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A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases

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ABSTRACT

In agriculture, one of the most challenging tasks is the early detection of plant diseases. It is essential to identify diseases early in order to boost agricultural productivity. This problem has been solved with machine learning and deep learning techniques using an automated method for detecting plant diseases on large crop farms which is beneficial because it reduces monitoring time. In this paper, we used the dataset "Plant Village" with 17 basic diseases, with a display of four bacterial diseases, two viral illnesses, two mould illnesses, and one mite-related disease. A total of 12 crop species are also shown with images of unaffected leaves. The machine learning approaches viz support vector machines (SVMs), gray-level co-occurrence matrices (GLCMs), and convolutional neural networks (CNNs) are used for the development of prediction models. With the development of backpropagation ANNs, artificial intelligence for classification has also evolved. A K-mean clustering operation is also used to detect disease based on the real-time leaf images collected.

1. Introduction

Agriculture is one of the major sources of income for farmers. Plant diseases can be prevented from spreading if they are detected at the early stages of their development. Phytopathological conditions that affect leaves and refer to both plants and their byproducts. The abiotic variable is a biological factor such as bacteria, fungi, or algae, as opposed to factors such as rain, moisture, and temperature. Methods for automating the detection of plant leaf diseases have been developed using artificial intelligence, machine learning, and Deep learning [1]. These methods can accurately and swiftly identify plant leaf diseases without involving humans. In agriculture, deep learning is the most widely used application. Consequently, agricultural output can be grown, controlled, and improved [2]. Deep learning is essential for smart farming, which includes modern agricultural tools, technology, and algorithms. Which include image classification, feature extraction, transformation, and pattern analysis, are frequently solved with deep learning.

Plant diseases may be categorized by machine learning based on various features. Before effectively extracting features, preprocessing, such as image enhancement, color adjustment, and segmentation, is necessary [3]. Various classifiers can be used after feature extraction. K-nearest neighbor (KNN), support vector machine (SVM), decision tree, random forest (RF), naive Bayes (NB), logistic regression (LR), artificial neural networks (ANNs), and convolution neural networks (CNN)s are a few well-known classifiers. A typical symptom can be seen in (Fig. 1), which depicts an infected leaf. In general, symptoms are more visible than signs; however, signs can help identify a particular pathogen more effectively [4]. Pathologists frequently diagnose disease based on symptoms rather than waiting for laboratory results to confirm symptoms.

1.1. Convolutional neural network (CNN)

The convolutional neural network (CNN) analyzes multidimensional data using deep feed-forward neural networks. The accuracy of different convolution filters of dimensions 2×2 and 3×3 depends on the number of epochs used to implement the filter. This depends on the size of the filter. A visual representation of the progress of the pooling procedure can be seen in (Fig. 2) and (Fig. 3).

1.2. Artificial neural network (ANN)

A neural network is a model that simulates how a biological system processes information, such as the brain. Artificial neurons or processing elements (PEs) are connected by coefficients to form a network structure. Data patterns and connections are discovered rather than programmed through experience [5]. Artificial neural networks can be used to extract patterns from complex data due to their ability to understand complex data.

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Fig. 1. leaf is infected with anthracnose, a fungus that causes lesions.

1.3. Support vector machines (SVM)

In machine learning, the Support Vector Machine (SVM) uses a linear classifier as the basis for learning. Support vector machine (SVM) is a supervised learning technique that can be used for object classification and function approximation. [6], while it is most typically employed for classification. There are frequently endless viable linear classifiers for classification issues, some of which are better than others.

A hyperplane has been obtained by applying SVM to this region, as illustrated in (Fig. 4). Support vectors on both sides of the plane, or sides of the plane, are aware of nearby hyperplane locations. Fig. 5

1.4. Industry 4.0 for plant healthcare

Over the past century, the plant healthcare industry 4.0 has undergone a significant change, which has significantly impacted the industry. A new method or technique for detecting plant diseases is always being developed and innovated by researchers and experts in the field. This is done in order to improve upon the existing method. An analysis of the impact of Industry 4.0 on plant healthcare systems (IHC) is presented in this paper [7]. A number of factors were taken into consideration when establishing the IHC framework. These factors included scheduling challenges, security concerns, industry 4.0, plant healthcare, as well as issues related to resource allocation, data openness, plant disease, and more. In order to make a company's operations more sustainable, Industry 4.0 technology can be utilized. The purpose of this study is

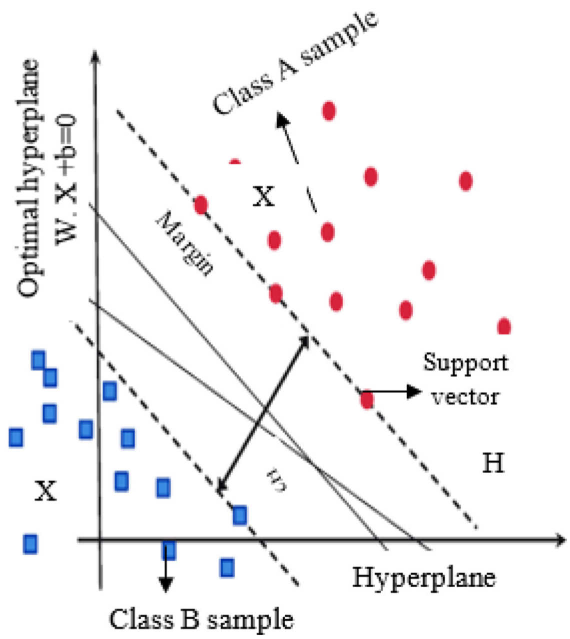

Fig. 4. SVM-based classification.

to review the existing research status and opportunities for future research concerning Industry 4.0 technologies. This is in order to achieve manufacturing sustainability by utilizing a methodical literature review method. A detailed discussion of industrial sustainability is given regarding many of the various Industry 4.0 technologies [8]. According to the results of this study, new research areas and future research directions have been identified for several Industry 4.0 research fields. These research areas can be useful for both companies and academics to achieve manufacturing sustainability by implementing Industry 4.0 technology. There are many benefits that organizations may gain from

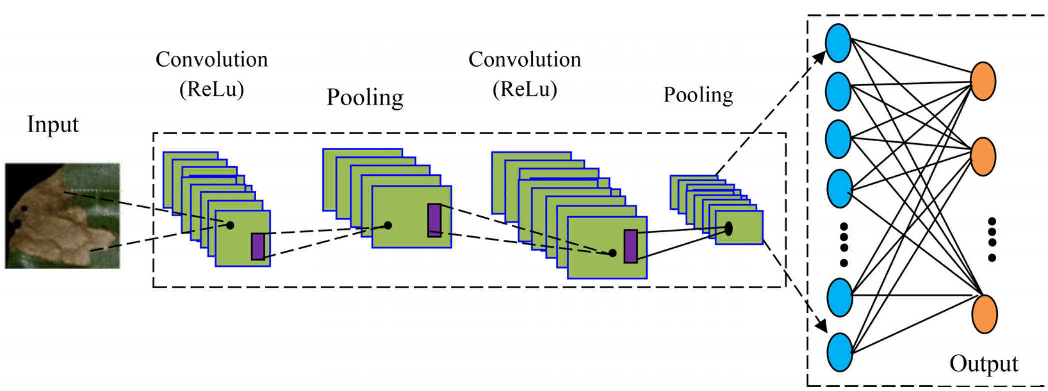

Fig. 2. Classification of plant diseases by CNN.

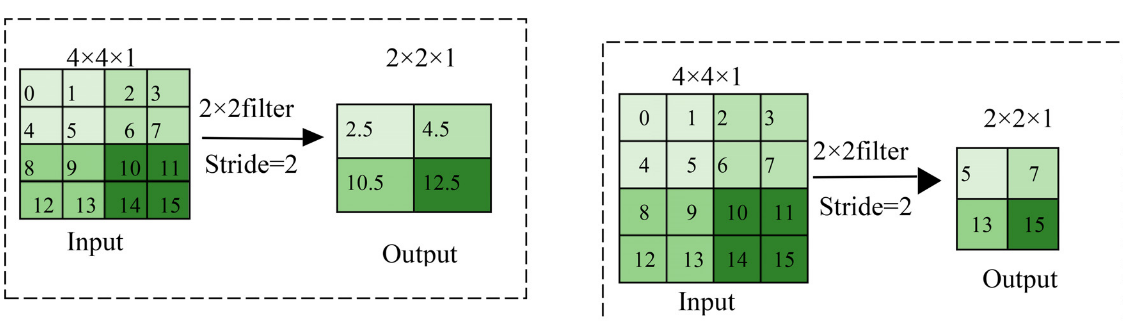

Fig. 3. Depicts the functioning of pooling.

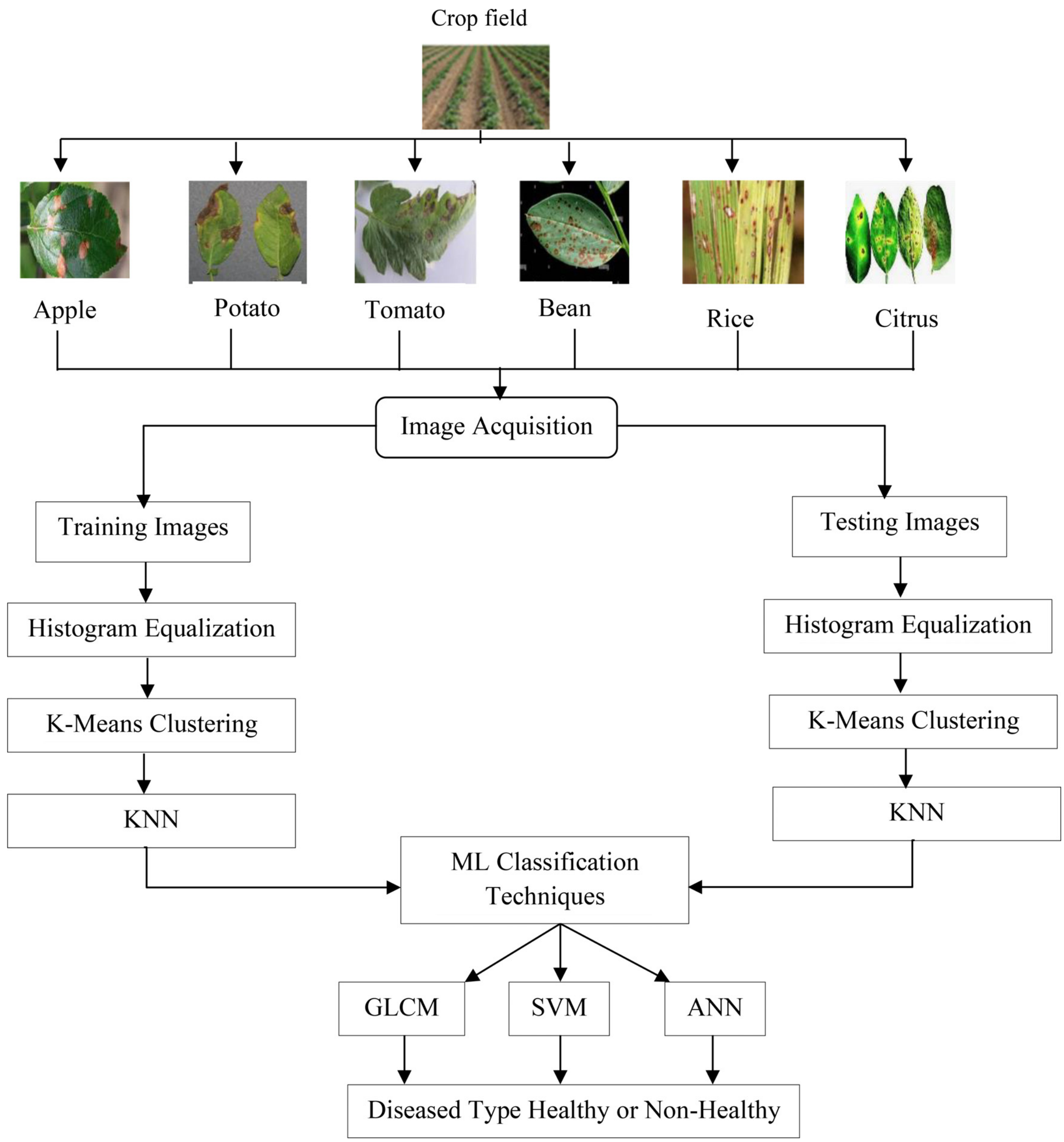

Fig. 5. A proposed model for the detection of diseases.

Industry 4.0, including real-time data analysis, enhanced visibility, autonomous monitoring, and increased output as a result of the use of data analysis in real-time [9]. In addition to the integration of horizontal and vertical systems that characterize Industry 4.0, collaboration is one of the defining characteristics of the technology. There is no doubt that innovation is one of the most significant aspects of any organization, industry, or nation. There are several applications of Industry 4.0 that are possible, and its implementation will change the workplace in several ways.

This paper will be arranged similarly to Section 2, which is a list of the numerous previous studies that have been conducted in this field. Section 3 explains the current study's methodology, followed by several ML and DL approaches. In Section 4, the experimental setup is described in more detail. In Section 5, experimental findings are presented along with a comprehensive analysis. The last section of the study discusses the potential future work that could be conducted based on the current work.

A. Motivation

A machine-learning approach for identifying plant diseases must prioritize accuracy and speed. Developing techniques such as automated disease detection and categorization using leaf image processing is necessary [10]. Farmers will find that this is a valuable strategy that will enable them to be informed in time to greatly reduce the risk of the disease spreading over a huge area. The solution can be broken down into four main components. In the first phase of the process, a An RGB picture of a leaf is used to construct a color transformation structure, which is then used to convert the RGB image into a new color space [11]. Using a K-means clustering technique, the image is then divided depending on the clustering outcomes. As part of the second stage, any excess leaf area (green area) has to be removed from the leaf. Our third step is to compute once the segmented item has been segmented, the textural characteristics of the segmented infected object [12]. The fourth phase involves feeding the retrieved characteristics through a trained neural network.

Table 1
This table provides information about several recent research papers.

Years	Sources of Literature	Methodology for selecting features	Classification Approach	Datasets	Accuracy (%)
2022	Aliyu M. Abdu et al.	SVM, DL	Supervised learning	Plantvillage dataset	95.30%
2022	Savvas Dimitriadis	Naïve Bayes	Supervised learning	Kaggle dataset	89.20%
2022	Asma Akhtar et al.	K-Mean, KNN, RNN	Unsupervised learning	Plant leaf dataset	87.42%
2021	Kiran R. Gavhale et al	ANN, CNN	Supervised learning	Leaf images	91.51%
2021	Jagadeh D. Pujari et al.	PNN, SVM, GLCM	Supervised learning/unsupervised	Image Data Set	96.51%
2021	Sharada P.Mohanty	Neural Network	Supervised learning	Image Net	83.13%
2020	Srdjan Sladojevic	SVM, Neural Network, Decision Tree	Supervised learning	Pictures of Plant Village Tomato Pictures Apple Pictures Rice Pictures Potato	94.31%
2020	P.Ferntions	Neural Network	Supervised learning	Alex Net, Google Net, Over-Feat, VGG	97%
2020	S. Sannakkiet et al.	SVM	Supervised learning	Image Dataset	85%
2019	TejalChandi waeetet al.	ANN SVM	Supervised learning	Manual Dataset	82.34%
2019	Yan Guo et al.	ANN SVM	Supervised learning	Plant Village	96.45%
2019	Yan Guo et al.	CNN	Supervised learning	Apple dataset	93.81%

B. Our contribution

The development of a deep learning model for identifying various plant diseases;

- Identification of the best transfer learning method for multi-class plant disease classification and optimal recognition accuracy;
- By recommending a multi-class, multi-label transfer learning-based CNN model, we can address the distinct labelling and class issues in recognizing plant diseases.
- Using a revolutionary algorithm with two stages intended to enhance plant disease identification in real environment images delivers quick results and is suitable for real-time application.
- The new dataset comprises many annotated images of leaves recorded in real surroundings.

2. Literature review

This section aims to provide a critical assessment of the literature available to categorize and identify plant diseases and classification. Research can be divided into two categories: ML-based approaches and DL-based approaches [13]. An early diagnosis of crop health and disease can be achieved by applying appropriate management approaches, such as fungicide sprays, drugs for specific diseases, and pesticide-based vector control. In addition to making illness prevention easier, this could also increase productivity. Identifying healthy and diseased leaves is essential for controlling crop loss and boosting yield [14]. Machine-learning techniques are becoming increasingly popular for identifying disease in plants, which are discussed in this section of (Table 1).

A comparison is made between two widely utilized deep learning and Machine learning to identify plant diseases using leaf image data (DL) [15]. Many of these image-processing techniques previously relied on simple machine learning architectures. [16] The Deep Learning network is gradually overtaking other technologies as the industry standard for pattern identification and image recognition. Compare the two techniques using normal settings and take into consideration the three important elements of design, processing capacity, and training data volume, both models.

3. Proposed system

The process of training is suggested as a method for detecting plant diseases [17]. The plants are photographed using a digital camera at this point. Preprocessing methods are then applied to these images [18]. Feature extraction is used to collect important visual characteristics after preprocessing for training the locations of neighboring hyperplanes are known to support vectors on both sides of the plane, or sides of the plane [19]. These vectors are separated using a defined margin that must be as large as possible.

3.1. Dataset

The proposed methodology and traditional machine learning models were applied to a public dataset of 8350 images of damaged and healthy plants of the specified plants obtained from the plant village.org website. [20]. The plant village org website has hundreds of pictures of healthy and diseased crop plants that are open and available. There are 250 healthy potato images, 1500 early blight images, 1500 late blight images, 2000 healthy maize images, 550 grey leaf spot images [21], 1550 images of common rust, and 1000 images of northern leaf blight in the dataset. The original dataset was used for training, validating, and testing the methods [22]. The collection covers a variety of images, including high-resolution images, samples from the early medium, and the last infection status [23]. The plant's surroundings have also been downloaded as an excellent scenario for training and testing the suggested methodology in (Fig. 6). A raw image is shown from the downloaded dataset.

3.2. Performance metrics

The Confusion Matrix, sometimes referred to as a contingency table, offers a comprehensive perspective by summarizing the classification outcomes by tabulating the expected and actual categories, it shows the individual outcomes for each category [24]. Calculating the confusion matrix provides a clearer picture of what the classification model does correctly and where it is worse [25]. The performance of each approach is assessed using a variety of measures. Accuracy, precision, recall, and F1 score are metrics used to compare the proposed method to five traditional machine-learning classifiers.

a. Accuracy

Is the proportion of samples in the overall dataset that were correctly categorized. The formula used to compute it is as follows:

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FP + FN}$$

b. Precision

False-negative occurs when a test for common rust is negative but the plant still has the disease.

$$\text{Precision} = \frac{TP}{TP + FP}$$

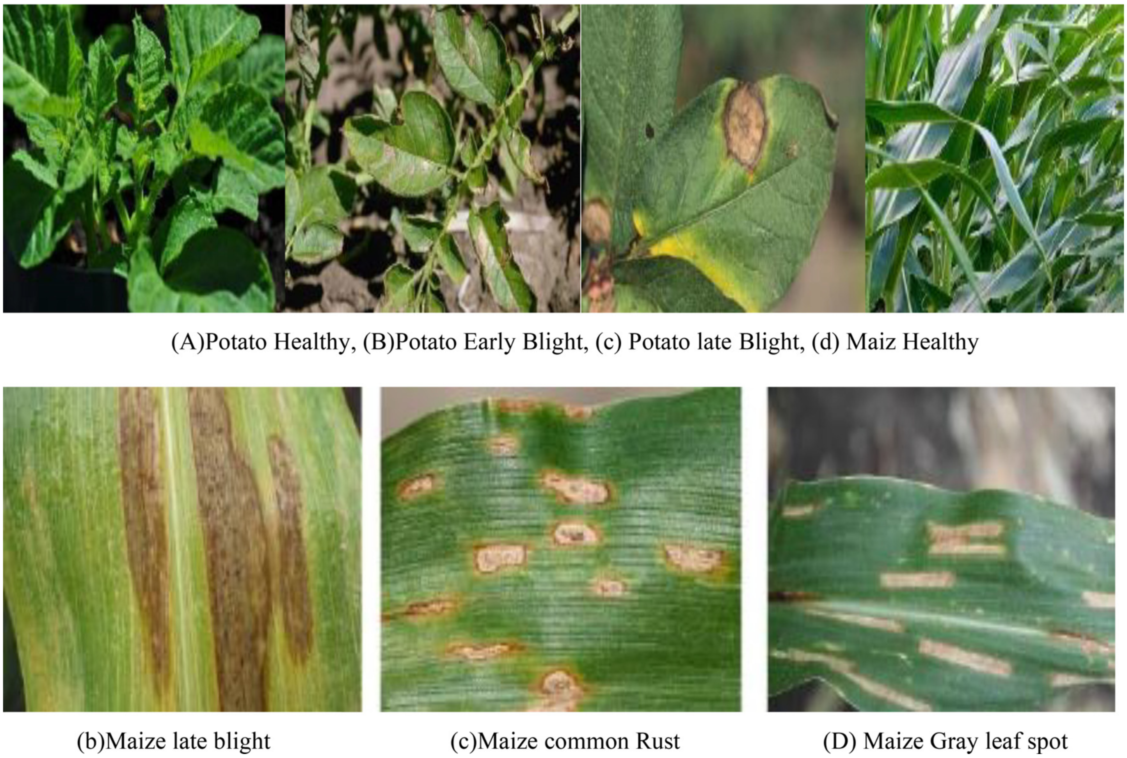

Fig. 6. Images from the dataset showing healthy and diseased potatoes and maize.

c. Recall

Recall is used to measure the real positive rate and is defined as follows:

$$\text{Recall } = \frac{TP}{TP + FN}$$

d. F-score

As can be seen below, the F-score is a harmonic mean of recall and precision:

$$\text{F} - \text{score } = \frac{2* \text{ Precision } * \text{ Recall}}{\text{Precision } + \text{ Recall}}$$

- Where TP stands for True positive: A plant is considered to have the disease if the outcome of a common rust test is positive. This is referred to as a true positive.
- A true negative for a maize disease is when the outcome of a standard rust test is negative, suggesting that the maize does not contain the disease [26].
- False positives occur when a common rust test for a disease of maize returns a positive result even though the disease is not present in the maize. A false negative is when a test for common rust comes back negative but the plant has the disease.

4. Result and discussion

The complete process of the suggested technique is discussed in this part, along with the experiments that address existing challenges in plant disease detection tasks to address the current constraints and overcome the issues in current plant disease detection approaches to the detection of plant diseases. In the proposed approach, several crucial phases of creating a model for detecting plant diseases are discussed, including adding new datasets and methods for data augmentation, comparing different methods for detecting and classifying objects, and proposing a novel method for detecting plant diseases. The number of hidden layers versus the efficiency of neural networks an experimental the efficiency of neural networks depends on the number of hidden layers. The number of hidden layers represents the number of states in the network's neurons. When there are at least n x n hidden layers, the network's efficiency is at its peak. The letter n denotes the number of features per training set (Table 2) [14].

The efficiency is dependent on the termination error rate, as shown in (Table 3). The termination error rate represents the maximum allowable mistake in classifying values in a neural network. The network's efficiency is optimal for a high termination rate. The higher the termination rate, the better the neural network's performance. (Fig. 7) depicts a graphical depiction of the analysis in terms of Termination Error Rate vs Neural Network Efficiency, demonstrating that the network is at its best when the termination error is set to 0.00001.

The network is trained and tested on 200 samples, of which 10 samples are alterneria, 30 samples are BBD, and 100 samples are Anthracnose in (Table 4), demonstrates the disease recognition rate when the parameters indicated. (Table 5), indicates that the performance of a neural network is dependent not only on the number of features, the number of hidden neurons, and the termination error rate but also on the quality of the sample image.

Optimization must be tested with the number of feature values, hidden neurons, and termination error rates in varied input situations to successfully classify samples to their appropriate classes. The system's capacity to correctly categories samples into their appropriate classes can be used to assess its performance. As a result of the above-mentioned experimental analysis, the network's efficiency is higher when the number of features in an image is 170, the number of hidden neurons is 51, the termination error rate is.0000001, and the input image is in a light environment with a minimum distance of 1.5 or 2.5 feet between the input image and the camera (Figs. 8 and 9) [17].

After testing both models, it was discovered that the model of the segmented picture outperformed the colour and grayscale models. (Fig. 10) (a) illustrates an experiment for recognizing crop types. As shown in (Fig. 10) (b), there is significant accuracy development in the early

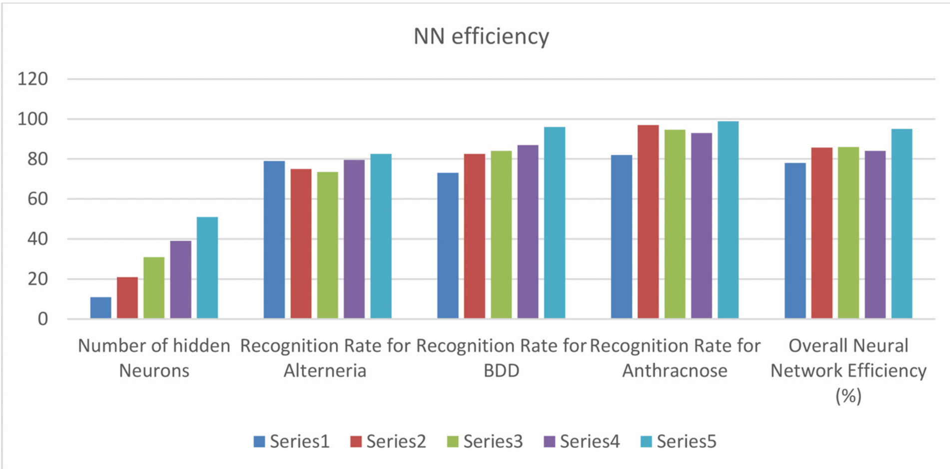

Fig. 7. Hidden neurons vs NN efficiency graphical analysis.

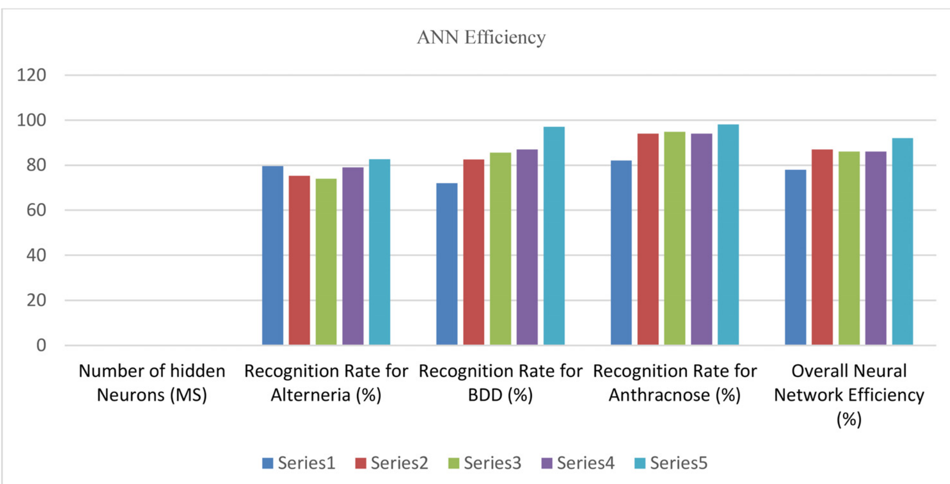

Fig. 8. Graphical analysis of termination error rate vs ANN effectiveness.

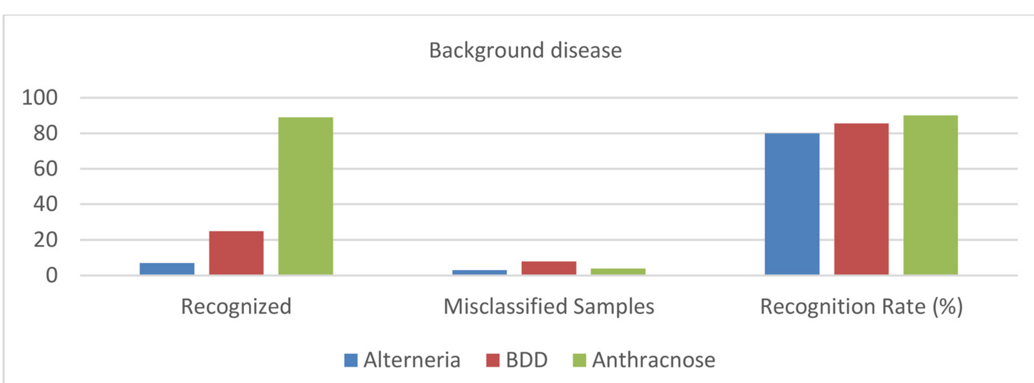

Fig. 9. Disease recognition rate against a uniform background.

Fig. 10. (a) Sets of training and validation achieved the required accuracy and Fig. 10(b). The loss obtained for the training and validation sets.

Table 2
Shows a comparison of the current approaches.

Refer—ences	Method	Performance	Advantage	Limitation
[27]	Crop disease categorization was done using the k-FLBPCM framework and SVM.	Accuracy=95.53%	The research helped improve the accuracy of classification for plants with comparable morphological features.	The detection accuracy of distorted samples decreases.
[28]	The purpose of identifying various plant diseases, the DLQP approach with the SVM classifier was introduced.	Accuracy=94.63%	This work is reliable in detecting the classification of plant leaf diseases in input samples with large scale and angle variations	More work needs to be done on classification performance.
[29]	In order to compute features, the GLCM approach was combined with the Harris method, and the SVM classifier was used to categorise diseases of tea plants.	Accuracy=97.48%	The method can distinguish the afflicted leaves portion from a complicated background.	The computational cost of this method is significant.
[30]	In addition to K-means clustering, GLCM techniques, and GLCM techniques, an SVM classifier was also used.	Accuracy=91.61%	From the unclear samples, the work may find unhealthy plant leaves.	When samples have large brightness changes, classification performance suffers.
[31]	The disease affecting the tomato crop was identified and classified using a CNN-based architecture.	Accuracy=94%	It is a computationally efficient method.	The issue with this strategy is that it over fits a select few classes.
[32]	The DL framework AlexNet and the KNN classifier were used to categorise tomato leaves as healthy or diseased.	Accuracy=78%	Low-intensity images can be used to identify the damaged area.	This method is inefficient and time-consuming.
[33]	For the purpose of classifying plant diseases, a deep Siamese network and a KNN classifier were merged.	Accuracy=92.68%	For samples with complicated backgrounds, the method enhanced classification accuracy.	This approach has a problem with over-fitting when applied to a large dataset.

Table 3
NN efficiency vs. number of hidden neurons.

Number of hidden Neurons	Recognition Rate for Alterneria	Recognition Rate for BDD	Recognition Rate for Anthracnose	Overall Neural Network Efficiency (%)
11	79	73	82	78
21	75	82.6	97	85.7
31	73.5	84	94.6	86
39	79.5	87	93	84
51	82.6	96	98.9	95

Table 4
Neural network efficiency vs termination error rate.

Number of hidden Neurons (MS)	Recognition Rate for Alterneria (%)	Recognition Rate for BDD (%)	Recognition Rate for Anthracnose (%)	Overall Neural Network Efficiency (%)
0.01	79.6	72	82.1	78
0.001	75.3	82.5	94	87
0.0001	74	85.6	94.8	86
0.00001	79	87	94	86
0.000001	82.6	97	98.1	92

Table 5
Disease recognition rate against a homogenous background.

Disease	Recognized	Misclassified Samples	Recognition Rate (%)
Alterneria	7	3	80
BDD	25	8	85.6
Anthracnose	89	4	90

stages before later convergence. A reduction in the loss function indicates a more rapid learning process. The Deep CNN model was chosen for testing once the training and validation phases were finished. The findings of the trained models were also evaluated on new data and contrasted with those of cutting-edge machine learning techniques, and they were quite suggestive. For different epochs, the model's accuracy and loss are determined. For the training and validation set, a loss was attained, and the training and validation set also saw an accuracy reached (Table 6) [18].

The accuracy and loss of the MHGSO optimized DenseNet-121 architecture are assessed using the training and validation datasets. In (Table 7), Accuracy is determined following training and parameter correction for the enhanced DenseNet-121 architecture. The MHGSO-optimized DenseNet-121 architecture is fed the test pictures, and the error rate is compared to the real class. Following each iteration, the model's behavior is calculated based on the loss value. The proposed model's robustness and ability to converge can be confirmed using accuracy and loss values.

Table 6
Shows the design of a neural network.

Number of input neurons	170
Number of output Neurons	5
Hidden layers	51
Iterations	5000
Termination error rate(ms)	.0000001
gradient	0.002
Recognition Rate of Neural Network (%)	95

Table 7
Accuracy, precision, recall and F-measure.

Experiment	Accuracy	Precision	Recall	F1-score
Rice	0.98	0.951	0.751	0.974
Apple	0.96	0.875	0.850	0.786
Bean	0.94	0.761	0.876	0.638
Potato	0.95	0.982	0.523	0.451
Tomato	0.97	0.643	0.976	0.986
Overall	0.99	0.987	0.982	0.976

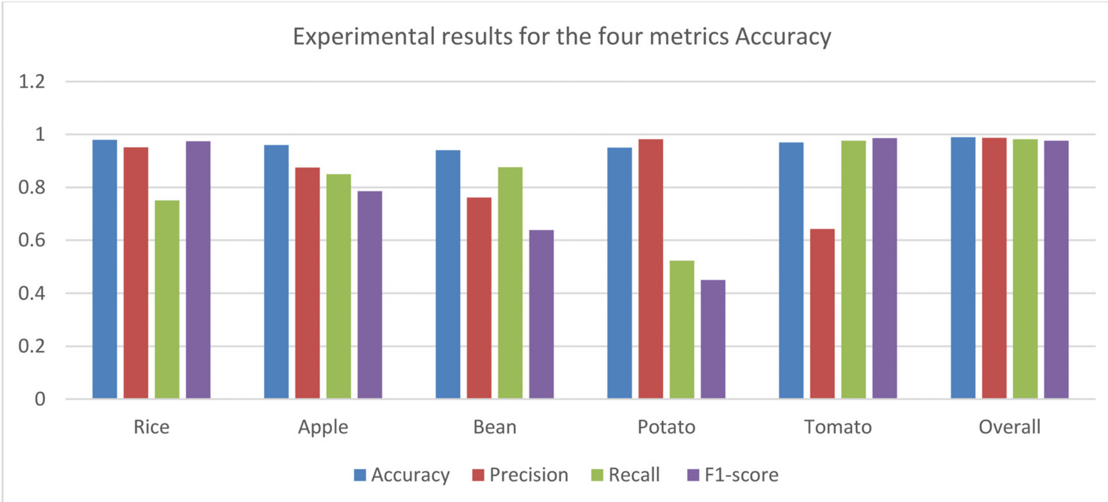

Fig. 11. Overall accuracy of metrics.

The proposed approach achieves an overall accuracy of 99% and 98% for Rice trees and apples and 96%, beans 94 % potato 95%, and 97% for Tomato trees. Using precision, recall, and f-measure metrics, multiclass classification problems, such as the one in this study, are evaluated for a set with only one symptom pool for each class (e.g., disease), and the results are presented in (Fig. 11). In this research, the purpose was to find distinct machine learning models that could identify plant diseases accurately and present evidence to support the predictions that each model generated, as well as to justify their choices in order to conduct this study, Convolution Neural Networks and Artificial Neural Networks, Support Vector Machines, and GLCM models were utilized. A variety of criteria were used to evaluate the models in this study, including Accuracy, Precision, Recall, and F1-score, to evaluate their quality. Using neural networks to assess explain ability, Explainable Artificial Intelligence was applied. Both models were tested on the same dataset, known as the plant village dataset, which was used to test each model. The results of the comparison of the two models using performance measures reveal that in the application of detecting plant diseases, the CNN model outperforms the KNN model in terms of its performance.

5. Conclusion

Firstly, the images were collected for training and validation, then images were preprocessed and augmented, and finally the deep CNN was trained and fine-tuned. In order to test the performance of the newly developed model, different tests were conducted. The purpose of this paper is to present automated methods for real-time segmentation and classification of images for detecting plant diseases. Among the most effective techniques for detecting and classifying diseased plants are neural network modification, K-means segmentation, SVM, CNN, and ANN. An overview of intensive learning, deep learning, and recent studies on plant leaf disease identification is presented in this paper. A deep learning algorithm trained with the plant village dataset can identify leaf diseases accurately. The accuracy of classification can be improved through data augmentation, large datasets with high variability, and other methods. Early detection of plant illnesses was possible using small leaf samples and hyperspectral images. Furthermore, we discussed some important issues associated with plant disease recognition and categorization that may significantly affect the model's performance. A real-time-based system will allow researchers to investigate new aspects of agricultural disease recognition and classification by guiding them to understand the factors that may significantly affect the performance.

As part of future work, the model will be trained to recognize plant diseases across a wider land area. This will be done by combining aerial images captured by drones and convolution neural networks for object detection. The authors hope that extending this research will result in a valuable contribution to sustainable agriculture, affecting crop quality for future generations.

Declaration of Competing Interest

Please check the following as appropriate: All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript. The following authors have affiliations with organizations with direct or indirect financial interest in the subject matter discussed in the manuscript

References

[1] P.K. Sethy, N.K. Barpanda, A.K. Rath, S.K. Behera, Deep feature based rice leaf disease identification using support vector machine, Comput. Electron. Agric. 175 (May) (2020) 105527, doi:10.1016/j.compag.2020.105527.

[2] J. Chen, J. Chen, D. Zhang, Y. Sun, Y.A. Nanehkaran, Using deep transfer learning for image-based plant disease identification, Comput. Electron. Agric. 173 (November 2019) (2020) 105393, doi:10.1016/j.compag.2020.105393.

[3] M. Aamir, et al., An adoptive threshold-based multi-level deep convolutional neural network for glaucoma eye disease detection and classification, Diagnostics 10 (8) (2020), doi:10.3390/diagnostics10080602.

[4] J. Singh and H. Kaur, *Plant disease detection based on region-based segmentation and KNN classifier*, vol. 30. Springer International Publishing, 2019.

[5] P. Pławiak, M. Abdar, J. Pławiak, V. Makarenkov, U.R. Acharya, DGHNL: A new deep genetic hierarchical network of learners for prediction of credit scoring, Inf. Sci. 516 (2020) 401–418 *(Ny)*, doi:10.1016/j.ins.2019.12.045.

[6] C.R. Rahman, et al., Identification and recognition of rice diseases and pests using convolutional neural networks, Biosyst. Eng. 194 (2020) 112–120, doi:10.1016/j.biosystemseng.2020.03.020.

[7] G. Geetharamani, J. Arun Pandian, Identification of plant leaf diseases using a nine-layer deep convolutional neural network, Comput. Electr. Eng. 76 (2019) 323–338, doi:10.1016/j.compeleceng.2019.04.011.

[8] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, S. Bhardwaj, Potato leaf diseases detection using deep learning, in: Proceedings of the International Conference on Intelligent Computing, Information and Control Systems, 2020, pp. 461–466, doi:10.1109/ICICCS48265.2020.9121067. *ICICCS 2020*.

[9] J. Rashid, I. Khan, G. Ali, S.H. Almotiri, M.A. Alghamdi, K. Masood, Multi-level deep learning model for potato leaf disease recognition, Electronics 10 (17) (2021) 1–27, doi:10.3390/electronics10172064.

[10] N.R. Deepa, N. Nagarajan, Kuan noise filter with Hough transformation based reweighted linear program boost classification for plant leaf disease detection, J. Ambient Intell. Humaniz. Comput. 12 (6) (2021) 5979–5992, doi:10.1007/s12652-020-02149-x.

[11] R. Karthik, M. Hariharan, S. Anand, P. Mathikshara, A. Johnson, R. Menaka, Attention embedded residual CNN for disease detection in tomato leaves, Appl. Soft Comput. J. 86 (2020) 105933, doi:10.1016/j.asoc.2019.105933.

[12] S. Gehlot, A. Gupta, R. Gupta, SDCT-AuxNetθ: DCT augmented stain deconvolutional CNN with auxiliary classifier for cancer diagnosis, Med. Image Anal. 61 (2020) 101661, doi:10.1016/j.media.2020.101661.

[13] Y. Zhang, C. Song, D. Zhang, Deep learning-based object detection improvement for tomato disease, IEEE Access 8 (2020) 56607–56614, doi:10.1109/ACCESS.2020.2982456.

[14] G. Sambasivam, G.D. Opiyo, A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks, Egypt. Inform. J. 22 (1) (2021) 27–34, doi:10.1016/j.eij.2020.02.007.

[15] I. Ahmed, P.K. Yadav, An automated system for early identification of diseases in plant through machine learning, in: Soft Computing: Theories and Applications: Proceedings of SoCTA 2021, Springer Nature Singapore, 2022, pp. 803–814.

[16] M.H. Saleem, J. Potgieter, K.M. Arif, Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers, Plants 9 (10) (2020) 1–17, doi:10.3390/plants9101319.

[17] I. Ahmed, P.K. Yadav, Plant disease detection using machine learning approaches, Expert Syst. (2022) e13136.

[18] A. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari, V.H.C. de Albuquerque, Seasonal crops disease prediction and classification using deep convolutional encoder network, Circuits Syst. Signal Process. 39 (2) (2020) 818–836, doi:10.1007/s00034-019-01041-0.

[19] A. Khamparia, A. Singh, A.K. Luhach, B. Pandey, D.K. Pandey, Classification and identification of primitive kharif crops using supervised deep convolutional networks, Sustain. Comput. Inform. Syst. 28 (2020), doi:10.1016/j.suscom.2019.07.003.

[20] X. Xie, Y. Ma, B. Liu, J. He, S. Li, H. Wang, A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks, Front. Plant Sci. 11 (June) (2020) 1–14, doi:10.3389/fpls.2020.00751.

[21] N.K. Trivedi, et al., Early detection and classification of tomato leaf disease using high-performance deep neural network, Sensors 21 (23) (2021), doi:10.3390/s21237987.

[22] Y. Shi, L. Han, A. Kleerekoper, S. Chang, T. Hu, Novel CropdocNet model for automated potato late blight disease detection from unmanned aerial vehicle-based hyperspectral imagery, Remote Sens. 14 (2) (2022), doi:10.3390/rs14020396.

[23] S. Ali, M. Hassan, J.Y. Kim, M.I. Farid, and M. Sanaullah, “applied sciences FF-PCA-LDA : intelligent feature fusion based PCA-LDA classification system for plant leaf diseases,” 2022.

[24] C. Karthik, N. Ulaganathan, Application for plant's leaf disease detection using deep learning techniques, Int. Res. J. Eng. Technol. (2020) 4507–4513 [Online]. Available www.irjet.net .

[25] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, S. Gupta, ToLeD: tomato leaf disease detection using convolution neural network, Procedia Comput. Sci. 167 (2019) (2020) 293–301, doi:10.1016/j.procs.2020.03.225.

[26] D. Argüeso, et al., Few-shot learning approach for plant disease classification using images taken in the field, Comput. Electron. Agric. 175 (May) (2020), doi:10.1016/j.compag.2020.105542.

[27] W. Albattah, M. Nawaz, A. Javed, M. Masood, S. Albahli, A novel deep learning method for detection and classification of plant diseases, Complex Intell. Syst. 8 (1) (2022) 507–524, doi:10.1007/s40747-021-00536-1.

[28] V.N.T. Le, S. Ahderom, B. Apopei, K. Alameh, A novel method for detecting morphologically similar crops and weeds based on the combination of contour masks and filtered Local Binary Pattern operators, Gigascience 9 (3) (2020) 1–16, doi:10.1093/gigascience/giaa017.

[29] W. Ahmad, S.M.A. Shah, A. Irtaza, Plants disease phenotyping using quinary patterns as texture descriptor, KSII Trans. Internet Inf. Syst. 14 (8) (2020) 3312–3327, doi:10.3837/tiis.2020.08.009.

[30] G. Kuricheti, P. Supriya, Computer vision based turmeric leaf disease detection and classification: a step to smart agriculture, in: Proceedings of the *International Conference on Trends in Electronics and Informatics*, 2019, pp. 545–549, doi:10.1109/ICOEI.2019.8862706. *ICOEI 2019*Icoei.

[31] A. Abbas, S. Jain, M. Gour, S. Vankudothu, Tomato plant disease detection using transfer learning with C-GAN synthetic images, Comput. Electron. Agric. 187 (April) (2021) 106279, doi:10.1016/j.compag.2021.106279.

[32] A. Batool, S.B. Hyder, A. Rahim, N. Waheed, M.A. Asghar, Fawad, Classification and identification of tomato leaf disease using deep neural network, in: Proceedings of the *International Conference on Engineering and Emerging Technologies*, 2020 *ICEET 2020*, doi:10.1109/ICEET48479.2020.9048207.

[33] S. Jadon, SSM-net for plants disease identification in low data Regime, in: Proceedings of the *IEEE / ITU International Conference on Artificial Intelligence for Good*, 2020, pp. 158–163, doi:10.1109/AI4G50087.2020.9311073. *AI4G 2020*.