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A comprehensive review on detection of plant disease using machine learning and deep learning approaches

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ABSTRACT

Agriculture plays a significant part in India due to their population growth and increased food demands. Hence, there is a need to enhance the yield of crop. One of these important effects on low crop yields is diseases caused by bacteria, fungi and viruses. This can be prevented and handled by means of applying plant disease detection approaches. Machine learning techniques will be employed in the process of disease identification on plants as it mostly applies information themselves and offers fabulous techniques for detection of plant diseases. Methods based on Machine learning can be employed for the identification of diseases because it mainly applies on data superiority outcomes for specified task. In this approach, a comprehensive review has been made on the various techniques employed in plant disease detection using artificial intelligence (AI) based machine learning and deep learning techniques. Likewise, deep learning has also gained a great deal of significance in offering better performance outcome for detecting plant disease in the computer vision field. The deep learning advancements were employed to a range of domains that leads to great attainment in the machine learning and computer vision areas. The comparative study is made in terms of machine and deep learning techniques and their performance and usage in various research papers is related to show the effectiveness of deep learning model over machine learning model. In order to prevent major crop losses, the deep learning technique can be used to detect the leaf diseases from captured images.

1. Introduction

The advancements of IoT, AI and the Unmanned Aerial Vehicles are integrated together to provide the support to agricultural fields to detect the plant leaf diseases and report that properly to the respective individuals with proper accuracy ranges. In this modern civilization, nobody is interested in farming and agriculture due to the hurdles the farmers are facing every day. So, that all young generation people are switch over their residence to modern cities to lead a safe life and avoid such agriculture field hurdles. The issue of the proficient plant diseases protection is closely linked to viable change in climate and agriculture [13]. Studies show that climate change may vary pathogenic stages and rates; host resistance may also be altered, leading to physiological variations in host-pathogen co-operations [23]. The actuality that nowadays, diseases more freely transferred around the globe than ever before complicates the situation. New diseases may occur where they have not been identified previously and, inherently, where local expertise to combat them is not available [27] (see Table 1).

The unreliable use of pesticides may cause long-term pathogens to develop resistance and seriously decrease the ability to combat it. One of the pillars of precision farming [25] is the prompt and exact interpretation of diseases in plants. It is crucial that the financial and other resources are not unnecessarily wasted and thus that the production is healthier by addressing the problem of developing long lasting pathogenic resistance and alleviating the adverse effects of climate change.

Adequate and timely identification of diseases, which includes early impediment, has never been more significant in this changing environment. Plant pathologies can be detected in a number of ways. Some diseases have no apparent syndromes or the response is too late to act and a refined examination is required in those situations. However, most illnesses create a manifestation of some sort in the spectrum visible, so that a trained professional examination is the primary technique for the detection of plants. A plant pathologist should have better observational proficiency to identify characteristic symptoms in order to obtain exact plant disease diagnostics [31]. Alterations in symptoms determined by sick plants may result in inaccurate diagnosis because it could be more difficult for amateur and hobbyists to determine than for a professional pathologist. The beginners in gardening and the experienced specialists

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Table 1
A review on plant disease segmentation techniques.

Plant disease Segmentation techniques	Merits	Demerits
Threshold Method [37]	i) Any prior knowledge of the picture is not needed. ii) Fast, basic, and low-cost computationally. iii) It's easy to use and acceptable for real-life scenarios.	i) The resulting image cannot guarantee that the segmented regions are contiguous since spatial information can be overlooked. ii) The choice of a threshold is important. iii) Extremely sensitive to noise.
Clustering method [30]	i) It is easy to obtain homogeneous regions. ii) Faster in terms of computation. iii) The smaller the value of K, the better K-means operates.	i) Worst-case scenario conduct is bad. ii) It necessitates clusters of similar size.
Edge detection method [34]	i) It works well with pictures that have a higher contrast among regions.	i) Worked badly for a picture with a lot of edges. ii) It's difficult to find the right object edge.
Regional method [35]	i) It helps you to choose between interactive and automated image segmentation techniques. ii) The movement from the inner point to the outer region establishes more distinct entity boundaries. iii) In comparison to other approaches, it provides more reliable performance.	i) More computation time and memory was required, and the process was sequential. ii) User seed selection that is noisy results in faulty segmentation. iii) Splitting segments appear square due to the region's splitting scheme.

can greatly benefit from an automated system devised to detect plant conditions with the appearance and visual symptoms of the plant as a verifier of disease diagnoses.

Improvements in computer vision offer opportunities to increase and strengthen the practice of accurate plant protection and to broaden the market for precise agriculture computer vision applications. In order to detect and classify plant diseases, the utilization of common technology for digital image processing like color detection and threshold [32] was employed.

Different approaches to deep learning are recently being used for plant diseases detection and the most popular of these are CNN. Deep learning is a new trend in machine learning, with state-of-art results in many areas of research, including computer vision, pharmacy and bio-informatics. Deep learning benefits from the capacity to use raw data directly without the use of handcrafts32]. The use of deep learning, for two main reasons, has recently produced good results both academically and industrially [20]. First, every day is generated large amounts of data. These data may therefore be used to develop a profound model. Second, the computational power of the Graphics Processing Unit allows deep models to be trained and leveraged in computing parallelism.

2. Plant disease detection using machine learning techniques

Presented Machine learning techniques application in the Agricultural sector for analyzing soil fertility. Agricultural industry was regarded as the concerned research areas all the time [26]. This approach venture for analyzing the soil data depends on several constraints, categorize this and enhance the competence of each representation with the use of various grouping. The agricultural research has been profited through technological progress like data mining, automation. Today, data mining is employed in a huge areas and various off-the-shelf system of data mining yield and area explicit application of data mining software's were presented, however in agricultural soil datasets data mining is a young field of research reasonably (see Fig. 1).

A method to more accurately identify plant diseases was presented by S·H., et al. [28]. The method provided a thorough explanation of the ML approach used to categorize the signs of plant diseases. However, the method did not fully understand the factors that influence disease detection. The huge of data amounts that are virtually harvested nowadays with the crops have to be estimated and must be employed for full extent. The preprocessing procedure for input image is shown in Fig. 2. Before extracting the features, some background noise should be eliminated to obtain precise findings. In order to smooth the image, a Gaussian filter is utilized once the RGB image has been transformed to grayscale. Stresses the extent to which multiple environmental factors impact rainfall and also uses decisions on crop production such as disease detection and selection of crop [24]. Plant disease detection through some automated technique is useful since it reduces a large amount of monitoring work in large crop farms and detects disease symptoms at an early stage. Here are some image segmentation techniques that can be used to detect and classify plant diseases automatically by using DL techniques. Offered the proportional review of GIS-dependent prediction of crop boundary algorithms of machine learning [26]. Presented a coffee, cocoa and technical rice sustain software which focus on the feedback of consumer and exterior information, with climate and location which in turn supports the process of selection, identification, avoidance of pests, control, and selection of fertilization, among others [28].

Presented the electronic computer design for examining the paddy images of farmer and notify them [10]. The primary intention of offering the method intended for classification of rice diseases is to endorse identification and classification of rice disease [12] that covers artificial and supports vector neural networks. The forecast crop takes parameters account like quantity of precipitation, maximum and minimum temperature, type of soil, importance of soil pH and the humidity. Data was attained from Maharashtra's agriculture website.

The data was broken down into nine regions of farming [14]. The updated neural MLP network was developed by a new feature activation and random revised estimation of crop yield, bias and weight values through several. An updated neural MLP network will be developed with the new activation feature and revised random crop yield estimation weight and bias values, via various weather datasets. The model of MLP has been employed for testing wit proven functionalities of activation that covers bias and weights. In order to improve efficiencies and accuracy of neural networks, this study analyses the result of various activation potential and proposes various basic functions such as DharaSig, DharaSigm and SHBSig. Furthermore, three additional activation functions with small differences were developed with the DharaSig functions DharaSig 1, DHaraSig2 and DharaSig3. Suggested the method of ET0 for the data mining estimation which was then explored by semi-arid china with the use of restricted data in climate. The algorithm of k-Nearest Nearest Neighbor capability was employed in China [11]. Also, a KNN dependent model of ET0 forecast was employed for validating the equation PM-56.

Traditional farming practices include manually collecting data, dealing with inclement weather, sprinkling pesticides on diseases, and other practices that put farmers' lives in jeopardy, especially in drought-prone areas. Concerning the current situation in conventional farming, there has been an urgent need for predicated data in farming that can assist farmers in identifying and responding to real-time problems. To help them solve their problems, we'd like to propose a method that uses a Decision Tree Classifier to predict cotton crop diseases based on temperature, soil moisture, and other variables [33,41].

It focuses on using plant imaging for maize plant disease detection-controlled machine learning methods such as Naive Bayes (NB), Decision Tree (DT), Nearest Neighbor (KNN), Vector Machine Support (SVM) and Random Forest (RF). The above classification strategies are studied

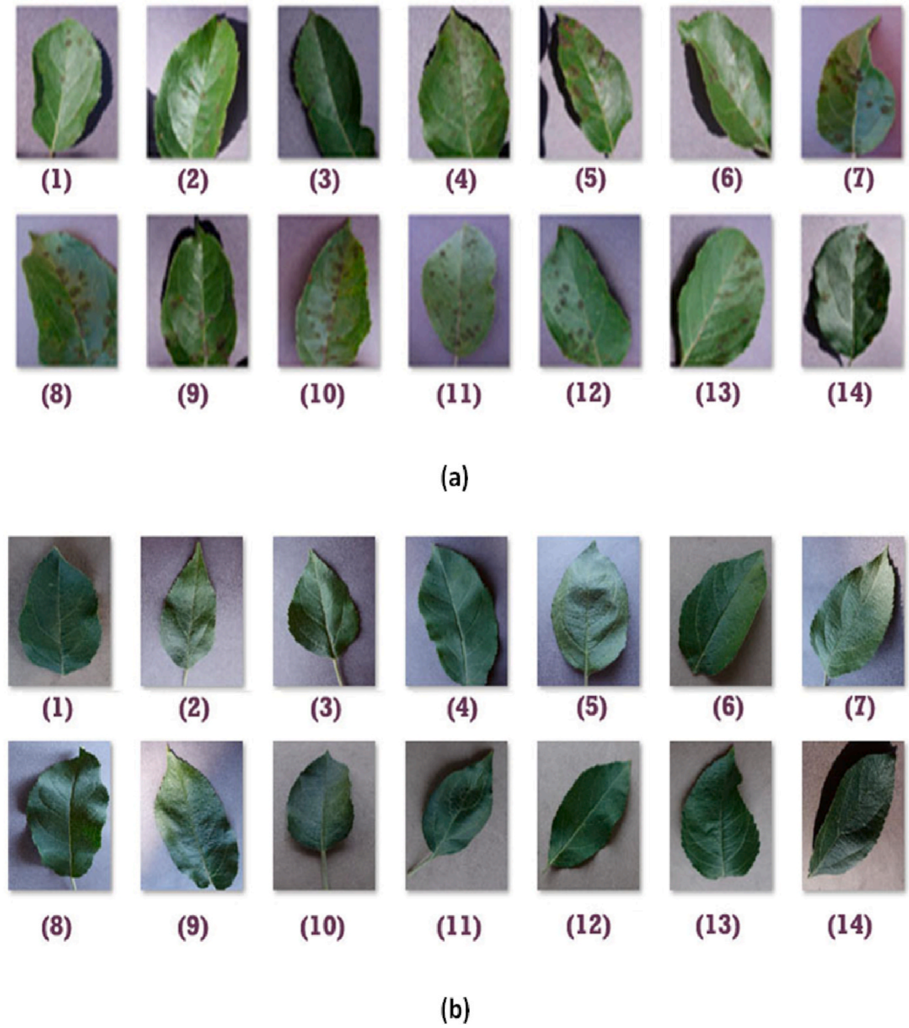

Fig. 1. (a) Diseased leaf image samples and (b) healthy leaf image samples.

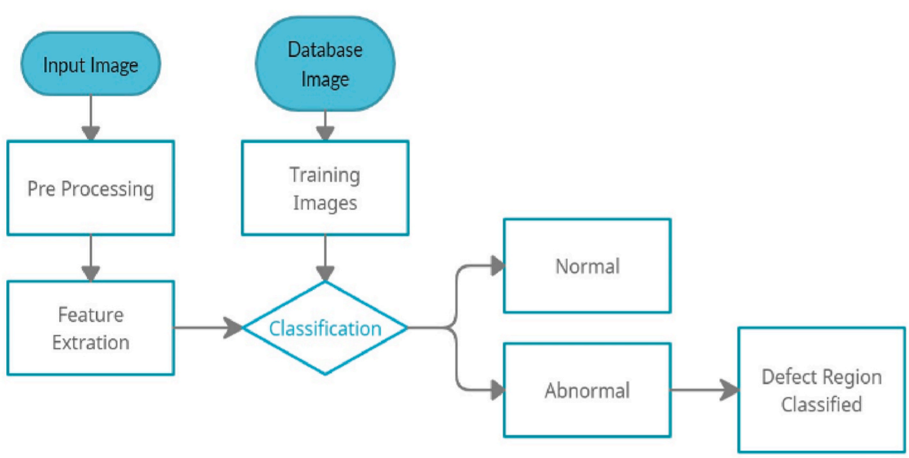

Fig. 2. General steps for Crop detection.

and compared to determine the best model for plant disease prediction with the highest accuracy.

i) It’s a probabilistic classification scheme.
ii) Theorem of high independence presumption.
iii) The value of a certain function is unaffected by the value of some other feature [1,8,52].

It presents two new technologies for automatic fruit counting in fruit tree canopy images, one is based on dense segmentation based on texture and the other is based on detection of fruit based on shape and

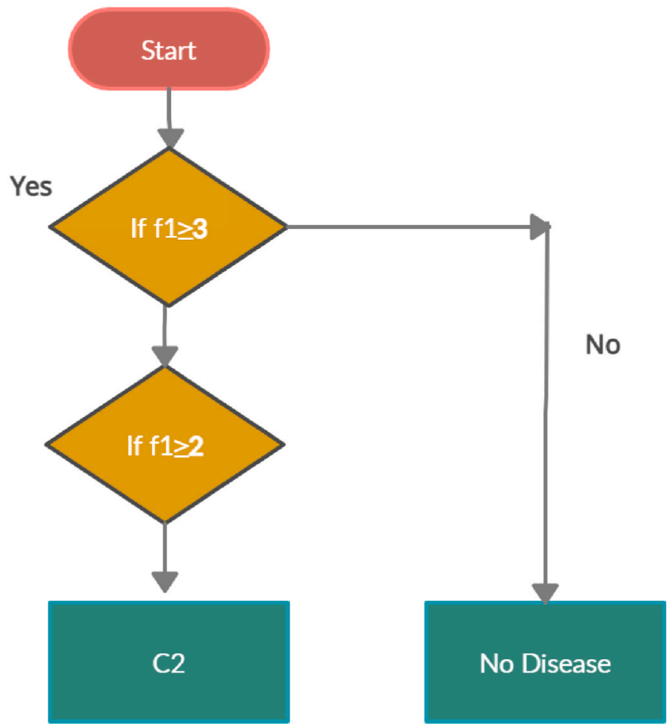

Fig. 3. Decision Tree Flow chart.

shape. Compares with the use of existing technologies a) Contour segmentation and nearest neighbor pixel classification system, and then b) Super pixel based support vector machine method and classification [9,48,53].

Support vector machines and artificial neural networks were used to allow the vision system to detect weeds based on their pattern. In sugar beet fields, four species of common weeds were studied. a) It's focused on decision planes, which are used to establish decision boundaries. b) It has two phases of service.1) the offline protocol 2) The online procedure, c) For preparation and classification, a multi-class support vector machine, which is a set of binary vector machines, is used. Fourier descriptors and moment invariant features were among the form feature sets. The overall classification accuracy of ANN was 92.92%, with 92.50% of weeds correctly identified [2].

Machine learning techniques combined with adequate image processing principles have a lot of potential for providing intelligence for designing an automation system that can distinguish fruits based on their form, variety, maturity, and intactness [21,56]. The machine will even tell you what diseases the herbal plant can help you with. A features dataset of 600 images was used for the preparation, with 50 images per herbal program [3,42,54].

In the year of 2020, the authors "Pushkara Sharma et al.", proposed a paper related to crop disease identification via leaves with respect to machine learning model and the image pre-processing methodology [15]. The first motto of this work is to identify the disease and protect the complete plant as well as control the disease by doing some precautions accordingly. This paper adapts the artificial intelligence logic in order to identify the plant leaf disease and providing the appropriate alert to prevent plants from the diseases as well as avoiding the huge loss ahead. This paper proves the efficiency level of the classification approach in order to pre-processing benefits in resulting portions as well as the accuracy levels of prediction is also good.

2.1. NB classifier

Gaussian Naive Bayesian calculates each attribute's continuous values, and also, their distribution depends upon a Gaussian distribution that is also referred to as Normal Distribution. The results of Gaussian distribution draw as a shape of bell curve, which is regularity of the mean values and to be calculated as,

$$p\,(x_1/y) = \frac{1}{\sqrt{2\Pi\sigma_y^2}} \exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right) \rightarrow \tag{1}$$

2.2. KNN classifier

KNN classifier used for classification issues and regression issues, but usually, KNN helps for classification problems. KNN is a diagnostic of distribution tree algorithm. If there is no imagination for distribution of data, so is referred to as Non-parametric, i.e., the structure calculated from the attributes of data set. KNN used for prediction when the data sets never obey the hypothetical mathematical imaginations. KNN doesn't necessary any training data for further proceeds. So it referred to as the Slow Learning (SL) algorithm—all the training data helps in the testing data.

2.3. DT classifier

DT classifier is the dominant and acceptable method for classification and prediction process. DT has a structure of tree-based concept, where every internal node describes a feature test, every branch describes as a test result, and every terminal node holds a label of data. Decision trees can generate understanding rules quickly. A decision tree is a value-based method, accessible and helpful because of its easily understandable flowchart estimation. The flow chart of DT shown in Fig. 3.

2.4. SVM classifier

The analysis of regression and classification, SVM to be helps. SVM calculates the hyperplane that have the increased margin within the two classes of data. The hyperplane vectors are referred to as Support vectors. By considering essential situations, SVM could build a margin of hyperplane that splits the hyperplane vector completely into two non-intersecting classes. In several cases, however, this is not applied, so this classifier will find hyperplanes of the support vectors that increase the margins and reduce the classification errors.

2.5. RF classifier

RF is a supervised algorithm can handle regression and classification methods. It is primarily concerned for classification related issues. A forest manages collection of trees, and high number of trees means it is referred to as a Strong. Alike the decision trees, the RF also discovers the dataset based decision tree approach. It got the prediction results from the entire tree and then selects better outcome by choosing the defined process. It is referred to as an ensemble technique, which is better than a single DT classifier because over-fitting to be reduced through the average performance.

2.6. MLP classifier

A MLP is the concept which is based on regression. By this method, the input dataset is being altered by the conversion of non-liner based learners. The changes from the input data, which is a linearly distinct characteristic. The input data layer that alters into as a hidden layer. Only a single hidden layer is used in MLP Classifier, or else works as an Artificial Neural Network. Even the multiple hidden layer usages are benefits for the classification purpose.

3. Logistic regression (LR)

Logistic Regression is a supervised prediction machine learning

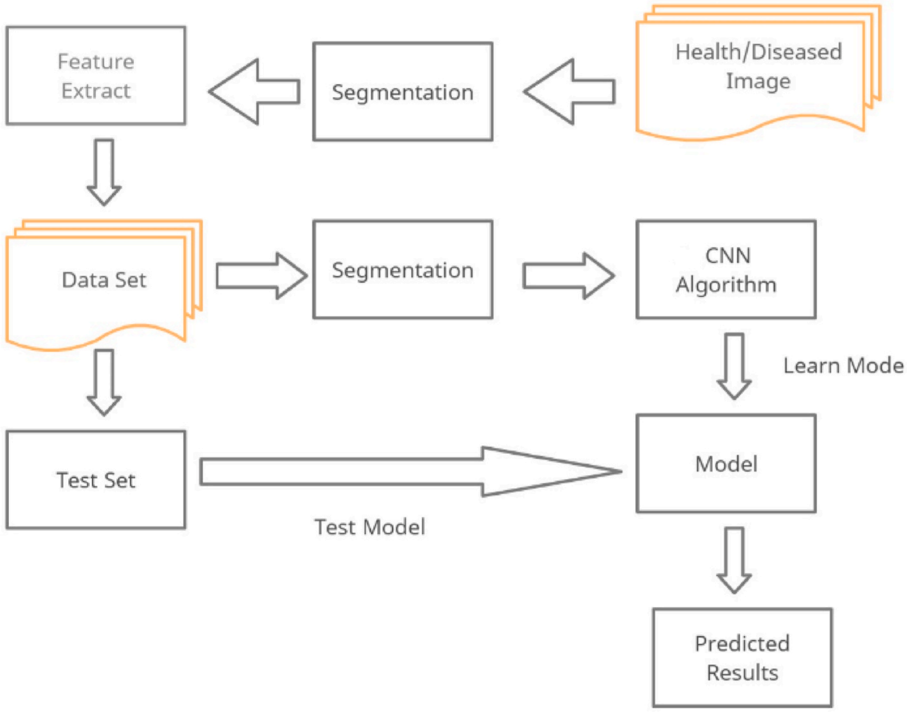

Fig. 4. System architecture for plant leaf disease detection.

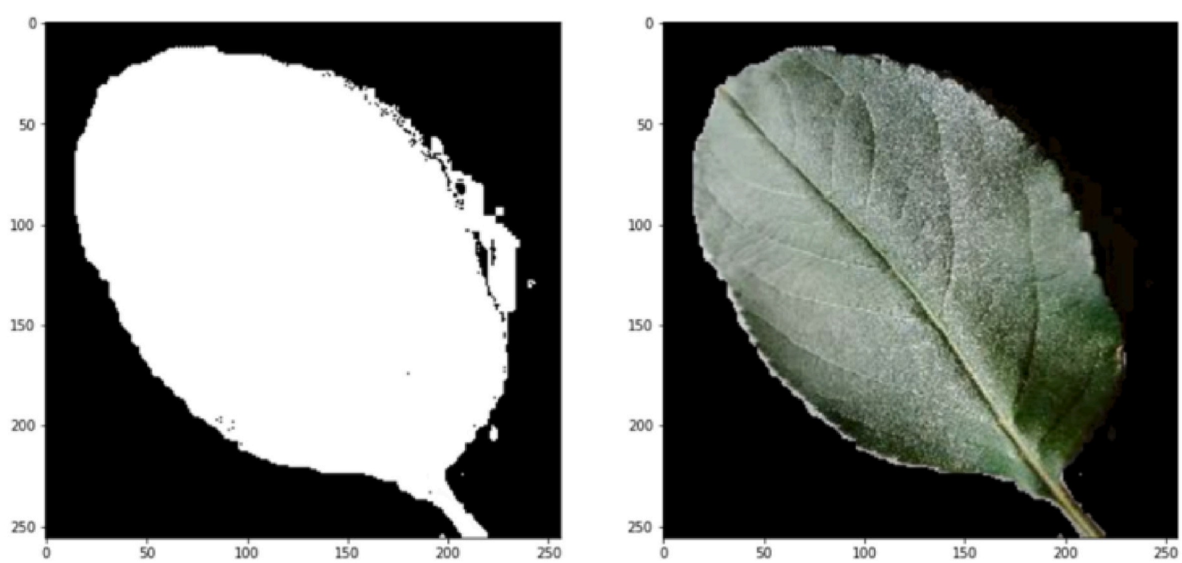

Fig. 5. Classification result analyses.

algorithm. The linear regression consists of two forms, basic and multiple linear. Simple linear regression has an individual and multiple linear regressions, as seen in equations (2) and (3), has several independent variables

$$Y = b_o + b_1 * x \rightarrow \quad (2)$$

$$Y = b_0 + b_1 * x_1 + b_2 * x_2 + \dots + b_n * x_n \quad \rightarrow (3)$$

In this case X is the independent variable and the Y outcome is the dependent. The goal of linear regression is to find the right line for the details observed as shown in Fig. 3. The most appropriate line fits the data set observations. We may classify probabilities between 0 and 1 using logistic regression. Since we just concern ourselves with the prediction rather than with the likelihood, the likelihood is called greater than 0.5 since yes and less than 0.5 as no.

4. Artificial intelligence and deep learning based plant disease detection

[22] Presented a technique of deep learning for detection of disease in plants that could cause damage in crops and agriculture resulting in loss of crop yield. The current deep learning methods expansion found their plant disease detection application, thereby contributing the robust tool having higher results on accuracy [46]. The present shortcomings and limitations of offered detection of plant disease models are discussed and presented.

In the year of 2020, the authors "MonuBhagat et al.", proposed a paper related to plant leaf disease detection with respect to classical

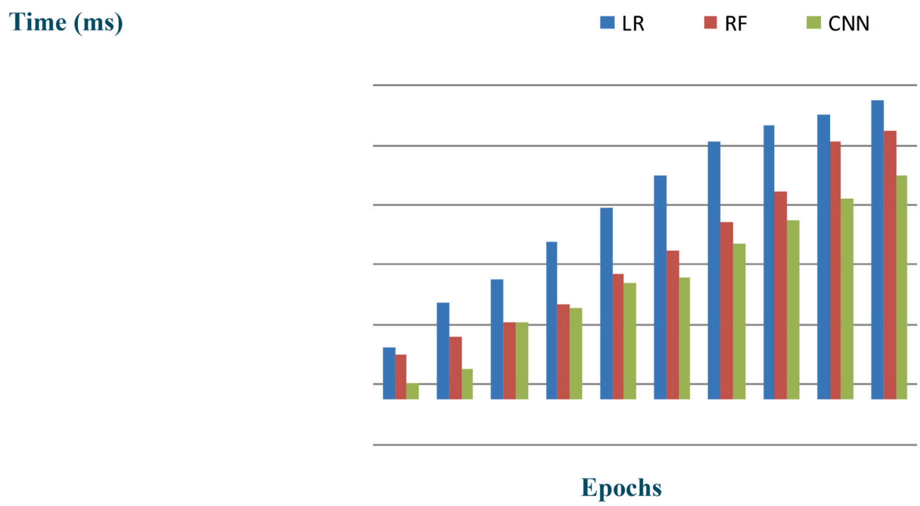

Fig. 6. Processing time estimations of deep machine learning approaches (LR, RF and CNN).

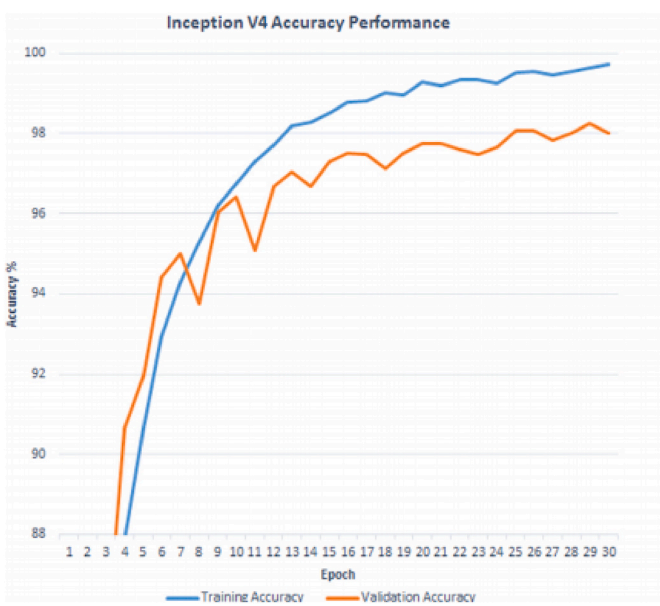

Fig. 7. Performance Estimation of Inception v4 Accuracy.

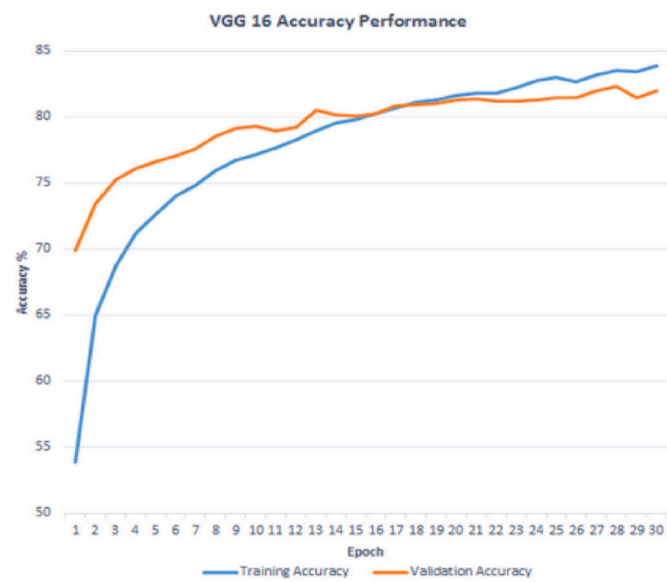

Fig. 8. Performance estimation of VGG 16 accuracy.

Support Vector Classification methodology [4]. In this paper the authors illustrated such as: agriculture and its associated businesses are the major economic source of the Indian country and it contributes around 60–70% of the economic growth of the nation. The major problem identified on this paper is the crop leaf disease detection problem, in which the problem is estimated by means of several classification logics in literature but all are stuck in certain level of issues [56]. So, that a well-known Support Vector Classification model is utilized in this approach in order to attain high accuracy level in results.

[5] Suggested a novel extract approach for the optimized sub-set function. Cultivation depending on the forms should be tracked for algorithm items based on the vector machine help classification. The performance provided by the technologies can be best rated with a total accuracy of about 89.6% points.

[6] Suggested the idea focused on fuzzy sets. When the fluidity can occur, the brightness amount should be assumed in-pixel in the images for the calculated degree. When the ambiguity of images is treated effectively in the fuzzy package IFSs is processed [50]. When the activation of the segmentation can be calculated by the satellite by which the unknown capture images can be decreased. Then, the segmentation of the deficit of the crops for the clustering technique will fuse an image, since it depends on the interval between the intuitionist fuzzy set.

[7] Using a chart rice crop based neural network algorithm and forecast the yield in the district of Terai [55].evaluated production, water output (WEE), output in precipitation usage (PUE) and net crop returns based on proven crop responses to the use of water by integrating the rotation of grass/broadleaf.

[28] Presented a professional knowledge support program for rice, coffee and cocoa production, focused on the user's input, and external details, such as position and environment, which will assist the selection processes, tracking, surveillance, detection, pest prevention, selection of fertilizer, among others.

[10] Presents the creation of an automated device that analyses and provides advice to farmers on infected paddy photos. The key aim of designing a system for classifying rice diseases is to simplify the detection and classification of rice diseases [12], which include vector supports and artificial neural networks. The crop forecast takes account of parameters such as precipitation quantity, minimum and maximum temperature, soil type, humidity and the importance of soil pH [49,51]. Data was obtained from Maharashtra's agriculture website. Data was broken into nine farming regions.

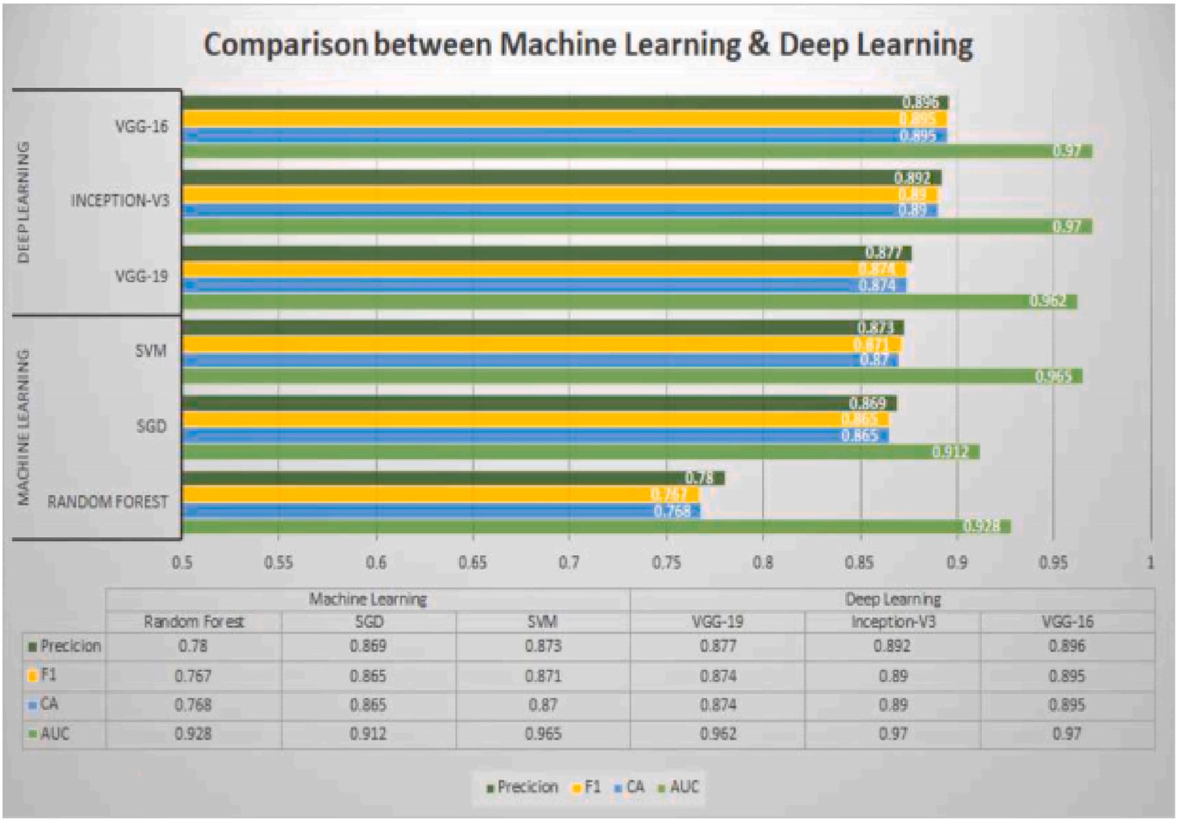

Fig. 9. Review on machine and deep learning techniques comparison.

[17] Defining and organizing according to their relative importance key variables which affect the yield of sugarcane and creating mathematical models of predicting the yield of sugarcane through the use of data mining techniques (DMs). To that end, the data bases of several sucrose mills in Sao Paulo, Brazil, were analyzed using three DM techniques. Meteorological variables and plant management have been studied using the following approaches of DM: forest random, raise, and vector assistance, and the resulting models have been evaluated using an independent dataset. Compare. Random forest algorithm is used.

The application of machine learning techniques in agriculture to the study of soil fertility [18] was discussed. Agriculture has long been one of the research fields of concern. This research is aimed at evaluating; classifying and enhancing soil data according to different factors [38, 43]. Technical developments like robotics, data processing have taken advantage of agricultural science. Data mining nowadays is used in large fields, and many off-shelf database mining products and domain specific data mining applications sell softwares, but data mining is a comparatively new field of study in agricultural soil datasets. The vast volumes of data now virtually obtained in connection with plants could be processed and used entirely [19]. By evaluating all these challenges and problems, such as atmosphere, temperature, moisture, snow, moisture, there is no correct way of fixing the situation faced by us and technology. Indian agriculture has various ways to improve economic development.

[11] k-Nearest Nearest Neighbor Algorithm Potentials, an ET0 estimation data mining tool, have been explored in semi-arid China, using minimal climate data. Furthermore, the PM-56 equation was checked with a KNN dependent ET0 prediction model.

[14] Established activation features and newly developed activation functions, including weights and bias value, have evaluated the MLP model. This research analyses the outcome of various activation capabilities and proposes several new basic activation functions such as DharaSig, DharaSigm and SHBSig, in order to increase the efficiency and accuracy of neural networks [44]. In addition, the DharaSig function DharaSig1, DHaraSig2 and DharaSig3 were created by three new activation functions with minor variations.

[29] Developed operating laws that are relevant and weighted aggregation operators that were required. In it the characteristics of a neutral type in the membership degrees of the group and the sum of probability are specified by a new neutral addition and scalar multiplication operational rules. Any aspects of the legislation introduced are analyzed.

Failures in crops are fairly common [47]. At the same time agriculture is impacted by even other causes, such as agricultural degradation, overused fertilizers and insecticides, stresses on toxic substances and radiation, etc. Many bugs have been shown to be insecticide-resistant. Early plant prediction will solve crop production issues Hence an appropriate technique of decision making is required for the collection and cultivation process of crops.

In the year of 2020, the authors "SurampalliAshok'et al.", proposed a paper related to Tomato plant's leaf disease identification with respect to deep learning methodologies [16]. This proposed approach is introduced to recognize the crop Leaf infection utilizing picture preparing strategies to Tomato crop, in which it is dependent on Image segmenting, bunching and open source methodologies, accordingly all adding to a solid, safe, and precise arrangement of leaf illness with the specialization to Tomato crops [39]. It concentrates more on tomato crop and its associated diseases as well as in further scope the specifications of other plant assisted diseases with proper prediction scenario is discussed.

[36] Presented a deep learning based scheme, the recent breakthrough research in the field of computer vision. It is the most promising one for fine grained classification of disease similarity as this scheme evades the labor-intensive feature extraction and the segmentation based on threshold [40,45].With the use of apple black root images in the dataset of plant village are annotated through botanists having four stages of severity as the ground truth, a deep convolution network series that are trained for diagnosing the disease severity.

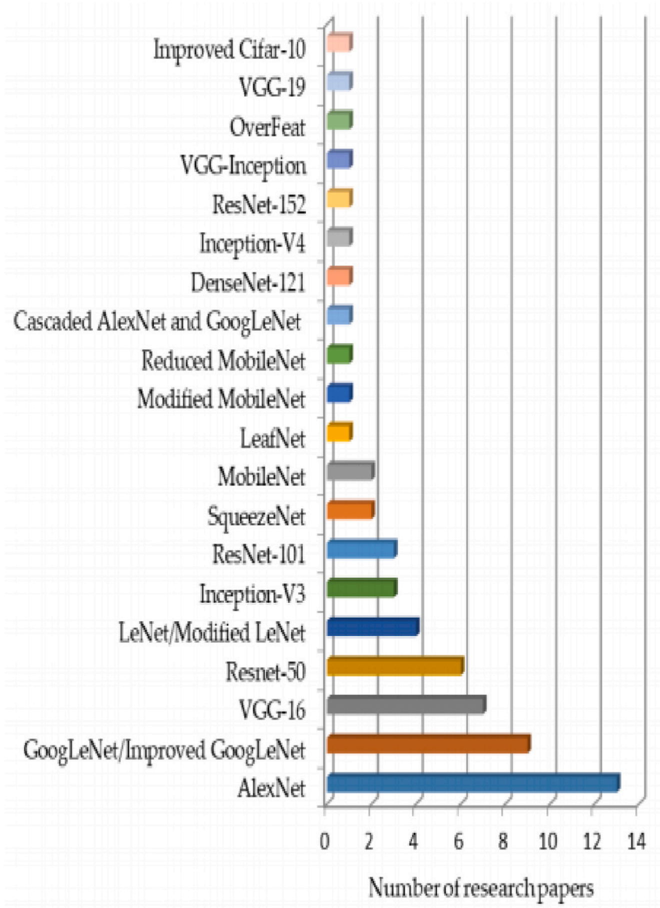

Fig. 10. Review on Various Deep Learning Techniques used in Number of Research Papers.

5. Convolution neural network (CNN)

The main purpose of this methodology is to classify the images with the given perspective. It is quite different when compared to other neural network methods. Generally CNNs use small pre-processing contrast with calculations of other arrangement of image. This imply that the classification learn the channel which in usual calculation were it is hand-built. The convolutional layer is the structure of center square of a CNN. The parameters layer consist of a group of channels (or pieces) that are learnable, and having a small open field, on the other hand get to full info volume complexity. Therefore, the system learns channels which are initiated once it classifies some sort of specific highlight at some spatial positioning information.

5.1. Inception–V4

Inception V4 is the 48 layered deep CNN network which is the Image Net model extension. The model constructed comprises of asymmetric and symmetric blocks which covers convolution on making the map of features on applying the filter to image, average computation of feature map for all pixel, maximum pooling layer, average pooling (8 × 8), and maximum pixel which aids in reducing the computation cost parameters numbers for the purpose of learning. The inputs of same size, normally drop outs are combined after the pooling which aids in decreasing the overfit, increasing the accuracy, the fully-connected layer is responsible for connecting neurons to each layers. The norm of activation is made with softmax and batch norm that is employed for loss compute.

5.2. VGG–16

VGG known as “visual geometry group” introduced by the oxford university who made this type of deep CNN model for the “Image Net Large scale recognition of visual challenge” (ILSVRC) held in 2014. This structure comprises of best function up to date on comparing the other deep neural networks. Though several kinds of parameters exists, this structure only focuses on the padding convolution layer, fully connected layer, max pool having the outcome of softmax layer.

5.3. VGG –19

This is similar to VGG-16 and the other VGG variants having an extra feature of three convolution layer which facilitates the identification of image in an effective manner. The basic idea is making the small size and constant convolution on designing the deep neural networks.

6. Comparative review on machine and deep learning techniques

Fig. 4 illustrates the final image masking concatenation of the processed image, in which the lower and upper green and brown masking images are concatenated with convolutional logic with respect to the generated model.

Feature extraction is performed over the input images to obtain discriminating information. Different types of features such as color, texture and shape etc. Could be useful to detect the specific diseases in the plants. The set of features is provided as input to the classifier, which labels the plant as healthy or non healthy and/or identifies the disease. The effectiveness and applicability of such systems highly depends on the classification accuracy. The key role of feature extraction in plant disease detection is to learn the features automatically. Mostly the attributes such as shape, texture and color of plant leaf images are utilized to detect plant infections. Image feature is a piece of information related to a content/object which helps to recognize it uniquely. Convolutional neural networks were established to solve problems with image data, but they also perform if given sequential inputs. The convolution process analyzes the brown (affected portion) color variation range with the estimated threshold level of the defined algorithm models, if the variation level exceeds the threshold limit of 200, the image will be marked as unhealthy (diseased) or else the respective image color variation is below 200, it will be considered as a healthy leaf (see Fig. 5).

Fig. 6 is the representation of estimating processing time of deep machine learning approaches for various machine learning techniques like LR, RF and CNN. Te time consumed for processing is estimated and is related to illustrate tem in graphical form.

Fig. 7 signifies the performance estimation of inception v4 accuracy. The training and testing accuracy is estimated and the outcome is sown in graphical representation form. Similarly, it is the representation of VGG 16 accuracy performance (see Fig. 8).

Fig. 9 signifies the comparative estimation of machine and deep learning techniques. The comparison is estimated and the outcome is shown in graphical form.

The review made in various numbers of research papers using machine and deep learning techniques are surveyed and their usage is compared in the bar graph illustration in Fig. 10.

7. Conclusion

An extensive research study is conceded out on various kinds of machine and deep learning techniques for plant disease recognition and classification. After this, other techniques of classification in machine learning might be employed for may be used for plants disease detection and in the intellect of aiding the farmers an automatic disease detection of all kinds of disease in the crop that were to be detected. This analysis discusses various approaches of DL for the plant diseases detection.

Furthermore, several techniques/mappings were summarized for recognizing the disease symptoms. Here the development of deep learning technologies in recent years for the identification of plant leaf diseases. We anticipate that this work will be a useful tool for scientists looking into plant disease detection. Also, a comparative study is also made between machine and deep learning techniques. Though a great deal of noteworthy progress was noticed in recent years, there were still some research gaps that should be addressed and to implement effective techniques for plant disease detection.

CRediT authorship contribution statement

C Jackulin: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Writing – original draft, preparation, Writing – review & editing. **S. Murugavalli:** Supervision, and, Validation.

Declaration of Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Sunil S. Harakannanavara, Jayashri M. Rudagi, Veena I. Puranikmath, Ayesha Siddiqua, R. Pramodhini, Plant leaf disease detection using computer vision and machine learning algorithms" *Global Transitions Proceedings* 3 (1) (2022) 305–310.
[2] R. Sujatha, J.M. Chatterjee, N. Jhanjhi, S.N. Brohi, Performance of deep learning vs machine learning in plant leaf disease detection, Microprocess. Microsyst. 80 (2021), 103615.
[3] C.K. Sunil, C.D. Jaidhar, N. Patil, Cardamom plant disease detection approach using EfficientNetV2, in: IEEE Access, vol. 10, 2021, pp. 789–804, https://doi.org/10.1109/ACCESS.2021.3138920, 2021.
[4] M. Bhagat, D. Kumar, I. Haque, H.S. Munda, R. Bhagat, Plant leaf disease classification using grid search based SVM, in: 2nd International Conference on Data, Engineering and Applications (IDEA), 2020, pp. 1–6.
[5] J. Cui, X. Zhang, W. Wang, L. Wang, Integration of optical and SAR remote sensing images for crop-type mapping based on a novel object-oriented feature selection method, Int. J. Agric. Biol. Eng. 13 (2020) 178–190.
[6] V. Ananthi, Fused segmentation algorithm for the detection of nutrient deficiency in crops using SAR images, in: Artificial Intelligence Techniques for Satellite Image Analysis, Springer, 2020, pp. 137–159.
[7] T. Baidar, Rice Crop Classification and Yield Estimation Using Multi-Temporal Sentinel-2 Data: a Case Study of Terrain Districts of Nepal, 2020.
[8] K.P. Panigrahi, H. Das, A.K. Sahoo, S.C. Moharana, Maize leaf disease detection and classification using machine learning algorithms, in: Progress in Computing, Analytics and Networking, Springer, 2020, pp. 659–669.
[9] Y. Majeed, J. Zhang, X. Zhang, L. Fu, M. Karkee, Q. Zhang, et al., Deep learning based segmentation for automated training of apple trees on trellis wires, Comput. Electron. Agric. 170 (2020), 105277.
[10] S. Das, S. Sengupta, Feature extraction and disease prediction from paddy crops using data mining techniques, in: Computational Intelligence in Pattern Recognition, Springer, 2020, pp. 155–163.
[11] K. Feng, R.S. Tian, Forecasting Reference Evapotranspiration Using Data Mining and Limited Climatic Data 54, Taylor Francis, 2020, pp. 363–371.
[12] T.K. Fegade, B. Pawar, Crop prediction using artificial neural network and support vector machine, in: Data Management, Analytics and Innovation, Springer, 2020, pp. 311–324.
[13] M. Loey, A. ElSawy, M. Afify, Deep learning in plant diseases detection for agricultural crops: a survey, Int. J. Serv. Sci. Manag. Eng. Technol. 11 (2020) 41–58.
[14] S.H. Bhojani, N.J.N.C. Bhatt, Applications, Wheat Crop Yield Prediction Using New Activation Functions in Neural Network, 2020, pp. 1–11.
[15] P. Sharma, P. Hans, S.C. Gupta, Classification of plant leaf diseases using machine learning and image preprocessing techniques, in: 2020 10th International Conference on Cloud Computing, Data Science & Engineering, Confluence), 2020, pp. 480–484.
[16] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S.G. Sophia, B. Pavithra, Tomato leaf disease detection using deep learning techniques, in: 2020 5th International Conference on Communication and Electronics Systems, ICCES), 2020, pp. 979–983.
[17] R.G. Hammer, P.C. Sentelhas, J.C.J.S.T. Mariano, Sugarcane Yield Prediction through Data Mining and Crop Simulation Models, vol. 22, 2020, pp. 216–225.
[18] R. Chaudhari, S. Chaudhari, A. Shaikh, R. Chiloba, T. Khadtare, Soil fertility prediction using data mining techniques, International Journal of Future Generation Communication and Networking 9 (Issue 6) (2020).
[19] M. Champaneri, D. Chachpara, C. Chandvidkar, M. Rathod, Crop yield prediction using machine learning, Int. J. Sci. Res. 9 (2020).
[20] S.S. Kumar, B. Raghavendra, Diseases detection of various plant leaf using image processing techniques: a review, in: 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), 2019, pp. 313–316.
[21] M. Türkoğlu, D. Hanbay, Plant disease and pest detection using deep learning-based features, Turk. J. Electr. Eng. Comput. Sci. 27 (2019) 1636–1651.
[22] M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, D. Stefanovic, Solving current limitations of deep learning based approaches for plant disease detection, Symmetry 11 (2019) 939.
[23] U. Shruthi, V. Nagaveni, B. Raghavendra, A review on machine learning classification techniques for plant disease detection, in: 2019 5th International Conference on Advanced Computing & Communication Systems, ICACCS), 2019, pp. 281–284.
[24] K. Lavanya, A.V. Jain, H.V. Jain, Optimization and decision-making in relation to rainfall for crop management techniques, in: Information Systems Design and Intelligent Applications, Springer, 2019, pp. 255–266.
[25] S. Kaur, S. Pandey, S. Goel, Plants disease identification and classification through leaf images: a survey, Arch. Comput. Methods Eng. 26 (2019) 507–530.
[26] P. Tamsekar, N. Deshmukh, P. Bhalchandra, G. Kulkarni, K. Hambarde, S. Husen, Comparative analysis of supervised machine learning algorithms for GIS-based crop selection prediction model, in: Computing and Network Sustainability, Springer, 2019, pp. 309–314.
[27] T. Bera, A. Das, J. Sil, A.K. Das, A survey on rice plant disease identification using image processing and data mining techniques, in: Emerging Technologies in Data Mining and Information Security, Springer, 2019, pp. 365–376.
[28] K. Lagos-Ortiz, J. Medina-Moreira, A. Alarcón-Salvatierra, M.F. Morán, J. del Cioppo-Morstadt, R. Valencia-García, Decision support system for the control and monitoring of crops, in: 2nd International Conference on ICTs in, Agronomy and Environment, 2019, pp. 20–28.
[29] H. Garg, Neutrality operations-based Pythagorean fuzzy aggregation operators and its applications to multiple attribute group decision-making process, J. Ambient Intell. Hum. Comput. (2019) 1–21.
[30] S. Zhang, Z. You, X. Wu, Plant disease leaf image segmentation based on super pixel clustering and EM algorithm, Neural Comput. Appl. 31 (2019) 1225–1232.
[31] J. Shirahatti, R. Patil, P. Akulwar, A survey paper on plant disease identification using machine learning approach, in: 2018 3rd International Conference on Communication and Electronics Systems (ICCES), 2018, pp. 1171–1174.
[32] N. Ganatra, A. Patel, A survey on diseases detection and classification of agriculture products using image processing and machine learning, Int. J. Comput. Appl. 180 (2018) 1–13.
[33] S. Ramesh, R. Hebbar, M. Niveditha, R. Pooja, N. Shashank, P. Vinod, Plant disease detection uses machine learning, in: 2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C), 2018, pp. 41–45.
[34] A. Badage, Crop disease detection using machine learning: Indian agriculture, Int. Res. J. Eng. Technol 5 (2018).
[35] J. Singh, H. Kaur, Plant disease detection based on region-based segmentation and KNN classifier, in: International Conference on ISMAC in Computational Vision and Bio-Engineering, 2018, pp. 1667–1675.
[36] G. Wang, Y. Sun, J. Wang, Automatic image-based plant disease severity estimation using deep learning, Comput. Intell. Neurosci. 2017 (2017) 1–8. https://doi.org/10.1155/2017/2917536, 2917536.
[37] V. Singh, A.K. Misra, Detection of plant leaf diseases using image segmentation and soft computing techniques, Information processing in Agriculture 4 (2017) 41–49.
[38] S. Ren, K. He, R. Girshick, J. Sun, R.-C.N.N. Faster, Towards real-time object detection with region proposal networks, IEEE Trans. Pattern Anal. Mach. Intell. 39 (6) (2017) 1137–1149.
[39] M. Mehdipour Ghazi, B. Yanikoglu, E. Aptoula, Plant identification using deep neural networks via optimization of transfer learning parameters, Neurocomputing 235 (2017) 228–235.
[40] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic, Deep neural networks based recognition of plant diseases by leaf image classification, Comput. Intell. Neurosci. 2016 (2016) 1–11. https://doi.org/10.1155/2016/3289801, 3289801.
[41] Y. Atoum, M.J. Afridi, X. Liu, J.M. McGrath, L.E. Hanson, On developing and enhancing plant-level disease rating systems in real fields, Pattern Recogn. 53 (2016) 287–299.
[42] F. Qin, D. Liu, B. Sun, L. Ruan, Z. Ma, H. Wang, Identification of alfalfa leaf diseases using image recognition technology, PLoS One 11 (12) (2016). Article ID e0168274.
[43] S.P. Mohanty, D.P. Hughes, M. Salathé, Using deep learning for image-based plant disease detection, Front. Plant Sci. 7 (2016) article 1419.
[44] E. Gawehn, J.A. Hiss, G. Schneider, Deep learning in drug discovery, Molecular Informatics 35 (1) (2016) 3–14.
[45] J.G.A. Barbedo, A new automatic method for disease symptom segmentation in digital photographs of plant leaves, Eur. J. Plant Pathol. 147 (2) (2016) 349–364.
[46] S.J. Pethybridge, S.C. Nelson, Leaf doctor: a new portable application for quantifying plant disease severity, Plant Dis. 99 (10) (2015) 1310–1316.
[47] C. Szegedy, W. Liu, Y. Jia, et al., Going deeper with convolutions, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR '15), June 2015, pp. 1–9. Boston, Mass, USA.
[48] A.M. Mutka, R.S. Bart, Image-based phenotyping of plant disease symptoms, Front. Plant Sci. 5 (2015) article no. 734.
[49] Y. LeCun, Y. Bengio, G. Hinton, Deep learning," *Nature* 521 (7553) (2015) 436–444.
[50] E. Omrani, B. Khoshnevisan, S. Shamshirband, H. Saboohi, N.B. Anuar, M.H.N. M. Nasir, Potential of radial basis function-based support vector regression for

apple disease detection, Measurement: Journal of the International Measurement Confederation 55 (2014) 512–519.
[51] D.L. Hernández-Rabadán, F. Ramos-Quintana, J. Guerrero Juk, Integrating SOMs and a bayesian classifier for segmenting diseased plants in uncontrolled environments, Sci. World J. 2014 (2014) 1–13. https://doi.org/10.1155/2014/214674, 214674.
[52] M.D. Zeiler, R. Fergus, Visualizing and understanding convolutional networks, in: D. Fleet, T. Pajdla, B. Schiele, T. Tuytelaars (Eds.), Computer Vision–ECCV 2014, Springer), 2014, pp. 818–833.
[53] E.L. Stewart, B.A. McDonald, Measuring quantitative virulence in the wheat pathogen zymoseptoriatritici using high-throughput automated image analysis, Phytopathology 104 (9) (2014) 985–992.
[54] J.G.A. Barbedo, An automatic method to detect and measure leaf disease symptoms using digital image processing, Plant Dis. 98 (12) (2014) 1709–1716.
[55] D.C. Nielsen, M.F. Vigil, J.G. Benjamin, Evaluating decision rules for dry land rotation crop selection, Field Crop. Res. 120 (2011) 254–261.
[56] H. Al Hiary, S. Bani Ahmad, M. Reyalat, M. Braik, Z. ALRahamneh, Fast and accurate detection and classification of plant diseases, Int. J. Comput. Appl. 17 (1) (2011) 31–38.