Technological Advancements in Automated Crop Pest and Disease Detection: A Review & Ongoing Research

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Technological Advancements in Automated Crop Pest and Disease Detection: A Review & Ongoing Research

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***Abstract*—Automated crop pests and disease detection have fateful effects on food safety, leading to significant deterioration in agriculture products. The effects of crop diseases and pests can be so severe that a harvest may even be ruined entirely. Therefore, automatic recognition and diagnosis of crop disease is required in the agricultural field. However, Fast and accurate crop disease detection is still a challenging and error-prone task. Earlier, traditional methods were used to detect abnormalities in crops caused by fungus, pests and nutritional deficiency. Moreover, in some cases, it is time-consuming, expensive and impractical. To overcome these issues, experimental research is being performed into the use of image processing techniques for crop disease detection using machine learning, artificial intelligence, deep learning, generative adversarial networks and the internet of things. In this study, a comprehensive literature review of current studies is performed in crop disease and pest recognition using image processing to extract the features and algorithms used in prediction studies. In particular, several models have reported better accuracy on specific data sets. In contrast, in the case of different data sets or field conditions, the performance of the models degraded significantly. Despite this, progress has been encouraging so far. Furthermore, different inputs gained from the literature indicate that the aforementioned techniques provide better accuracy in comparison with existing techniques. Additionally, a detailed study has been performed on several unresolved challenges to develop a framework for automated crop pests and disease detection to use in real field conditions.**

***Index Terms*—Machine learning, Deep learning, Generative adversarial networks, and Internet of things.**

I. Introduction

In the global economy, agriculture plays a important role in feeding the human and live-stock populations. The agriculture state in-country is directly related to the quantity and quality of products, especially crops. According to the Ministry of Agriculture Farmers Welfare annual report 2020-21, more than 57.8 % of the total population is directly or indirectly depends on agriculture in India. Moreover, numerous factors are responsible for crop production loss, such as pests, weeds, and disease dysfunctions, are the major prime factors in India for 20-25 per cent loss of the whole crop production [1]. Over the past two decades, the growth rate in the agriculture field is declining tremendously. As a result of this trend, several challenges such as weather forecasting, rural-urban migration, population growth, leads to the significant threat to world food security.

Due to the fact that there will be a slight increase in the agricultural land in the future, so there is need to improve the productivity of existing farmland that will be the key in solving food insecurity. To meet this, it demands faster maturing, livestock breeding, Planting high-yielding crops and Crop varieties resistant to drought and disease. Further, considering a rapid decline in agricultural employment between 2017 and 2030 owing to greater employment in other fields of the economy, introducing technology in agriculture domain becomes of paramount importance [2]. Furthermore, with the advancement of new technologies, the use of chemical pesticides has increased a lot, which has shown a negative effect on people's health and polluted the environment. Therefore, people are moving towards the use of crops grown organically. However, the government is placing most stricter regulations to ban the products grown with the usage of chemicals. Weather forecasting has been an important factor that seeks the relationship between the live-stock, humans, and growth of several diseases in crops. Change in climate pattern leads to occurrence of diseases and pest. Many researches have pointed out that disease occur mainly when the crops grown for the first time [3]. Moreover, in certain situations agricultural experts are not trained enough to deal with new disease and pest fails to provide support to the farmers.

To address these issues, precision agriculture is gaining attention among the farmers in order to increase crop productivity in a sustainable manner. Precision agriculture is the technology enabled techniques that covers modern techniques and decision support system for the proper management of farms in more controlled and accurate way [4]. Moreover, techniques such as robotics, drones, terrestrial vehicles, devices for variable spraying of pesticides, data analytics, and navigation system in tractor using Global Positioning System helps in increasing the productivity. Furthermore, the application of image processing in fusion with the current technologies such as artificial intelligence (AI), machine learning (ML), deep learning (DL), generative adverserial networks (GAN), and internet-of-things (IOT) in crop disease detection and pest recognition has shown the better results. Furthermore the fusion of technologies has become the hot spot research area for the researchers to address the issues of accurate and early detection of diseases and pests [5]. A number of possible forthcoming revolutions in agriculture technologies such as digital twins [6], federated learning [7], block chain [8], fog computing [9], edge computing [10], and robotics [11] here the accuracy has been reached to perception of human level. Current research efforts are aimed for the attainment of such high levels of accuracy in crop disease detection and pest recognition.

In image processing techniques, computer programs are used to manipulate and analyze images recorded with a different types of sensors including infrared imaging devices, visible light cameras, and detectors with frequency bands. Moreover, various research has been done in the field of crop disease and pest recognition in hyper-spectral models [12]. However, these hyper-spectral imaging instruments are very costly and not easily reachable to extension workers and ordinary farmers. Therefore, in the present scenario these image processing techniques with the fusion of artificial intelligence technologies employed in the crop disease detection and pest recognition. Figure 1 depicts the technological support in leaf pest and disease detection.

1) Image processing techniques can be used to for fast and accurate predictions in recognizing crop pest and disease recognition based on stem, flowers, fruits, and images of leafs.
2) The severity of disease can be determined by measuring the size of the discolored or deformed area in relation to the whole fruit, leaf, and flower.
3) Tracking the details about disease progression in plants that could be difficult to discover by human observers, such as in identifying the symptoms and the stage of infection.
4) This also helps the researchers and scientists to under go the investigation in the lab to find the characteristics of sowing a new crop cultivation.
5) The information obtained through image processing techniques can be distributed immediately and inexpensively to people at remote locations.
6) An accurate diagnosis will yield a more efficient use of pesticides. This will decrease production costs.
7) Extension officers can consult human experts remotely rather than traveling to individual farms.

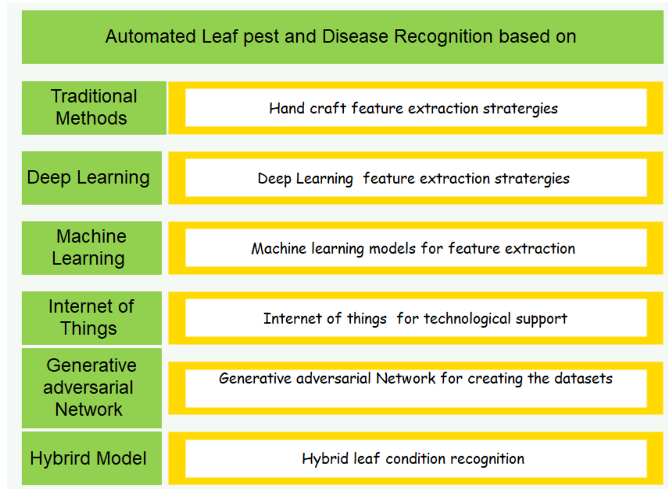

Fig. 1. Technological support in leaf pest and disease recognition

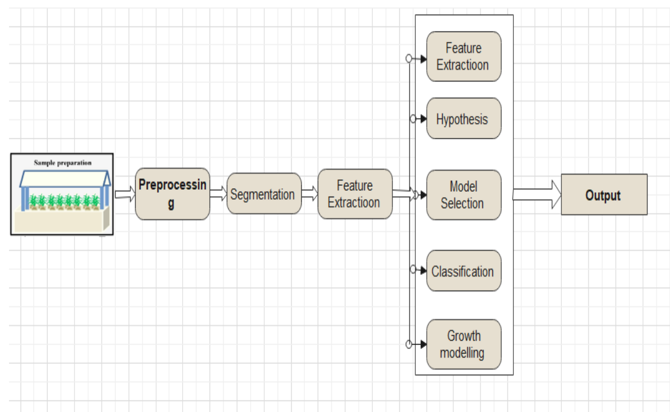

Fig. 2. Feature extraction and classification workflow

II. Related work

A. Leaf disease recognition using deep learning techniques

Over the decade, convolutional neural networks have determined phenomenal performance as feature classifiers and extractors in the field of image processing. Furthermore, this concept has been successfully applied in several areas, it has recently entered into the field of agriculture to accomplish different tasks such as pest recognition and crop disease detection, flower and fruit counting, weed detection, and fruit grading. Particularly, DL has been widely used since 2015 for recognizing leaf diseases detection using image processing techniques. DL representation method that seeks to find the optimal way to represent data optimization techniques instead of semantic features. As a result of the learning process, features are extracted automatically rather than manually. Furthermore, DL constitutes the modern techniques in agriculture that will be useful for the food industry to grow in robotics, big data, pest detection, disease diagnosis, marketing and automation. Figure 2 highlights the overall workflow incorporating the feature extraction and classification workflow.

For training CNN, large datasets consisting of thousands of images are required. However, crop disease detection, such a diverse and massive datasets have not yet mobilized and availed for the use by different researchers. In order to create a better CNN classifiers for detecting plant diseases, transfer learning is currently the most efficient method used for experimentation. Moreover, Transfer learning is the process of transforming pretrained CNNs using smaller datasets with a different distribution than what large datasets earlier used to build the CNNs from scratch. Moreover, Transfer learning is the process of transforming pretrained CNNs using smaller datasets with a different distribution than what large datasets earlier that are used to build the CNNs . Studies demonstrated that use of pretrained models CNN on dataset dataset provides better result for crop disease detection. [13].

Kawasaki et al. [14] proposed a novel CNN architecture for disease detection in cucumber leaf such as Zucchini yellow mosaic and yellow spot viruses infection. The study shows that data augmentation has more contribution in recognising the performance than enlarging the several training epochs. Furthermore, the researchers addressed different architectures to improve the classification using several augmentation strategies.

Durmusßet al. [15] demonstrated the work done in proposing a extended work by training AlexNet, CNNs on SqueezeNet using the platform nvidia jetson. However, there is a slight decrement in the accuracy achieved by Alexnet in comparison to the workdone in where TITAN X GPU is used. Furthermore, the results indicate that crop disease detection algorithms could be experimented to run in real time. However, this study shows that in embedded applications in order to attain high performance initially train the model on a traditional GPU and then deploy the training model to embedded system. The study conducted by Brahimi et al. [13]the comparison of googlenet and alexnet CNNs from the starting point and for the detection of nine tomato leaf disease using transfer learning. Furthermore, two classifiers are used such as SVM and RF in training the network. The study demonstrate that pre-trained CNNs shows bettter performance than the CNNs from the scratch and CNN models in comparison to SVM and RF classifiers performed better. Furthermore these networks are very critical in image disease detection and knowing this is essential to minimize CNN models. These also highlighted that combination of different CNN classifiers produced higher recognition accuracy and this will be helpful to detect symptoms of disease from high-resolution images.

The studies of different authors [16] presented the alternative approach was taken by applying DL in object detectors. Furthermore, Single Shot Multi-box detector and faster region-based CNNs architectures are used to classify and find the region containing diseases which are based upon the features inside the bounding box. In order to use these detectors with CNNs, different architectures were investigated such as ResNetXt-101, ResNet-101, AlexNet, GoogLeNet, ZFNet, VGG-16. Barbedo et al. [17] highlighted that in order to classify leaf diseases using DL, image of individual spots and lesions is require rather than entire leaves. However, there are still some issues are not resolved is the problems with exact automatic background removal and segmentation of the images into individual lesions. Further, the compact deep CNN system used to implemented detect plant diseases on mobile phones. Furthermore, CNN models can be deployed on mobile devices, which will make this technology more accessible and

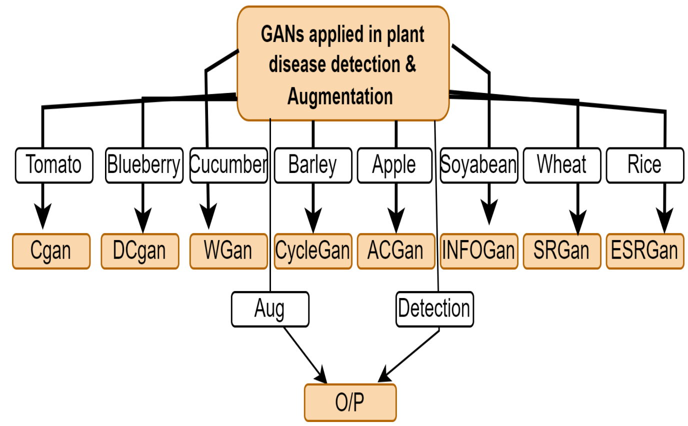

Fig. 3. Geneative Adverserial Network

beneficial to farmers.

B. Leaf disease recognition using generative adversarial network

In the past half decade generative adversarial networks(GANs) has been introduced in the field of generating synthetic images. Furthermore, CNNs has been widely used in the leaf disease detection and pest recognition. However, CNNs have been applied in this fields and proven to be a effective approach, despite this the major issue has been overlooked that is of limited training dataset. This has led to the problem of over fitting of data. Moreover, with the evolution of GANs based methods prediction accuracy has been increased and resolved the problem of over fitting of data when training data is limited. In [18] Goodfellow et al. GANs are mainly used to address the data scarcity problem. The structure of GANs consists of two networks such as discriminator and a generator. In this the training data distribution is captured by the generator whereas a discriminator determines the probability that whether an image came from the generator or from training data. Moreover,the goal is to increase the capacity of the generator to fool the discriminator, which is trained to distinguish real images from synthetic ones. Using this method, a dedicated GANs is required which will generate synthetic images, and that is used to train leaf disease and pest identification system. Figure 3 depicts the different types of generative adversarial networks applied in varieties of agricultural applications such as crop disease, fruit, and vegetables.

Arsenovic et al. [19] addressed the generation of crop images artificially using Generative Adversarial Networks (GANs). Furthermore several variants of GAN architectures as been proposed in past few years such as CGAN, DCGAN, ProGAN, and StyleGAN. The conditional GAN (CGAN), is used to represent multimodal data generation in a better way. In our study, StyleGAN generated leaf images with the best results at the 256×256 image pixel resolution. These GAN networks were not successful in training on field images due to the busy background, a problem that remains unresolved even after more training on field images. However,on the test set networks trained on GAN created images achieved about 1 percent better accuracy than networks trained only on natural images. Furthermore, a new two-stage CNN known as Plant DiseaseNet (PDNet) was also introduced [19]. Also stage one (PDNet-1) used a detector YOLOv3 with feature extractor Alexnet for predicting bounding box in the leaf of crops. Moreover, a new plant diseasenet known as the stage two (PDNet-2) consist of softmax layer, a CNN architecture of 32 layers, pooling layer for averaging globally, and 42-way layer fully connected. The map score attained by PDNET-1 is 0.9165 while in case of PDNet-2 attained is 93.67 percent crop disease recognition accuracy. It should be noted that, the GANs holds a lot of potential that can be used to generate the training images artificially and very useful to resolve the problem of scarcity of data.

C. Leaf disease recognition using Machine Learning

Machine learning is one of the most prominent approach for the crop pest and disease recognition. Crop disease recognition is one the challenging problem in agricultural field. Furthermore, several models have been addressed and validated so far. From the studies it has been concluded that crop disease recognition is not a trivial task, instead it has to pass through the several complicated steps. In the present scenario, crop disease recognition models can recognise the actual disease in the crops, but a better prediction is still desirable. ML is a branch of AI and computer Vision which focuses on learning, just like the way humans learn. ML is useful in determining the correlation and pattern and knowledge discovery from the data sets. Furthermore, several models are trained on the datasets, and output is based upon the past experience. In order to built predictive models several features are required, such as determining the parameters of the model using historical data in the training phase. While in case of testing phase, for the performance evaluation the historical data can be used which has not been used in training phase. A ML models can be predictive or descriptive, it depends upon the research problems and questions. Furthermore, in order to make the future predictions predictive models whereas to extract some information from the sampled data collected and explain what has happened descriptive models are used. Further,in the study, it has been found that in order to built high performance predictive models in machine learning different challenges need to be faced. Furthermore, it is very difficult to select the right model to solve the challenging problem at hand, and to handle the large volume of data in the underlying platforms.

As ML now became an integral part for the precision agriculture, where crop pest and disease recognition can be done. This also presented a tool for discrimination and detection of healthy plants and smut fungus during the crop growth. Ebrahimi et el. presented a new technique for the automatic pest detection using SVM classification [20]. Further, they also proposed a novel method for screening and detection of disease bakanae in rice seedlings. Furthermore, identification of crop disease and pest recognition using image processing in fusion with machine learning algorithms have been applied in the sample crops such as in fruit leaves, brinjal leaf, potato, peanut leaf and groundnut leaf.

D. Leaf disease recognition using internet of things

With the advancement of technology in last one decade is witnessing the new era of computing that is shifting from traditional approaches to the intelligent ones. The internet of thing (IOT) constitutes a recent modern technique use in different applications such as health , agriculture, and in business and many more [21] with large potential and promising results. With this the domain the field of agriculture is getting immensely fortified. The IOT has been introduced in agriculture sector to improve the quality and quantity in this field. This can only be achieved through the early disease recognition before the harvesting of crops. With the emergence of IoT, major controlling resources have been added in the area of disease detection in plant phenology, assisting in preventing disease outbreaks. Pandiyan et al. [22], developed a novel platform for analysing data from heterogeneous IoT with advanced segment extraction. Different levels such as, service level, platform level, and connectivity level were used to perform the several tasks namely data aggregation, automatic identity identification and transmission. The study has been on leaf gestures for the better identification of diseased leaves done. Zhao et al. [23] proposed a novel learning system that can automatically recognize the crop diseases form the cluttered background.

Kale et al. [24] presented support system in decision making in smart farming with the help of smart fertilizers. Moreover, lack of judgment lead to the inappropriate decision. In this study, genetic algorithm and IOT were used in system design. Further, in designing the system for plant disease detection an improved genetic algorithm with extreme learning machines classifiers along with IOT was proposed.

Pawara et al. [25], addressed the different disease such as spot in fruit & leaf spot, bacterial blight in pomegranate. Furthermore, a sensor based and hidden markov model model has been introduced in model system design with the several parameters were taken into the consideration such as leaf wetness, air humidity, and soil wetness. Sharma, V. and Tripathi, A.K. [26] highlighted the systematic survey of meta-heuristic algorithms in IoT based application. Moreover, presented a real time monitoring system for the collection of environmental data with cloud storage and IOT for crop disease identification and detection. For classifying the environmental data support vector machine regression was used. Further, demonstrated a prototype for smart farming capable of disease detection and diagnosis in plant using web enabled system that is IOT based. In this study, septoria plant disease was investigated for experimentation. The overall summary of the technologies, type of crop, disease identification, and algorithm are described in Table I. Here, different abbreviation's namely DL stands for DL, ML stands for machine learning, IOT stands for internet of technology.

TABLE I
CLASSIFICATION OF ALGORITHMS BASED ON APPLICATIONS

Technologies	Type of crop	Disease detected	Algorithm	Ref
M L	Apple	Early blight, Apple rust	Radial bias function neaural netwrok (RBFN)	[27]
M L	Sugrcane	Red rot, leaf spot, mosaic virus	Support Vector Machine (SVM)	[28]
M L	Tulsi	Maturity of leaves in tulsi	Multi layer perceptron	[29]
M L	Vine	Powdery mildew	One Class Classifier	[30]
D L	Tomato	Early blight	Convolutional neural network based transfer learning models such as resnet	[31]
D L	Potato	Late blight , Early blight	Deep Convolutional neural network (DCNN)	[32]
D L	Rice	sheath rot , bacterail blight	Deep neural network (DNN) with jaya optimized algorithm	[16]
IoT	Banana	sigatoka disease	GLCM and RFC	[33]
IOT	Pomegranate	Fruit spot, bacterail blight	HMM and sensor based model	[25]
IOT	Rice	bacterail blight	Drone based IOT architecture	[34]

III. FUTURE RESEARCH DIRECTIONS

Aforementioned technologies is anticipated to increase the potential of agricultural industry to feed the forthcoming generations. Integration of different technologies is the urge of the modern practices in agriculture field. A number of possible forthcoming revolutions in agriculture technologies such as digital twins [6], federated learning [7], block chain [8], fog computing [9], edge computing [10], and robotics [11]. These technologies play an important role for the futuristic adaptations in the several diversified dimensions namely harvesting of crops, fruit counting, weed detection & management, forestry, livestock farming, fertilization & irrigation, scouting of crops, and pest surveillance. In the recent times, a majority of work has been done in the crop disease and pest identification using image identification. However, few work has been done using the satellite images thought lack of dataset is still a major constraint in this field. Historical dataset can be a game changes in the effective estimation the growth of crops, fertility status, and salinity issues. These challenges can be easily managed using the aforementioned techniques. Digital twin technology can be a new revolutionized field which can efficiently helps in the 3D view with different shapes of plant growth. However, dataset is still a major challenge to perform the experimental work using these techniques. Another one is the federated learning is a new approach in machine learning field which works in a decentralized manner, hence reduces the load of the different severs when large amount of data is trained. However, efficient GPUs are required to perform the experimental work which are widely not available. These technologies can trigger the different nascent perspectives which can be in the future work for precision agriculture.

IV. DISCUSSION AND CONCLUSION

This documents demonstrates the comprehensive review of research efforts done in agricultural domain using image processing techniques. In the ongoing research a survey have been performed for the crop pest and disease identification system using DL models, GAN, ML, and IOT. Furthermore, the accurate diagnosis depends on the type of technology used, hence fusion of multi modals can led to the development of such system. Lately, these technologies are capable enough to use in several areas such as, health, sentiment analysis and object detection. In the agricultural field, different technologies have been addressed such as land monitoring, crop yield prediction, disease detection, and crop identification. Moreover, several fusions have been employed in the agricultural field to improve the early crop disease detection. Many of these fusion modals have shown the promising results with the high potential for the early prediction of pest and disease. Our findings demonstrates that these technologies provides better performance than other traditional techniques.Further in existing literature some research gaps are highlighted for future work in this area. In the current time, research efforts have been made to overcome the problem of limited data set using generative adversarial networks. Further efforts should also made to develop the models for backdrop removal and assimilate distinct types of data namely disease incidence history, topographical location, and weather forecasting data in order to increase reliability and efficiency in the disease detection systems. However, identification of syndrome in disease that occurs on the different part of plants such as stem has not been highlighted by the researchers. The overall benefits of using these technologies is to apply these in the field of agriculture, to encourage the researchers to the move towards the advancement of sustainable farming for increasing the food production.

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