Pests and Diseases Detection of Cotton Crops Using Artificial Intelligence based Techniques: A Review

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Abstract: Cotton is a commercial and fiber crop that generates profit for agronomists. 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 previous researches has been carried out 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 study, as well as overall performance based on the various metrics used. Our findings shows that machine learning and its advanced learning techniques outperform traditional image processing techniques in terms of exactness and other viable methodologies.

Key-words: Cotton Pests and Diseases, Soil Degradation, Machine Learning, Agronomists, Image Pre-processing, Segmentation Techniques.

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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, 2021). 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., 2022). 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., 2021).

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., 2023) (Liakos et al., 2020). 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., 2022.). 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, 2024). 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.

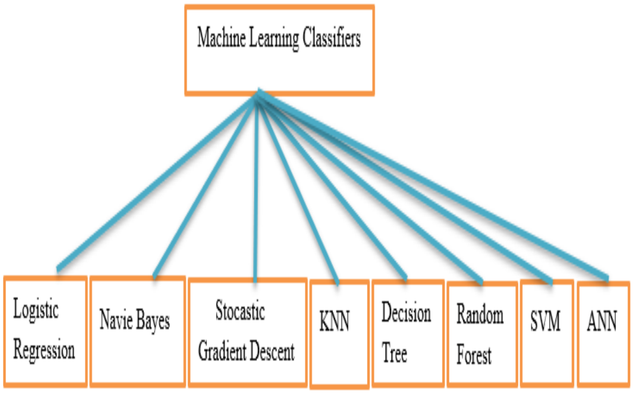

Fig 1: Machine Learning Algorithm Classifiers (Meisner, 2021)

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.

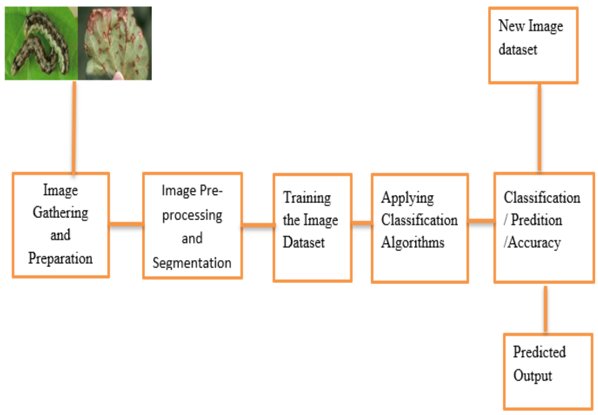

Fig 2: Machine Learning Process on Cotton Pests and Diseases (Shah, 2021)

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., 2024) (Kamilaris & Prenafeta-Boldú, 2022) (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., 2023). 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.

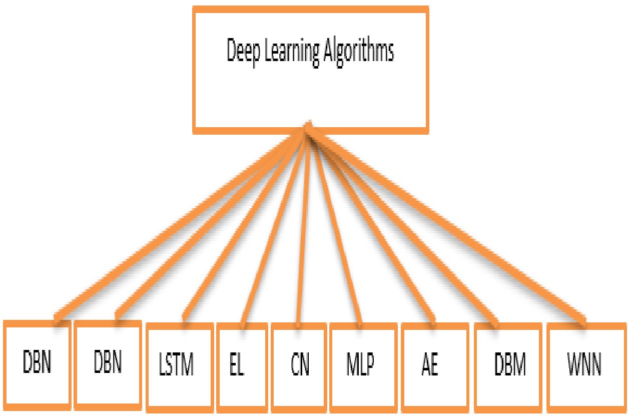

Fig 3: Deep Learning Algorithms(Shakeel, 2020)

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., 2022).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.

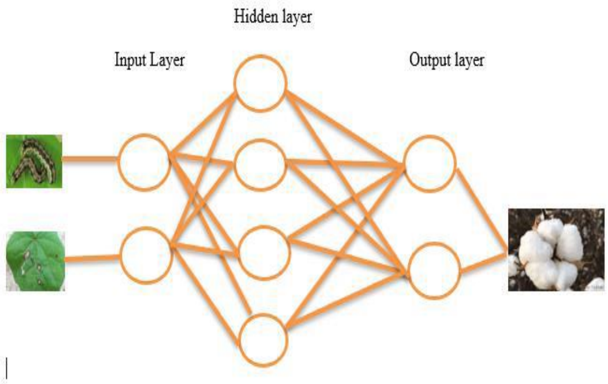

Fig 4: Deep Learning Process on Cotton Pests and Diseases (Xiao, 2020)

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

3.2 Related Works

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.

The research work conducted by (Parikh et al., 2016) aimed to provide information regarding the detection of severity estimation in cotton plant disease and Grey Mildew disease detection. 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.

Furthermore, the study carried out by (Sarangdhar & Pawar, 2017) used IoT to develop a model for detecting and controlling five different cotton leaf diseases. 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.

According to (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 pre-emptive measures and reduce crop losses.

The work of (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.

Moreover, a study proposed by (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.

4. Methodology

This section shows how, the ML and DL in the cotton crop were classified into two sections, including disease and pest detection. The reviewed works 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.

4.1 Machine Learning to Identify and Classify Pest Images

With the advancement of science and technology, the amount of image data is increasing, along with the time required to classify the image data. Therefore, scholars are studying how to use machine learning to recognize and classify images. Machine learning is divided into supervised learning and unsupervised learning, the main difference being whether or not the machine is able to automatically extract features from the data structure.

i. Supervised Learning

During the machine training process, it is necessary to provide machines with labeled data. For example, after a machine has seen 1,000 labeled images of apples and oranges, we can give a test image and asked whether the image contains apples or oranges.

ii. Unsupervised Learning

There is no need to label the data in advance, and the machine does not know whether or not the result of its classification is correct during learning. The machine must find the rules from all of the input examples in order to classify on its own.

In summary, supervised learning adds artificial labels to the input data and uses regression analysis methods to obtain the predicted results. Unsupervised learning finds suitable patterns from a large amount of data through algorithms and classifies the data automatically.

4.2 Deep Learning to Identify and Classify Pest Images

Deep learning is based on the machine learning framework, so the training process first involves unsupervised learning and clusters the training data set to learn what sort of data will be classified. Supervised learning is then performed to label the expected output value of each entry with the feature vectors in the training data set given as input and the expected classification given as the output. . Finally, the loss function is used to calculate the standard deviation between the expected output and the actual output.

There are two common approaches in deep learning for pest identification and classification. The VGG19 method for image feature extraction and recognition in the detection of 24 types of pests from crop images.

Furthermore, 12 different pests were detected and classified using several CNN approaches and compared the classification results with machine learning methods such as SVM and Fisher. The classification accuracy of the machine learning method was 80%, and the classification accuracy rate of the CNN method was 95%.

i. **Supervised Learning:**
Recurrent Neural Networks (RNN): Well-suited for sequence data, effective in capturing temporal dependencies.
Long Short-Term Memory Networks (LSTM): A type of RNN that captures long-term interdependence by solving the vanishing gradient problem.
Convolutional Neural Networks (CNN): Well-known for tasks involving images, but it may also be used for analyzing spatial patterns in network data.

ii. Unsupervised Learning:
Unsupervised models for data compression and feature learning.
Generative Adversarial Networks (GAN): Commonly used to create new data samples, it consists of a generator and discriminator.

iii. Hybrid Learning:
Capsule Networks: Designed to increase hierarchical pattern recognition efficiency.
Deep Reinforcement Learning: Adaptive learning in dynamic environments, where decisions are made in response to continuous input.

4.3 Using Image Augmentation to Increase the Pests Training Sample Database

Data augmentation methods can be roughly divided into Geometric Transformation and Photometric Transformation methods. Ding and Taylor. studied the impact of different data augmentation methods on image recognition rate. Three geometric transformations (flipping, rotating, and cropping) and three luminosity transformations (color jittering, edge enhancement, and fancy principal component analysis). The amplified image samples and the original image samples are used as training data for training on the CNN model. The experimental results showed that each amplification method improves the accuracy of CNN, where the impact of cropping is the most obvious. Therefore, the authors speculate that the training samples generated by the cropping method will avoid the over-fitting of data and improve CNN performance. In addition to augmenting the images by geometric and photometric transformations, it is also possible to transform the image style through the CycleGAN or transfer the features of objects to other objects to increase the number of training samples. The aforementioned apple anthracnose identification research uses the CycleGAN to increase the number of training samples and improve the accuracy of image recognition. Perez and Wang's research (supplementary source of literature) have also found that geometric transformation and brightness variation of image and CycleGAN are able to enhance the image recognition accuracy.

4.4 Identify the Location of the Pest with the Target Detection Model

With the advancement of technology and the development of artificial intelligence, deep learning has significantly increased the efficiency of image recognition, resulting in many different artificial intelligence models that have encouraged the development in image recognition technology.

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 can be enhanced. First, apply the best suitable algorithm and image processing techniques using AI to solve the issues discussed in the gap session. Additionally, different types of pests and diseases datasets for classification, prediction, and accuracy can be improved.

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