Applications of Artificial Intelligence in Crop Disease Diagnose and Management

Taswar Ahsan[1,2], Mahnoor Khan[1], Maqsood Ahmed[2], Tehseen Zafar[3], Ansar Javeed[4*]

Abstract— The use of Artificial Intelligence (AI) in agriculture has recently gained prominence. The fundamental notion of AI in agriculture is flexibility, high performance, accuracy, and cost prosperity. This article investigates the use of artificial intelligence (AI) in the diagnosis and control of plant diseases. The application's benefits and limitations, as well as the approach for utilizing expert systems for enhanced productivity, are all highlighted. Present study overview the several application of AI，i.e, Neural Networks，Support Vector Machines，Hyper-spectral imaging, Alex net, Explanation block and Fuzzy logic. These approaches have accuracy, pace and affordability for sustainable safe food production.

Index Terms— Mini Artificial intelligence, Disease diagnose, Disease control，Neural Networks，Support Vector Machines， Hyper-spectral imaging， Alex net， Explanation block

1 Introduction

Safe production of food with high quality and yield is a tough task. To maintain the sustainability of healthy food production, with low cost, there are urgent need to practices the innovative approaches. The novel techniques should be state of the art and environment friendly to deal all challenges in safe production of food [1].

Novel technologies have transformed the agriculture division, permitting it to undergo a revolution which favorably enabled the sector to experience a whole new increase in productivity and profitability [2]. The first and second waves of the modern agriculture revolution were mechanization and the green revolution, undergoing genetic modification. The third wave is considered to be Precision Agriculture through which the required inputs can be applied to the methods by determining the three factors, i.e. what, where and when the inputs are needed. Currently, Precision Agriculture has been updated with enriched knowledge of the farm systems as larger aggregates of data can be easily available [3].

In October of 2016, the USDA (United States Department of Agriculture) said that due to the use of Precision Agriculture techniques, the operative profits and net returns enlarged [4]. While taking the surrounding environment into consideration, an increasing number of different techniques have been implemented within farms in order to manage and sustain their production. Nevertheless, the use of such methods has raised various trade offs and uncertainties. Rendering the analysis of markets, the elements that assist in embracing sustainable agronomic technologies involve properly educating and training farmers, information sharing, easier access to monetary resources, and increasing the number of consumers demanding organic food stuffs [5]. Whenever new techniques are applied, the task of data collection from crops should be valuable and relevant, as the data itself is not useful as it is usually just numbers or pictures or pictorial representations. Technologically advanced farms have demonstrated many important advantages, i.e. saving money and labor, improving production and cost reduction with less effort, and yielding high quality food through approaches that are environmentally pleasant [6].

In order to make the best use of these advantages, it all depends on the farmers' willpower to implement new technologies in their fields, and the potential of each specific farm in terms of scale economies, as with farm size, the profit margin upsurges [4]. The Agricultural division lately has manifested AI applications in its field of work. Several challenges have been encountered in order to take full advantage and increase the yield of crops, which comprised many obstacles, like lack of knowledge of technology by farmers, infestation of pests and the diseases spread by them, low output, requirements for profound data covering all the details, and improper soil treatments. The flexibility, extraordinary performance, correctness, precision, and cost-effectiveness are the focal highlights of AI applications in agriculture. So, an evaluation of its applications in disease management and diagnosis of plant diseases has been described [7]. The strong points and restrictions of the AI applications and the techniques used to utilize expert systems for higher output have been discussed with a distinct emphasis. Plant diseases decrease agricultural yield and the quality as agriculture tries to sustain a fast-expanding population. Post-harvest disease losses in agriculture may be devastating. Farming includes a lot of decisions and uncertainty. Weather varies from season to season, as do the prices of farming goods, soil degrades, crops become unviable, weeds smother crops, pests destroy crops, and the environment changes. Farmers must deal with these

- Taswar Ahsan; [1]University of Central Punjab, Pakistan, [2]Shenyang Agricultural University, China. E-mail: taswar.micro@gmail.com
- Mahnoor Khan; [1]University of Central Punjab, Pakistan, E-mail: dawndarkness17@gmail.com
- Maqsood Ahmed; [2]Shenyang Agricultural University, China, E-mail: maqsoodahmed200@hotmail.com
- Tehseen Zafar; [3]University of Gujrat, Pakistan, E-mail: tehseenzafar593@gmail.com
- *Ansar Javeed; [4]Henan University，China， E-mail: ansarjaveed@henu.edu.cn . Corresponding Author

unknowns. Despite the breadth of agricultural practice, this study focuses on soil, crop, disease, and weeds as significant factors to agricultural productivity. It is vital to investigate the use of AI in agriculture in terms of soil, crop, disease, and pest control. The current digital information era has revolutionized crop management. Raw measurements of critical agricultural characteristics have to be processed effectively. Information collected from the cultivation, soil or the environment is included in the data. Filter procedures and AI algorithms are also required to get just the correct data. An illustration of the AI technology shown in the fig. 1.

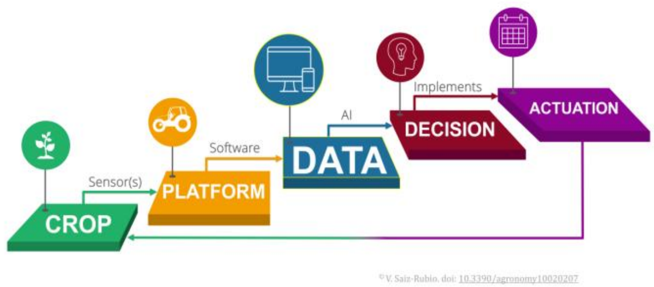

Fig. 1.Information-based management cycle for advanced agriculture. This figure was Reproduced (Adapted) by the permission of [5] Copyright 2020, MDPI, (CC BY 4.0).

2 Disease Detection in Plants

The inhibition and control of infections and infectious agents must be guaranteed as plants are extremely susceptible to diseases as they are in constant exposure to the external environment. The factors upon which the rate of proliferation of disease is determined are vulnerability to diseases and prevailing crop conditions [9-10]. Detection and diagnosis of plant diseases has been crucial to avoid losses in the harvest and in the amount of cultivated yields [11-12]. The series of symptoms are displayed by a diseased plant which includes colored or shaded spots and streaks that occur on different parts of the leaves, seeds, and stems of that plant. Therefore, in various regions of the world, rapid disease identification can be challenging. But with the improvements in computer vision, profound knowledge has shifted towards the use of smartphone-assisted disease diagnosis. Computerized techniques have been considered more constructive as the extensive work of keeping an eye on large areas of farms and identifying the disease symptoms in the crops at early stages of the disease is tremendously unmanageable [13]. A study in 2011 showed that, mostly in developing countries, the expense of relying on the visual observations of specialists to detect and diagnose plant diseases had not been cost-effective [14].

So, for the automatic identification, recognition, and classification of plant diseases, an image processing based software solution was directed to be used. By using the image processing method to increase output and decrease costs arising from assigning professionals in the field to detect plant diseases, many different unconventional systems can be designed to study the traits of plants and their diseases [15]. The image processing technique is convenient as it can be used with the aim of distinguishing the diseased leaf, stem, and fruit, or to compute the disease affected area and find its shape, or to determine the affected area's color, or to conclude the size and shape of fruits, etc. Through the aid of automation of image analysis experiments, the manual analysis scenario can be extended beyond its probability by modifying the rate-limiting phase of image acquisition [16].

For the detection and identification of diseases through computer visualization, several procedures and algorithms have been put into use. In classifying related diseases and plants, a 99.53% success rate was reached by using deep Convolution Neural Networks [17]. Neural Networks were also used for detection of diseases in many other crops, like rice crops [18-20]. A comprehensive illustration of Neural Networks is given in the fig. 2.

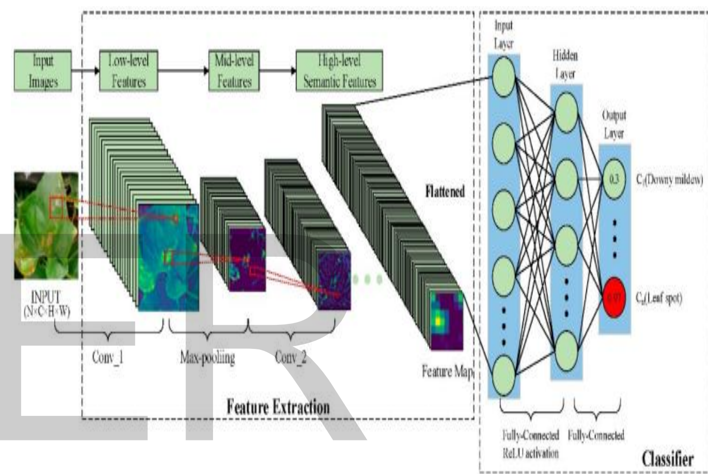

Fig. 2. Convolution neural networks for snake gourd leaf disease classification. In Figure 4, we input a batch of images into the feature extraction network to extract the features and then flatten the feature map into the classifier for disease classification. This process can be roughly divided into the following three steps.1.Step 1. Preparing the Data and Prepossessing 2.Step 2. Building, Training, and Evaluating the Model 3.Step 3. Inference and Deployment. [21], Copyright 2021, MDPI, (CC BY 4.0).

Some other substitutes which proved to be more proficient model foundations in some cases were the K-means algorithm [22], PCA (Principal Component Analysis), CV (Coefficient of Variation) [23], and SVM (Support Vector Machines) [24]. An experimental study conducted in 2014 showed that using K-means clustering along with SVM (Support Vector Machines) delivered better outcomes than using ANN (Artificial Neural Networks). The K-means clustering was used to classify the population into two main groups, i.e. healthy and infested, monitored by SVM [25]. Illustration of Support Vector Machine is given in the fig. 3.

Another constructive manner of detection of disease in plants was to use color and texture to distinguish and categorize different agriculture/horticulture as studying the combination of these features was valuable in identification of diseases [27].

International Journal of Scientific & Engineering Research, Volume 13, Issue 2, February-2022
ISSN 2229-5518

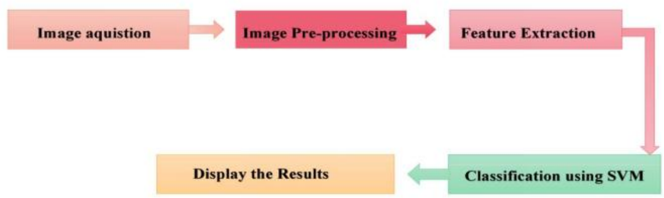

Fig. 3. SVM process Shows the phases included in the plant disease classification. In the image acquisition phase the images of diseased plant leaves or fruits are collected either from internet or captured by using the digital camera. These images are prepossessed by applying various prepossessing techniques to enhance the image clarity and also to remove the noise. In the third phase features are extracted from these images for further processing. Support vector machine classifier was used for classification to detect the type of the disease and finally the accurate result will be displayed. (illustration is adapted and modified from [26].

For detection of diseases in Malus domestica plants, techniques such as K-mean clustering, Bayes classifier color and texture analysis were applied. A system was developed with the help of networked cameras, sensors, and a machine learning algorithm by Israeli start-up Prospera that monitors the crops and warns the farmers the moment any disease attacks a plant [28].

To process the hyper-spectral data, accessible neutral network techniques were used, which greatly emphasize detection of plant diseases [29]. The yellow rust disease in the wheat crop was automatically detected by using neural networks technique and additional specifically multi-layered perceptron's approach. Using the services of ANN (Artificial Neural Networks) technology, the classification performance for assessment of a total of five thousand, one hundred and thirty-seven leaf spectra was amplified from ninety-five percent to over and above ninety-nine percent, [30]. Advanced techniques for identifying the diseases of plants, which can easily provide reports of the detection of diseases at early stages in order to prevent and control disease dispersal, encompass linking spectroscopic and imaging techniques with autonomous agricultural vehicles [31].

Precision based methods such as profile based techniques and Molecular methodology can be easily approached. On the other hand, in circumstances where symptoms can be visually observed, imaging and spectrographic techniques have been rendered ideal as the results are out in a few minutes and these procedures can be controlled without any complexities. Hyper-spectral imaging is defined as the technique in which a wide-ranging spectrum of light is applied to each pixel and this striking light hits the pixels that get broken down into spectra and then are analyzed to provide information. As shown in the fig.4. The data from hyper-spectral fluorescence imaging and multi-spectral fluorescence imaging was combined with the sole purpose of detection at early stages of diseases, even before the symptoms become visible, and thus allowed the differentiation of diseased plants from healthy plants and had an accuracy of 94.5% [32]. As shown in the fig. 5. Similarly, other techniques like fluorescence imaging were used and bright fluorescent lights or emission lights were given off by the samples which were being studied contrary to their black backgrounds. In a similar way, the temperature of the crops is detected by infrared thermal imaging. An experimental study was conducted by [34].

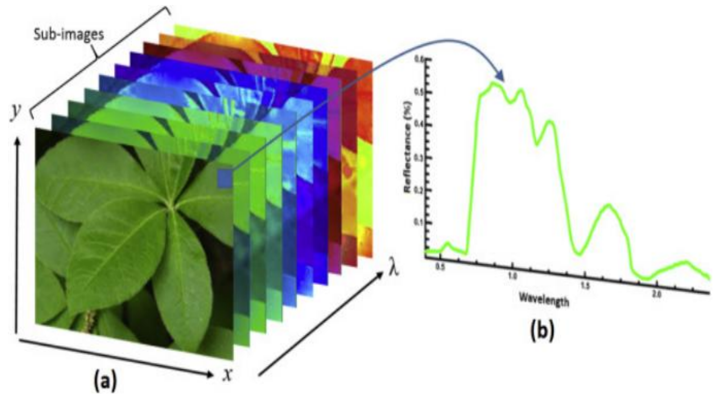

Fig. 4. Example of hyper-spectral image acquired from a green leaf. (a) Stack of narrow band sub-images forming a 3-D hypercube; (b) reflectance spectrum of a particular pixel. [32].

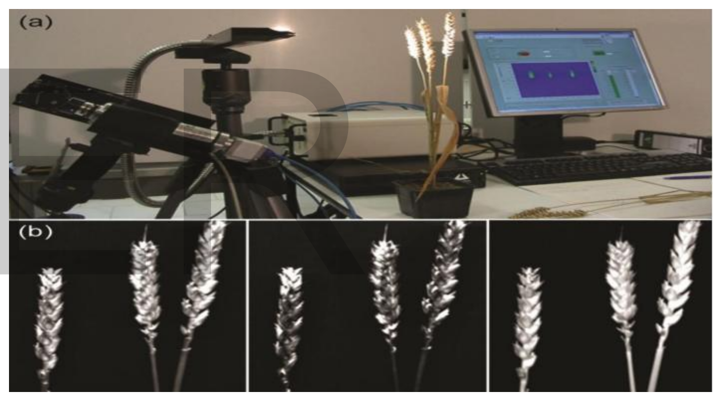

Fig. 5. (a) Hyper-spectral image scanner; (b) Reflexion images of a Fusarium-infected wheat sample at different spectra channels (from left to right: red: 550 nm, green: 685 nm, blue: 765 nm). This figure was added by the permission of [33].

Alex Net and VGG16 (Visual Geometry Group) net, which are both deep learning based architectures, were used and the data set provided by Plant Village was taken as an input. Of a total of thirteen thousand, two hundred and sixty-two pictures taken for classification accuracy, the VGG16 (Visual Geometry Group) net had an accuracy of 97.29% and Alex Net had an accuracy of 97.49%. A number of factors were involved in the evaluation of the performance of the models that were carefully noted; the number of pictures taken, setting mini-batch sizes, and varying the weight and bias learning weight. The factors such as the number of pictures taken seemed to have a noteworthy influence on the performance of the simulations. It was also observed that with the increase in the rate of weight and bias learning, the accuracy of the VGG16 net decreased. The decent values of accuracy were obtained by the Alex Net when the concern was the computational load, as it requires little time for accomplishment, in contrast to the deep VGG16 net, which takes more time to execute the results.

International Journal of Scientific & Engineering Research, Volume 13, Issue 2, February-2022
ISSN 2229-5518

Machine Vision-based approaches allow non-destructive detection of plant diseases at early stages in the development process [35]. Illustration of the Alex net presented in the fig. 6.

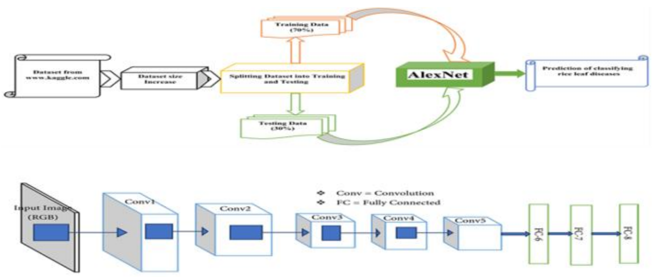

Fig. 6. Alex Net neural network illustration. The schematic procedures of our proposed work are illustrated in Figure 2. We divided our data set into two parts as like as training data and test data. 70% and 30% data of our data set were used as training and test data respectively. Therefore, our data set contained 630 training images and 270 test images.Finally, Alex Net neural network was applied for prediction of classifying rice leaf diseases. The working procedures of Figure 3 and corresponding actions are shown in Table 1. This network has five convolution layers and three fully connected layers. If we remove any of the convolution layers of our network, then its performance will drastically degrade. The first layer termed as the image input layer used input color images of size 227-by-227-by-3. This figure was Reproduced (Adapted) by the permission of [36].

The procedure starts with the steps of preparation of the sample and acquisition of images. The next step is the evaluation followed by trait identification, and then ranking is done, leading towards the classifier development, which in many cases uses the SVM algorithm. The machine vision based process used for the detection and identification of diseases of crops showed accuracies of 87.9% for the rice crops [37], 87.50% for the chili-pepper crops [38] , and 90.15% for the papaya crops [39] respectively. Through modifying the image processing techniques by comparing the features such as color and texture of different individual leaves, visual differentiation has been completed to distinguish between various common features of citrus plant diseases, [40]. The key purpose of the research was to implement the machine-based-vision tactic to spot citrus diseases. The Color co-occurrence technique was used to conclude whether the texture based hue, saturation, and intensity (HSI) color features along with the statistical classification algorithms can be used under research laboratory circumstances to detect diseased citrus leaves and normal citrus leaves. Using SAS discriminant analysis, the aftermath was variable sets being reduced and probable classification accuracies being assessed. Through the SAS discriminant analysis, the achieved classification accuracies were: 81%, 95.8%, and 100%. When the intensity feature was used, above eighty-one percent was recorded. Accuracy when the hue and saturation features were used separately, approximately ninety-six percent were obtained, but via the HIS features, a hundred percent of accuracies were attained on all of the data models. The analysis inquired that under measured laboratory conditions, in order to detect and classify diseased citrus leaves from normal citrus leaves, these methods would be convenient.

In 2012, an experiment used a related method for the detection of diseases in chili plants through the use of software for leaf image and data processing [41]. The results showed that the cost of production and maintenance was lessened and a high quality of chili yield was obtained. Thus, it was revealed to be one of the most operative and fastest methods for detecting diseases in chili plants. A survey study conducted by [42] presented an algorithm for image segmentation technique along with the classification of leaf diseases of plants. Various other classification techniques for plant leaf diseases detection that can be applied were added in their survey. For image segmentation, the genetic algorithm was put into service, which created many more solutions for optimization and played a vital role in the detection of plant leaf diseases and other diseases. The plant samples collected as inputs: banana leaves affected by early scorch disease (Fig. 4), rose and bean leaves having bacterial infection, bean leaves infected by fungal causative agent and lemon leaves diseased by sunburn disease. The segmented images of the outputs of all these plant inputs were identified and classified into different categories of plant diseases. With the intention of improving recognition and identification rates in the classification process of diseases, these methodologies could be exercised further: The Bayes Classifier, Artificial Neural Network, Hybrid algorithms, and Fuzzy Logic.

3 Disease Management

Disease control is vital if the concern is to have an agricultural harvest producing an optimal and high-quality yield. Plant and animal diseases are a prime limiting and restricting issue concerning the upsurge in yield. Various elements, such as soil type, dry climate, wind, rain, temperature, genetics, etc., have played a specific role in the development of these plant and animal diseases. So, in large scale farming, dealing with the after effects raised by these elements and the unsteady nature of causative factors of some infections, has become a massive challenge that can generate many other challenges, resulting in the uncontrolled spread of infectious agents. Table 1 displays the applications of AI in disease management in the literature. Farmers should undertake an integrated disease management and control model to efficiently control the spread of diseases and limit the losses occurring due to the disease-causing agents, using all the possible measures, i.e. physical, chemical, and biological [7].

Thus, AI applications for management and control of disease have become a necessity, as the approaches to managing and controlling farms for long periods of time and many expenses have become time-consuming and uneconomical [43-44]. EB (Explanation block) had provided a better understanding of the logic trailed by the kernel of the expert system [45]. The system for representing intelligent interpretations for disease management of crops has been using a new method of rule promotion based totally on Fuzzy Logic. A simple Illustration of the process is given in the fig. 7. The TTS (Text-To-Speech) converter has been used to provide the functionality of a text-to-talking user interface and offers a highly-operative interactive user interface on the web for live on-line interactions [47].

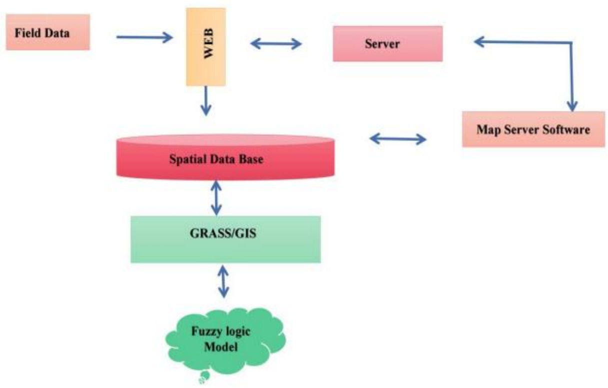

Fig. 7. An illustration of Fuzzy logic, decision support mechanism. Fuzzy Logic and Geographic Information Systems for Pest Control in Olive Culture. (illustration is adapted and modified from [46].

For the improvement of the system that detects diseases and offers suggestions for treatment, a rule-based and forward-chaining inference engine has been used [48]. A brief description of the artificial intelligence's applications are presented in the table 1.

4 Demerits of Artificial intelligence applications

Despite all these advantages, however, the AI technology nevertheless has certain problems. First of all, the greatest societal concern is the danger of unemployment. In effect, the bulk of repetitive labour and activities may be replaced with intelligent machinery and robots; thus, there is significant human intervention, which will cause serious problems in the standards of employment.For example, machines can only accomplish those jobs that are designed for or developed to complete with other technological obstacles. Anything they tend to crash or produce irrelevant results may be a background for them. The high expense of creating and maintaining smart machines and smart computers might also be viewed as technological constraints of AI technologies, particularly as AI upgrades daily, which makes it necessary to update hardware and software with time to fulfil the most recent needs. Machines require costly repair and upkeep. The high costs of these applications, which may increase the price of the items, are further problems. In addition, there may be certain danger and fears for sustainability, including the huge energy consumption, electronic waste problems, market concentrations, employment movements, and even the ethical framework, beyond the potential offered by intelligent and computerized technology.

5 Future prospective

The world's population is anticipated to exceed nine billion by 2050, necessitating a 70% increase in agricultural production to meet the need. Only approximately 10% of this extra output may come from empty areas, with the remainder being met by existing production intensification. In this context, the adoption of cutting-edge technology solutions to improve farming efficiency remains a critical requirement. Current agricultural intensification techniques need large energy inputs, but the market wants high-quality food [54]. The worldwide industry is geared to convert robotics and autonomous systems (RAS). The technology will have a major influence on big economic sectors with relatively low productivity such as agricultural food (from farm to retail).

6 Conclusion

Current studies indicated presented the applications of artificial intelligence (AI) in the diagnosis and control of plant diseases. The application's benefits and limitations, as well as the approach for utilizing expert systems for enhanced productivity, are all highlighted. Present study overview the several application of AI， i.e, Neural Networks， Support Vector Machines， Hyper-spectral imaging， Alex net， Explanation block and Fuzzy logic. These approaches have accuracy, pace and affordability for sustainable safe food production. The use of Artificial Intelligence (AI) in agriculture has recently gained prominence. The fundamental notion of AI in agriculture is flexibility, high performance, accuracy, and cost prosperity.

List of abbreviations

Artificial Intelligence (AI)
Principal Component Analysis (PCA)
Coefficient of Variation (CV)
Support Vector Machines (SVM)
Artificial Neural Networks (ANN)
Visual Geometry Group (VGG)
Explanation block (EB)
Text-To-Speech (TTS)

Declaration Statement

Institutional Review Board Statement: N/A
Informed Consent Statement: N/A
Ethics approval and consent to participate: N/A
Conflict of Interest: The authors declare no conflict of interest.
Contributions: Taswar Ahsan, Maqsood Ahmed conceived and designed the study. Taswar Ahsan and Mahnoor Khan collected the data and wrote the paper. Tehseen Zafar, and Ansar Javeed, helped in collecting the data and final validation. All authors read and approved the final manuscript.
Availability of data and materials: N/A

Acknowledgment

The authors wish to thanks, Dr. Ansar Javeed, for his financial support.

International Journal of Scientific & Engineering Research, Volume 13, Issue 2, February-2022
ISSN 2229-5518

References

[1]. Lioutas, E.D. and C. Charatsari, *Smart farming and short food supply chains: Are they compatible?* Land Use Policy, 2020. **94**: p. 104541.

[2]. Himesh, S., et al., *Digital revolution and Big Data: A new revolution in agriculture.* CAB Rev, 2018. **13**(21): p. 1-7.

[3]. Mohr, S. and R. Kühl, *Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior.* Precision Agriculture, 2021: p. 1-29.

[4]. Schimmelpfennig, D., *Farm profits and adoption of precision agriculture.* 2016.

[5]. Saiz-Rubio, V. and F. Rovira-Más, *From smart farming towards agriculture 5.0: A review on crop data management.* Agronomy, 2020. **10**(2): p. 207.

[6]. Díez, C., *Hacia una agricultura inteligente.* Cuaderno de campo, 2017(60): p. 4-11.

[7]. Eli-Chukwu, N.C., *Applications of artificial intelligence in agriculture: A review.* Engineering, Technology & Applied Science Research, 2019. **9**(4): p. 4377-4383.

[8]. Singh, S.S.J., *A Review on Usage and Expected Benefits of Artificial Intelligence in Agriculture Sector.* 2020.

[9]. Lucas, G.B., C.L. Campbell, and L.T. Lucas, *Introduction to plant diseases: identification and management*. 1992: Springer Science & Business Media.

[10]. Zadokar, A., et al., *Leaf disease detection of cotton plant using image processing techniques: a review.* International Journal of Electronics, Communication and Soft Computing Science & Engineering (IJECSCSE), 2017: p. 53-55.

[11]. Khirade, S.D. and A. Patil. *Plant disease detection using image processing*. in *2015 International conference on computing communication control and automation*. 2015. IEEE.

[12]. Kaur, S., S. Pandey, and S. Goel, *Plants disease identification and classification through leaf images: A survey.* Archives of Computational Methods in Engineering, 2019. **26**(2): p. 507-530.

[13]. Sethy, P.K., et al., *Deep feature based rice leaf disease identification using support vector machine.* Computers and Electronics in Agriculture, 2020. **175**: p. 105527.

[14]. Al Bashish, D., M. Braik, and S. Bani-Ahmad, *Detection and classification of leaf diseases using K-means-based segmentation and.* Information technology journal, 2011. **10**(2): p. 267-275.

[15]. Patil, J.K. and R. Kumar, *Advances in image processing for detection of plant diseases.* Journal of Advanced Bioinformatics Applications and Research, 2011. **2**(2): p. 135-141.

[16]. Spalding, E.P. and N.D. Miller, *Image analysis is driving a renaissance in growth measurement.* Current opinion in plant biology, 2013. **16**(1): p. 100-104.

[17]. Ferentinos, K.P., *Deep learning models for plant disease detection and diagnosis.* Computers and Electronics in Agriculture, 2018. **145**: p. 311-318.

[18]. Phadikar, S. and J. Sil. *Rice disease identification using pattern recognition techniques*. in *2008 11th International Conference on Computer and Information Technology*. 2008. IEEE.

[19]. Lu, Y., et al., *Identification of rice diseases using deep convolutional neural networks.* Neurocomputing, 2017. **267**: p. 378-384.

[20]. Sladojevic, S., et al., *Deep neural networks based recognition of plant diseases by leaf image classification.* Computational intelligence and neuroscience, 2016. **2016**.

[21]. Lu, J., L. Tan, and H. Jiang, *Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification.* Agriculture, 2021. **11**(8): p. 707.

[22.] Mehra, T., V. Kumar, and P. Gupta. *Maturity and disease detection in tomato using computer vision*. in *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)*. 2016. IEEE.

[23]. Schor, N., et al., *Robotic disease detection in greenhouses: Combined detection of powdery mildew and tomato spotted wilt virus.* IEEE Robotics and Automation Letters, 2016. **1**(1): p. 354-360.

[24]. Albahari, E., et al., *Lab Image and Field Image Contrast Quality Differentiation.* Image. **10**: p. 1024.

[25]. Omrani, E., et al., *Potential of radial basis function-based support vector regression for apple disease detection.* Measurement, 2014. **55**: p. 512-519.

[26]. Poojary, H. and S.B. Shabari. *A survey on plant disease detection using support vector machine*. in *2018 International Conference on Control, Power, Communication and Computing Technologies (ICCPCCT)*. 2018. IEEE.

[27]. Bashir, S. and N. Sharma, *Remote area plant disease detection using image processing.* IOSR Journal of Electronics and

TABLE 1.

Summary of A .I. Applications in plant disease management

App	Characteristics	Limitations	Ref.
(CVS), (GA), ANN	Works at a high speed. Can multi-task	Dimension-based detection which may affect good species	[45]
RBE, & (DB)	Accurate results inthe tested environment	Inefficacy of DB when implementing in large scale	[45]
Fuzzy Logic (FL), Web GIS	Cost effective, Eco-friendly	Inefficiency due to scattered distribution. Takes time to locate and disperse data. The location of the data is determined by a mobile browser	[46]
FL(WIDDS)	Good accuracy. Responds swiftly tothe nature of crop diseases.	Limited usage as it requires,internet service. Its potency cannot be ascertained as only 4 seed crops were considered	[49]
FL& TTS	Resolves plant pathological problems quickly	Requires high speed internet. Uses a voice service as its multimedia interface	[47]
ES	Faster treatment as diseases are diagnosed faster. Cost effective based on its preventive approach	Time consuming Needs constant monitoring to check if pest has built immunity to the preventive measure	[48]
ANN, GIS	95% accuracy	Internet-based. Some rural farmerswill not have access	[50]
Fuzzy XPest	High precision inforecast	Internet dependent	[51]
WBES	High performance	Internet and web based	[52]
ANN	Has above than 90% predictionrate	The ANN does not kill infections orreduces its effect	[53]

Note: ***App*** *(Applications),* ***Ref*** *(References)*

Computer vision system *(CVS),* **Genetic algorithm** *(GA), ANN:* **Rule-Based Expert** *(RBE),* **Data Base** *(DB):* **Fuzzy Logic** *(FL),* **Web GIS:** FL Web-Based, Web-Based Intelligent Disease Diagnosis System *(WIDDS):* **Text-To-Speech** *(TTS):* **Expert system using rule-base in disease detection** *(ES):* **Web-Based Expert System** *(WBES):* **Artificial Neural Networks** *(ANN)*

International Journal of Scientific & Engineering Research, Volume 13, Issue 2, February-2022
ISSN 2229-5518

Communication Engineering, 2012. **2**(6): p. 31-34.

[28]. Castro, D. and J. New, *The promise of artificial intelligence.* Center for Data Innovation, 2016. **115**(10): p. 32-35.

[29]. Golhani, K., et al., *A review of neural networks in plant disease detection using hyperspectral data.* Information Processing in Agriculture, 2018. **5**(3): p. 354-371.

[30]. Moshou, D., et al., *Automatic detection of 'yellow rust'in wheat using reflectance measurements and neural networks.* Computers and electronics in agriculture, 2004. **44**(3): p. 173-188.

[31]. Sankaran, S., et al., *A review of advanced techniques for detecting plant diseases.* Computers and electronics in agriculture, 2010. **72**(1): p. 1-13.

[32]. Mishra, P., et al., *Close range hyperspectral imaging of plants: A review.* Biosystems Engineering, 2017. **164**: p. 49-67.

[33]. Bauriegel, E. and W.B. Herppich, *Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to Fusarium spec. infections on wheat.* Agriculture, 2014. **4**(1): p. 32-57.

[34]. Rangarajan, A.K., R. Purushothaman, and A. Ramesh, *Tomato crop disease classification using pre-trained deep learning algorithm.* Procedia computer science, 2018. **133**: p. 1040-1047.

[35]. Backhaus, A., F. Bollenbeck, and U. Seiffert. *Robust classification of the nutrition state in crop plants by hyperspectral imaging and artificial neural networks*. in *2011 3rd Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. 2011. IEEE.

[36]. Matin, M.M.H., et al., *An Efficient Disease Detection Technique of Rice Leaf Using AlexNet.* Journal of Computer and Communications, 2020. **8**(12): p. 49.

[37]. Chung, C.-L., et al., *Detecting Bakanae disease in rice seedlings by machine vision.* Computers and electronics in agriculture, 2016. **121**: p. 404-411.

[38]. Ataş, M., Y. Yardimci, and A. Temizel, *A new approach to aflatoxin detection in chili pepper by machine vision.* Computers and electronics in agriculture, 2012. **87**: p. 129-141.

[39]. Habib, M.T., et al., *Machine vision based papaya disease recognition.* Journal of King Saud University-Computer and Information Sciences, 2020. **32**(3): p. 300-309.

[40]. Pydipati, R., T. Burks, and W. Lee, *Identification of citrus disease using color texture features and discriminant analysis.* Computers and electronics in agriculture, 2006. **52**(1-2): p. 49-59.

[41]. Husin, Z.B., et al. *Feasibility study on plant chili disease detection using image processing techniques*. in *2012 Third International Conference on Intelligent Systems Modelling and Simulation*. 2012. IEEE.

[42]. Singh, V. and A.K. Misra, *Detection of plant leaf diseases using image segmentation and soft computing techniques.* Information processing in Agriculture, 2017. **4**(1): p. 41-49.

[43]. Schepers, J. and W. Raun, *American Society of Agronomy, editors. 2008.* Nitrogen in Agricultural Systems.

[44]. Fang, J., C. Zhang, and S. Wang. *Application of genetic algorithm (GA) trained artificial neural network to identify tomatoes with physiological diseases*. in *International Conference on Computer and Computing Technologies in Agriculture*. 2007. Springer.

[45]. Balleda, K., et al. *Agpest: An efficient rule-based expert system to prevent pest diseases of rice & wheat crops*. in *2014 IEEE 8th International Conference on Intelligent Systems and Control (ISCO)*. 2014. IEEE.

[46]. Jesus, J., T. Panagopoulos, and A. Neves. *Fuzzy logic and geographic information systems for pest control in olive culture*. in *4th IASME/WSEAS International Conference on Energy, Environment, Ecosystems & Sustainable Development, Algarve, Portugal*. 2008.

[47]. Kolhe, S., et al., *An intelligent multimedia interface for fuzzy-logic based inference in crops.* Expert Systems with Applications, 2011. **38**(12): p. 14592-14601.

[48]. Munirah, M. and M. Rozlini. *An expert system development: its application on diagnosing oyster mushroom diseases*. in *2013 13th International Conference on Control, Automation and Systems (ICCAS 2013)*. 2013. IEEE.

[49]. Kolhe, S., et al., *A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the inferences in crops.* Computers and electronics in agriculture, 2011. **76**(1): p. 16-27.

[50]. Liu, G., et al. *An artificial neural network-based expert system for fruit tree disease and insect pest diagnosis*. in *2006 IEEE International Conference on Networking, Sensing and Control*. 2006. IEEE.

[51]. Siraj, F. and N. Arbaiy, *Integrated pest management system using fuzzy expert system.* 2006.

[52]. Virparia, P., *A Web Based Fuzzy Expert System for Insect Pest Management in Groundnut Crop 'Prajna'.* Journal Of Pure & Applied Sciences, 2007. **15**: p. 36-41.

[53]. Rumpf, T., et al., *Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance.* Computers and electronics in agriculture, 2010. **74**(1): p. 91-99.

54]. Panpatte, D.G., *Artificial intelligence in agriculture: An emerging era of research.* Anand Agricultural University, 2018.