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Pests And Diseases Detection Of Cotton Farm Using Artificial Intelligence Technologies: A Review

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Abstract

Cotton is a commercial and fiber crop that generates profit for agronomists in India and is the world's second-largest export crop after China. Cotton crops are harmed by excessive water use, soil degradation, and the use of harmful pesticides and fertilizers. Cotton diseases and sucking pests are the two biggest threats to the crop's rapid growth. In this study, an overview of papers has been finished utilizing machine learning and its advanced learning techniques, as well as image pre-processing and segmentation techniques, to detect and classify various diseases and pests. To identify the specific cotton diseases and pests under research, as well as overall performance based on the various metrics used. Our findings endorse that machine learning and its advanced learning techniques provide outperform ordinally utilized image processing techniques in phrases of exactness and other viable methodologies.

Buzzwords: Cotton Pests and Diseases, Artificial Intelligence, Machine Learning, Deep Learning, Image Pre-processing

1. Introduction

Agriculture is the primary source for cultivating plants, harvesting crops, raising livestock, to create surplus food that enables people to live in the world. The major agricultural commodities are Crops, Dairy, Edible, etc. are useful in day-to-day life. Almost 40 percentages of the people in the world are employed in agriculture. Although, the number of agriculture workers is decreasing in the past few years for growing crops, especially in developing countries like India. India is a developing country depending on agriculture and a backbone to the Indian economy. However, the population is declining in rural areas and ominous development with a population of more than one billion in urban (Kellengere Shankarnarayan & Ramakrishna, 2020). To overcome this, the green revolution had started to convert agriculture into an industrial system to adapt the modern technology.

In present-day innovation, automation in farming is the primary concern and advancing technology across India. This automation fulfilled the prerequisites of agronomists, expanded productivity, and gave billions of individuals the chances. Artificial Intelligence can be a form of automation that plays a vital role in agriculture to improve efficiency, manage challenges, and solve problems in various crop fields (Jha et al., 2019)(Talaviya et al., 2020). An AI predicts crop yield by including the technologies to gather information on soil moisture, leaf diseases, pest attacks, climatic conditions, growth of production in crops (Samanta & Ghosh, 2012). Robots, drones, sensors are used in agriculture with the help of AI has enabled agronomists to produce and improve quality output for giving required input (Talaviya et al., 2020). The major taught of AI in agriculture is its adaptability, excessive performance, exactness, and cost-adequacy(Eli-Chukwu, 2019).To develop smart farming using artificial intelligence by compiling data from various sources into datasets that can be accurately analyzed to reduce crop losses, increase yield and decrease the use of water, fertilizers, and pesticides (Deepak Panpatte, 2018). The agriculture datasets are divided into smaller parts, and their trends, behaviours were understood for handling a massive amount of data (Krishna et al., 2019). AI ought to be capable of taking care of business on agriculture datasets based on machine learning, deep learning domains that enhance the machines and help predict more accuracy (Jha et al., 2019).

2. Fundamental Perspective of Machine Learning

The essential motive of machine learning includes feeding the machine data from previous experiences for it to solve a problem and perform a specific task(Jha et al., 2019)(Liakos et al., n.d.). In every problem, ascribes are also known as elements or variables. An element can be ostensible (enumeration), paired (0,1), cardinal(A+,B+), or numeral(integer, real number) etc. The machine learning model's performance is evaluated by improving through experience, and various algorithms factual and numerical models are utilized. When the modelling system is completed, the trained model can classify and forecast based on previous experiences(Liakos et al., n.d.).Machine Learning has different algorithms to predict yield, diseases, and weed detection, crop quality, species recognition, water, and soil management for increasing the production level in cotton farming (Samanta & Ghosh, 2012). Cotton farming is an annual field crop that is the world's most popular fiber. However, the cotton crop is impacted by many factors such as pests and diseases, climatic conditions, cultivator, availability of nutrients and soil moisture, and cultural activities after cotton growth. The factors that can be affected to cotton crop can be classified, predicted, and find accuracy using machine learning algorithms.

2.1 Algorithms Exploiting in Cotton Pests and Diseases

The identification of pests and diseases is difficult for human eyes, the exact type that occurs on the cotton leaf or plant(Prajapati, 2016). The affected cotton crop classification and prediction are accomplished using machine learning algorithms. Images were utilized to fragment the images from regular cotton crops using the modified factorization-based active contour method (MFBACM). The color, texture, Correlation, edges are extracted from the segmented images. The segmented images fed into the machine learning classification algorithms such as Naïve Bayes (NB),K-Nearest Neighbours (KNN), Decision Tree (DT), Random Forest (RF), Stochastic Gradient Descent (SGD), Support Vector

Machine (SVM), Artificial Neural Network (ANN), Logistic Regression (LR)(Patil & Burkpalli, 2021). Fig 1 shows the classification of machine learning classifiers.

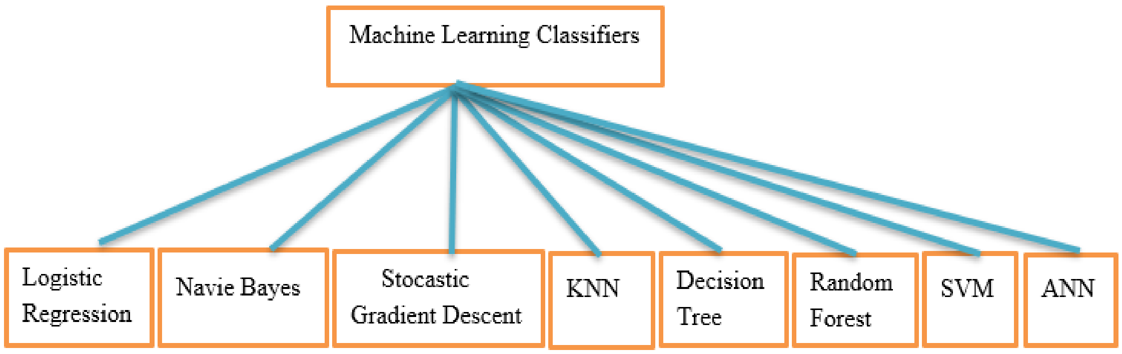

Fig 1: Machine Learning Algorithm Classifiers

Cotton crop pests and diseases data gathering means a collection of datasets in the form of images from various sources such as live data or data from different website sources to predict crop quality. After that, we can do the wrangling on cotton crop images for cleaning and get the quality images for deciding less time in cotton agriculture. It can use the analysis to discover useful information to draw proper cotton agriculture conclusions. Meanwhile, affected cotton data can be trained and tested by different classification models shown in Fig 1. At last, it can classify the data regarding various pests and diseases of cotton agriculture, and quality is to be predicted.

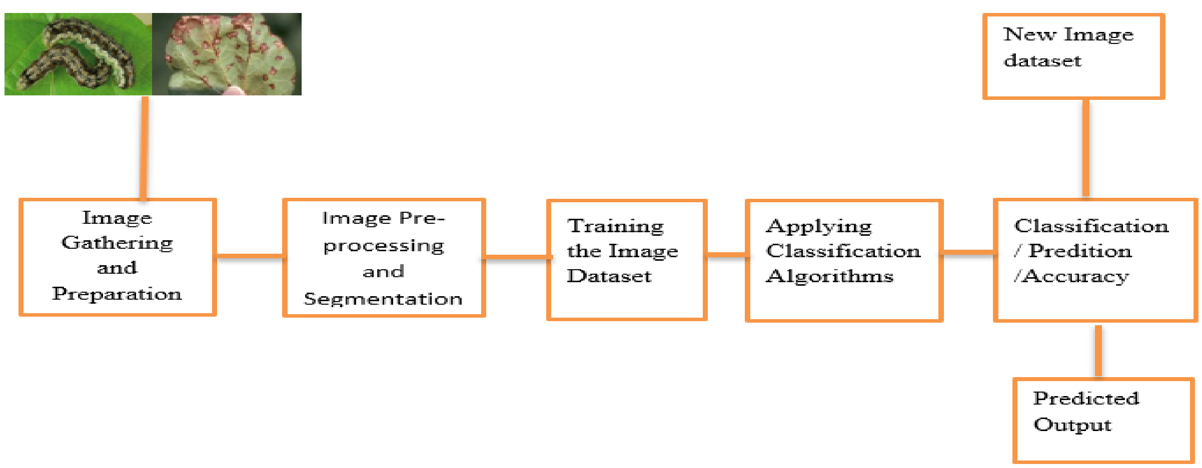

Fig 2: Machine Learning Process on Cotton Pests and Diseases

3. Fundamental Perspective of Deep Learning

Deep Learning (DL) is a branch of machine learning, the cutting edge of artificial intelligence. A neural network comprises these neural nodes, and each classifier node is referred to as a neural unit of perception (Dong et al., 2021). Another factor is that it has stowed away layers in the middle of the info layer and result layer to solve more complex problems using activation functions in the models can extend the classification precision and lessen regression problems(Dong et al., 2021)(Kamilaris & Prenafeta-Boldú, 2018)(Sane & Sane, 2021). Deep Learning can perform the classification and prediction based on various datasets such as videos and images. It can be applied to any datasets such as audio and speech recognition, natural language processing, weather, and agriculture crops such as cotton leaf disease, pest diagnostics, and other challenges(Kamilaris & Prenafeta-Boldú, 2018)(Singh et al., 2021).

3.1 Algorithms Exploiting in Cotton Pests and Diseases

The harmful biological hazards such as diseases and pests that occurred at the time of cotton growing crop periods that causes a huge amount of losses to the agronomists (He et al., 2013). The damaged cotton crop can be classified, predicted using deep learning algorithms. Image processing is performed on the natural cotton crop images for detection, segmentation, and classification to yield quality to agronomists (Meena et al., 2020). The segmented image fed into the deep learning algorithms such as Convolution Deep Belief Network (DBN), Ensemble Learning (EL), Capsule Network (CN), Multi-Layer Perceptron (MLP), Neural Network (NN), Long Short Term Memory (LSTM), Auto Encoders (AE), Temporal Long Short Term Memory (TLSTM), Spatial Long Short Term Memory (SLSTM), Deep Boltzmann Machine (DBM), Wavelet Neural Network (WNN). Fig 3 shows the classification, prediction of Deep Learning algorithms.

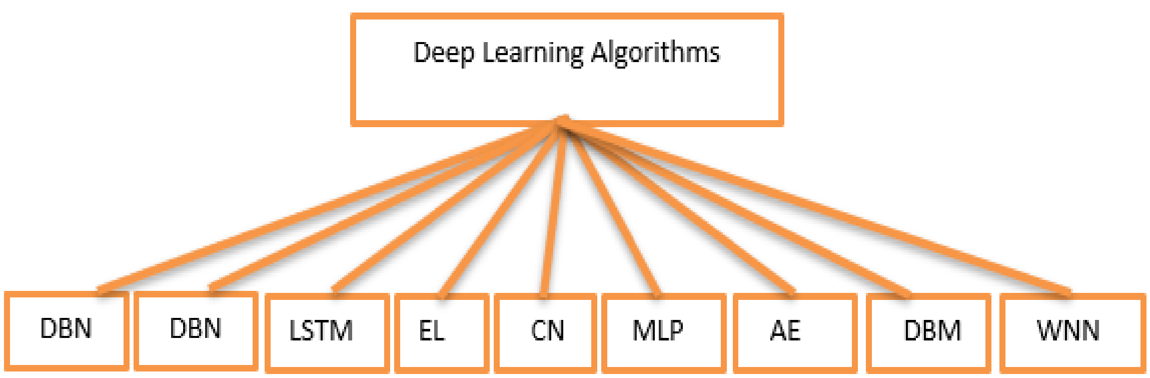

Fig 3: Deep Learning Algorithms

Cotton crop pests and diseases data gathering means a collection of datasets in the form of images from various sources such as live data or data from different website sources to predict crop quality. After that, we can do the image pre-processing on cotton crop images and then apply the Deep Learning algorithms for classification. Meanwhile, using various colors models to extract the damaged cotton pests and diseases images were implemented, namely RGB, HIS, Cyborg color models (He et al., 2013).It can use the analysis to discover useful information to draw proper cotton agriculture conclusions. So, the affected cotton data can be trained and tested by different classification models shown in Fig 1. At last, it can classify the data regarding various pests and diseases of cotton agriculture and quality is to be predicted.

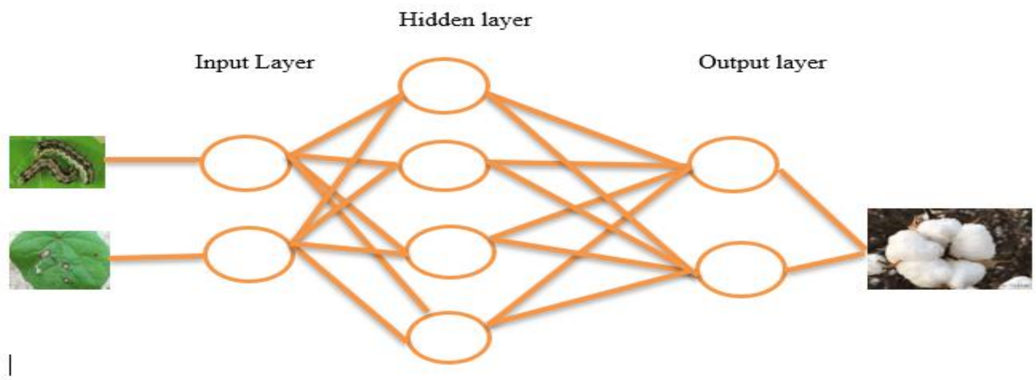

Image Processing+ Image Segmentation + Deep learning+ Feature Extraction+ Classification

Fig 4: Deep Learning Process on Cotton Pests and Diseases

4. Background

In India, farming in agriculture is practiced in various ways, depending on geographical conditions, product demand, labour, and technology. Commercial farming is a type of agriculture that focuses on producing a profit for agronomists in the market. Agronomists use irrigation, chemical fertilizers, insecticides, pesticides, and high-yielding seed varieties in this system (Farmingindia, 1913). Cotton is one of the commercial crops that has a significant impact on India's economy and produces the highest yields when compared to other countries around the world. India is the largest in terms of area. It is ranked second in terms of production (Kumar et al., 2021). Table 1 shows cotton production in metric tons that are taken from www.statista.com.

Country	Production in Metric
China	6,423
India	6,612
United States	3,181
Brazil	2,341
Pakistan	980
Uzbekistan	762
Turkey	631
Australia	610
Benin	316
Greece	305

Table 1. Cotton producing countries in metric tons in 2020/2021

Cotton Crops can be classified, namely organic cotton and non-organic cotton. Organic cotton refers to naturally cultivated grown in healthier soil barring the utilization of toxic pesticides, a pivot framework for the soil, and fertilizers to produce many quality textiles (Angelova, 2019). It occupies 1% of India's cotton production from all over the world and Madhya Pradesh occupies 43% of the total country. It can flourish in subtropical counties such as India, Turkey, China, and the USA. Organic cotton encourages and improves biodiversity and biological cycles, which benefits both human health and the environment.

Non-organic cotton is produced on similar soil over again, causing soil debasing, nutrient loss, and sickly harvests. It occupies a second place all over the world in terms of yield and production. Non-organic cotton crops known as regular cotton or conventional cotton which is genetically modified that can be harmful to human health and the environment too because of heavy usage of chemicals, pesticides, and fertilizers.

The organic and non-organic cotton classifies the species into four such as Gossypium Arboreum (short length, < 25mm), Gossypium Herbaceum (short length, < 25mm), Gossypium Hirsutum (Upland) (medium to long length, 25-35mm), and Gossypium Barbadense (long to extra-long length, 30mm and up) . For these four species, pests and diseases are the primary challenges in the cotton crop.

Cotton diseases and pests have posed a significant challenge to plant development and harvesting in many parts of the world. Natural and common cotton disorders are caused by an absence of nourishment, ecological pressure, and compound factors that cause lopsided characteristics.

Anthracnose Disease, Root Rot Disease, Boll Rot Disease, Leaf Spot or Blight Disease, Angular Leaf Spot, Vascular Wilt Disease are the cotton diseases occurred in the cotton crop from the initial to the final stage of production (Kumar et al., 2021). The major pests that harm cotton productivity are Bacterial Blight, Leaf Minor, Spider Mite, Pink Bollworm, Whitefly, and others. Fig 4& 5 shows the visualization of cotton diseases and pests images

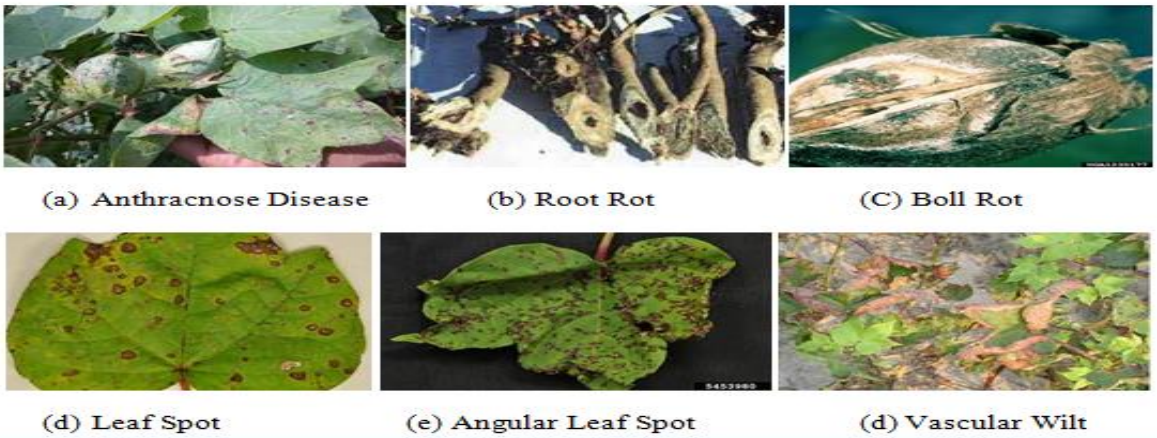

Fig 5: Visualization of cotton diseases images

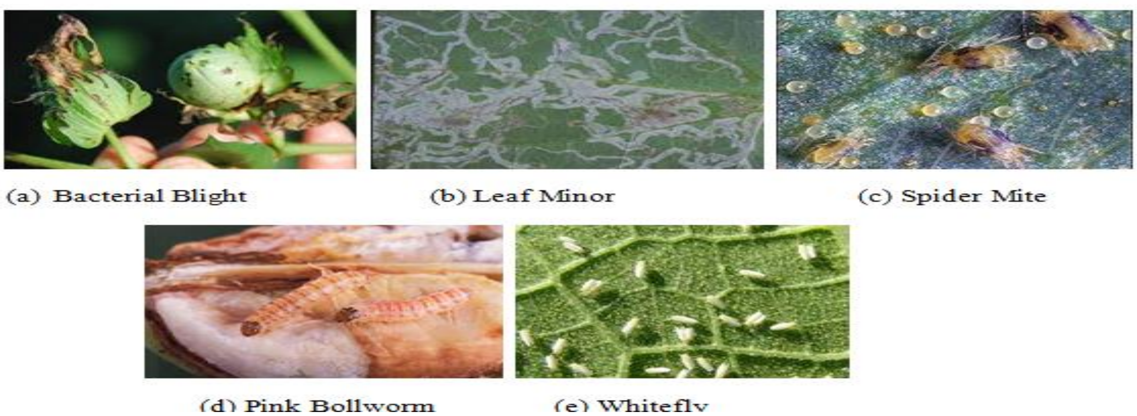

Fig 6: Visualization of cotton pests images

5. Methodology

The bibliographic analysis was classified into related work and work analysis. Search the databases Scopus, Science Direct, IEEE Xplore, Hindawi, MDPI, and web indexing databases Web of Science and Google Scholar for conference papers or journal articles in the first category. Along these lines, papers about cotton crops using machine learning and deep learning were filtered out. Initially, 25 papers have been identified as a result of this effort. The underlying variety of papers was decreased to 20 after restricting the search to papers that used the DL technique appropriately and produced meaningful findings.

In the second category, the ML and DL in the cotton crop were classified into two sections, including disease and pest detection. The journal papers addressed the precision and detection of cotton crops using machine learning and deep learning models, statistical measures, image pre-processing techniques, datasets, classes, labels, and performance models to acquire the quality harvest, cost-effectiveness, and productivity of the agronomists.

6. Literature Survey

This paper proposed that cotton disease detection is one of the essential precisions that can be achieved by implementing emerging technologies to produce a high-quality harvest that is also cost-effective to the farmer (Kumari et al., 2019). Cotton leaf diseases have been taken and identified the leaf spot at the initial stage using image processing techniques and machine learning techniques. Redistributing every pixel to its closest clusters decreases the number of distances and recalculates the cluster centroid, separating the images into three clusters. Each cluster is made up of different leaf image segments. The effects of K means are utilized to name each pixel in the image utilizing index values from three clusters. The following stage is to make a blank cell array exhibit to store the clustering results. The aspects are separated from the infection impacted leaf using a machine learning algorithm, and target data is fed into the neural network as a class vector for these features. The diseases were recognized and classified using a back propagation algorithm.

This work aimed to provide information regarding the detection of severity estimation in cotton plant disease and Grey Mildew disease detection (Parikh et al., 2016). The severity of cotton plants can be categorized into two stages 1. The first stage can characterize the small white spots with low frequency 2. The second stage has a large number of big white spots covered with a large number of portions. To detect the severity of disease, the cotton leaf can have two segments such as foreground and background. These segments can be given as input to classify the severity of the cotton leaf by merging white spots and generating large spots. Machine learning techniques can classify the severity of the cotton leaf with hue and luminous features. After training and testing, the disease images are processed twice for detecting the Grey Mildew and the severity of the cotton leaf.

Another study that is used for disease detection is that (Chopda et al., 2018), they provide the temperature data and soil moisture data to the server by the input sensors. The server then authenticates and transfers it to the database, where the input values are compared with the available dataset. The supervised learning algorithm is used to analyze and classify the cotton disease to predict Anthracnose and Grey mildew's specific disease to solve the problem.

In the other study that the author was developed a model for the detection of Cercospora disease to improve crop productivity (Shakeel et al., 2020). Unsupervised learning is utilized for the fragmentation of images in to clusters. The texture and color features are used to extract the features. After the features were extracted, supervised learning After the features were extracted, supervised learning is utilized to classify Cercospora leaf detection. Eventually, the accuracy and review execution assessment measurements are utilized to assess the precision.

This study used IOT to develop a model for detecting and controlling five different cotton leaf diseases (Sarangdhar & Pawar, 2017). Before classification, the cotton leaf image was used for pre-processing, segmentation, color mapping, and feature extraction. The supervised learning algorithm identifies and classifies five cotton leaf diseases and detects them. The name of the disease and its treatments will be given to agronomists through an android application after the disease has been recognized. This application shares the humidity, wetness, and warmth alongside water level in a container. Agronomists can transfer to manage the engine and sprinklers as needed. Cotton disease recognition framework and sensors for soil quality checking have interfaced using RaspbeeryPi, making it an individual and successful financial framework.

This study (Shah & Jain, 2019), detected cotton disease using an image acquisition technique, a pre-processing technique, an image enhancement technique, and other techniques applied to extract disease leaf detection. The Artificial Neural Network tool was used to process the image based on color changes, feature the predominant part of the afflicted leaf, and distinguish the disease kind dependent on data.

According to this study (Meisner et al., 2016), agronomists generally lack data-driven decision support on crop production, benefit, natural quality, and manageability to enhance pest management tactics. The processed Markov Decision Process (MDP) model was used to discover the optimal management policy for a cotton pest that balances yield loss and pesticide application cost using a dataset containing pests, pest management, and yield information.

The author (Dalmia et al., 2020), presented a method for detecting vulnerable pest attacks in cotton crops, such as pink bollworms and pesticide overuse. The deep learning technology is used to identify and count vermin spilled from the trap onto the sheet of paper. The count was then utilized to evaluate the extent of the infestation and provide pesticide recommendations based on the entomologist's guidelines.

The author developed a system (Azath et al., 2021), to increase the identification of cotton leaf diseases and pests by using the deep learning technique, Convolution Neural Network (CNN). In this system, cotton diseases and pests images are collected from various regions in Ethiopia and Southern Nations, Nationalities, and People Region (SNNPR) for acquisition and pre-processing. Dataset is partitioned using the K-fold cross-validation as K-values. After that, the cotton images are fed into an info layer and end with a result layer. The secret layer comprises of various layers of a cotton leaf, and the result will be named the class name of such a image likewise called the mark of cotton leaf diseases or pests.

In this study (Xiao et al., 2019), unsupervised learning and deep learning techniques are used to predict the occurrence of cotton pests and diseases. The unsupervised learning technique used to observe the affiliation rules between the climate elements and the prevalence of pests. The affiliation evaluation displays that temperature, muggy air, wind speed, and precipitation in different seasons are bound to happen cotton pests and diseases. Finally, the Long Short Term Memory(LSTM) method was developed to tackle the expectation of cotton pests, diseases, and yield prediction in the region.

This study proposed (Saleem et al., 2021), the prediction of whitefly pest attacks in cotton crops. Early prediction of insect invasions can be highly important in improving cotton farm productivity. Based on environmental parameters, the Insect Pest Prediction System (IPPS) was created using the Internet of Things(IoT) and Radial Basis Function Network(RBFN) . Various sensors are employed in IoT to forecast whitefly attacks and take preventive steps. The economic threshold leaves and RBFN algorithm are created to anticipate whitefly attacks using environmental data.

In this study (Jenifa, 2019), cotton classification, leaf diseases can produce the cotton yield. A deep CNN-based approach is used for identifying and classifying the five diseased leaves. The input image is a diseased cotton leaf, which is then transformed into a grey converted image, which is then converted into a segmentation image, and lastly, the output image removes the diseased area. For agronomists and botanists, industrialists, food engineers, and physicians, MATLAB identification of a damaged leaf is more accurate and error-free. It detects the damaged area while indicating whether the input leaf is afflicted or healthy.

The signs and symptoms of the major pests and diseases cannot be distinguished in the beginning phrases of this proposed framework (Caldeira et al., 2021), and the producer may have difficulty correctly identifying a lesion. The proposed model offers a deep learning-based solution for cotton leaf screening, allowing agronomists to monitor the health of their crops and make better decisions. In both the overall evaluation and the comparison between classes, the ResNet50 convolutional network demonstrated to be more capable of identifying lesions; nonetheless, the average difference between its results and those of GoogleNet is insignificant.

This model (Alves et al., 2020) was created to aid in developing environmentally friendly and cost-effective strategies for identifying the most harmful cotton pests in field conditions. This study introduces a classification framework for primary cotton pests (primary and secondary). Another ground-truth dataset of RGB cotton field images is presented as a novel deep residual learning design for robotically classifying principal pests from given images. The proposed Residual Neural Network (ResNet34) model attained the most significant level of accuracy when compared to other convolutional neural networks.

In this work (Huang et al., 2018), Spider mites are a serious pest that devastates the cotton industry. They fed the undersides of leaves, penetrating the chloroplast-containing cells, inflicting foliar harm and a decrease in yield. This paper offered a two-stage classification method for mite pervasion location based on machine learning methods. Two cotton fields were chosen for research, and UAV imagery was collected along with a ground investigation. On the collected multispectral imagery, mosaicking and geo-registration were done. A Support Vector Machine (SVM) was used for scene classification, and a transferred Convolutional Neural Network (CNN) was used for mite infestation identification. In terms of accuracy, this method surpassed others, demonstrating that it can detect mite infestations using UAV multispectral imagery.

A deep CNN model is proposed in this study (Udawant & Srinath, 2019), for accurately identifying whether a Cotton Leaf image is diseased or healthy. It is a better method for predicting the outcome than the Regular Neural Network. Cotton Leaf is classified with high accuracy using this model. The model's results show a high level of accuracy in distinguishing between healthy and diseased cotton plants.

In this paper (Chen et al., 2020), the problem of cotton pest occurrence was transformed into a time series multi-class classification problem. A Bi-LSTM network-based architecture was proposed to simulate the temporal link of climate characteristics and pests to forecast future pest and disease occurrences. It is the first time, to our knowledge, that a bi-directional recurrent neural network has been employed to handle the problem of pest and disease incidence prediction. To obtain the final prediction, the proposed network used a Bi-LSTM layer to model time series data and a fully-connected layer to map the output of the Bi-LSTM layer. Based on climate conditions and circulation characteristics, the model may estimate the occurrence of cotton pests and illnesses in the future, allowing agronomists to take preemptive measures and reduce crop losses.

The proposed method (Noon et al., 2021), includes collecting a dataset of four cotton plant leaf disease classes and a deep learning framework based on eight versions of the EfficientNet-B0 and two versions of the MobileNet models. Core versions of each of these models were created to be computationally light so that the trained model could also run on mobile devices. After rigorous testing, we determined that our deep learning model based on modified EfficientNet-B0 converges the earliest and is the most accurate on our augmented cotton leaf dataset. The promising results can now be improved to propose a lightweight deep learning model for a big plant leaf disease dataset.

The Vis/NIR hyper spectral imaging equipment and machine learning approaches were employed in this suggested study (Yan et al., 2021), to identify aphid infection in cotton leaves. Spectra, RGB pictures, and hyper spectral images comprising a single leaf were used to create classification models. The spatial information in RGB and hyper spectral images might be obtained and the spatial region characteristics that influence categorization outcomes. It was recommended that 1D CNN be used to quickly and reliably diagnose aphid infection. In the visualisation of 2D and 3D CNN, the spatial regions of cotton leaves changed after aphid infestation was identified. 3D CNN combines the advantages of 1D and 2D CNN and can be used to identify aphid infection areas as well as key spectral regions. The impacts of CNNs in various dimensions were compared based on the exploration of CNNs in multiple dimensions on aphid infection. The classification results for aphid infection produced by 3D CNN were better than 2D CNN but poorer than 1D CNN.

This study proposed (Li & Yang, 2020), a few-shot pest recognition model and demonstrated its viability on an embedded terminal utilizing FPGA and ARM. The proposed model has two different steps: first, it may work effectively with very little input data, reducing the complexity of image collection and annotation; second, the CNN feature extractor trained by the triplet loss makes the model more resilient. The ARM is a powerful controller, while the FPGA is a calculator, and the system runs at 2 frames per second.

Author	Data Sets	Diseases/ Pests Names	Image Processing Steps	ML/DL Models Used	Feature Extraction	Results
[21]	20	Bacterial Leaf Spot, Target Spot	Image Acquisition, Image Segmentation (diseased, Healthy)	K-Means ANN	Contrast, Correlation, Energy, Homogeneity, Mean, SD, Variance	85%
[22]	140	Grey Mildew	Image Acquisition, Image Segmentation (Ground, Disease)	KNN, HUE HSV	Contrast, Correlation, Energy, Homogeneity Mean, SD, Variance Image gradient	82.5%
[23]	2	Anthracnose, Wilt	No Image Processing Steps	Decision Tree along with parameters using Arduino	No Feature Extraction	Classified the Labels
[24]	30	Cercospora Leaf Spot (CLS)	Image Acquisition, Image Preprocessing, Image Segmentation	HSI Format, SVM	Color, Texture	96%

[25]	900	Bacterial Blight, Alternaria, Gray Mildew, Cercospora, Fusarium wilt	Image Acquisition, Image Pre-processing, Image Segmentation, Color Mapping	SVM RaspberryPi and sensors are used	Color, Texture, Mean, SD	83.26%
[26]	18	Cotton Disease	Image Acquisition, Image Preprocessing, Image Enhancement, Image Segmentation,	ANN using MATLAB	Color, Texture	Detects that cotton is affected with diseases or not (0 or 1)
[27]	1498	Lygus Hesperus	No Image Processing Steps	MDP Bayesian Linear Mixed Model	No Feature Extraction	80%
[28]	2469	Pink Bollworms	Image acquisition, Image Classification	Single Short Detector	Image Boundaries	90%
[29]	600	Bacterial Blight, Spidermite, Leaf miner	Data Acquisition, Vectorization, Normalization, Image resizing, Image Augmentation	CNN K-Fold Cross-Validation	Color, Epoch	96.4%
[30]	63	Aphid, Jassid, Leaf Diseases, Thrios	Data acquisition, Data preprocessing	Apriori Algorithm, LSTM based on Environmental Factors	No Feature Extraction	83.9%
[31]	416	Whitefly	No Image Processing Steps	IOT, RBFN Based on Environmental Factors	No Feature Extraction	000

[32]	500	Cercospora, Bacterial blight, Ascochyta blight, and Target spot.	Image Acquisition, Image Pre-processing, Image Segmentation	DCNN Using MAT LAB	Color, Texture	96%
[33]	60,65 9	Lesion Leafs	Image Acquisition, Image Pre-processing	GoogleNetRes Net50	SD, correlation, third moment, uniformity, and entropy	86.6% 89.2%
[34]	1600	Anthonomus grandis, Aphis gossypii, Helicoverpa armigera, Heliothis virescens, Pseudoplusia includens, and Spodoptera frugiperda Alabama argillacea, Bemisia tabaci, Horcias nobilellus, Pectinophora gossypiella, Spodoptera Eridania, and Tetranychus urticae Helicoverpa armigera, Heliothis virescens, and Spodoptera frugiperda	Image Augmentation	RNN ResNet34*	No Feature Extraction	98%
[35]	2700	Spidermite	Data Acquisition, Data Pre-processing Data Segmentation	SVM, AlexNet	Color, Texture	97.1%
[36]	1000	Diseased Cotton	No Image Processing Steps	CNN	No Future Extraction	
[37]	15343	Bollworm Aphid, Jassid Thrips, Whitefly Spodoptera, Mealybug/Miridbug, LeafBlight /LeafSpot	No Image Processing Steps	Bi-Directional RNN with LSTM with climate factors	No Future Extraction	95%

[38]	1711	curl virus, bacterial blight, and fusarium	Data Acquisition, Data Augmentation	EfficientNet-B0 MobileNet	No Future Extraction	99.95%
[39]	256	Aphids	Image Acquisition, Image Pre-processing	Multi-Dimensional CNN	No Future Extraction	98%
[40]	500 100	American bollworm, Madeira mealybug, Amorphoidea-arcuata, Mango mealybug, Ash weevil, Megapulvinaria Blossom thrips, Melamphaus, Brown cotton moth, Menida, Brown soft scale, Menida-versicolor Brown-spotted locust, Monolepta-signata, Cotton aphid, Myllocerus-subfasciatus, Cotton leaf roller, Myllocerus undecimpustulatus, Cotton leafhopper, Painted bug, Cotton looper, Pink bollworm, Cotton stem weevil, Plautia-crossota, Cotton Stem Weevil , Poppiocapsidea, Cream drab, Red-banded shield bug,	Image Acquisition, Image Pre-processing	CNN FPGA ARM	No Future Extraction	95.4% 96.4%

		Cutworm, Red cotton bug, Darth maul moth imago, Red hairy caterpillar, Darth maul moth, Solenopsis mealybug, Desert locust, Spherical mealybug, Dusky cotton bug, Spotted bollworm imago, Giant red bug, Spotted bollworm, Golden twin spot tomato looper, Tobacco caterpillar, Green stink bug, Tomentosa Grey mealybug, Transverse moth, Hermolaus, Tussock caterpillar, Latania scale, Yellow cotton scale,				

Table 2: Cotton diseases and pests processing table

Divergence and Detention

Subsequent to looking over the exploration papers on cotton pests and diseases, the breach had occurred in the previous research works. Some of the techniques had no accuracy for classifying pests and diseases without proper sample datasets [13-15]. Multi-class detection of plant diseases and pests has not been taken, and usage of pesticides recommendations and remedies were not given properly to the agronomists [16]. Most of the researchers had not used mobile applications to make robust decisions for the detection of pests and diseases [24-32]. Researchers used the techniques on fewer pests and diseases names to identify crop yield. No proper enhancement of optimization and monitoring on pests and diseases for getting a better crop yield. Researchers need top notch images with various shapes, backgrounds, and sizes and light intensity to accurately predict and detect pests and diseases [21]. Researchers need more standard data sources which can be used for multiple datasets; subsequently, it tends to be done in a quicker space. Some of the scientists had not considered the climate

factors to foresee the impact of pests and diseases on the crop.

7. Conclusion

Support Vector Machine algorithm of ML used few images to offer better performance and accuracy than other algorithms, Whereas Efficient-B0, MobileNet deep learning algorithms offered better performance and accuracy than other algorithms. This paper reviews ML and DL-based research efforts applied in cotton crops for classification and detection. After identifying the relevant paper, examined and focused on the pests and diseases datasets used, pre-processing tasks and data augmentation acquired, ML and DL algorithms they used, and accuracy according to the performance metrics employed by the researcher.

In the future work, the following steps are enhanced. First, apply the best suitable algorithm and image processing techniques using AI to solve the issues discussed in the gap session. Second, we collect the different types of pests and diseases datasets for classification, prediction, and accuracy. Finally, Collect the pesticides datasets and classify the pesticides to be suitable to the particular pests and diseases. To provide the recommendations and remedies to the agronomists robustly and portably to apply in all these steps.

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