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MACHINE LEARNING IN AGRICULTURE FOR CROP DISEASES IDENTIFICATION: A SURVEY

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ABSTRACT

The field of computer science known as machine learning is used to create algorithms that have the ability to self-learn or learn on their own. This is how the phrase "Machine Learning" came to be. Artificial intelligence in-cludes a subfield called machine learning. These days, machine learning and deep learning techniques are frequently used to classify and recognize leaf diseases. Recognizing leaf disease at an early stage is crucial in agricultural fields for all crops. Accurate disease detection at an early stage helps farmers boost production and their economy. The suggested study is a survey of more than 40 research papers that classify and identify plant leaf diseases using various machine learning and deep learning algorithms. It also discuss-es machine learning, its application to agriculture, as well as its benefits and drawbacks. Develop an automatic disease detection system for leaf disease classification and detection using web-based or mobile-based applications for future work. Using this survey to build a more accurate model for leaf disease classification and detection using machine learning with a wide range of datasets. This will be very beneficial for farmers to boost productivity and build their economies.

Keywords: Agriculture, Classification of Crop, Crop Diseases Detection, Disease in Agriculture, Farming, Leaf Disease, Pest Disease Identification

1. INTRODUCTION

For about 58% of Indians, agriculture is their primary source of income. India is among the top three countries in the world for producing grains like rice and wheat. Presently, India ranks second in the world for the production of several dry natural goods, horticulture-based raw materials, roots, and tuber crops, beats, farmed fish, eggs, coconut, sugarcane, and various vegetables. The fact that 166 million (56.6%) of the country's 313 million basic specialists are employed in "Horticultural and allied exercises" highlights the country's dependence on agriculture. Disease issues are causing a steady decline in the number of individuals working in agriculture and a migration to other industries. For the purpose of the feature, improving crop productivity and making farmers more prosperous economically are both crucial for ensuring human food security.

Most frequently, a plant's breakage and irregular growth are indicators of disease. The causes of infections can be both living and non-living. Organisms, bacteria, and infections are examples of living things that can spread biotic infections. Anti-microbial diseases are brought on by non-living environmental factors like soil compaction, wind, trees, salt damage to the soil, and supporting roots.

Pathogens, which are living things that cause plant diseases, must be harmful. A pathogen that is capable of generating certain plant diseases may qualify as a destructive pathogen. Some germs may lack the vigor to produce illnesses. This is probably the case. Bacterial infections in plants occur when pathogens, which are thought to be dangerous, get inside the plants through holes in the plant tissues. For any plant infections to occur, the environment where the pathogen and the plant will associate must be favorable Plant diseases cannot be completely eliminated, however, they can be managed and reduced while staying within a certain budget.

Early plant disease detection and halting disease transmission across the field are essential for increasing crop output. Animals and plants are harmed by plant diseases, which also affect agricultural output and market accessibility. Crops dis-eases day by day decreases crop production and yield.

Here are various crop production and yield statistics are broken down by the state in India.

Figure 1

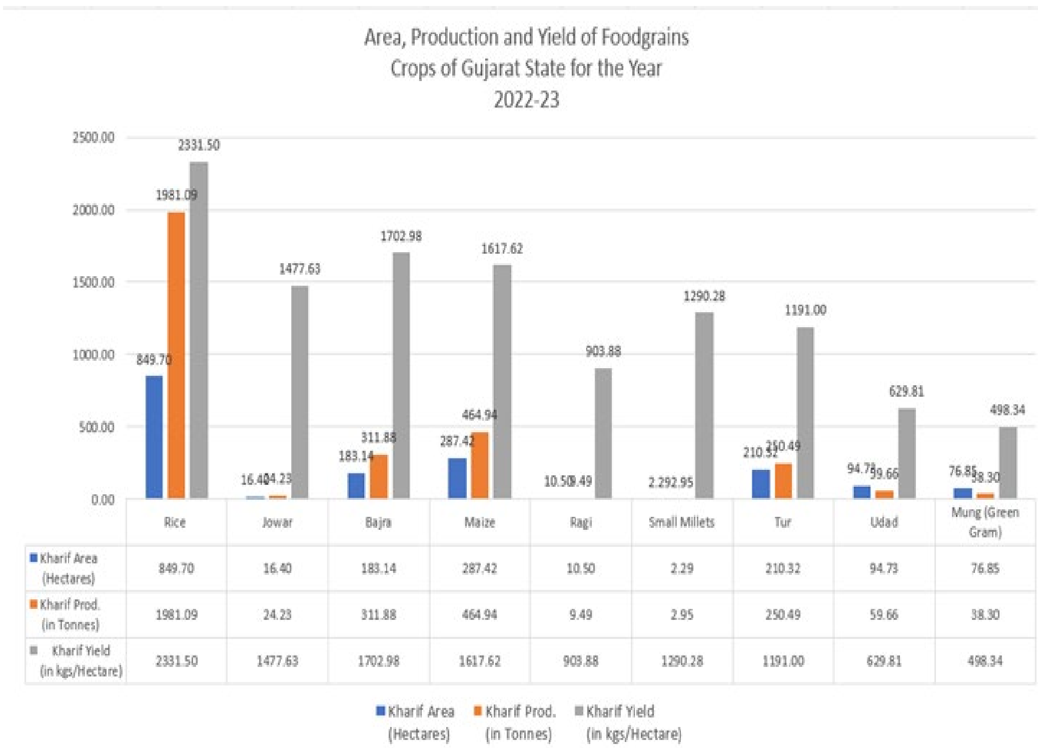


Figure 1 Crops with Oil Seeds: Area, Production, and Yield of Gujarat State for the Year 2022-23.

Figure 2

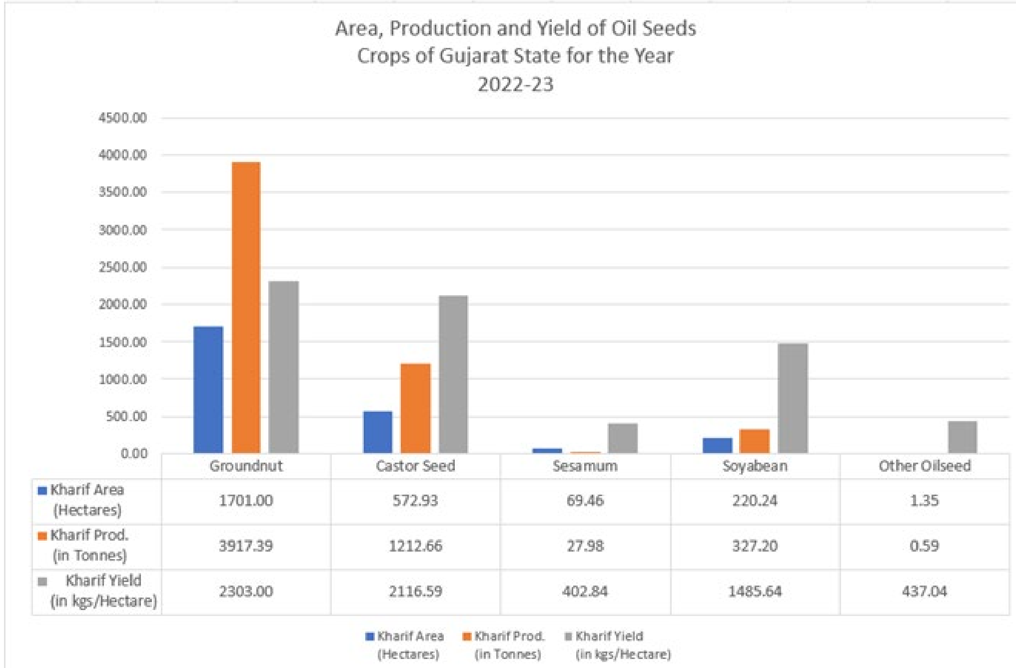


Figure 2 Crops Grown for Food: Their Area, Production, and Yield of Gujarat State for the Year 2022-23.

Additionally, some data regarding the yield and output of several crops during the previous few years is included below.

Figure 3

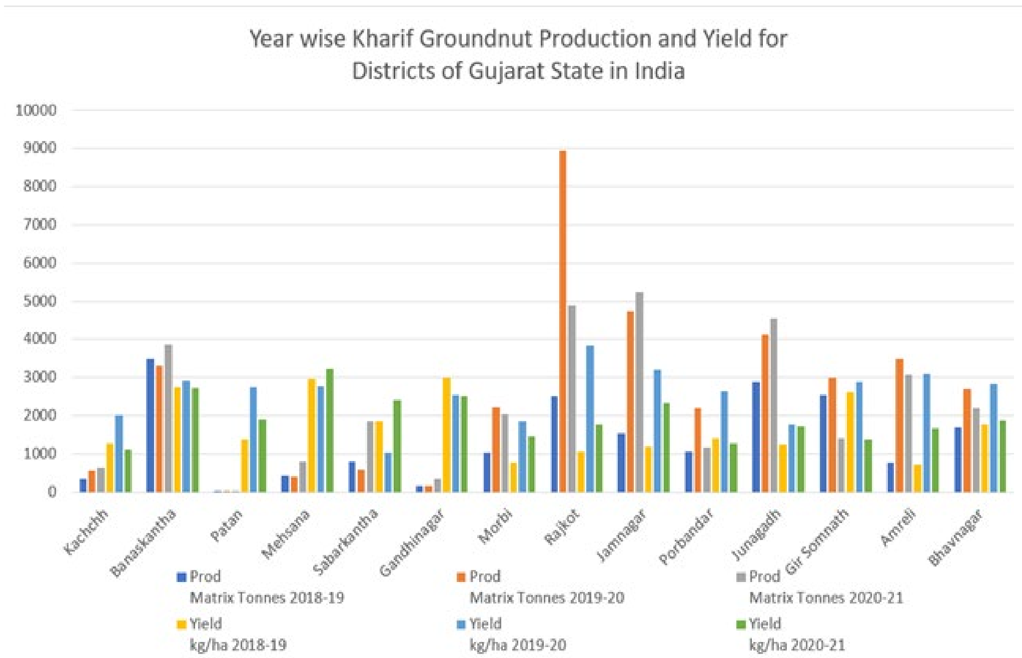


Figure 3 Area, Production, and Yield of Rice Production

Figure 4

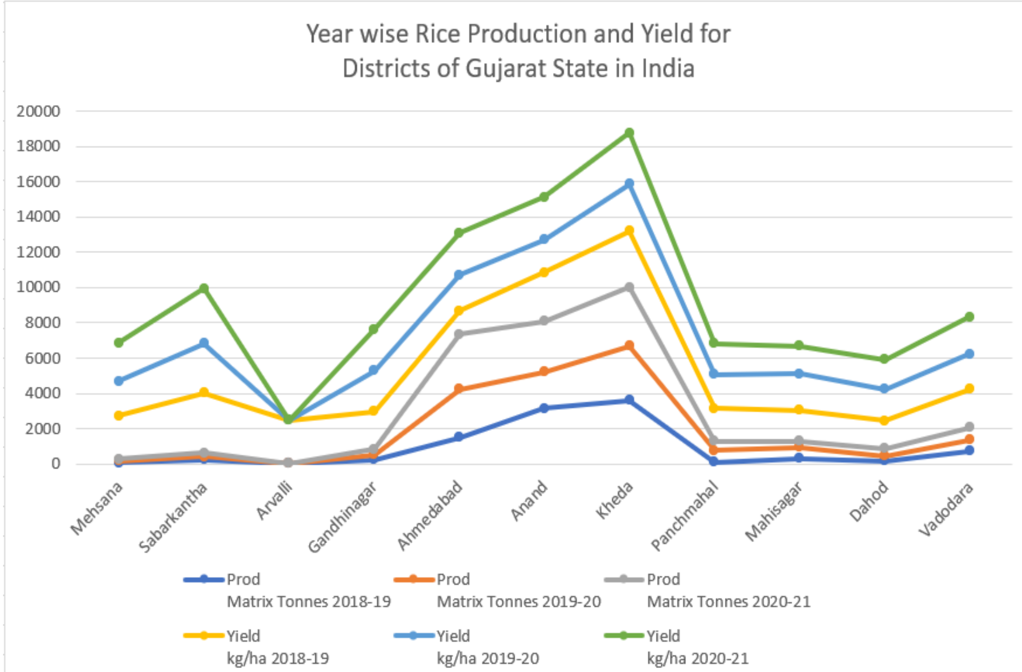
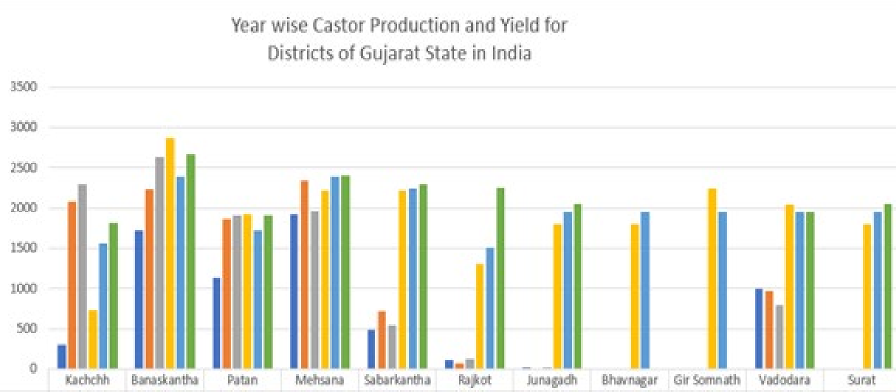


Figure 4 Year-Wise Kharif Groundnut Production and Yield

Figure 5



	Kachchh	Banaskantha	Patan	Mehsana	Sabarkantha	Rajkot	Junagadh	Bhavnagar	Gir Somnath	Vadodara	Surat
Prod Matrix Tonnes 2018-19	298.25	1722.16	1130.73	1929.37	495.27	121.37	14.87	3.15	4.87	992.25	3.18
Prod Matrix Tonnes 2019-20	2082.97	2235.75	1871.19	2336.69	714.71	80.91	9.35	1.71	2.04	970.43	2.35
Prod Matrix Tonnes 2020-21	2291.57	2638.96	1905.81	1960.38	541.79	124.4	20.13	0	0	796.04	1.81
Yield kg/ha 2018-19	726.81	2868.93	1917.27	2212.99	2218.76	1310.28	1808.65	1808.65	2243.8	2036.67	1808.65
Yield kg/ha 2019-20	1559.24	2395.87	1722.52	2389.84	2248.28	1512.04	1944.24	1944.24	1944.24	1947.09	1944.24
Yield kg/ha 2020-21	1814.4	2669.23	1913.7	2408.48	2297.49	2254.06	2060.26	0	0	1949.18	2060.26

Prod Matrix Tonnes 2018-19 · Prod Matrix Tonnes 2019-20 · Prod Matrix Tonnes 2020-21 · Yield kg/ha 2018-19 · Yield kg/ha 2019-20 · Yield kg/ha 2020-21

Figure 5 Year-Wise Cotton Production and Yield

Figure 6

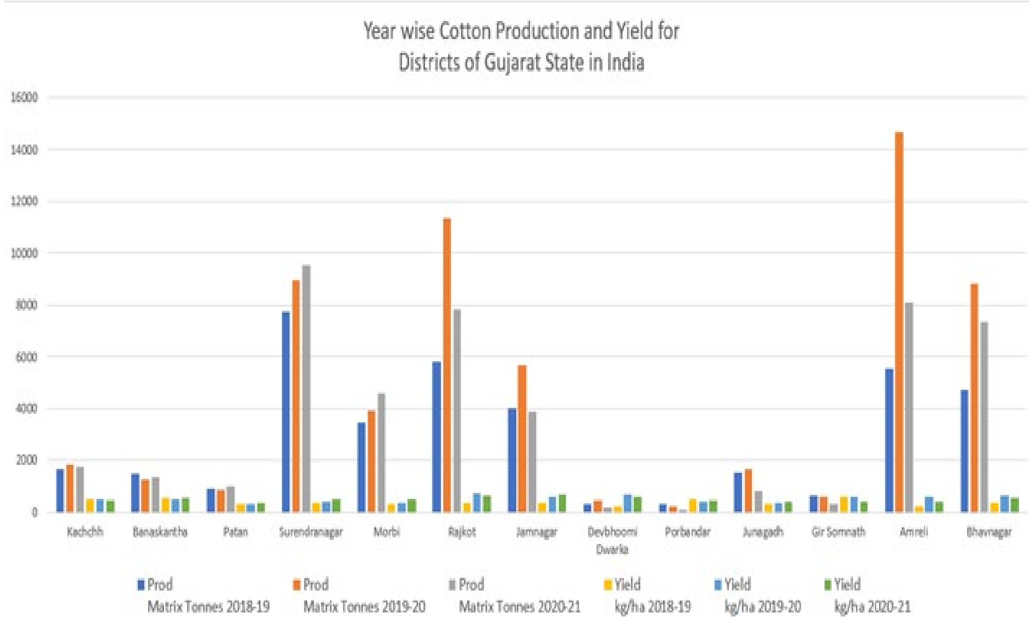


Figure 6 Year-Wise Castor Production and Yield

Based on the above statistics, in agricultural field day by day production of crops is decreasing. Statistics showing about year wise (last five years) crop production and yield of cotton, Castor, Groundnut, Rice, Foodgrains, and Oilseeds. The main objective is the need to develop a machine learning or deep learning-based model for the classification and detection of leaf disease.

The following sections include the remaining portions of this research. The what work that has been done till now was covered in Section 2, while Section 3 discussed machine learning. Section 4 discusses machine learning, its benefits, and drawbacks, as well as aspects of machine learning in agriculture. Finally, section 5 discusses the conclusion and the feature scope of the machine learning-based study.

2. RELATED WORK

The most recent years' worth of contemporary methods are included in the litera-ture reviews.

Saleem et al. (2019a), this paper shows the distinguished 13 diverse sorts of diseases in plants with the assistance of CaffeNet CNN engineering with an accuracy provided of 96.30% which was way superior to previous methods like SVM. Leaf illnesses on peanuts were identified by HSI recognizing touchy groups and hyperspectral vegetation files Saleem et al. (2019b).

Singh et al. (2020), this paper shows a general survey of the different methods of infection recognizable proof. It also provides a brief overview of unique imaging techniques useful for quickly identifying plant diseases. In this paper, their diverse calculation is utilized and it is precision like K-means Clustering & Neural Network with it accuracy of 80.2% also gay level co-occurrence matrix accuracy of 98.46%, SVM Classifier-98.46%, Quick Highlight Extraction Method-Image Spectroscopy-89.3%, Fluorescence acceptance, and ghostly Reflection Strategy-93% Singh et al. (2020).

Ullah et al. (2020a), this paper demonstrates using Convolutional Neural Network (CNN) to distinguish a few plant maladies using 38 distinctive classes containing 14 distinctive plants like Apple, Blueberry, Cherry, Orange, Potato, Corn, Grape, and Tomato Precision of the demonstration was 97.33% Sri Eshwar College of Engineering, & Institute of Electrical and Electronics Engineers. (n.d.). [1]

Kaleem et al. (2021a), Leaf diseases discovery strategy is presented in this paper by using an advanced approach using Machine Learning based support vector machine classifier. In this paper division, classification, and the highlight of extraction of diseases and their characteristics are the vital steps within the present approach. In this paper, their distinctive calculation is utilized and its precision is like K-Means and SVM-95.46%, ANN-79.96% Kaleem et al. (2021b).

Abade et al. (2021), this paper shows about plant diseases are recognized using convolutional neural networks to create visuals. This presented a different kind of plant disease and how the plant disease detection system work, also showing the evolution of CNN architecture. This paper also included basic ideas about transfer learning with some research questions Abade et al. (2021).

Patil and Burkpalli. (2021), this paper presents image classification for cotton leaves using machine learning algorithms. The classification of cotton diseases using machine learning is demonstrated in this paper, along with the extraction of various features from segmented images, such as color and texture features, using various machine learning algorithms, such as Random Forest and Support Vector Machine, Ada Boost, K-nearest Neighbor, and Naive Bayes. In this paper, color features show the classification of healthy and diseased, cotton leaf images with an accuracy of nearly about 96.69% which is more than as com-pared to another classifier. Images from real fields and a database of 3000 images with 2 groups of healthy and diseases were used to classify cotton leaf diseases Patil and Burkpalli (2021).

Raghavendra et al. (2021a), this paper discussed multiple disease classifications and detection for different plant leaves using a support vector machine. Image processing techniques are used in this research for the detection and classification of plant leaves Raghavendra et al. (2021a).

Ghosh et al. (2021a), This study covered the topic of applying a deep learning algorithm to detect disease in leaves. This paper discussed Bell Pepper and Tomato Plants. For these two plants used the CNN algorithm and transfer learning model to detect disease and also evaluate standard parameters like precision, recall, and F1-score. For this paper, the training data size, testing data size, and validation data size were respectively 80%, 12%, and 8% also the accuracy of these two plants is 96.5% using CNN architecture and 98.7% using DenseNet121 Ghosh et al. (2021b).

Manjula et al. (2022), this paper discussed disease detection in plants using deep learning. In this used digital images for plants to detect disease, more than 15% of images were taken from the plant village dataset. This paper used CNN Architecture for the detection of disease leaves and this model achieved an accuracy of 98.3% at the time of testing Manjula et al. (2022).

Nigam et al. (2021a), this paper discussed disease identification of wheat using a deep learning algorithm. In this paper more than 2000 images of wheat to identify disease. To identify wheat diseases, the CNN algorithm was used to detect the diseases and provide a much higher accuracy of this model. For the development of this model Caffe, Tensorflow, and Keras Frameworks with python libraries are used. In this paper, the CNN model identified wheat disease with 97.37% accuracy. Nigam et al. (2021a)

[1] https://ieeexplore.ieee.org/abstract/document/9117284

Table 1

Table 1 A Survey of the Literature on Current Deep Learning (DL) and Machine Learning (ML) Research

Authors and year	Name of Crop	Model Used	Number of Images	Model Accuracy
Saleem et al. (2019b)	Tomato	AlexNet, GoogleNet, ResNet		97.28%
Asad and Bais (2020)	Canola	VGG16, ResNet50	906	98.69%
Sladojevic et al. (2016)	13 different types of plant	CNN	4483	96.30%
Picon et al. (2019b)	Wheat	CNN	8178	96%
Patil (2021)	Cotton	Naïve Bayes, Random Forest, SVM, K-NN, AdaBoost	3000	96.69%
Ullah et al. (2020b)	Blueberry, Cherry, Grape, Corn, Potato, Orange, Peach, Bell, Strawberry, Raspberry, Soyabean, Tomato, Squash,	CNN	217204	97.33%
Raghavendra and Sathish (2021b)	Cucumber	Multi-vector SVMs	4128	81.03%
Kaleem et al. (2021b)	Cotton, Tomato, Coconut, Brinjal, Papaya, Chilli, Maize	SVM GLCM, K-Means Clustering	120	95.46%
Ferentinos (2018)	Tomato	CNN, ALexNet, VGG	87848	99.63%
Krishnaswamy and Purushothaman (2020)	Tobacco	MSVM, VGG16	1088	99.40%
Barbedo (2019)	Common Bean, Cassava, Citrus, Wheat, Sugarcane, Corn, Kale, Coffee, Cotton, Coconut Tree, Soyabean, Cashew Tree, GrapeVines	GoogleNet CNN	46409	94%
Hang et al. (2019)	Apple	CNN, VGG16	6108	91.70%
Chowdhury et al. (2021)	Tomato	EfficientNet	18161	99.95%
Rubini and Kavitha (2021)	Tomato	VGG16, DenseNet	17200	92%, 98.25%
Zeng et al. (2020)	Citrus	GAN	14056	92.60%
Ashwinkumar et al. (2021)	Tomato	optimal mobile network-based convolutional neural network (OMNCNN)	5452	98.70%
Caldeira et al. (2021)	Cotton	SVM, KNN, ANN, NFC	39215	80.30%, 71.10%, 76.60% 78.80%
Ahmad et al. (2020)	Fruits	CNN, AlexNet, VGG16, InceptionV1, InceptionV3	1000	92%
Xian and Ngadiran (2021)	Tomato	Extreme Learning Model (ELM)	1000	91.43%
Ghosh et al. (2021b)	Bell Pepper, Tomato	CNN, DenseNet121	18114	96.5%, 98.7%
Dyrmann et al. (2016)	Barley, Sugar Cornflower, Common Poppy Cleavers, Thale Cress, Tobacco, Cabbage family, Black Nightshade, Beet, Maize, Wheat, Annual Nettle, Broad-leaved grasses	Deep CNN	10413	86.20%

Agarwal et al. (2020)	Tomato, Potato, Grapes,	CNN, KNN, VGG16	55000	98.70%
Karthik et al. (2020)	Tomato	Residual CNN	50402	98%
Singh (2019)	Sunflower	Particle swarm optimization algorithm		98.00%
Ramesh and Vydeki (2018)	Rice	ANN	300	99%
Nigam et al. (2021b)	Wheat	CNN	2000	97.37%
Da Silva Abade et al. (2019)	Apple, Strawberry, Grape	Multichannel CNN ALexNet, GoogleNet	54306	99.59%
Tulshan (2019)	Plant Leaves	KNN	225	98.56%
Sri Eshwar College of Engineering, & Institute of Electrical and Electronics Engineers. (n.d.)	Turf grass, Wheat, Rice plant	SVM, ANN	100	98%, 92%

Figure 7

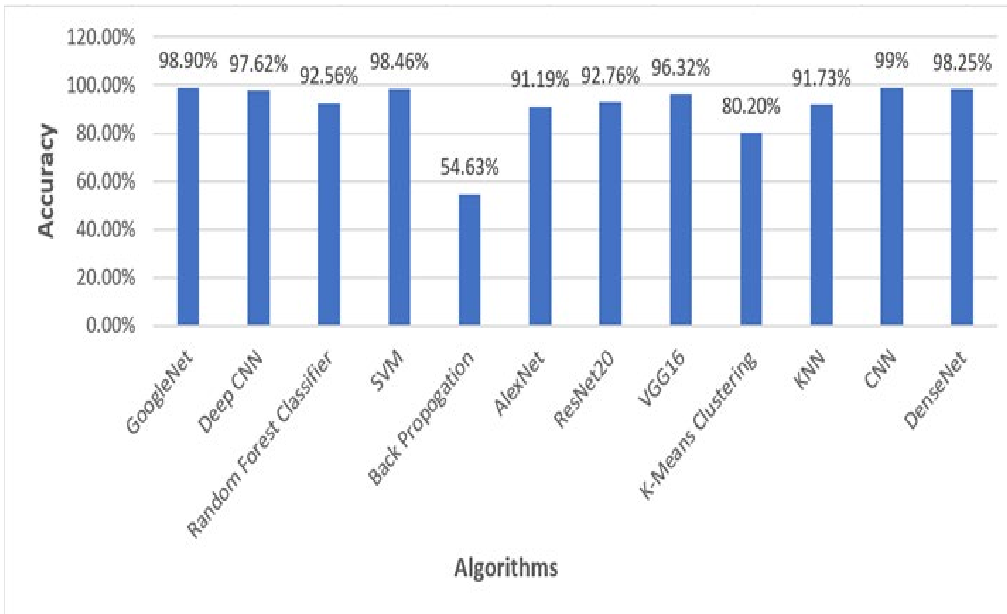


Figure 7 Categories Algorithm for Deep Learning and Machine Learning

Numerous methods have been used by researchers to identify diseases. The study discussed in this part provided us with an overview of various strategies used for a broad range of crops. Statistics demonstrate that machine learning algorithms provide excellent accuracy for disease identification. The table below demonstrates the classification techniques' accuracy for disease detection for various crops. Bajait and Malarvizhi, N. (2020)

3. MACHINE LEARNING

A subfield of computer science and artificial intelligence (AI) called "machine learning" aims to describe human learning by using data and algorithms to gradually increase a system's accuracy. To provide classifications or projections in data mining projects, algorithms are trained using statistical methodologies. Machine learning algorithms are typically created using accelerated solution development frameworks like TensorFlow and PyTorch.

Machine learning, a cutting-edge field of research, enables computers to learn on their own using past data. In order to build mathematical models and generate predictions based on previously collected data or information, machine learning applies a range of methodologies. At the moment, it is used for a variety of purposes, such as recommender systems, email filtering, Facebook auto-tagging, image identification, and speech recognition.

Machine learning is becoming more and more necessary because it can carry out tasks that are too complex for a person to undertake directly, machine learning is required. We need computer systems because it is difficult for us to manually access such a large amount of data, and machine learning can be useful in this situation.

4. DISCUSSION

Our research has demonstrated that ML performs significantly better in the vast majority of similar tasks.

4.1. USE OF MACHINE LEARNING IN AGRICULTURE

Regression analysis will be used to estimate the crop yield of an algorithm's land. In order to identify various crop species, a classification system will be used. Using a classification technique, to distinguish between crops and weeds by utilizing a classification algorithm, low-cost pest management can be carried out. To predict the weather using a forecasting algorithm. To improve the decision-making process.

4.2. ADVANTAGES OF MACHINE LEARNING

Increased data production quickly. solving difficult-for-a-human to solve complex challenges in decision-making in different sectors, including finance. Finding hidden patterns and eliminating informational content from data.

4.3. DISADVANTAGES AND LIMITATIONS OF MACHINE LEARNING

Despite its many benefits and growing popularity, machine learning isn't flawless. The following elements restrict it:

4.3.1. DATA GATHERING

Large, thorough, for machine learning training, fair and improved data sets are required. They might occasionally have to wait while new data is generated.

4.3.2. TIME AND MATERIALS

For machine learning to be effective, the algorithms must have enough time to mature and learn adequately to accomplish their goals with a high level of rele-vance and accuracy. Additionally, it consumes a lot of resources to operate. As a result, you may need a machine with more processing power.

4.3.3. ANALYSING THE RESULTS

The capacity to correctly analyze the data that the algorithms produce is another significant challenge. Additionally, you must pick the algorithms for your goal wisely.

4.4. FEATURES OF MACHINE LEARNING IN AGRICULTURE

Agriculture is already starting to benefit significantly from machine learning (ML), which will increase its effectiveness and efficiency. Data collection, processing, and analysis are key components of precision agriculture, which aims to increase agricultural productivity. A wide range of applications for machine learning in agriculture has the potential to produce excellent outcomes, including the detection of weeds and diseases, the prediction of crop yield and quality, the gathering of data, the generation of insights, and the forecasting of animal output.

The key to protecting crops from severe loss is early disease identification. Some farmers constantly examine the leaves or branches of trees as they grow in order to spot diseases, or they frequently apply pesticides to all crops equally in an effort to prevent infections. Both tasks are grounded on human experience, which is dangerous and prone to mistakes.

Which insecticide to use, when to apply it, and where to administer it depends on the type of disease, its stage, and the afflicted area. Applying pesticides to all crops without need may be harmful to both the crops and the farmers' health. Farmers can apply the proper pesticide at the appropriate time and location with the use of precision agriculture. Numerous studies combined the prediction of pesticides with the detection of plant disease.

Researchers should test their models against more realistic and generic datasets to show how well they can generalize to other real-world scenarios. For compara-tive purposes, the authors must adopt a variety of widely used performance indi-cators, including those listed in Table 1. It would be preferable if researchers made their datasets accessible to the public so that other researchers may use them. Last but not least, several of the solutions offered in the articles examined might soon be applied commercially.

5. CONCLUSION

In this study, we conducted a survey of agricultural machine learning research projects. We have found 40 publications that are relevant by analyzing the prob-lem and topic they address, the models they use, the data sources they utilized, the pre-processing tasks they used, the data augmentation strategies they used, and their overall performance as measured by the performance metrics they used. Then, in terms of performance, we evaluated machine learning in comparison to other methods already in use. Our findings demonstrate that machine learning outperforms other popular image processing techniques and provides superior performance.

In our upcoming work, we plan to extend the fundamental ideas and recommended methods of machine learning to more fields of agriculture where this cutting-edge strategy has not yet been successfully used. To overcome a range of computer vision and image analysis–based, or more generally–data analysis–based, categorization and prediction issues in agriculture, we hope that this sur-vey will inspire additional scholars to try machine learning.

The general advantages of machine learning are encouraging for its continued application to more intelligent, sustainable agricultural and secure food production.

For future courses, a comprehensive think about is required to get the variables influencing the location of plant infections. Requirements to work on the ad-vanced algorithm for eliminating problems due to classification also need an expert system like a mobile-based application for disease identification and de-tection

CONFLICT OF INTERESTS

The authors confirm that they have no known financial or interpersonal conflicts that would have appeared to have an impact on the research presented in this study.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Hirenkumar Kukadiya: Conceptualization, Investigation, Methodology, Data collections, Writing - original draft. Dr. Divykant Meva: Conceptualization, Supervision, Validation, editing.

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