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Performance of deep learning vs machine learning in plant leaf disease detection

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ABSTRACT

Plants are recognized as essential as they are the primary source of humanity's energy production since they are having nutritious, medicinal, etc. values. At any time between crop farming, plant diseases can affect the leaf, resulting in enormous crop production damages and economic market value. Therefore, in the farming industry, identification of leaf disease plays a crucial role. It needs, however, enormous labor, greater preparation time, and comprehensive plant pathogen knowledge. For the identification of plant disease detection various machine learning (ML) as well as deep learning (DL) methods are developed & examined by various researchers, and many of the times they also got significant results in both cases. Motivated by those existing works, here in this article we are comparing the performance of ML (Support Vector Machine (SVM), Random Forest (RF), Stochastic Gradient Descent (SGD)) & DL (Inception-v3, VGG-16, VGG-19) in terms of citrus plant disease detection. The disease classification accuracy (CA) we received by experimentation is quite impressive as DL methods perform better than that of ML methods in case of disease detection as follows: RF-76.8% > SGD-86.5% > SVM-87% > VGG-19–87.4% > Inception-v3–89% > VGG-16–89.5%. From the result, we can tell that RF is giving the least CA whereas VGG-16 is giving the best in terms of CA.

1. Introduction

Agriculture has been a major source of economic growth in India. The farmer selects the required crop based on the soil type, the location's weather condition, and economic value. As a result of rising populations, weather changes, and political uncertainty, the agricultural industries began to look for new methods to increase food production. This allows researchers to look for new high productivity innovations that are effective and accurate. Through the use of precise agriculture in information technology, farmers may collect information and data to make the right decision on high farm production. Precision agriculture (PA) is a modern technology that offers sophisticated techniques for optimizing farm production. Through making use of these sophisticated technologies, Economic development in agriculture can be achieved. PA can be used for many applications, such as plant pest identification, weed identification, crop yield production and detection of plant diseases, etc. To control pests, avoid diseases, and increase crop yield, a farmer uses pesticides. Crop diseases are causing problems for farmers due to low output and economic losses and industrial agriculture. Therefore, disease detection and severity are focused on the need to be defined as appropriate [1].

Agriculture assumes a significant part for individuals in India and the economy of the nation.

Regular manifestations include anomalous leaf development, color distortion, hindered development, withered, and harmed units. Even though infections and bug vermin can cause significant yield misfortunes or carry passing to plants and it's likewise legitimately influential to human wellbeing. These require cautious analysis and ideal taking care of to shield the yields from weighty losses [2]. In plants, infections can be found in different parts, for example, natural products, stem, and leaves. Leaf presents a few points of interest over blossoms and natural products at all seasons around the world [3–5].

Next-generation technologies, for instance, ML and DL have been used to grow the acknowledgement rate and the precision of the results. Distinctive investigates have happened under the field of ML for plant contamination acknowledgement and assurance, such traditional ML

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approach being sporadic forest, SVM, fuzzy logic, K-means system, Convolutional neural networks (CNN), etc. In agribusiness research, ML procedures are on a very basic level used to recognize, perceive, and anticipate crop diseases and plant pressure phenotyping. Unlike unmistakable confirmation of iotas subject to genomics data, ML procedures in plant disease research are significantly dependent on motorized stages, for instance, raised vehicles and ground robots with sensors to assemble steady data from fields [6, 7]. Ordinarily, data was removed from significant standard pictures or sensor data and a short time later pre-taken to dispose of immaterial noteworthy information. Space data in plant disease (PD) was fundamental for pre-dealing with and picking an authentic strategy, which could improve the presentation of ML conjecture [8]. ML methods were used regularly as gadgets to perceive plant diseases. The purpose behind such examinations is to perceive whether a sickness is accessible on plants. A couple of assessments have utilized ML to distinguish Huanglongbing (HLB) for citrus trees. Another critical utilization of ML is structure, which organizes PD into different stages or different sorts. The ML counts were genuinely applied to the gathering of fine development, an infectious organism that causes yield mishap in varieties of harvests [9,10].

Our main contribution in this work is as follows:

- We aimed to classify citrus leaf disease using both methods ML (SGD, RF, SVM) & DL (Inception-v3, VGG-16, VGG-19) to find out which one of these is performing better in disease detection.
- For classification problems stratified 10-fold cross-validation is applied, in which the folds are chosen such that each fold contains approximately the same ratios of the target class.
- When new images are given as the input for the system, it predicts the type of disease and helps to take contour action before the plants get affected more.
- The agriculture sector is the backbone of the nation and our work will support to optimize the yield from the field by detecting diseased plants earlier.

The rest of this article is structured as Section 2 presents the various existing works done in this area. The methodology proposed of the current work is presented in Section 3 followed by an explanation of various ML & DL methods referred. The experimental setup details are presented in Section 4. Section 5 presents the experimental results with their detailed discussion. The paper concludes in section 6 followed by possible future work of current work.

2. Related work

Around 70% of individuals in India rely upon agriculture. Thus, it is the business that should be packed regarding innovative work. A wide assortment of yields of being developed across India. Farmers have been following conventional ways to deal with develop harvests and more often than not, the yields are influenced by maladies which prompt a decrease in farming creation. The significant theory is "inordinate utilization of pesticides for plant malady treatment expands expenses and raises the risk of poisonous build-up levels on rural items". Significantly, it prompts misfortunes to farmers that influences their prosperity. More often than not, a decrease in crop causes worries in farmer families bringing about untoward episodes also. Recognizing nuisance effectively and knowing which pesticide is appropriate to control the malady tainting the yield is fundamental. Here, farmers in India are acceptable to the extent their experience goes. Be that as it may, there needs precision or exactness in determination. A large portion of the farmers relies upon the proposal of individuals overseeing the pesticide business. Farmers may utilize the pesticides recommended without knowing about the pesticide and its amount to be utilized. Subsequently, farmers may lose significant time and cash. Plus, it will influence plants/crops unfavorably. Thus, it is fundamental to look for master guidance to have an exact dynamic and regulating pesticides in the right amounts [11].

It has been discovered that different calculations and techniques, for example, linear & logistic regression, RF, clustering, Gaussian models, decision trees (DT), Naïve Bayes (NB), K-nearest neighbors (KNN), and SVM among others, can be utilized for this reason. Recently DL techniques have likewise extended in the farming region. Movement in computer vision and artificial intelligence (AI) can prompt new arrangements. These strategies give more exact forecasts than conventional techniques, which empower better decision-making. Inferable from progress in equipment innovation, DL techniques are presently utilized for tackling complex issues in a sensibly short measure of time. The consequences of the examination in this field are not paltry. DL is as of now a cutting-edge strategy for land spread characterization tasks, and could likewise demonstrate help for some different tasks. Different sorts of deep neural networks (DNNs) have accomplished remarkable outcomes in hyperspectral examination [12]. CNN's have performed well in crop order tasks [13], organic product tallying, yield expectation [14], ailment discovery [15], and imaging tasks [16]. AlexNet [17] and GoogLeNet [18] models have demonstrated best in class execution in these investigations [15, 19]. Also, it has been indicated that better outcomes are obtained if networks are pre-prepared [20, 21].

Authors in [22] give a thorough outline & easy to use scientific categorization of ML methods to empower the plant network to accurately & effectively apply the suitable ML strategies & best-practice rules for different biotic & abiotic stress attributes. [23] illuminates various types of PD, different progressed ML & image processing techniques to identify PD, this overview likewise gives significant examination holes that will help in further exploration towards acknowledging PA. [24] utilizes visualization & ML methods to arrange the backwoods land on the terrain dataset made out of the ASTER imaging instrument to get the understanding of the cumulated information by utilizing Box Plot & Heat Map. [25] aimed at tweaking & assessing cutting-edge deep CNN for picture-based PD characterization. [1] studied the phases of general PD discovery framework & near investigation on ML characterization methods for PD location. [26] proposed a method for plant leaf disease detection (PLDD) & characterization utilizing the KNN classifier. An improved artificial plant optimization (IAPO) calculation utilizing ML has been presented in [27] that distinguishes the PD & arranges the leaves into sound & tainted on a dataset of 236 pictures. [27] created the artificial intelligence-based programmed PLDD & order for snappy & simple location of ailment afterward characterizing it & performing expected solutions for fixing that malady. [28] introduced the AI-based automated PLDD and characterization for a brisk and simple recognition of illness and afterward characterizing it and performing expected solutions to fix that sickness. [29] presented the acknowledgement and categorization of maize plant leaf illnesses by utilizing a Deep Forest method. In [30], a global pooling dilated CNN (GPDCNN) is suggested for recognizing PD. [31] focused on the latest advancement over explores concerning ML for big data logical & various strategies with regards to current computing conditions for different community applications. [32] presented Few-Shot Learning (FSL) methodology for plant leaf categorization utilizing DL with little datasets. [33] presents an assortment of methods intended to speak to, improve & enable multi-disciplinary & multi-institutional ML research in medical care informatics. [34] researched the practicality & possibility of presymptomatic recognition of tobacco infection utilizing hyperspectral

Table 1
Dataset description.

Disease	Number of images
Black spot	171
Canker	163
Greening	204
Melanose	13
Healthy	58
Total images	609

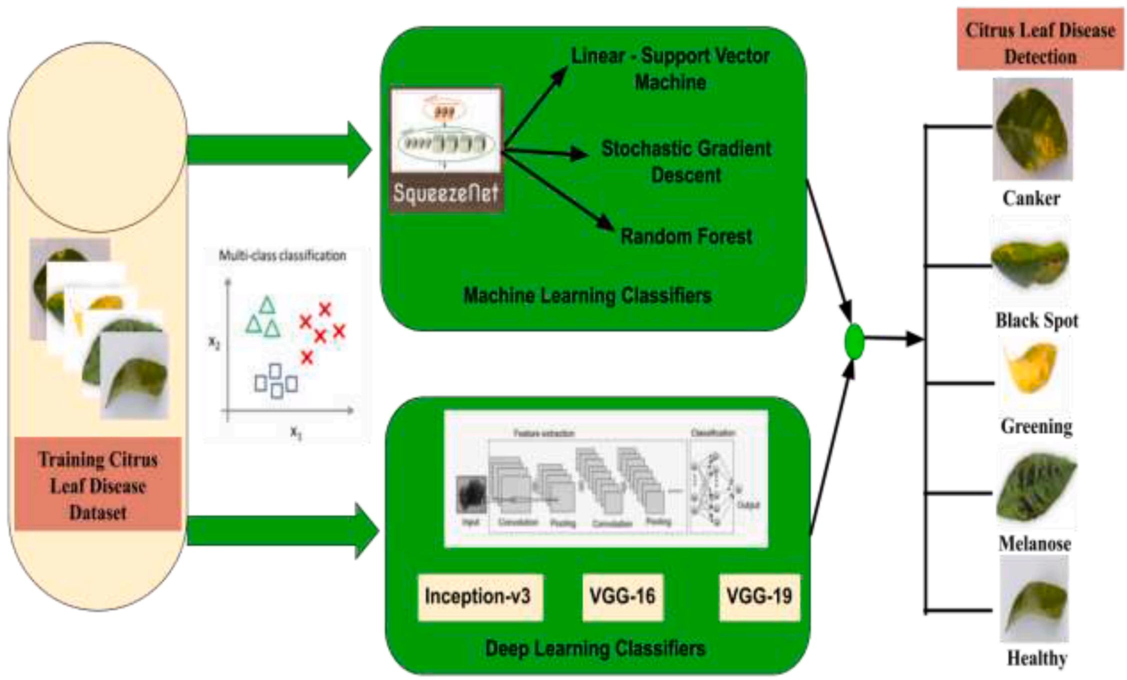

Fig. 1. The workflow of citrus leaf disease detection.

imaging, joined with the variable choice strategy & ML. [35] introduced a novice plant leaf malady recognition model dependent on a DCNN method. [36] gives strategies on the most proficient method to apply ML inside any association & assess the viability, reasonableness, & effectiveness of ML applications. [37] a lightweight CNN method is introduced to analyze grape sicknesses, including dark decay, dark measles & leaf scourge. [38] introduced a disentangled CNN approach with 8 hidden layers for tomato illness recognition. We have presented a tabular review of some of the existing work and presented in Table 1 as follows:

Reference No	Advantages	Disadvantages
[39]	Depict a summed up, measured ML work process for separating phenological information from pictures of herbarium examples, and talk about their merits, impediments, and expected future enhancements of their work process.	Training data sets need to be created through proceeded with the digitization of herbarium examples and comment of example pictures.
[40]	Actualizes Extreme Learning Machine (ELM) calculation for plant sickness expectation dependent on a dataset gathered continuously situation specifically Tomato Powdery Mildew Disease (TPMD) dataset	By utilizing different pre-handling techniques, for example, feature selection, re-sampling, dimensionality decrease, and so on with ELM calculation could have been checked as well maybe accuracy enhanced then.
[41]	Surveyed DL strategies on plant leaf infection discovery and its finding	Some computer vision techniques could have been incorporated
[42]	Planned to understand the modernized technique to perceive the species & distinguish early sickness of the spices by alluding to these qualities.	On the establishment of the plausibility study set out over, this framework might be situated to the normalization of spice species and early infection in computational models created utilizing more volume of information.
[43]	Contrasted & equitably assessed the absolute most recent existing strategies in this field, & assess the best combination of calculations that can be utilized to build up an exceptionally exact characterization framework for leaf sickness.	Various other strategies would in any case be valuable in photographic recognizable proof of leaf illnesses, & can subsequently be utilized to improve the general exhibition of the strategy under examination.
[44]	Attempted recognition of harvest infections utilizing AI procedures, particularly with SVM & artificial neural network (ANN)	It's a review paper and doesn't show any implementation
[45]	Surveys related research articles from the period of 2007 and 2018 with an attention to the advancement of best in class.	It's a review paper and doesn't show any implementation.

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(continued)

3. Proposed methodology

ML is meant for parsing the data and learning from it. Based on the requirement they applied to get the decision. Several algorithms were developed to address the various tasks of classification, clustering, association rule mining, outlier detection, and so on. Deep Learning is part of the evolution of ML that addresses the various types of datasets in a compatible manner. For the task of image recognition, CNN is used in a great manner in the deep learning environment. The resemblance of the structure correlates with the human recognition process from pupils till it gets converted into information that could be understood by the brain cells. The number of layers that constructs the architecture determines the working of the various CNN models. Based on the dataset size and deeper the network plays a vital role in the performance of the model. It is conveyed that a DL classifier helps in a better understanding of the considered dataset along with the deployed architecture. The flow of work illustrated in Fig. 1. begins with the citrus leaf disease dataset and for the process of multi-class classification used the ML and DL classifiers to make the predictions.

3.1. Citrus leaf disease dataset

Citrus fruit is grown across the world and its best immune system support for the human. Pakistan is placed in the 12th position in the cultivation of citrus fruit across the world. It produces 2.36 million tonnes from the 199,000 acres of the lands. Various types are pummelo, sweet oranges, grapefruits, mandarins, and lemons. The entire plant is holding the health benefit components. It acts as a great source of flavonoids, antioxidants, and polyphenols that help in treating various diseases like Alzheimer's, Cardiovascular, Leukaemia, Parkinson's, and so on. The dataset used in this work was gathered manually with the guidance of experts and citrus research center, Government of Punjab, Pakistan located in Sargodha city. Captured the images with DSLR with the resolution of 72 dpi and size is 256 × 256 pixels respectively. The dataset is a collection of infected and healthy citrus leaves and fruits. In our work, we utilized the leaves dataset and it's further classified based on the most prevalent leaf diseases [46, 47]. Dataset description of citrus leaves considered for the work is mentioned in Table 1.

3.2. Multi-Class classification

Each sample in the dataset will be mapped to one class label. Based on the values of features, the classification process classifies the record into a particular target. Number of algorithms both in ML and DL perspective developed to work on the training dataset to generate a model and in turn predict the class for the testing dataset. Repeated training of the model with varied combinations is the success factor in the data mining arena. In DL, CNN is having a great impact on the classification of image and text datasets [48,49]. In the case of our work, 5 class labels based on the features of the images get classified. The various concepts behind determining the training and testing data are k-fold cross-validation and random sampling methods. In the former method, the original sample is randomly partitioned into subsamples of k equal size. A single subsample is maintained from the k subsamples as the validation data for model testing, and the remaining k-1 subsets are used as training samples. In the later random method, based on ration the training and testing are separated [50,51].

3.2.1. Squeezenet (SN)

Image embedding is used to provide the format that can be handled by ML and in our work, SN is utilized. Images are given as input and produce the vector of numbers that could be used for further processing using ML algorithms. This embedder works faster and an internet connection is not mandated [52].

3.2.2. Linear-support vector machine (L-SVM)

SVM is the trending classification algorithm used frequently in ML. The initial stages were applied only in the binary classification and later optimized the hyperplane-based algorithm to work with a multiclass environment. SVM and variant – SVM are the types and based on the kernel type, various functions used in SVM are linear, polynomial, radial basis function, and sigmoid. Optimization parameters are numerical tolerance and iteration limit [53,54]. The linear kernel is mentioned as given in equation 1.

$$k(y, y_i) = sum(y * \ y_i) \tag{1}$$

Where the product of 2 vectors y and yi is the sum of the product of each set of input values.

In our work, SVM with cost 1.00 and regression loss epsilon of 0.10 in the linear kernel environment with numerical tolerance of 0.0010 and iteration limit of 100 is used as the optimization parameter. The function of the kernel is transforming the input space that is low dimensional into a higher dimensional space.

3.2.3. Stochastic gradient descendent (SGD)

It is an iterative approach used for optimizing an objective function by utilizing the smoothness attributes. SGD is considered a significant optimization strategy. Algorithmically, in SGD, a random point is found in a function and then travels down its slope till it influences the bottom point of that function. In the process of moving down, the gradient is computed and it's updated by putting in the parameter values. Compute the step size and till gradient reaches 0 need to learn. Various parameters that govern the SGD are loss function, regularization, learning parameters, and several iterations [55,56].

The mathematical expression is as follows:

SGD in contrast accomplishes a parameter apprise for each training sample a[i] and label l[*i*]

$$\theta = \ \theta - \ \eta . \ \nabla_\theta K\left(\theta; a^i; l^i\right) \tag{2}$$

Here in Eq. (2), η is called as step size a.k.a. learning rate, $K(\theta; a(i); \ l(i))$ is called empirical risk, a(i), b(i) is the training examples & θ is a parameter vector. This high variance happens because of the frequent updates and loss function will fluctuate.

In our work, the Classification loss function of the squared hinge and regression loss function of Huber with epsilon 0.10 for both is applied. In the case of regularization, Elastic Net with a strength of 0.00001 and a mixing parameter of 0.15. The inverse scaling learning rate with an initial learning rate of 0.0100 and an exponent of 0.2500 are used as learning parameters. With a tolerance of 0.0010 and iteration of 5 with shuffle, data is applied over the citrus leaf disease dataset.

3.2.4. Random forest (RF)

RF Classifier uses an ensemble apprenticeship approach for classification, that uses several decision trees during the training process and average outputs of tree predictions individually. This algorithm creates a forest with a random number of trees. Standard decision tree algorithms are rules-based and are based exclusively on a system of rules for data set prediction. In comparison to this, RF classifiers, rather than using the GI or benefit information for the root node estimation, consider the root node and randomly divide the functions. Each tree outputs the prediction and the class that possesses more votes is considered as the final result. It is commonly used in ecology, land cover classification, and many experiments related to spectral images. The number of trees and growth control are parameters that decide about the processing and output of the model [57,58]. In our work, based on the quantum of the data set, 10 trees with an attitude of replicable training and in growth control ensured the split subset not to fall below 5.

3.2.5. Inception–V3

Inception – V3 is the 48 layered DCNN that is the extension of GoogleNet. Constructed model comprises of symmetric and asymmetric blocks, that includes convolution – creating feature map by applying a filter to the image input, average pooling – computing the average from the feature map for each patch, max-pooling – maximum pixel and that helps in reducing the computation cost by decreasing the number of parameters for learning purpose, concerts – combining the same size inputs, dropouts - normally placed after pooling that helps in increasing accuracy and reduce overfitting, fully connected layer – connects neurons of each layer to other layers neuron. Activation norm is done with batch norm and softmax used to compute loss [59,50,60].

3.2.6. VGG–16

Visual Geometry Group (VGG) from the University of Oxford built this deep convolutional neural network for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) held in 2014. The structure of it is considered the best to date in comparison with other deep neural networks. Even though varied types of parameters exist, this architecture focussed only on convolution with padding, max pool fully connected layer with output softmax layer [61,62].

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	125	0	3	42	1	171
	Melanose	2	4	2	2	3	13
	canker	8	0	137	17	1	163
	greening	29	0	4	166	5	204
	healthy	4	0	4	14	36	58
	∑	168	4	150	241	46	609

Fig. 2. Confusion Matrix for RF.

3.2.7. VG –19

It's similar to VGG-16 and another variant of VGG with an additional three convolution layer that effectively facilitates image identification. The base idea is building with constant and small size convolution in designing deep neural networks [63].

4. Experimental results and discussions

The presented work is carried out utilizing the Orange Data Mining 3.26.0 tool with 8 GB RAM & 1 TB memory-based personal computer.

4.1. Machine learning vs deep learning classifiers

In our study, the 10-fold cross-validation stratified classification problem is applied, in which the folds are selected such that each fold comprises roughly the same proportions of the target class. A sampling of data for training and testing is a phase that helps and ensures the complete data is utilized most fully. The accuracy of the model primarily depends on the sampling technique involved in the model.

Based on the analysis certain pros and cons made us decide on the following learning methods. SVM works good in all sorts of data and issue with overfitting is less. Execution time is comparatively less. Cheaper computation and handle the data in a normalized manner. The way stochastic gradient descent works makes the computation faster and converges results at the earliest. Similarly, random forest works well in a non-linear structure, manages outliers, and overfitting with better accuracy. As a part of the ImageNet Large Scale Visual Recognition Challenge (ILVSR), several deep learning algorithms evolved to classify the large images to the right label. In the initial stages, VGG was developed and later based on that learning inception evolved. They are so powerful and popular deep learning algorithms that work with image datasets.

4.2. Confusion matrix

A matrix that shows the class of each instance based on classifier algorithms utilized and paved the way to various performance measures that determine the system tendency. The number of classes determines the dimension of the confusion matrix. The 5-class model creates a 5 × 5-dimension confusion matrix. It will provide clear information about the mapping of the right and wrong class. Predicted class labels are indicated in rows and actual class labels mentioned in the columns. Based on this mapping, each cell is considered as either True Positive (TP), True Negative (TN), False Positive (FP) & False Negative (FN). Based on the prediction it is named. When predicted matches with actual class and both are positive then it is called TP. When predicted matches with the actual class and both are negative then is said as TN. The prediction is not the correct and actual value is negative but positive prediction then it falls under FP. The false prediction and actual value are positive but negative predictions then it is FN [64]. Various performance measures are arrived at with the help of the mentioned prediction parameters.

4.3. Confusion matrix for ml

Fig. 2-4 shows the confusion matrix of the ML algorithm namely RF, SGD, and SVM. Diagonals hold the data about correctly classified instances and values above and below the diagonals are misclassified instances. In-case of RF, SGD, SVM correctly classified images to their target labels are 468, 527, 530 respectively.

4.4. Confusion matrix for dl

DL is the optimized way of building the model to have better classification by neural network structure. Fig. 5-7 illustrates the confusion matrix of the DL algorithm namely VGG-19, Inception- V3, and VGG-16. Diagonals hold the data about correctly classified instances and values above and below the diagonals are misclassified instances. In-case of VGG-19, Inception – V3, VGG – 16 correctly classified images to their target labels are 532, 542, 545 respectively.

4.5. Evaluation results

Fig. 8 depicts that in the case of the actual Black spot class the predicted values of Melanose class are not present and the Healthy & Canker class is having very little impact. In the actual Melanose class, all the other classes have very little significance. In terms of the actual

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	140	1	1	26	3	171
	Melanose	0	13	0	0	0	13
	canker	2	2	151	6	2	163
	greening	24	0	3	166	11	204
	healthy	0	0	0	1	57	58
	∑	166	16	155	199	73	609

Fig. 3. Confusion Matrix for SGD.

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	134	0	2	35	0	171
	Melanose	1	11	0	0	1	13
	canker	3	0	151	8	1	163
	greening	22	0	3	177	2	204
	healthy	0	0	0	1	57	58
	∑	160	11	156	221	61	609

Fig. 4. Confusion Matrix for SVM.

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	135	0	1	34	1	171
	Melanose	1	11	0	0	1	13
	canker	3	0	152	7	1	163
	greening	22	0	1	178	3	204
	healthy	0	0	0	2	56	58
	∑	161	11	154	221	62	609

Fig. 5. Confusion Matrix for VGG-19.

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	141	0	3	26	1	171
	Melanose	0	11	1	1	0	13
	canker	4	0	153	4	2	163
	greening	13	0	2	183	6	204
	healthy	1	0	0	3	54	58
	∑	159	11	159	217	63	609

Fig. 6. Confusion Matrix for Inception-V3.

		Predicted					
		Black spot	Melanose	canker	greening	healthy	∑
Actual	Black spot	144	0	2	25	0	171
	Melanose	0	13	0	0	0	13
	canker	1	0	153	8	1	163
	greening	20	0	1	179	4	204
	healthy	1	0	0	1	56	58
	∑	166	13	156	213	61	609

Fig. 7. Confusion Matrix for VGG-16.

Fig. 8. Pie Chart for RF.

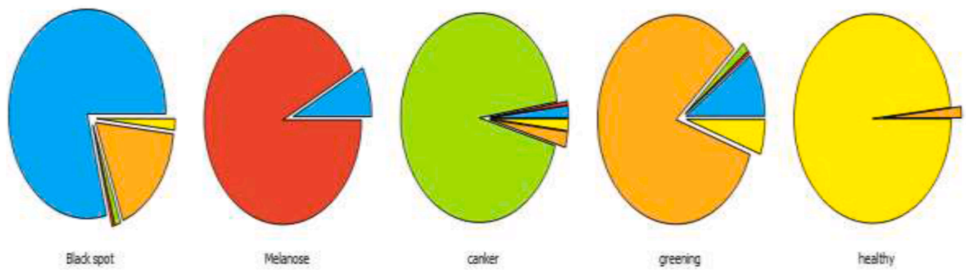

Fig. 9. Pie Chart for SGD.

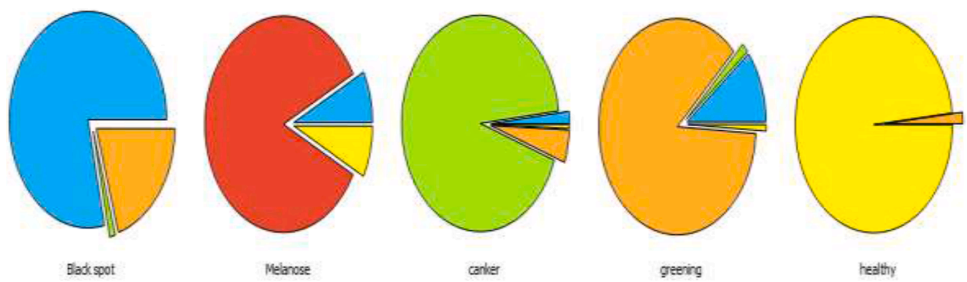

Fig. 10. Pie Chart for SVM.

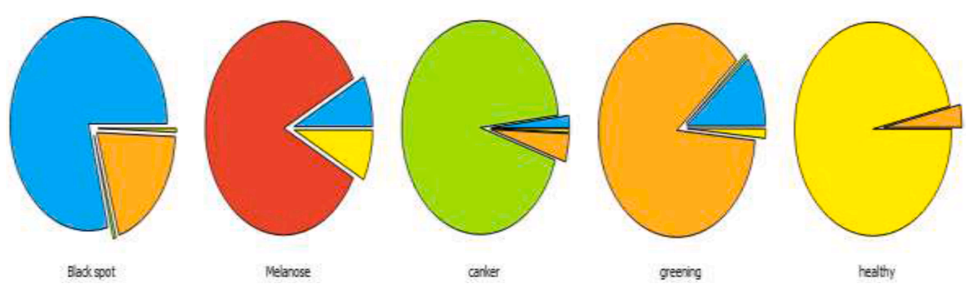

Fig. 11. Pie Chart for VGG-19.

Canker class, the predicted Melanose class is not present and the Healthy class is having very little significance. Similarly, in the actual Greening class, the Melanose class remains absent and the Healthy & Canker class is having less significance, while in the actual Healthy class Melanose class is not present.

Fig. 9 presents that in the case of actual Black spot class predicted values of Melanose class & Canker class is having very little impact. In terms of actual Canker class, the predicted Melanose class is not present and the healthy class is having very little impact. Similarly, in the actual Greening class, Melanose class is not present and the Canker class is having less impact, while in the actual healthy class Melanose class is not present.

Fig. 10 shows that in the case of the actual Black spot class the predicted values of the Melanose & Healthy class remain absent, while in the case of the actual Melanose class the Canker and Greening class remains absent. In terms of the actual Canker class, the predicted Melanose class is not present, while in the actual Greening class the predicted Melanose class remains absent. In the actual Healthy class, the Blackspot, Melanose, Canker classes are not present but the Greening class is having less significance.

Fig. 11 depicts that in the case of the actual Black spot class the predicted values of Melanose class are not present and the Healthy & Canker class is having very little impact. In the actual Melanose class, the impact of the predicted Canker & Greening class is not present whereas Blackspot & Healthy classes have very little significance. In terms of the actual Canker class, the predicted Melanose class remains

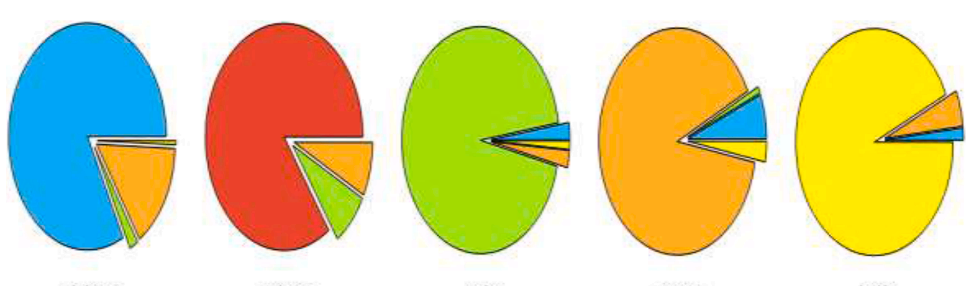

Fig. 12. Pie Chart for Inception-v3.

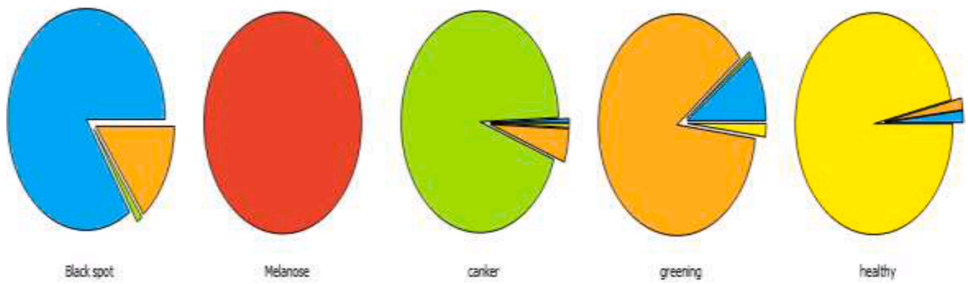

Fig. 13. Pie Chart for VGG-16.

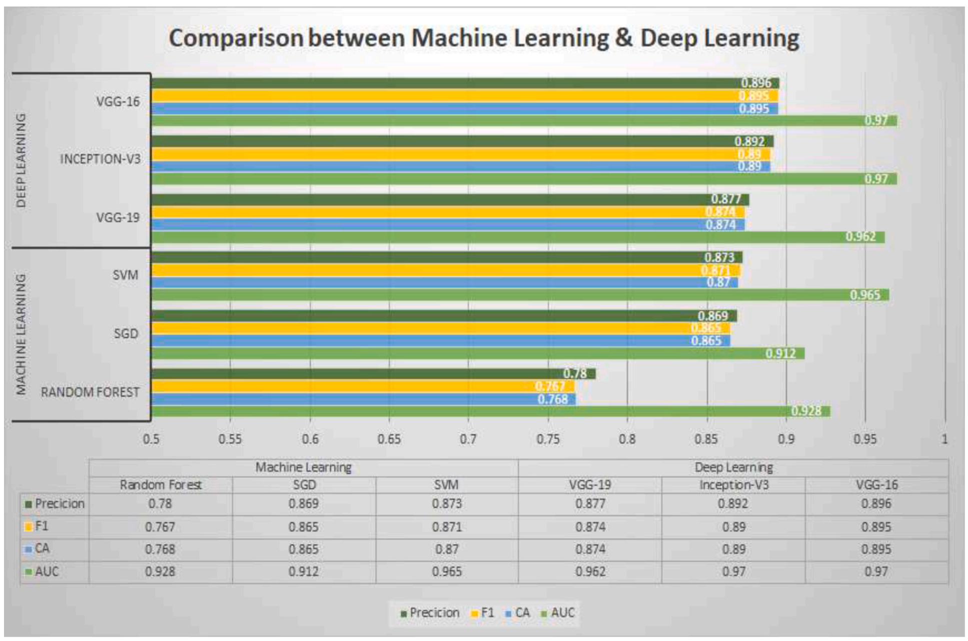

Fig. 14. Comparison between ML & DL methods.

absent whereas the Healthy class is having very little significance. Similarly, in the actual Greening class, the predicted Melanose class remains absent whereas the Healthy & Canker class is having less significance, while in the actual Healthy class the predicted Blackspot, Melanose & Canker were not present & Greening class have nearly negligible impact.

Fig. 12 presents that in the case of actual Black spot class the predicted values of Melanose class remains absent and the impact of the Canker & Healthy class remains negligible, while in the case of actual Melanose class the classes Blackspot & Healthy remains absent whereas the Canker & Greening class remains negligible. In terms of actual Canker class, the predicted Melanose class is absent whereas Healthy class is having very little impact. Similarly, in the actual Greening class, the predicted Melanose class is not present and the Canker class is having less impact, while in the actual Healthy class the predicted Melanose & Canker class is not present but the Greening & Blackspot class is having very less significance.

Fig. 13 shows that in the case of the actual Black spot class the predicted values of Melanose & Healthy class remain absent, while in the case of the actual Melanose class except for the predicted Melanose class all other classes remain absent. In terms of the actual Canker class, the predicted Melanose class is not present & the Blackspot & Health classes impact remains negligible, while in the actual Greening class the predicted Melanose class remains absent but the Canker class is merely significant. In the actual Healthy class, the predicted Melanose & Canker classes are not present but Blackspot & Greening class is less significant

Performance metrics help in deciding the quality of the model. F1 as shown in Eq. (6), is more suited in case of the irregular target distribution. It is the weighted middling of precision and recall. Recall parameter, as shown in Eq. (5), discusses properly-recognized +ve instances by overall right +ve instances. Precision, as shown in Eq. (4), provides the relation between predicted +ve instance with all predicted +ve instances. AUC is the term that gets value based on the area under the receiver operating characteristics curve.

$$Accuracy = TP + TN \ /(TP + TN + FP + FN) \tag{3}$$

$$Precision = TP/(TP + FP) \tag{4}$$

$$Recall = TP/(TP + FN) \tag{5}$$

$$F1\ Score = 2TP/(2TP + FP + FN) \tag{6}$$

As shown in Fig. 14, we compared the (ML and DL) algorithms in the citrus leaf disease detection dataset [46,47]. RF, SGD, and SVM under ML have the increasing value of the performance measures for all the precision, F1, accuracy, and AUC. In this work neurons in the hidden layers are 100, 100, 50 respectively. Activation function used in Rectified Linear Unit (ReLu) [65]. Here we have used Adam [66] solver model is with a regularization value of 1. The number of iterations used with a replicable training approach is 200. In both cases, 10-fold stratified cross-validation with a replicable training set is used as the sampling technique. VGG-19, Inception-V3, and VGG-16 are having increasing orders for all the measures. On the whole, DL is having higher performance in comparison. RF gives the lowest accuracy of 76.8% whereas VGG-16 gives higher accuracy of 89.5%.

5. Conclusion

AI is the area that makes the meet in the middle between information communication technology (ICT) with various application sectors. Decision making is provided by the algorithms prevailing in AI. ML and DL are the major performers in the domain. DL works similarly to the neural structure of the human brain with the layers and optimizers that helps to build a reliable model proving higher accuracy. In our work both learning, approaches are considered and DL results are appreciable in comparison with ML. Various measures like precision, F1 score, accuracy, and area under the curve are considered. On comparison, we achieved CA of RF as 76.8% > SGD as 86.5% > SVM as 87% > VGG-19 as 87.4% > Inception-v3 as 89% > VGG-16 as 89.5%. Images are captured and sent to the system on the regular basis by the stakeholders so farmers will help to decide the pesticide to be used to prevent damages. Incorporating the concept of IoT, cloud computing, big data to gather the images, storing, transferring and processing of the same in GPU environments will be a great support. As a possible future work, we plan to utilize fuzzy logic & bio-inspired methods which may have a significant impact in case of better CA of the system even after using a small-sized dataset.

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.

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