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Research Article

A Comprehensive Review of Crop Disease Identification Through Modern Artificial Intelligence Technology

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Abstract: India is a developing country. The 65% of India's people live in villages, whose main occupation is agriculture. India has certainly made progress in the field of information technology. The IT advancement and technology is direct impact on agriculture. After the advent of the 21st century, modern agricultural technology got a boost in India. In the present era, farmers are moving towards farming using modern and scientific methods. AI based technology is the foundation of modern technology. Equipped with modern equipment and applications for prevention of pests and diseases in crops. The AI technology quickly and speedily identify the diseases occurring in crops can very easily treated with accuracy high accuracy. In this review, we have studied a lot of AI and their sub-domain machine learning (ML) method application in agriculture, especially on crop leaf diseases. ML technology can be used to identify leaf disease in the captured images.

Keywords: Machine Learning, Tomato disease, CNN, Artificial Intelligence (AI), Agriculture, Disease, Food Crops

1. Introduction

India is an agricultural country; agriculture is the main occupation of the farmers of India and source of income. The agriculture has also big impact in Indian economy. The main reason for poor production of crops in agriculture is insects and diseases affecting the crops. Diseases occur in crops due to changes in weather and lack of nutrients. Insects and bacteria found in crops spoil the crops and make them sick. More than 30% of people around the world are employed in the agriculture sector, which has a direct or indirect economic impact on a country. Artificial Intelligence (AI) has the potential to revolutionize this industry [1]. Adoption of advanced modern technologies use Artificial Intelligence can help in overcoming these challenges by early identification of crop diseases. Crop Disease Detection (CDD) and Prevention is based on AI and ML. This technology has operated through smart mobile phones and connect to modern IoT devices, which are high resolution cameras, drones and agrometeorology equipment. By creating a large database of images or data captured through cameras, drones, AI devices, processing and comparing the images from the data base will provide accurate and fast results. One of the most widely used AI technologies in crop disease is ML. ML algorithms, such as convolutional neural network (CNN), K-Nearest Neighbor (K-NN), Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF) and Deep Belief Network (DBN) have been applied to the classification of crop diseases from digital images. [2]. In this technologically advanced era, with AI, there are many mobile apps available for CDD, diagnosis and management, each with a variety of features. These apps need to be classified and reviewed following a proper framework that ensures their quality. This study aims to present an approach to evaluating plant disease detection AI based methods, which includes providing ratings of distinct features of the apps and insights into the exploitation of AI used in CDD [3]. These functionalities combine AI, image processing techniques, grading methods, ML and novel neural network (NN) like deep learning (DL) to provide information about a large range of crop varieties and their diseases. The DL technique has been applied. are supported by image data-sets. The application of AI is enhanced by technological advances in ML, Machine Vision, DL, NN. Technology has become complementary with agriculture in today ‘s world by the virtue of progress in development like robots, temperature and moisture sensors, drones, devices, machines, GPS development and information advancement [1].

Agriculture is an essential industry to meet the basic food needs of the world's growing population. Identification of plant diseases appears to be an important task that must be performed in agriculture. Detecting the presence of infection in plants is an important issue in the agricultural business because of how often diseases harm them. To identify diseases in the leaves, it is necessary to observe and regulate the plant processes. This constant factory inspection takes a lot of time and labor of human labor. An interesting way could be to use modern digital farming technology to quickly and easily identify plant diseases [4].

2. Related Work

The foundation of the research review papers selected
1. Papers related to DL and ML algorithms and methods.
2. Papers also related to crop disease detection

CDD mentioned by Anwar H et al. [5] Wheat rust disease (WRD) is extremely detrimental to wheat crop health and it severely affects the crop yield, increasing the risk of food insecurity. Artificial intelligence (AI) and deep learning (DL) offer efficient and accurate solutions to such real-world problems. To overcome this limitation, in this work, they introduce an annotated real-world semantic segmentation dataset named the NUST Wheat Rust Disease (NWRD) dataset. in experiments, promising results were obtained using the UNet semantic segmentation model and the proposed adaptive patching with feedback (APF) technique, which produced a precision of 0.506, recall of 0.624, and F1 score of 0.557 for the rust class. In the future, we plan to improve the preprocessing module and the detection pipeline, which will consequently improve the segmentation results. Plant disease studies by Hasan M et al. [6] Early diagnosis of rice disease detections and classifications using CNN & RGB images processing methods. This technique proposes to detect rice disease of rice brown spot, rice bacterial blight and leaf smut with reliable outcomes in disease classifications. The model is trained using an augmented dataset of 2700 images (60% data) and validated with 1200 images of disease-affected samples to identify rice disease in agricultural fields. The model is tested with 630 images (14% data) testing accuracy is 97.9%. Gonitijo da Cunha et al. [7] Worked on only rice disease to bacterial spot, early detection of tomato bacterial spot disease utilizing remote sensing and artificial intelligence. The five datasets had a total of 1640 spectral reflectance points, 757 of them related to diseased plants and 883 of them related to Healthy plants of rice. In this study, five optimized machine learning algorithms (MLAs), such as Linear Discriminant Analysis (LDA), Partial Least Squares Discriminant Analysis (PLSDA), Weighted K-Nearest Neighbours (W–KNN), Support Vector Machine (SVM), and Ensemble Boosting Tree (EBT), were utilised for early detection of TBS in transplant houses. he highest weighted spectral components for accurately detecting TBS-affected plants. The PLSDA model presented the highest F1 score (90%) on early detection of TBS. Plant Disease Detection Using Deep Convolutional Neural Network by Pandian J Arun et al. [8] In this research, they proposed a novel 14-layered deep convolutional neural network (14-DCNN) to detect plant leaf diseases using leaf images. A new dataset was created using various open datasets. The dataset consists of 147,500 images of 58 different healthy and diseased plant leaf classes and one no-leaf class. Three image augmentation techniques were used: basic image manipulation (BIM), deep convolutional generative adversarial network (DCGAN) and neural style transfer (NST). The proposed DCNN model achieved 99.9655% overall classification accuracy, 99.7999%weighted average precision, 99.7966% weighted average recall, and 99.7968% weighted average F1 score. In the future, we plan to estimate the possibility of plant disease and analyze the severity using the deep learning technique. Moreover, we will extend disease detection from plant leaves to other parts of the plants, such as flowers, fruits, and stems. Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications by Andrew J et al. [9] Early diagnosis of plant diseases using accurate or automatic detection techniques can enhance the quality of food production and minimize economic losses. in this paper, he utilized convolutional neural network (CNN)-based pre-trained models for efficient plant disease identification. We focused on fine tuning the hyperparameters of popular pre-trained models, such as DenseNet-121, ResNet-50, VGG-16, and Inception V4. The experiments were carried out using the popular Plant Village dataset, which has 54,305 image samples of different plant disease species in 38 classes. A comparative analysis was also performed with similar state-of-the-art studies. The experiments proved that DenseNet-121 achieved 99.81% higher classification accuracy, which was superior to state-of-the-art models. Bhuvaneshwari S et al. [4] discuss ML and DL methods to recognize plant diseases. applying deep learning techniques and algorithms to identify fruit leaf disease has a lot of potential in modern agriculture. The research employs cutting-edge algorithms such as Xception, Inception V3 and ResNet-50, which produce good accuracy. The proposed architecture called Leaf Network (LNet) produces improved efficiency than the above listed Convolutional Neural Networks. As a result, Leaf Network (LNet) has an accuracy of 98.68% compared with all four Algorithms. In future work, its performance can be improved by addressing it. It may be extended for vegetables and field crops in future. Harakannanavar S et al. [10] The use of technologies like Computer vision and Machine Learning (ML) helps to fight against diseases. The idea behind the paper is to bring awareness amongst the farmers about the cutting-edge technologies to reduces diseases in plant leaf. Tomato is merely available vegetable, the approaches of machine learning and image processing with an accurate algorithm is identified to detect the leaf diseases in the tomato plant. Finally, the extracted features are classified using machine learning approaches such as Support Vector Machine (SVM), Convolutional Neural Network (CNN) and K-Nearest Neighbor (K-NN). The accuracy of the proposed model is tested using SVM (88%), K-NN (97%) and CNN (99.6%) on tomato disordered samples. Arunabha M Roy et al. [11] In this paper, a deep learning enabled object detection model for multi-class plant disease has been proposed based on a state-of-the-art computer vision algorithm. The proposed model has been improved to optimize for both detection speed and accuracy and applied to multi-class apple plant disease detection in the real environment. The mean average precision (mAP) and F1-score of the detection model reached up to 91.2% and 95.9%, respectively, at a detection rate of 56.9 FPS. The overall detection result demonstrates that the current algorithm significantly outperforms the state-of-the-art detection model with a 9.05% increase in precision and 7.6% increase in F1-score. an improved model based on the start-of-the-art YOLOV4 algorithm has been utilized for disease detection. Plant Disease Detection using Deep Learning by Chohan M et al. [12] plants are affected by several disease caused by bacteria, fungi and virus. The model is able to detect several diseases from plants using pictures of their leaves. Plant disease detection model is developed using neural network. First of all augmentation is applied on dataset to increase the sample size. Later Convolution Neural Network (CNN) is used with multiple convolution and pooling layers. PlantVillage dataset is used to train the model. We have performed different experiments using this model. 15% of data from PlantVillage data is used for testing purpose that contains images of healthy as well as diseased plants. Proposed model has achieved 98.3% testing accuracy. Maniyath S et al. [13] The Modern approaches such as machine learning and deep learning algorithm has been employed to increase the recognition rate and the accuracy of the results. This paper makes use of Random Forest in identifying between healthy and diseased leaf from the data sets created. Our proposed paper includes various phases of implementation namely dataset creation, feature extraction, training the classifier and classification. feature vectors are extracted for the test image using HoG feature extraction.

3. Methodology

The review work started with background information on crop disease identification, mitigation, and prevention using machine learning (ML) and deep learning (DL) techniques. In the current research work, we have reviewed the following AI technologies.

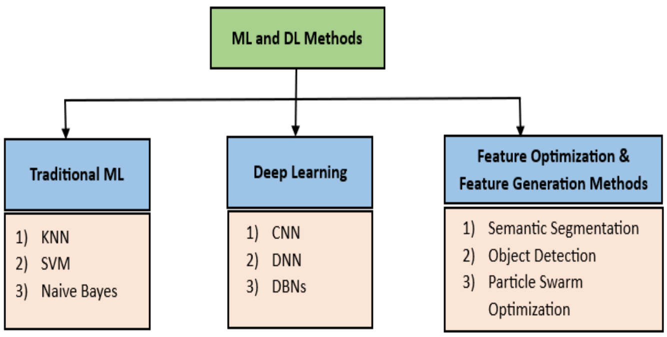

Figure 1. Machine Learning (ML) and Deep Learning (DL) Methods

3.1 Traditional ML Techniques

Machine learning and deep learning are branches of AI. In AI, traditional machine learning and deep learning techniques are often being used for crop disease identification in agriculture. Traditional ML approaches that have been used significantly for crop disease detection include feature extraction and classification. These techniques take features from images, such as color, texture, and shape, and use them to train a classifier to distinguish between healthy and unhealthy crops.[14].

3.1.1 K-Nearest Neighbors (K-NN)

It is one of the most basic classification methods applied to machine learning scenarios. For example, it relies on and performs classification by identifying the nearest neighbors for the target and determining the type of query to be performed for the benefit of these neighbors. It determines the shortest distance between a specific point and other points in K-NN classification. To classify a plant leaf, the distance between the training and test samples is calculated [15].

3.1.2 Support Vector Machine (SVM)

A supervised machine learning approach called Support Vector Machines (SVM) can be applied to problems involving regression and classification. However, it is usually applied to classification challenges. Using this process each data item can be viewed as a point in n-dimensional space, where n is the number of features you have and the value of each feature is a certain coordinate. We then perform classification by finding the hyper-plane that effectively divides the two classes [16].

3.1.3 Naive Bayes (Statical Methods)

In AI, the Naive Bayes classifier is a supervised machine learning (ML) algorithm used for classification tasks, such as text classification. It solves classification problems and is based on the Bayes theorem. Naive Bayes is a probabilistic classifier and the basics of Bayesian statistics, being able to estimate parameters more easily makes Naive Bayes a simpler classifier. There are statistical methods like SVM and NB used various authors in their works.

3.2 Deep Learning

A branch of machine learning called "deep learning" uses multiple high-level abstraction layers to model the ideas of deep neural networks. This skill has made agricultural management more thoughtful [17]. In recent years, deep learning (DL) has emerged as a promising, new and innovative method for data processing. It can be seen as an advanced form of artificial neural network (ANN), which is a widely used AI technique nowadays.[18]. DL is a ML technique that builds ANNs to imitate the way the brain functions., DL is also known as deep structured learning or hierarchical learning, and it uses layers of hidden data, usually more than six, although non-linear processing is generally greater to extract characteristics from data and to transform the data at various levels of abstraction. DL has been used in a variety of industries including agriculture [19].

3.2.1 Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is created, trained, and used for classification purposes. To achieve the best performance in disease recognition, the CNN is fine-tuned by changing layers and adjusting additional parameters [20]. This comprehensive solution uses modern image processing techniques and machine learning algorithms to improve leaf disease detection and management. [20]. Deep neural networks, particularly Convolutional Neural Networks (CNN), have been shown to produce excellent results for image recognition.[21] CNN -based networks can be trained to detect disease in plants by providing them with a large number of images of healthy and sick plants, and the trained model can later be used to predict disease in plants using images of plant leaves.[22]. The CNN model is widely used in deep learning. The key to CNN's advantage in image identification is its enormous model capacity and rich information created by its fundamental structural features. Simultaneously, CNN's achievements in computer vision tasks have contributed to the growing recognition of deep learning.[23].

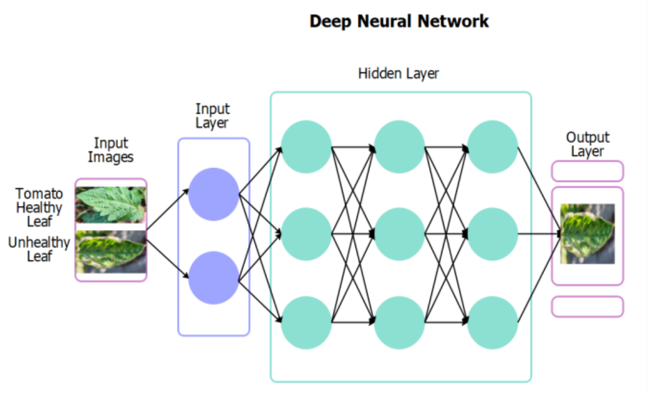

Figure 2. Architecture of CNN

This CNN architecture shows two classes of tomato leaves: healthy and unhealthy.

3.2.2 Deep Belief Networks (DBN)

Deep Belief Network (DBN) is recognized as a deep learning method, mostly used for feature extraction and classification. Using a sequence of weights w = w1, w2, ...wl, the DBN learning method obtains the weights w and uses them iteratively to train the entire network. Finally, an unsupervised restricted Boltzmann machine (RBM) is used to combine the connection weights with a back propagation learning process. Using the labeled training dataset, this learning enables proper gradient determination. It then modifies the parameters for the best possible output layer classification, providing feedback for gradient reduction. Finally, the DBN is applied to predict the instance for classification with the least error [24].

3.3 Feature Optimization and Generation

Feature optimization is the process of reducing the number of features to reduce the computation complexity and increase the performance of a machine learning model. [25]. This method works by estimating the basic function or connection between the data to be input and the output. The basic purpose of training a machine learning system is to minimize the amount of error between the expected and actual output.

The process of creating new features from already existing features is known as feature generation. Finding new combinations and representations of our data that can be helpful for machine learning models is the purpose of feature generation.

3.3.1 Image Classification

The deep learning-based image recognition technology is more robust and accurate at recognizing images than other methods because it does not require the extraction of specific features; instead, iterative learning is used to find the right features. This allows the technology to acquire both global and contextual features from images [23].

3.3.2 Semantic Segmentation

Image segmentation is the process of separating the image into pixels and their related features. It creates a high-level image by transferring the low-level image. The effectiveness of an image analysis primarily hinges on the accuracy of the segmentation procedure. The process of segmentation incorporates contextual and non-contextual elements. The segmentation procedure makes use of multiple algorithms [26]. Classify leaf diseases to extract useful segments. Genetic algorithm is used to complete the component segmentation process, it is used to detect leaf disease.

3.2.3 Object Detection

Object detection is one of the most widely researched tasks in computer vision. Object-level classification models classify images based on specified object classes.[27]. Deep learning-based methods for detecting plant diseases and pests in agricultural applications contain three major links: data labeling, model training, and model inference. Model inference receives increased attention in real-time agricultural applications. One of the most fundamental challenges in computer vision is object positioning. Additionally, it is the task that is most similar to traditional pest and plant disease detection. Its goal is to get precise information about the object's position and category.[23].

3.3.4 Particle Swarn Optimization (PSO)

Eberhart and Kennedy first presented PSO (Particle Swarm Optimization), which is used to optimize continuous nonlinear functions. It was discovered by simulating the social behaviour of bird block. Every one of the velocities of volume less particles that make up the swarm indicates a workable solution in the set of solutions. Through particle movement within the solution space, the algorithm determines the best possible solution [28]. Previous years have seen a lot of activity in this field of research and development. Machine learning methods may be helpful in identifying the disease. Using an ensemble learning classifier based on combination rules and voting techniques, a novel feature optimization technique called PSO (average probability) is proposed [29].

4. Results and Discussion

In study we investigated the different work in AI and ML their significant contribution in the field of agriculture. In the investigation compared the methodology, dataset, result and their best finding in year wise.

In this investigation we specially focus on tomato leaf disease the models are compared. This model based on ML and AI algorithm to detect and classify images. The table I shows the major finding of different researchers they all give results.

Table.1. Existing model in Machine Learning Methods and their performance

Authors & Year	ML and DL Methods			Ref.
	Dataset Details	***Methodology***	***Result%***	
Anwar H, Khan S (2023)	Analyzing large amounts of dataset of wheat crop	Segmentation model, adaptive patching with feedback (APF)	produced a precision of 0.506, recall of 0.624, and	[5]

Authors & Year	ML and DL Methods			Ref.
	Dataset Details	*Methodology*	*Result%*	
		technique	F1 score of 0.557 for the rust class	
Hasan M, Rahman T (2023)	Augmented dataset of 2700 images (60% data) and validated with 1200 Images	Convolutional neural network (CNN), RGB value using image processing	The model is tested with 630 images (14% data); testing accuracy is 97.9%	[6]
Gonitijo da Cunha V, Hariharan J(2023)	Total images of 1640	(MLAs), (LDA), (PLSDA), (WeKNN), (SVM), (EBT),	PLSDA model received the highest F1 score (90%)	[7]
Pandian J, Kumar V (2022)	Total 147,500 images	14-DCNN, MGPUs, BIM	DCNN model accuracy 99.9655% Precision 99.7999%, recall 99.7966%, weighted average F1 score 99.7968%	[8]
Andrew J, Eunice J (2022)	54,305 image	CNN,, DenseNet-121, ResNet-50, VGG-16, and Inception V4	DenseNet-121 achieved 99.81% accuracy	[9]
Bhuvaneshwari S, Surendiran R (2022)	12854 images	Xception, Inception V3 and ResNet-50, Leaf Network (LNet),	(LNet) has an accuracy of 98.68%	[4]
Harakannanavar S, Rudagi J (2022)	Tomato leaves	SVM, CNN and K-NN.	CNN accuracy 99.6%	[10]
Arunabha M Roy, Bhaduri J (2021)	Apple plant with multi-class	RCNN	F1-Score 91.2%	[11]
Chohan M, Khan A (2020)	Plant Village dataset is used	CNN	98.3% accuracy	[12]
Maniyath S, Vinod P (2018)	large data sets	SVM, Gaussian NB, LR, LDA, RF And Histogram of an Oriented Gradient (HOG).	RF accuracy 70.14	[13]

According to Table I researcher have worked many architectures and models in the field of agriculture dataset. Researchers have been used for many different datasets in their research work conducted. The below table II shows accuracy and finding best in table I summary.

Table.2. Summary of best finding in table (I)

S.No.	Accuracy and compared different Architecture's	
	Architecture	*Accuracy (%)*
1.	CNN	99.60
2.	SVM	90.00
3.	DCNN	99.79
4.	DenceNet	99.81
5.	KNN	97.00
6.	LNet	98.68
7.	RF	70.14

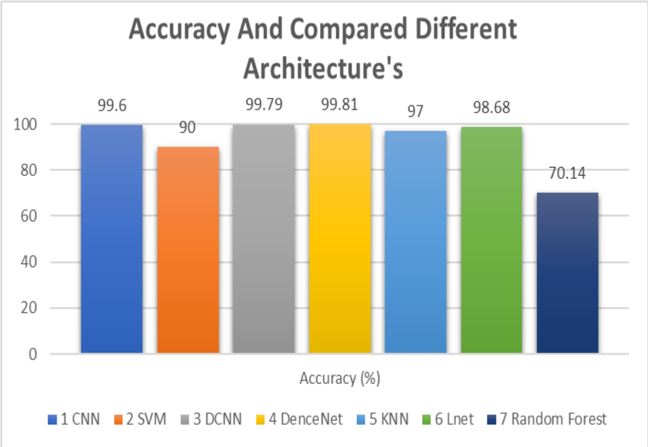

Figure 3. Accuracy and compared with different Architecture

In this bar chart 3 shows the performance of different models. A graph shows the comprehensive review of various researchers have been done in their related research work into the insect and diseases of agriculture.

5. Conclusion and Future Scope

The ML based different classifications algorithms are described based on their finding. The finding of their work they used different classification algorithms, CNN, K-NN, SVM, RF, NB, DenseNet, LNet, Object detection, and statistical methods. All authors have achieved the results with high accuracy using ML method in crop disease identification, their experimental results are very interesting and supporting the researcher's. In the future, real tomato datasets will be collected with higher resolution using advanced data capturing technology. Applying these with alternative datasets will make tomato crop disease identification models more robust, accurate, fast, and computationally efficient. The collected dataset will be applied in many ML algorithm. The ML algorithm will be hyper-tuned and optimize. Implementing the Real Tomato Disease dataset (RTDD). The RTDD will be applied in disease detection model in field of agriculture.

Conflict of Interest
The authors declare no conflict of interest.

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