotton Plant Disease. (2023)	It focuses on 5 types of diseases on leaves and contains 26k plus files	Cotton plant disease 🌱🍃🍃🍃 [63]
Cotton-leaf-infection (2022)	The dataset contains 1786 images in four categories	cotton-leaf-infection [64]

Source: Authors, (2026).

V. CONCLUSION

Cotton cultivation plays a vital role in various domains consequently impacting a nation's economy. Through cotton various countries are getting benefitted either in the form of raising their economy or addressing the demand of cotton. At the same time due to improper methods of cultivation or monitoring, it is like a bane to the farmers often leading to deaths. The prime cause for this situation is cotton crop being affected with diseases. Effective disease management is highly essential so as to avoid losses. Deep learning, the state of art technology is offering amazing experience in various sectors and agriculture is not an exception. In this paper, various cotton crop diseases are discussed and deep learning based cotton disease detection techniques have been reviewed. The gaps are presented in the form of Research insights which would be useful to the future research. Also few datasets related to cotton crop diseases are presented.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: K. Kishore Kumar and Movva Pavani.

Investigation: K. Kishore Kumar

Discussion of results: Movva Pavani.

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