Deep Learning for Crop Disease Detection: Techniques and Challenges

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Abstract: Crop diseases are an imminent threat to the world's food security since they are so common, which makes accurate and efficient detection techniques necessary. Through image analysis, deep learning—more specifically, convolutional neural networks (CNNs)—has emerged as a game-changing method for recognizing and categorizing plant diseases. Recent developments have shown how well deep learning models work to interpret intricate patterns in agricultural data, offering encouraging answers to persistent problems with crop disease identification. This review looks at the newest methods and discusses the challenges that come with using these technologies, like inconsistent disease symptoms, high computing needs, and poor data quality. This research emphasizes the significant influence deep learning could have on improving agricultural practices and safeguarding crop health by examining recent achievements and prospective future advancements.

Keywords: Deep Learning, Crop Disease Detection, Convolutional Neural Networks (CNN), Agricultural Technology, Plant Pathology, Image Analysis, Machine Learning in Agriculture, Precision Farming

I. Introduction

The World Bank emphasizes the importance of agricultural development in reaching global development goals, pointing out that it will be necessary to alleviate extreme poverty, promote shared prosperity, and feed a projected 10 billion people by 2050 [2]. Food security and national income, particularly in emerging nations, are largely dependent on agriculture, according to the International Atomic Energy Agency [3]. Food insecurity, which is frequently caused by poverty, hinders a nation's capacity to expand its agricultural markets and economies, according to the National Institute of Food and Agriculture. Growth in the agriculture sector is also very successful in alleviating poverty[4]. The World Economic Forum emphasizes the need for immediate assistance for the world's most undernourished people as well as the necessity for modern agriculture to reform in order to enhance productivity without damaging the environment[5].

Crop diseases pose a serious threat to the agriculture industry, which is essential to human civilization. Plant diseases must be identified early and accurately to be managed and controlled effectively, which can greatly reduce the negative effects on crop quality and output. Deep learning has been popular as a potent weapon in the fight against crop diseases in recent years. Convolutional neural networks (CNNs) are one type of deep learning model that has demonstrated exceptional success in recognizing disease trends from complicated agricultural datasets by utilizing sophisticated algorithms and computational methodologies. This review paper explores the cutting-edge deep learning methods that are revolutionizing the field of crop disease diagnosis and addresses the obstacles that need to be addressed before these methods can be fully utilized in real-world applications [1].

More than a century ago, with the introduction of the first tractor in 1913, technology was brought to agriculture. With so much commercial technology available today, mechanical technology has undergone an astonishing transformation [6].Reduced need for human labor was the outcome of this productivity boost. That might not be sufficient, though, to meet global demand in the coming years. Precision agriculture is a farm management concept that was developed in the 1990s to increase production efficiency. It is based on crop variability observation, measurement, and action, with the aim of maximizing returns while conserving resources[7].

The idea of "smart farming" emerged more recently as a result of the application of widely used industry technology to agriculture, including robotics platforms, Internet of Things (IoT), and remote sensing[8]. In order to meet the difficulties of agricultural production with regard to sustainability, food security, productivity, and environmental effect, smart farming is crucial. Analysis and comprehension of agricultural ecosystems are required to address these issues, and this calls for ongoing variable monitoring. Massive volumes of data are produced as a result, some of which require real-time processing and storage[9].

Images that can be analyzed using various image analysis techniques to identify plants, diseases, etc. in various agricultural situations can make up this data. Support vector machines (SVM), K-means, and artificial neural networks (ANN) are a few machine learning-based image processing approaches[10]. Deep learning (DL) is a contemporary technique that has been successfully applied across numerous domains. As a subset of machine learning methods, DL shares similarities with artificial neural networks (ANNs) but offers enhanced learning capabilities, leading to higher classification accuracy[11].Several techniques utilizing specialized hardware, such as Field-programmable Gate Arrays (FPGA) [13] and Graphics Processing Units (GPU) [12] are employed to expedite the processing duration of intricate deep learning models. A large number of recent research studies utilizing deep learning in agriculture can be found in the literature due to the field's exponential expansion. In light of the hardware used to operate the program, this paper reviews recent applications of DL approaches to several agricultural sectors.

II. Concepts of deep learning:-

The simplest definition for these three fundamental terms may be as follows.

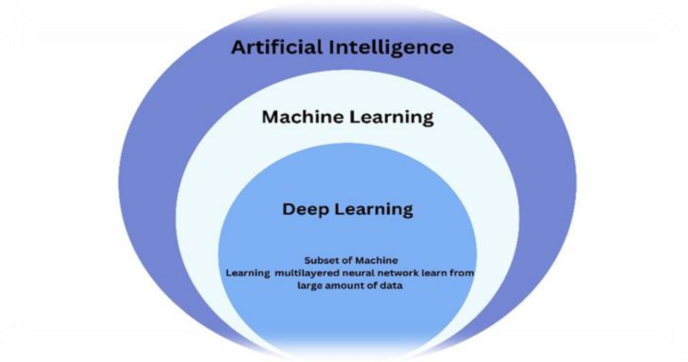

Fig 1: Deep Learning

2.1 Artificial Intelligence:- Method for developing software that imitates human behavior. Frequently used in projects when the intended systems demonstrate the capacity to reason, learn, generalize, or derive meaning.

2.2 Machine Learning:- A subset of Artificial Intelligence. creates statistical methods so that computers can learn and get better over time.

2.3 Deep learning (DL):- A subset of machine learning is called deep learning., characterized by the use of multi-layer neural networks (NN). These algorithms excel at interpreting unsorted data by leveraging patterns and features they have learned. Inspired by the basic principles of brain biology, deep learning is particularly effective when dealing with large quantities of input data.

In the early days of computer vision systems, developers relied on methods such as the [96] and [97], which did not utilize neural networks (NN). These methods, though relatively complex, were based on straightforward reasoning. As computer hardware advanced, the first techniques employing neural networks began to emerge. The time required for training simple neural networks reduced dramatically, from months to mere minutes or hours. The most significant breakthrough in applying neural networks to computer vision tasks was the development of Convolutional Neural Networks (CNNs), specifically designed for image recognition.

Machine learning approaches based on artificial neural networks (ANNs) include DL as a subset. Deep learning has several uses, including image processing and natural language [14]. Research in a variety of fields, including agriculture, has seen the successful application of various deep learning architectures, including Fully Convolutional Networks (FCN), Recurrent neural networks (RNN), Convolutional neural networks (CNN), and Recursive neural networks, Deep Neural Networks (DNN), and Deep Belief Networks (DBN). Multiple layers of abstraction in DL allow for a hierarchical representation of data, extending the complexity of ANN. Higher levels of image processing, for instance, are capable of identifying objects or faces, but lower levels are limited to identifying edges.

ReNet, VGG, AlexNet, and GoogleNet are well-known deep learning models that are freely accessible for research. An advantage of these models is that the majority of them have previously undergone pre-training on public data sets, meaning the network is prepared to recognize multiple features.

DL has experienced great success in a number of industries recently, including agriculture. DL can utilize datasets for feature extraction more effectively than other learning algorithms. Because of its usefulness, DL is getting more and more popular among scholars for their study projects. In this section, we mostly go over the development of DL and provide various cutting-edge models and techniques.

DL is an ML technique that creates artificial neural networks (ANNs) that mimic brain activity. In reality, DL is sometimes referred to as deep structured learning or hierarchical learning. To extract features from data and alter it at different levels of abstraction, it uses layers of hidden data, typically more than six, though non-linear processing is typically more.

The general research methodology. At the beginning, 10 scholarly databases were searched using keywords in light of our particular review objectives. To choose the review's primary goal, filters were employed. This section presents an overview of the DL models that are applied in agriculture. DL models that are not relevant to the agriculture industry are therefore not taken into consideration here. We examined the models' relationship to DL after they had been filtered. We next looked at these models. Ultimately, it is apparent what happened.

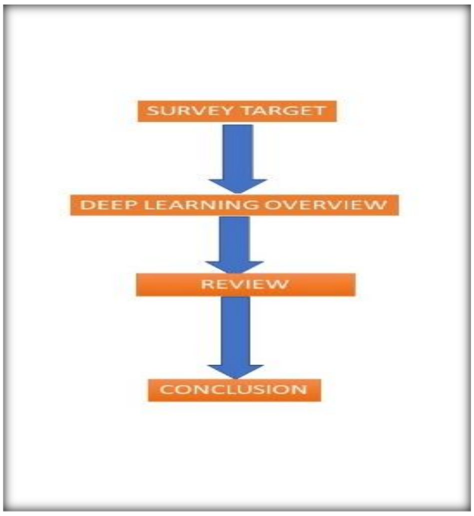

Fig 2: Research method flowcart

III. Development of Deep Learning:-

Two parts constitute the entire DL evaluation [16]. Between 1943 to 2006 was the first phase, and from 2012 to the present is the second. Both periods have seen the discovery of numerous new technologies and algorithms.

The start of DL occurred in 1943. A threshold logic was provided by Walter Pitts and Warren McCulloch [17] to copy human thought processes. Next, it established the framework for ANN [18–21] and DL.Rosenblatt Frank (1957) invented the perceptron [22].Rosenblatt presented a unique McCulloch-Pitts neuron [23, 24] that he called the "Perceptron," which was capable of autonomously learning binary categorization.

Henry J. Kelley's initial implementation of the continuous backpropagation paradigm [25]. Although his model is based on Control Theory [26, 27], it paves the way for future advancement and will be used in ANN. Instead of using other generic rules that were in use in the past, Stuart Dreyfus demonstrated backpropagation using the chain rule [28].

Neocognitron [29], the first CNN [30,31] architecture designed to identify patterns in visual data, such as handwritten letters, was proposed by Kunihiko Fukushima.

Geoffrey Hinton, Rumelhart, and Williams effectively implemented backpropagation [32] in a neural network in 1986. It made it possible for researchers to train enormous DNNs quickly [33], which was previously a significant barrier. Yann LeCun [34] used backpropagation to teach a CNN how to detect handwritten numerals.

In a paper they released in 2006, the authors of [35] introduced DBN. Training with a lot of data is significantly more efficient.

The DL community has always had difficulty locating sufficient labeled data. This is the reason Stanford scholar Fei Fei Li founded ImageNet [36] in 2009. There are 14 million properly labeled photos in ImageNet. Alex Krizhevsky created the GPU-implemented CNN model known as AlexNet in 2012 [37]. With an accuracy of 84%, it took first place in the ImageNet image categorization competition. When compared to other results, it showed the greatest accuracy gain.

Next, Ian Goodfellow created GAN [67]. The ability of GAN to synthesize data that is representative of the actual world creates new opportunities for the use of DL in the domains of science [70], fashion [68], and art [69]. A human champion and Deepmind's DRL model competed in the game of Go [71] in 2016. where a deepmind's DRL model defeated the human champion. This is a significant accomplishment for the DL community.

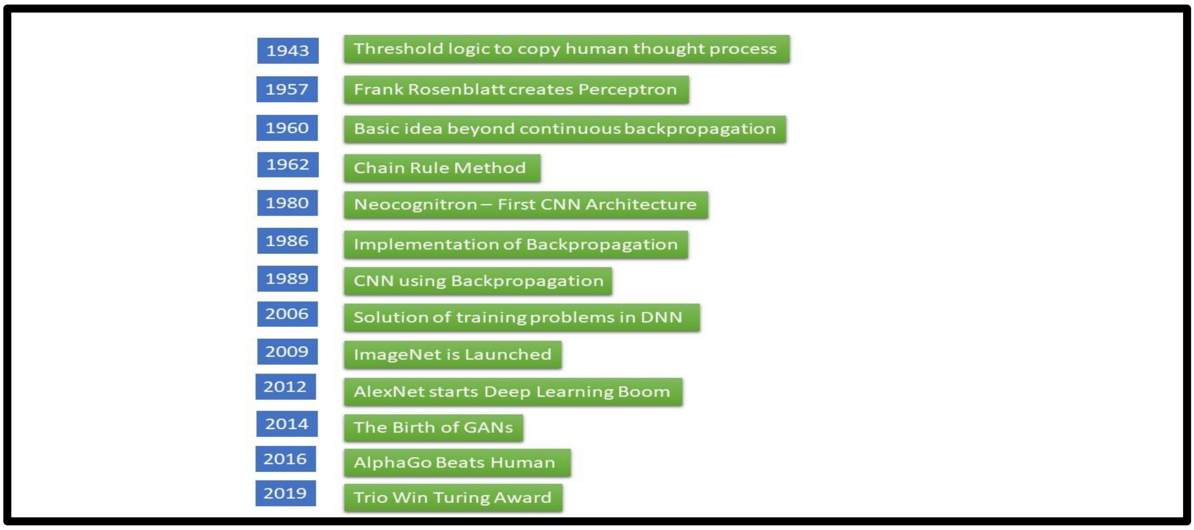

Fig 3: Deep Learning evolution from 1943 to 2019

IV. Analysis of Learning

Data is analyzed by DL, a subset of ML, using a hierarchical neural network. These hierarchical neural networks, which resemble the human brain, are made up of interconnected neuron code. The DL hierarchy permits a non-linear method to process data in a number of layers to incorporate extra information in each succeeding layer, in contrast to other linear programs now in use in the machine.

4.1 Learning Models:-

The DL was founded in 1943 by Warren McCulloch and Walter Pitts. Following then, a number more DL models emerged. This page contains the data regarding the models that were created between 2017 and 2021. Researchers created a great deal of models throughout that time. We'll go over the models that are most in demand.

The authors presented a number of models in 2017, including DenseNet [38], CapsuleNet [39], IRCNN [40,41], IRRCNN [42], RefineNet [43], PSPNet [44], Mask-RCNN [45], and Fast-RCNN [46]. In 2018, the DL model's expansion is still ongoing. Several noteworthy models, including DeepLab [49], R2U-Net [48], and DCRN [47], were developed in that year. The following year, Google AI created EfficientNet [50,51]. This model has piqued the curiosity of several scholars ever since. UnitedModel [52], which was based on CNN architecture, was proposed in 2020. In 2021, researchers will continue to develop new models. This year, ConvXGB [53], which is based on XGBoost from Chen et al. and CNN, was also released.

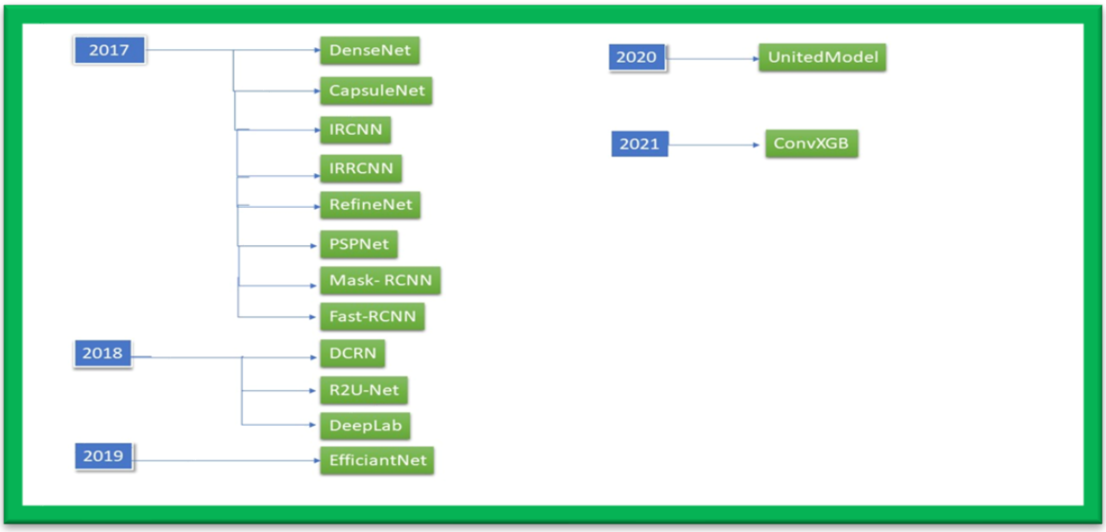

Fig 4: Visualization of evolution of various Deep Learning models from 2017 to till date

4.1.1 CNN:-

An image recognition application uses a specific kind of ANN called CNN [54]. An MLNN with two or more hidden layers is what this network is. Typically, a sequence of convolutional layers make up CNN's concealed layers. The main building block of CNN is the convolutional layer. It retrieves high-level information from the incoming signal. Pooling layer application comes after convolution layer. Based on the applications, pooling operations are configured. To reduce dimensionality and choose the most important feature, the pooling process is primarily utilized. A sequence of convolution and pooling layers precede the fully connected layer, which is the final layer in the CNN structure and may consist of one or more layers. Convolutional Neural Networks, often known as CNNs, employ sliding windows to scan a full image and calculate a probability that an object is present in each window classifier. Although there are several classifications, the most have low confidence scores. The confidence score indicates the likelihood, or more simply, the level of assurance, that the item in question is present. Due to the large number of comparisons, this method is effective but slow. CNN is rarely employed as a real-time classifier because to its large compute load.

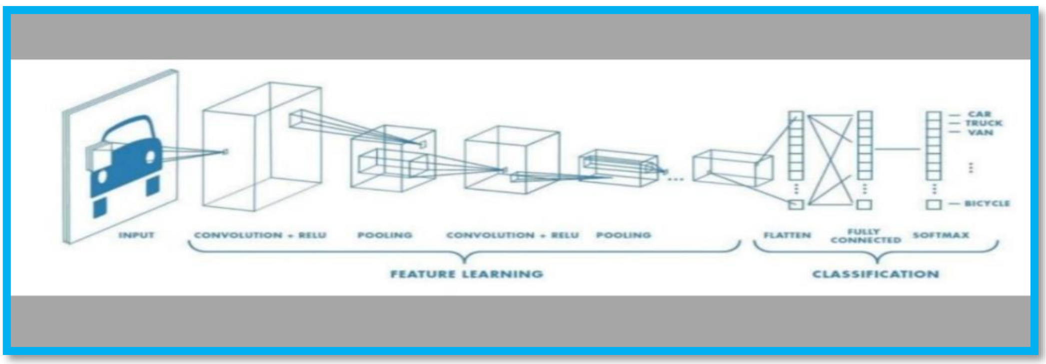

Fig 5. The basic architecture of the CNN

The CNN algorithm can be enumerated in these four points:

1. The input image is divided into segments.
2. CNN classifier is applied to each picture cut, calculating a confidence score for each defined category.
3. Classified tags are only kept in storage when the confidence score surpasses a predetermined level.
4. The objects with the highest confidence scores have rectangles drawn around them.

4.1.2 DNN:-

DNN [55, 56] is often an FFNN [57], where data flows forward between levels and never touches a node again as it moves from the input to the output layer. DNN architectures produce compositional models, where the object is represented as a layered composition of primitive images. The cloud's massive datasets enable the creation of more precise models by capturing high-level patterns in additional vast layers. The two neural network phases, inference and training, stand for the development process.

4.1.3 RNN:-

Neural networks that have loops that enable data storage within the network are known as RNNs[58]. To put it succinctly, RNN predicts future events by reasoning from past experiences [59]. Vectors can be sequenced by recurrent models, which makes it possible for the API to carry out increasingly complicated operations. Regular applications of RNN include language translation [60], natural language processing [61], and speech recognition [62], among other ordinal or temporal challenges.

4.1.4 DCNN:-

Different from regular CNN, DCNN [63] is a form of DL approach that uses more hidden layers (usually more than 5) to improve prediction accuracy and extract more data. One kind of DCNN increases the quantity of hidden layers, whereas the other increases the quantity of hidden layer nodes. The DCNN approach is a supervised learning task that finds features for classification using unprocessed data. In computer vision [64] tasks including object location, detection [65], and image classification [66], it has been widely and successfully applied.

4.1.5 AlexNet:-

Alex Krizhevsky founded AlexNet, a CNN [15]. In the ILSVRC 2010 competition, it performed better than any other contemporary technique in classifying photos from ImageNet [67]. Three fully connected layers and five convolutional layers make up AlexNet's eight layers. Among its features are overlapping pooling, multiple GPUs, and ReLU nonlinearity. AlexNet is an advanced model capable of achieving high accuracy on even the most difficult data sets. Eliminating the convolutional layer causes a significant decline in its performance. It serves as the primary framework for all object retrieval tasks and offers a wide range of possible uses in artificial intelligence and computer vision. In the future, AlexNet might be more widely used than CNN when utilizing AlexNet images.

4.1.6 ResNet:-

The most significant advancement in the DL community during the last many years was probably ResNet [68]. With hundreds or even thousands of layers prepared, ResNet nevertheless achieves amazing outcomes for its clients. Its strong representational capabilities has enhanced the performance of numerous computer vision applications, including image identification. ResNet comes in various varieties, such as ResNet-18 [69], ResNet-34 [70], ResNet-50 [71], ResNet-101 [72], ResNet-110 [73], ResNet-152 [74], ResNet-164 [75], and ResNet-1202 [73].

4.1.7 CaffeNet:-

CaffeNet represents a variant of AlexNet [76]. The CNN for classification, known as AlexNet, took part in the 2012 ImageNet Large Scale Visual Recognition Challenge. CaffeNet does not train using relighting data-augmentation, and pooling takes place prior to normalization, which is the main distinction between CaffeNet and AlexNet.

4.1.8 Inception Model:-

CNN uses the Inception module to layer 1 × 1 convolutional dimensionality reduction, resulting in deeper networks and more efficient calculations. Overfitting and computational overload are two issues that these modules are intended to address. The workaround, to put it briefly, is to use different kernel filter sizes on CNN instead of stacking them one after the other and setting their operating level sequentially. The versions of it that exist include inception V1, also known as GoogLeNet [77], inception V2 [78], inception V3 [79, 80], inception V4, and inception ResNet [81].

4.1.9 VGG16:-

The CNN architecture known as OxfordNet, or VGG16 [83], took first place in the 2014 ILSVR (Imagenet) competition. This model was presented in an article titled "Very deep convolutional networks for large-scale image recognition" [84] by K. Simonyan and A. Zisserman from the University of Oxford. Among the best model architectures available now is this one. Like its moniker, VGG16, it contains sixteen weighted layers.

4.1.10 LSTM:-

Developed in the 1990s by Sepp Hochreiter and Juergen Schmidhuber, LSTM [85] is a form of RNN that is now widely used for image [86], sound [87], and time series analysis [88] since it uses memory gates to solve the vanishing gradient problem.

V. Review of Deep Learning Models for Yield Prediction, Disease Detection, and Weed Detection

5.1 Yield Prediction:-

To act swiftly, national and regional decision-makers need to be able to predict agricultural yields. When using an accurate crop production forecast model, farmers may make judgments about what to grow and when. Crop output can be predicted using a variety of techniques.

The most important component of good agriculture is yield prediction since it helps with yield mapping, yield estimating, grain supply (including crop management), and demand (i.e., increasing productivity). A few studies on yield prediction have been discussed.

A comprehensive yield prediction framework that links the raw data to the paddy productivity forecast values was proposed by the authors of [89]. The system is based on supervised smart farming. To calculate crop yield, they build a model in this suggested work termed DRQN, an RNN DL algorithm over the Q-Learning RL method. This work's primary objective was to improve food production by lowering error and raising forecast accuracy.

A DCNN framework for automatically identifying and categorizing several biotic and abiotic paddy crop stressors is developed by the authors of the paper [90] using field photos. Utilizing the pre-trained VGG16 CNN model, the work classified automatically deformed paddy crop photos captured during the growing stage. The trained model obtained an average of 92.89% more accuracy.

5.2 Disease Detection:-

One of the most crucial problems in agriculture is the control of pests and illnesses in greenhouses and outside (on agricultural land). The most popular method of pest management is evenly spraying insecticides across the planting area.
Despite its effectiveness, this method is costly and detrimental to the environment. Environmental effects can include overproduction in agriculture, secondary harm from groundwater pollution, effects on local ecosystems and fauna, etc. DL techniques can help bring the issues down to a manageable scale.

Pre-trained models such as VGG19 for the classification of illnesses including early blight, late blight, and healthy in potato leaves are given to the authors [92].
They have a 97.8% accuracy rate. CNN is used by the authors of a different study [91] to identify five different tomato leaf diseases. Their accuracy was 99.84%.

5.3 Weed Detection:-

Weed management and identification is another crucial issue in agriculture. Many farmers claim that weeds pose the biggest threat to agricultural productivity. Identification of weeds is essential for sustainable agriculture since weeds are hard to spot and tell apart from crops. Similarly, accurate weed recognition and classification at a low cost without negatively impacting the environment can be achieved by the combination of sensors and DL algorithms. The use of DL for weed detection may pave the way for the creation of robots and other tools that will clear weeds and reduce the need for chemicals. There have been four papers published on the use of DL for agricultural weed detection. The inception model (V2) is used by the authors of paper [94] to identify weeds in crops. Their approach model has a 98% accuracy rate in weed detection. The authors of paper [95] suggested a novel model that combined R-FCN with ResNet-101. They also contrast RFCN and Faster R-CNN with their suggested model. With 81% accuracy in identifying farmland weed, their model outperforms Faster R-CNN and R-FCN overall.

Conclusion:-

We have conducted a survey of DL-based technologies and their uses in agriculture in this paper. A number of agricultural applications, including as disease diagnosis, weed identification, and yield prediction, have made use of DL. DL has gained popularity as a research area in recent years, and many applications have been created. However, there is still a great deal of untapped agricultural potential in DL that needs to be realized. Our intention with this study is to inspire more scholars to investigate deep learning (DL) and use it to address a range of agricultural issues. We intend to use the general ideas and DL best practices described in this survey in future work to additional agricultural industries that have not yet made full use of this cutting-edge technology.

The general benefits of deep learning are numerous:

1. **High Accuracy**: High levels of accuracy in DL models can be attained in a variety of tasks, including image recognition, classification, and prediction. These tasks are critical for applications such as weed identification and disease detection.
2. **Automated Feature Extraction**: In contrast to conventional machine learning models, deep learning models have the ability to automatically extract pertinent features from unprocessed data. This eliminates the need for human feature engineering and facilitates the processing of intricate data types like sensor and picture data.
3. **Scalability**: Large datasets can be handled by DL models, which makes them appropriate for evaluating enormous volumes of agricultural data gathered from fields, drones, and satellites.
4. **Adaptability**: By refining previously trained models or creating new architectures suited to particular tasks, DL models can be customized for a range of agricultural applications, providing versatility across diverse agricultural domains.
5. **Real-Time Processing**: Time-sensitive tasks like disease diagnosis and crop monitoring require DL models to process data in real time, giving farmers instant insights and recommendations.
6. **Continuous Improvement**: When DL models are exposed to additional data, they can get stronger over time and produce predictions that are more correct every time.
7. **Integration with IoT**: By integrating DL with Internet of Things (IoT) sensors, smart farming systems that are capable of self-monitoring and managing agricultural activities can be developed.

These advantages show how deep learning has the power to transform agriculture by raising productivity, sustainability, and efficiency. Nevertheless, additional investigation and advancement are required to completely utilize these benefits and tackle the distinct obstacles encountered in various agricultural

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