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Original Article

An Optimized Hyper Parameter Tuned Convolution Neural Frame for Potato Leaves Disease Prediction

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Abstract - *Image processing is an exciting concept in several digital applications for identifying features precisely. Hence, this technology is chiefly utilized in agriculture applications to predict the disease affection in plat and leaves. However, the complex image has reduced the exactness rate of classification and segmentation. In this present work, the potato leaves are normal, and disease images are considered. Hence, a novel Ant Lion-based Hyper-Parameter tuned Convolution Neural Approach (ALHTCNA) has been designed with the required parameters to maximize the exactness score. Initially, the preprocessing function was activated to obtain error-free data. Consequently, the error-free data is moved to the classification frame, in that feature extraction, segmentation, and disease classification process has functioned. The considered disease types in the present work are Early-Blight (EB) and Late-Blight (LB). If the tested data did not contain these disease features, it is considered healthy leaves. Moreover, the planned design is implemented in the python platform, and the metrics are validated and compared with other schemes and has observed the finest segmentation and specification exactness score.*

Keywords - *Image processing, Segmentation, Feature extraction, Potato leaves data, Disease specification.*

1. Introduction

Image processing is an attractive and interesting concept for predicting and segmenting the infection from the image data [1]. Several numerical technologies have been introduced, but image processing technology has been established to know the highly illustrated disease affection region [2] from the potato image data [3]. Moreover, the image process models are executed with the help of neural network procedures and optimization strategies [4]. In the case of the neural strategies, both deep learning (DL) [5] and machine learning (ML) [30] have afforded the finest solution in segmenting the disease area. Considering the ML and DL concepts, the technique called as neural convolution model has been applied to image processing concepts [7]. The incorporation of hyperparameters has provided the finest outcome [8]. Also, most image data is too complex to process; in those cases, the neural model's optimization function has been employed to tune the hyperparameters [9]. The leaf disease prediction with image processing is detailed in fig.1. There are several jobs in the country, but agriculture is crucial for all living [10]. Moreover, the government has no other expectations in the agriculture fields [11]. In addition, the potato is the finest versatile crop in India, accounting for around 28.9% of total agricultural production [29]. Potatoes are the world's biggest agricultural food product, behind rice, wheat, and maize [13]. Besides, India is the world's second-greatest producer of potatoes, producing 48.5 million tonnes per year [14]. Furthermore, Potatoes are high in vitamins (particularly C and B6), potassium, and fiber [31]. It decreases the total amount of blood cholesterol and aids in treating disorders like cancer, hypertension, and heart disease [16].

Moreover, Diseases have a detrimental influence on agricultural and forest ecosystems. Microorganisms, genetic abnormalities, and viral infections such as fungi, bacteria and viruses are the primary causes of many diseases. Potato leaf infections are caused mainly by bacteria and fungi [17].

The following are some of the major emphases of this research: Initially, we can collect the datasets like normal and disease potato leaf images from the net source and train to the system

- Then a novel ALHTCNA was designed with optimized hyperparameters to segment the affected portion of the leaf
- Moreover, the fitness function of the Ant Lion is used to find the disease severity and types
- Here, the tuning function of the hyperparameter has provided the finest segmentation and classification results.

Then the proposed model's performance was compared with existing ones, and the efficiency was verified regarding the accuracy, precision, F-measure, and recall.

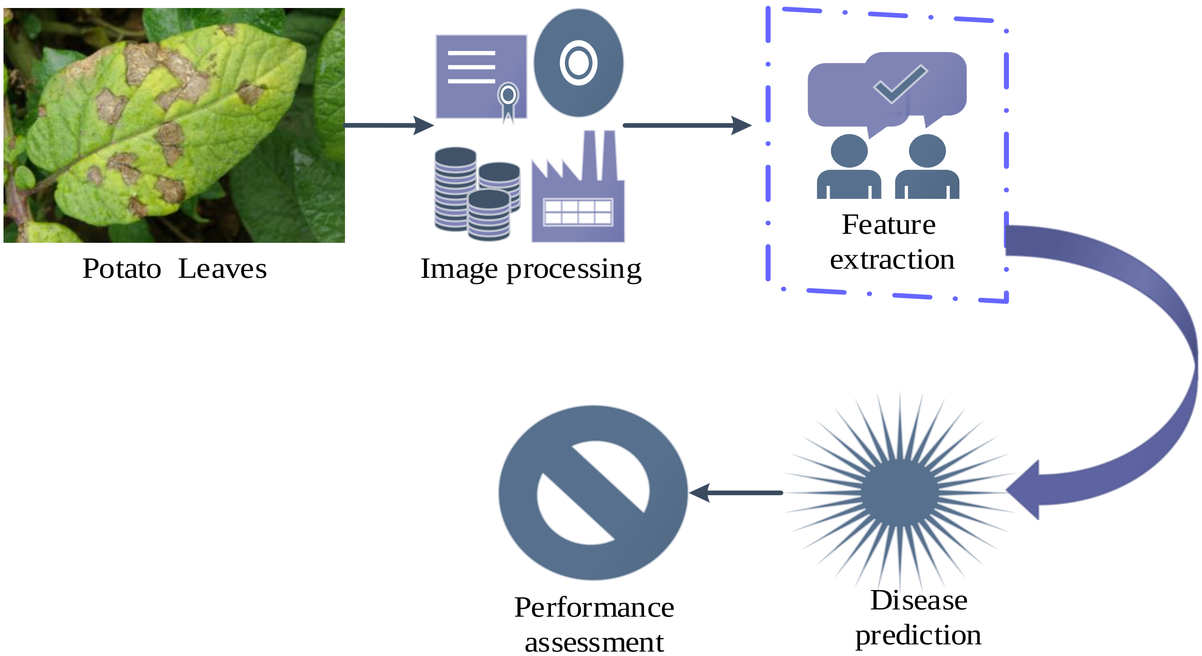


Fig. 1 Image processing in leaf disease prediction

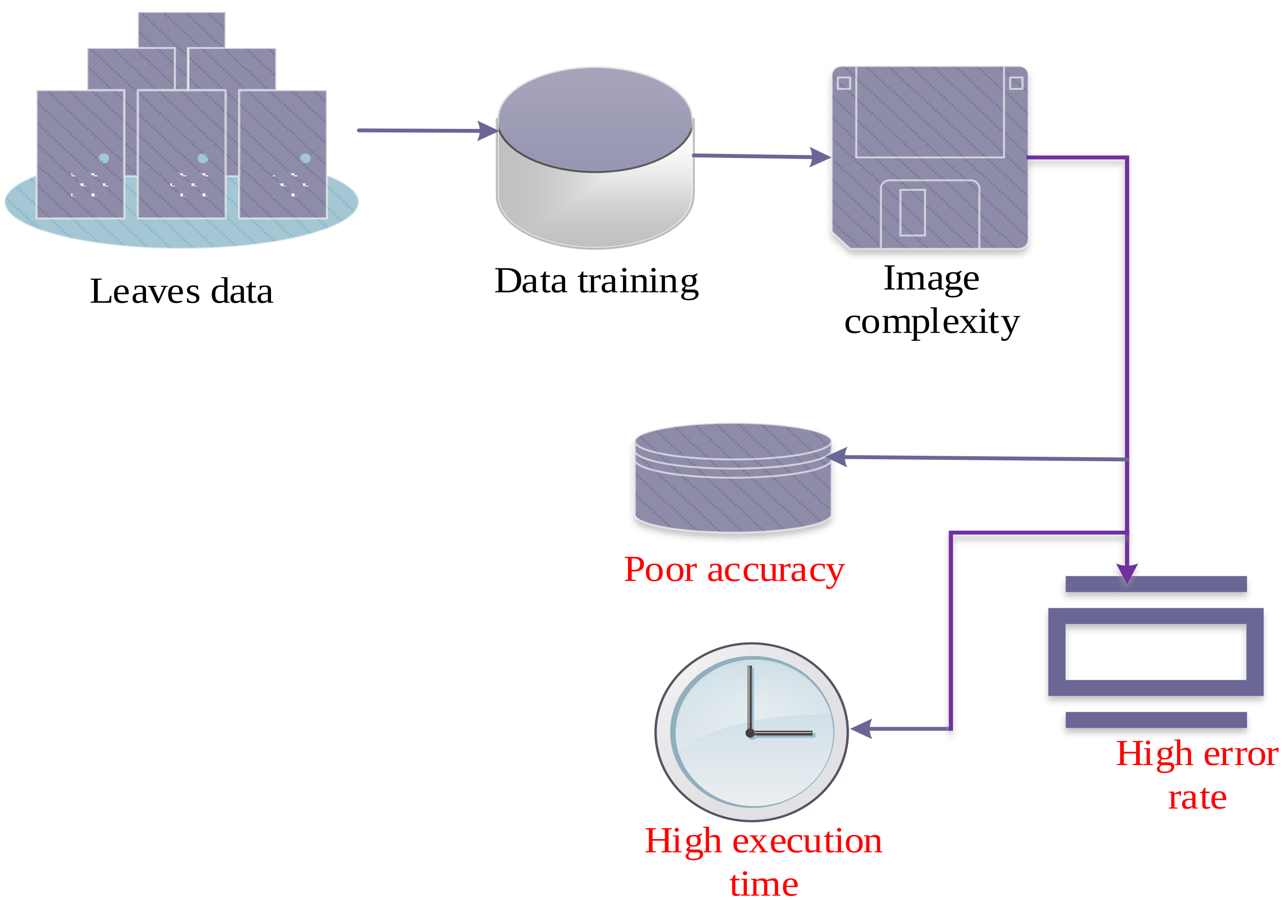


Fig. 2 System model with common problems

Therefore, detecting and identifying these infections on such valuable vegetation pushes us to develop an automated strategy to improve crop output, increase producer profit, and further contribute to the nation's economy [17]. Several models, such as the optimized convolution model [32], transfer learning [21], etc., exist in predicting the affected region from image data. But the appropriate outcomes are not found because of the image complexity and high resource usage. So the present research has been planned to design a novel optimized Convolutional neural approach to segment the affected region in the potato leaves.

The research justifications in the present paper are arranged as follows. The connected tasks of the plant leaf disease prediction system are described in depth in the second part. Section 3 illustrates the fundamental leaf disease prediction method with a problem. The fourth part highlights the implemented new approach to the mentioned leaves disease prediction challenge. Moreover, part 5 summarises the developed scheme's effectiveness, and section 6 wraps up the study discussion and conclusions.

2. Related Works

Recent literatures related to infection detection in leaves are described as follows:

To segment the affected region from the potato leaf images, the technique called the convolutional model has been implemented by NourEldeen M. Khalifa*et al* [32]. Here, the Adam optimization module is combined with the convolutional classification. The implemented optimized convolution model has gained an infection rate detection exactness score of 99%. This model has not taken the previous layer output as the input of the following layer. Hence, it needs more duration to execute the process.

To value the strength rate of the DL and ML functions in the plant leaf disease prediction. R. Sujatha *et al.* [20] have made a comparative analysis among DL and ML concepts in predicting the infectious region of the trained plant leaves. The experimental process verified that the DL has performed much better than ML models in detecting the disease region of the plant leaves. However, the average accuracy was only obtained.

Zhencun Jiang *et al.* [21] have developed an efficient transfer learning procedure to forecast and segment the disease in the Wheat leaf data. Here, the data is gathered from the Kaggle site; it contains both normal and abnormal leaf image data. The training and testing process is done using the transfer learning model. Finally, it has been observed that the transfer learning procedure gained 97% of disease forecasting accuracy. However, it has required more resources to execute the process.

Detecting leaf diseases is an important factor for the agriculture field to analyze plant growth. Krishnamoorthy N*et al* [22] have introduced a Convolution neural system. Hence, it has gained an average exactness rate of 95.67%. Here, multiple leaf image data has been taken and analyzed for the effectiveness of the designed model. In addition, if the image was too complex, it obtained more resources and time to segment the disease-affected region. Also, it has tended to obtain less prediction accuracy.

HenanSun*et al* [33] have experimented with predicting the infection part in the apple leaf data. Hence, the mean block device has been used to do the real-time implementation, and the average prediction results have been found. Moreover, it has required more time and resources to predict the affected disease in the image data. Also, the designed device is only suitable for apple leaves. In addition, the designed devices are executed the prediction process with the help of the convolutional neural process.

3. System Model and Problem Description

Image processing is the trending field in all digital and real-time fields; it is also advanced in agriculture by analyzing leaf disease. The present research has focused on improving the soil properties and fertilizers in the potato leaf disease prediction system. Several models have been implemented in the past, but the complex image can maximize classification difficulties; this reason has given less classification and segmentation accuracy.

The detected issues from the past works in segmenting leaf disease-affected areas are high execution duration, maximum error rate, and poor accuracy. Hence, the basic leaf disease diagnosis system with problems is described in fig.2. The present article has planned to implement a novel optimized deep learning model to segment the disease from the trained dataset to address these issues.

4. Proposed ALHTCNA for Potato Leaf Disease Prediction

The planned research aimed to design a novel Ant Lion-based Hyper-Parameter tuned Convolution Neural Approach (ALHTCNA) to predict and segment the disease affection in potato leaf datasets.

The data is put into the classification layer after the preparation function is completed and without errors. The feature extraction, segmentation, and prediction model have designed the classification layer. Moreover, the disease region in the potato leaves has been predicted segmented with a high exactness rate with Ant lion fitness's help in the dense layer of neural convolution model. Finally, the types of diseases were classified, and the parameters were calculated. Fig. 3 provides an illustration of the suggested architecture. The effectiveness of the suggested approach is also assessed using data on healthy leaves. No features were detected in healthy leaf data during the disease feature forecasting module. Thus, the presented model can sufficiently specify the disease from the leaf data.

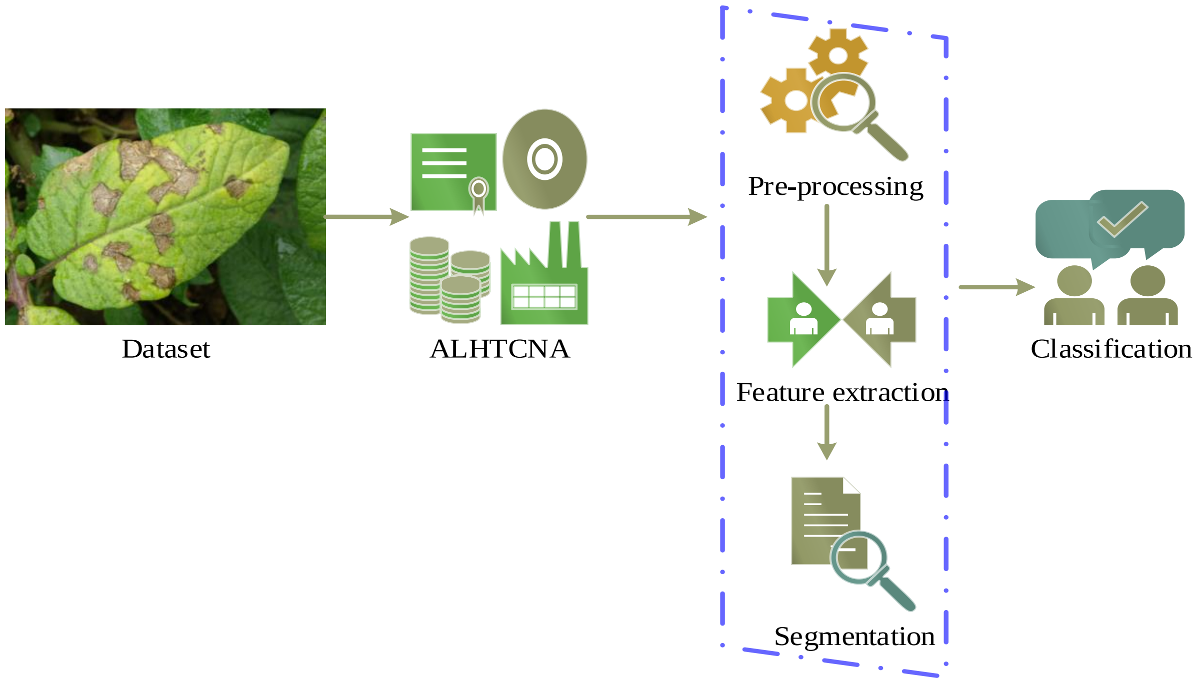


Fig. 3 Proposed architecture

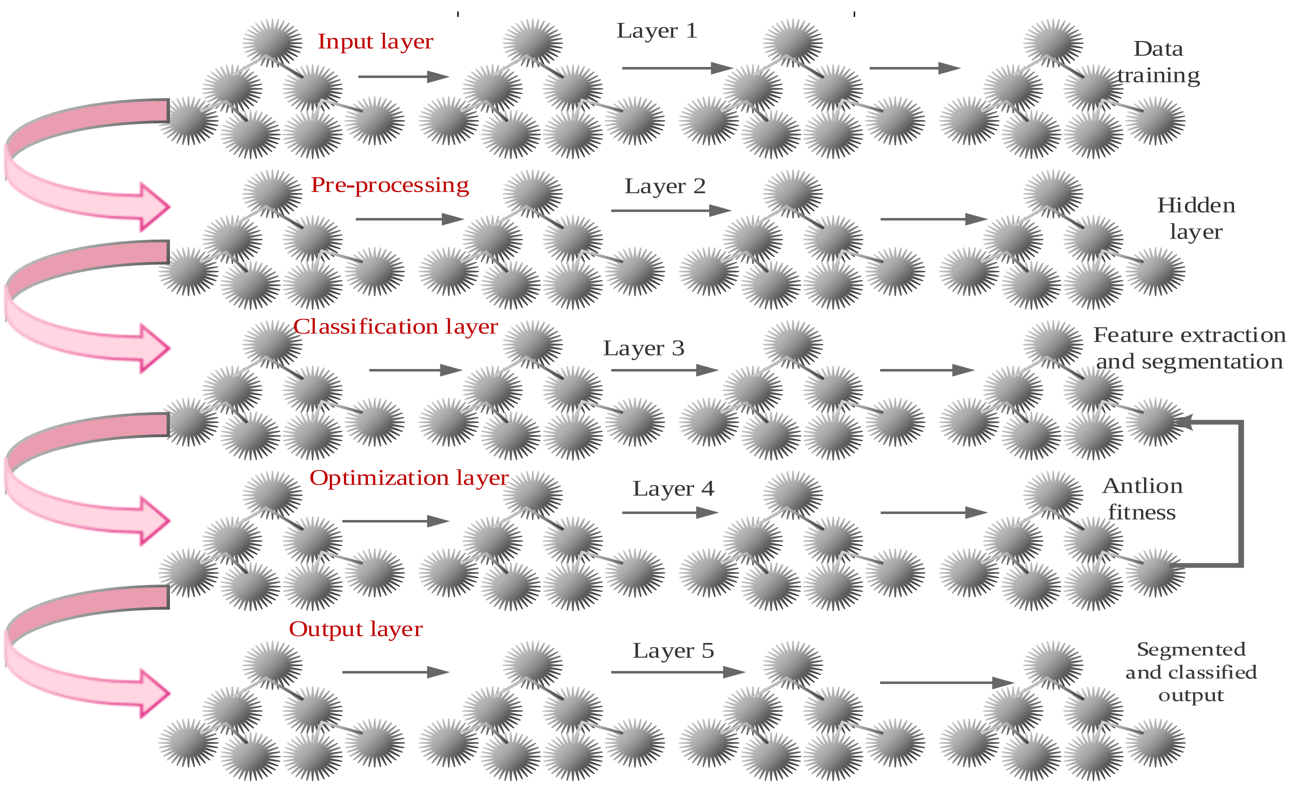


Fig. 4 Layers of ALHTCNA

4.1. Design of ALHTCNA

The planned technique has been incorporated some key layers, such as the input frame, hidden layer, classification, parameter tuning, and output layer. The designed segmentation and prediction module is operated based on the convolutional neural procedure [18] and the Ant lion algorithm [27]. Usually, the ant lion algorithm has been attracted to the research field by their hunting behavior. Moreover, the training function has been executed by Eqn. (1)

$$F(P_l) = P_l\ (1,2,3,4,5,6 \dots . n) \qquad (1)$$

Here, P_l represents the potato leaf data and $F(P_l)$ is the dataset training function. As a result, the preprocessing operation is carried out, and the learned potato leaf data is saved in the hidden layer. In this present research problem solution, the fitness of the ant lion process is utilized to predict and detect the infected region in the potato leaf data.

The proposed scheme has included five layers: data training, noise removal, classification, parameter tuning (optimization), and output. These specifications are detailed in fig.4.

4.1.1. Preprocessing

To get the best segmentation and prediction outcomes in the image processing concept, the noise from the training data must be removed.

$$E_r(P_l) = P_l - \alpha\left(\frac{x}{t_f}\right) \qquad (2)$$

Here, $E_r$is the noise removal parameter variable, $\alpha$is the noise tracking variable, x is the noise feature, and the present total features are determined ast_f. Hence, the noise removal function is executed in eqn. (2). Here, the noise features were neglected from the present total features.

4.1.2. Feature Extraction and Disease Feature Prediction

Here, the feature extraction is performed by fixing the random value with the use of the Ant lion fitness. To identify the present features in each leaf, zero labels were taken in Eqn. (3).

$$F_t = \frac{B_{Sd}\ (=0)}{t_f} \qquad (3)$$

Here, the feature monitoring parameter is denoted as$B$, each leaf image is determined as $G$and $F_t$determines the feature tracking process.

The fixed disease features value is 0.5; the disease features were identified from the tracked features by applying the threshold range. Hence the feature forecasting process is explained in eqn. (4).

$$P_d = \begin{cases} 0 & F_t > 0.5 \\ 1 & no\ feature \end{cases} \qquad (4)$$

Algorithm:1 ALHTCNA

start
{
$int\ P_l$;
// initializing potato leaf data
Preprocessing ()
{
$int\ E\ r, x, t_f;$
// initializing preprocessing parameter
$\alpha \rightarrow x(P_l)$
// αmonitors the present noise-trained data
$\alpha \rightarrow remove\quad noise(P_l)$
// the predicted errors were removed
}
Feature extraction ()
{
$\boldsymbol{int\ B}, \boldsymbol{G};$
// initializing feature extraction variables
$\boldsymbol{F_t} \rightarrow \boldsymbol{B}(\boldsymbol{G})$
// the present features in each image has been tracked
}
Disease prediction()
{
$\boldsymbol{Fix} \rightarrow \boldsymbol{disease\quad threshold}$
// fixing disease threshold
$\boldsymbol{rand\quad selection}(\boldsymbol{test\quad data})$
$\boldsymbol{if}(\boldsymbol{F_t} > \boldsymbol{0})$
{
Disease feature
}else(normal)
// By applying this condition, the disease features are predicted
}
Segmentation()
{
$\boldsymbol{int\ S_d}, \boldsymbol{P_d}$
//here, the segmentation
$\boldsymbol{if}(\boldsymbol{S_d} = \boldsymbol{P_d}(\boldsymbol{G}))$
{
$\boldsymbol{segment} \rightarrow \boldsymbol{P_d}(\boldsymbol{G})$
}else (healthy leaves)
//By performing these conditions, the affected region has been segmented
}
Classification()
{
$\boldsymbol{if}(\boldsymbol{seg\_data} > \boldsymbol{S_d})$
{
EB disease
}Else if $\boldsymbol{seg\_data} \leq \boldsymbol{S_d})$
{
LB disease
}end if (healthy)
// by analysing these conditions, the disease types were classified
}
}
Stop

In the Ml concepts, the features were labeled as 0's and 1's, so the feature prediction module has utilized the 0 and 1 classes. Here, the label "1" represents that the image data has no features and the label "0" determines the present features in the specific image.

4.1.3. Segmentation

Once the disease features are forecasted, then it is saved in the Convolutional neural memory with the S_d. Consequently, the affected area has been tracked and segmented by taking the average between saved and predicted features. Moreover, the segmentation function is illustrated in eqn. (5).

$$seg(A_r) = \frac{S_d + P_d}{2} \tag{5}$$

Here, the saved infection features are denoted as $\boldsymbol{S_d}$ and the forecasted feature are determined as $\boldsymbol{P_d}$. Moreover, A_r is the affected region, and the seg has denoted the segmentation parameter.

4.1.4. Classification

The potato leaf diseases considered in this present research are Early-Blight (EB) and Late Blight (LB). If the tested potato leaf is not under both categories during the classification, it is considered healthy leaves.

$$C_d = if\ \left(seg(A_r)\right) > S_d = EB \tag{6}$$

Here, the disease EB has been categorized using Eqn. (6), and the LB disease categorization functions by eqn. (7)

$$C_d = if\ \left(seg(A_r)\right) \leq S_d = LB \tag{7}$$

For the multiple classes, **c**lassification is more important to find the types of each parameter. This research problem has concentrated on disease classification; more than one disease is considered. So, performing classification is more important.

The working process of the designed ALHTCNA is explained in algorithm.1 and fig.5. In this image processing approach, the main function of the designed model is forecasting the disease feature with high accuracy and affected region segmentation.

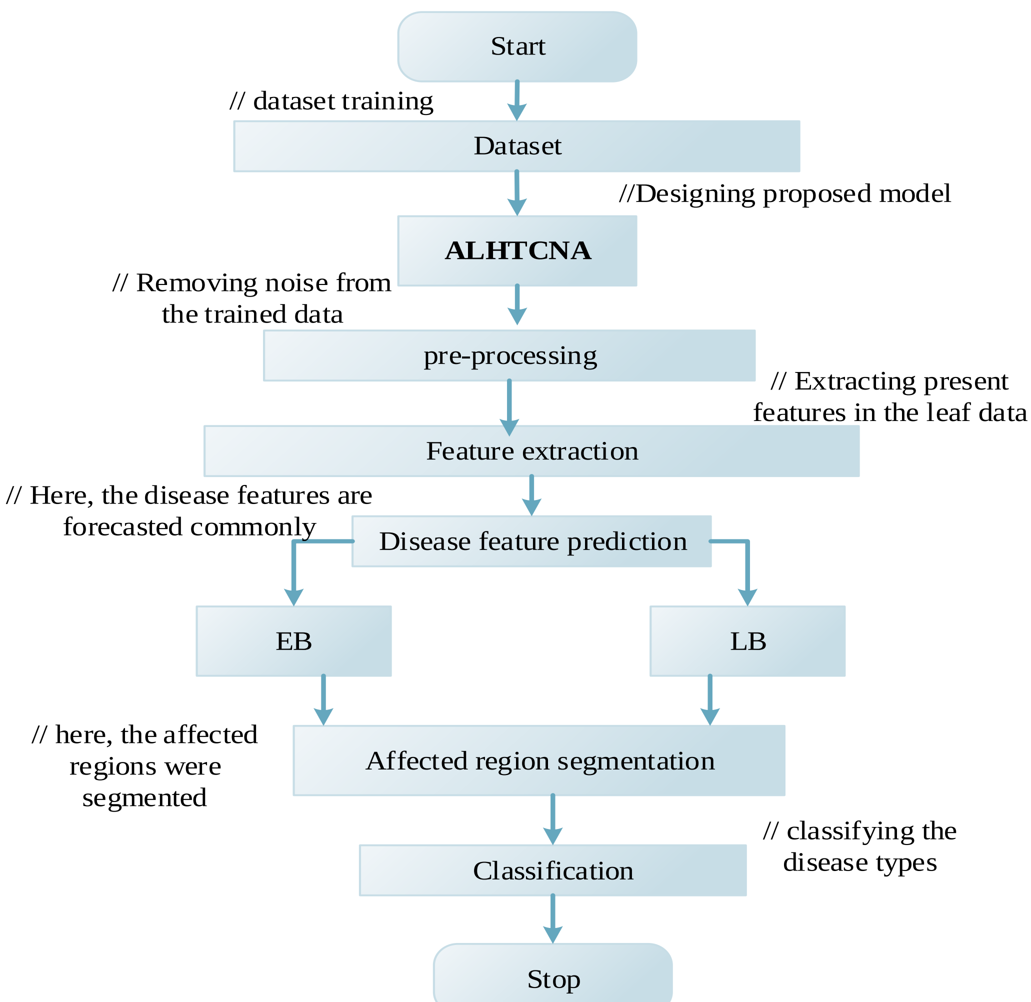
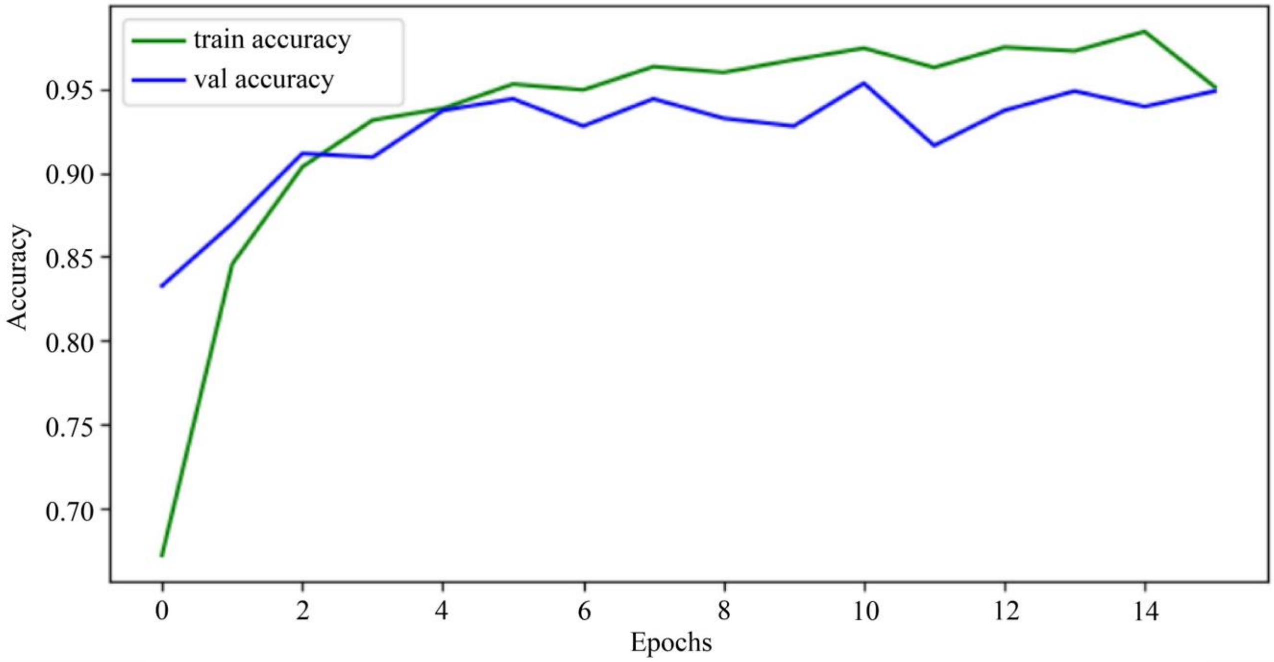


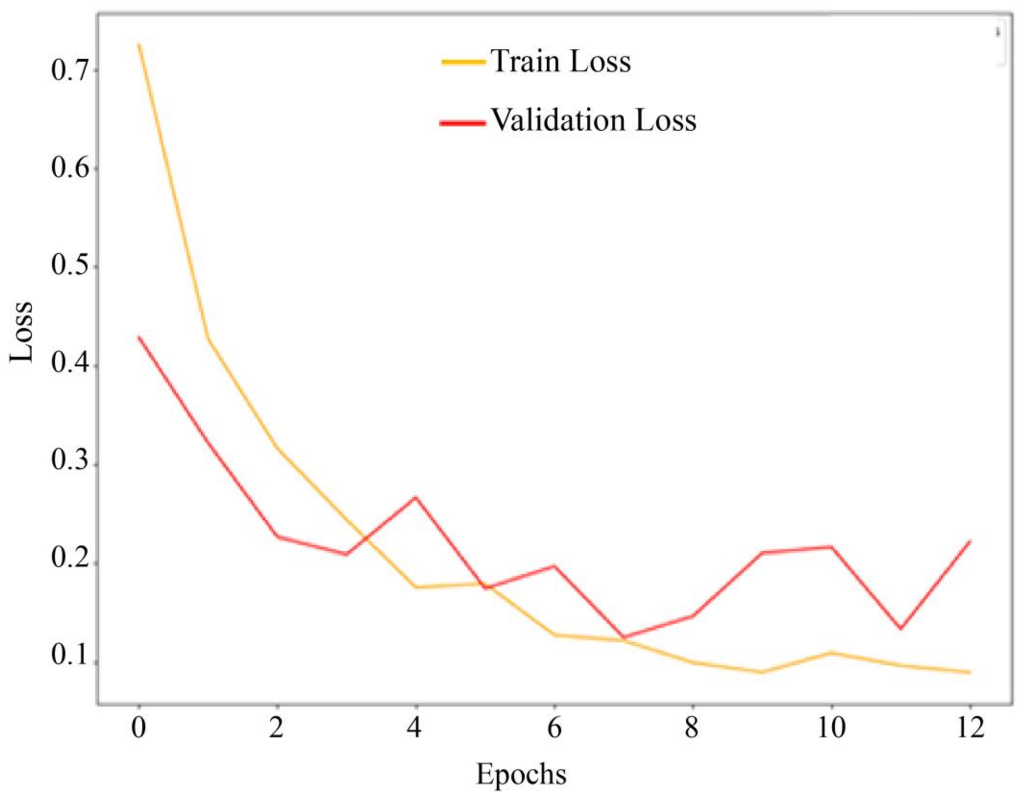
Fig. 5 Working flow of ALHTCNA

5. Results and Discussion

Python is used to implement the strategy, while Windows 10 is the operating system of choice. The system is first trained using picture data of potato leaves downloaded from the Kaggle site. As a result, a brand-new ALHTCNA has been developed, complete with all the necessary criteria for accurate illness type segmentation and classification. The execution parameters are described in table.1.



a)



b)

Fig. 6 Training performance: a) Accuracy, b) loss

Table 1. Execution specification

Parameter	Specification
Platform	Python, pycharm
version	3.8
Operating system	Windows 10
Data	image
Objective	Disease prediction
Total images	2152

The prediction and segmentation outcomes were highly dependent on training loss and accuracy. Here, the training accuracy parameter has been obtained based on the ability range of the proposed approach in classifying training samples among two images. Moreover, the validation accuracy has described the ability range of testing exactness scores. Hence, the training and validation accuracy is detailed in fig.6, (a).
In the training phase, loss validation is the crucial parameter for analyzing the loss percentage in both training and testing models. Here, the training loss has indicated the miss classification in the training samples, and the validation loss has represented the possibility of miss classification in testing cases. The procedure for training and validating loss is given in fig.6 b.

5.1. Case Study

To measure the working range of the proposed ALHTCNA, some of the test images have been adopted, such as EB, LB, and healthy leaves.

5.1.1. Case:1

The severity of the disease EB is based on irrigation, dew or rain. Moreover, the primary symptoms for EB are irregular or circular, with small black or dark-brown black spots. Hence, These spots have enlarged between 3/8 inch in diameter and are gradually angular-shaped.

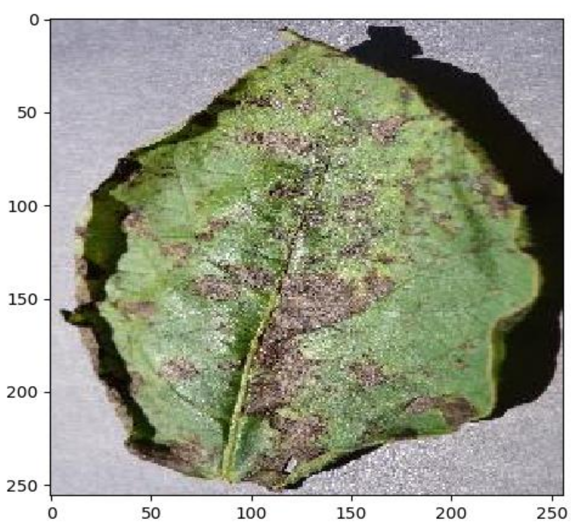


Fig. 7 EB input image

The EB input image that was taken to test the system is detailed in fig.7; it contained several dark-brown spots.

The process feature prediction contains three cases that filter the noise from the tested data feature analysis by matching the saved disease features. Finally, the analyzed features were predicted with a possible high accuracy. Moreover, fig.8 contains the features of EB disease; once the features were detected, then the segmentation function was initiated.

The tracked EB features during the segmentation process are described in fig.9 a), and the segmented outcome is illustrated in fig.9 b).

5.1.2. Case:2 Healthy leaf

To check the function of the ALHTCNA in the healthy leaf data, one of the healthy leaves is taken as an input for the validation illustrated in fig.10. Here, the healthy data has no dark or brownish spots.

The disease feature is absent in the healthy leaf data, which is described in fig.11so, there are no predicted features in the feature analyzed frame. Hence, the segmentation frame is also in empty condition, so it is not described.

5.1.3. Case:3 LB disease

The disease LB occurred because of fungal infections; these infections have degraded crops' growth and have tended to cops yield failure. Moreover, this can affect the potato too severely. The input image of LB is described in fig.12, and the feature analysis outcome is illustrated in fig.13.

The leaf neurons are more visible after the filtering function than the original image. Moreover, in the second step, the normal and abnormal features were analyzed by matching the analyzed features with the detected LB disease features.

Moreover, the tracked features and the segmented LB-affected region are defined in fig. 14. Here, the features were tracked using the predicted features from the given test data.

5.2. Performance Analysis

The metrics like precision, recall, f-measure, and accuracy have been validated to measure the segmentation and classification exactness score.

5.2.1. Confusion Matrix

The confusion matrix has been analyzed to analyze the true and predicted score from the test data. Hence, using confusion matrix Maps, the performance metrics were measured with a highly possible exactness score.

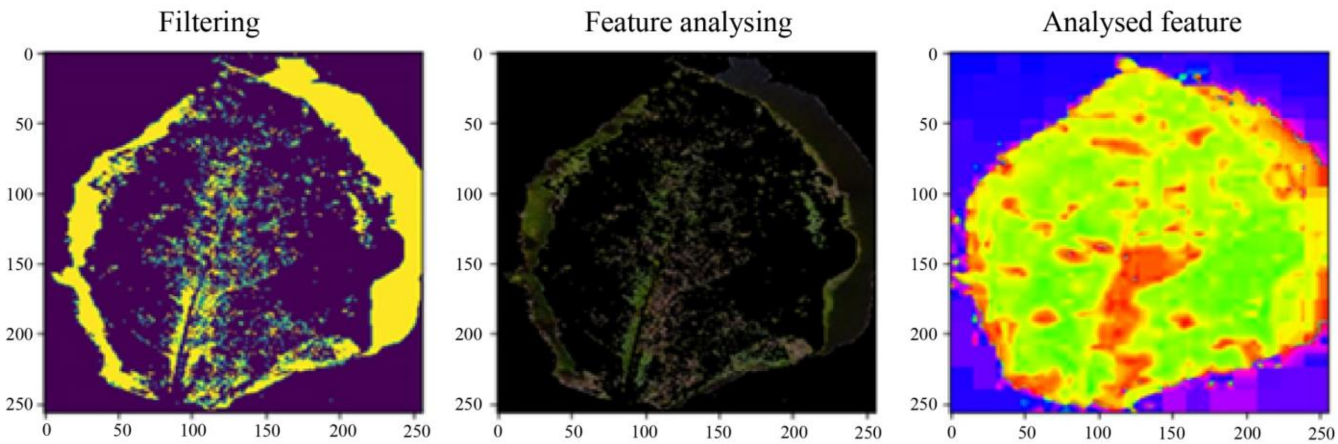
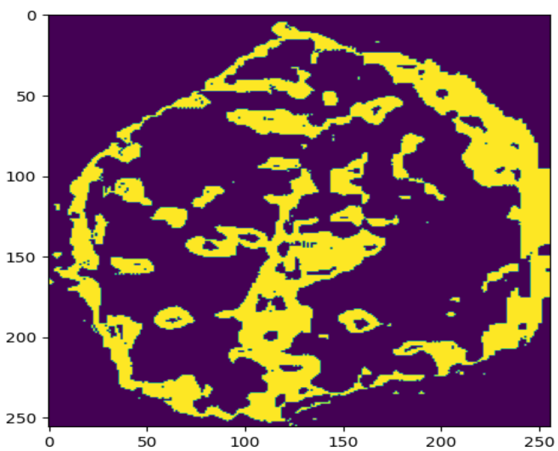
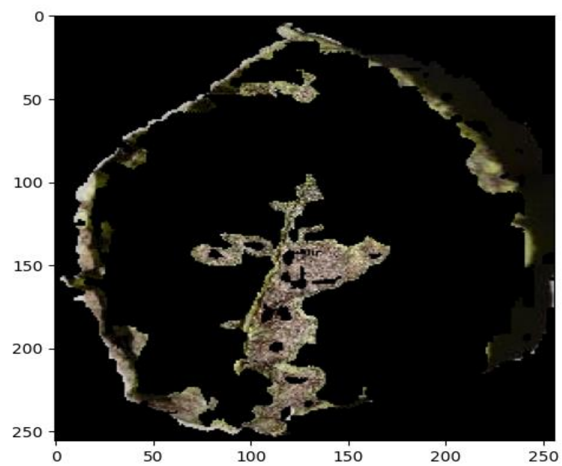


Fig. 8 Feature prediction



a) Tracked features



b) segmentation

Fig. 9 EB leaves disease: a)tracked features, b)segmentation

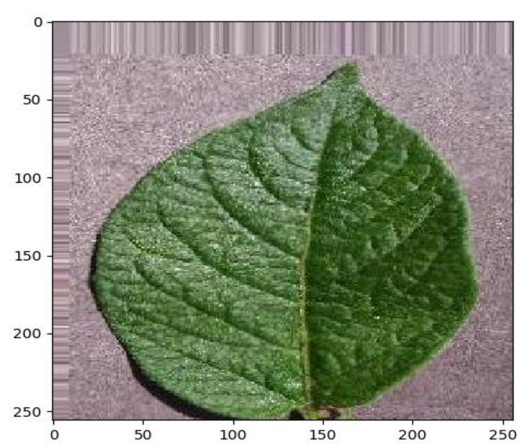


Fig. 10 Healthy leaf input data

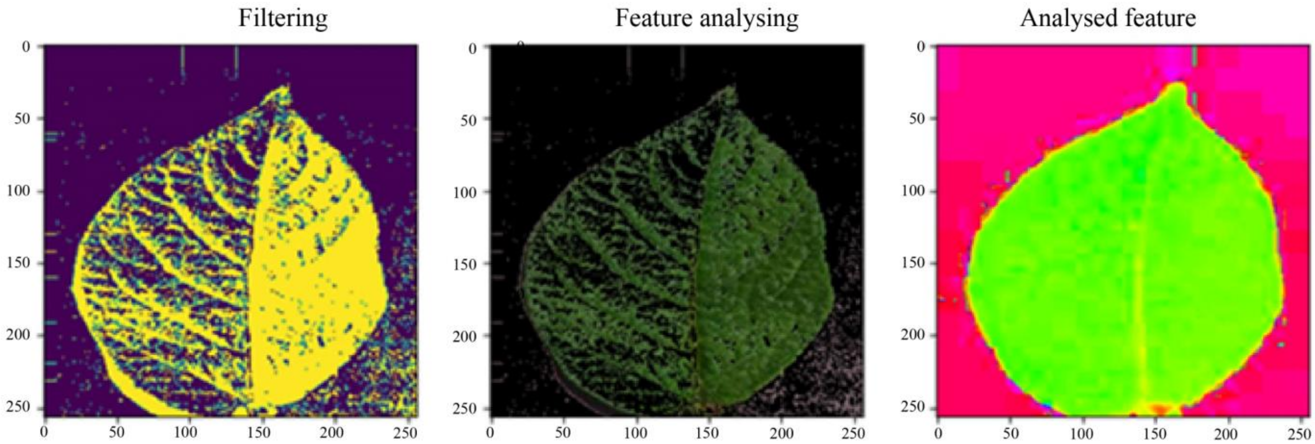


Fig. 11 Feature analysis of healthy leaves

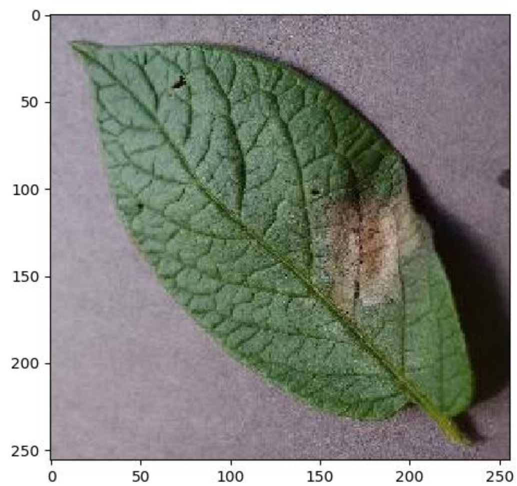


Fig. 12 LB input image

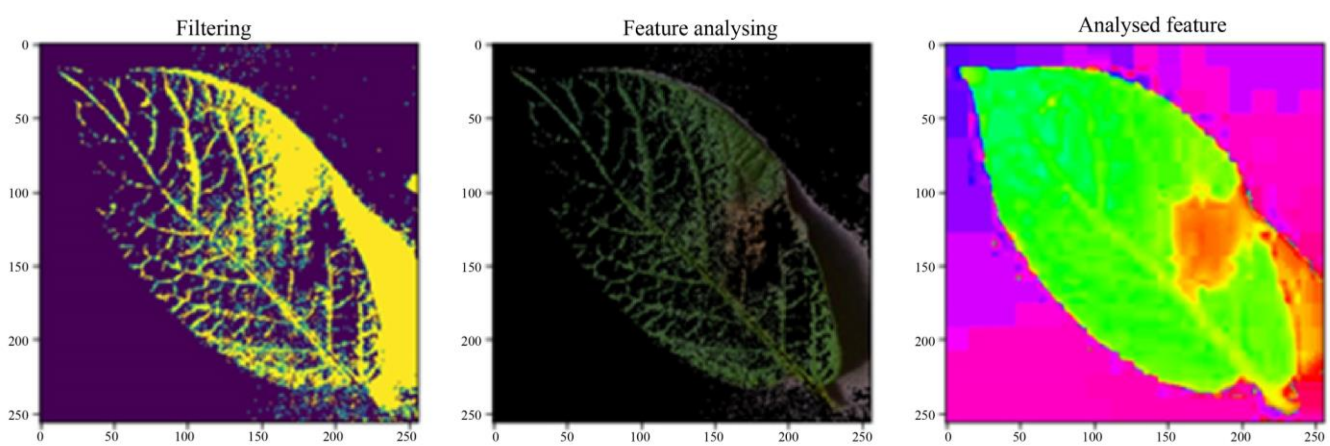
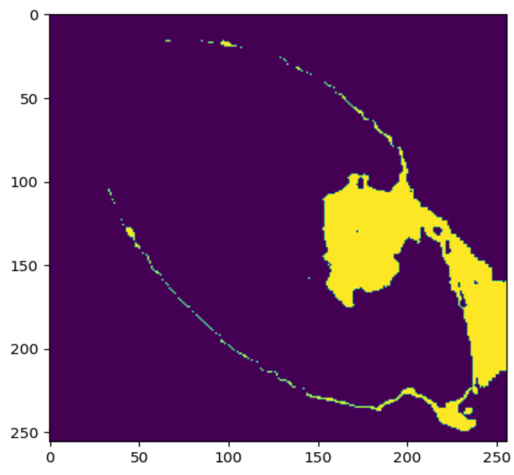
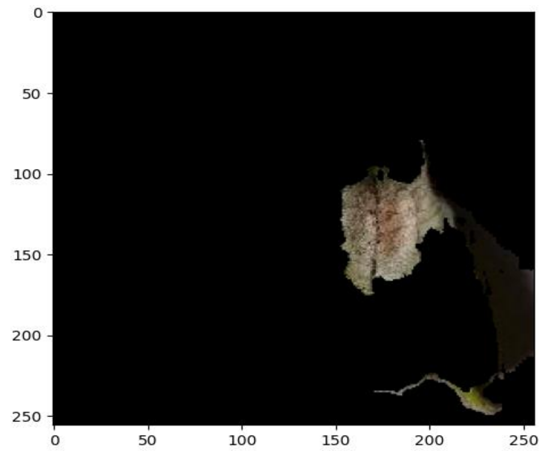


Fig. 13 Feature analysis of LB



a)



b)

Fig. 14 LB disease: a)feature tracking b)segmentation

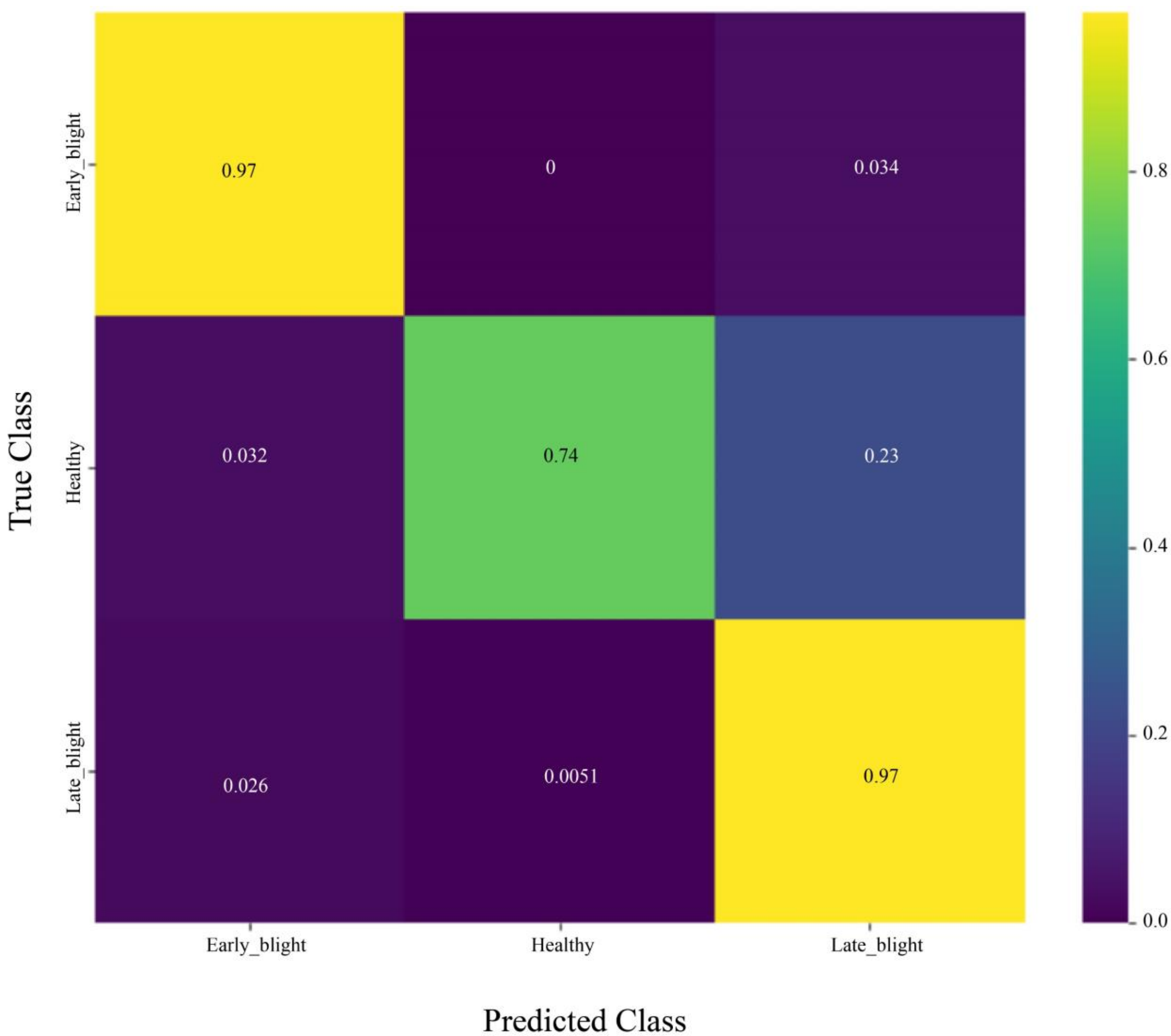


Fig. 15 Confusion matrix

Here, three classes have considered finding true and false EB, healthy, and LB scores. The obtained confusion matrix is pasted in fig.15.

Accuracy

The robustness of the designed novel ALHTCNA is verified by measuring the exact range of the segmenting parameters. Hence, the disease region is segmented from the entire predicted leaf features.

$$Accuracy = \frac{Exact\ segmentation\ on\ A_r}{Entire\ leaves\ Features}\ X\ 100 \quad (8)$$

The formulation for validating the accuracy score is described in Eqn. (8) here, the accuracy score has been measured for segmentation in segmenting all trained diseases.

Precision

To identify the similar exactness score for each trail, the parameter precision was measured using the true and positive scores.

$$precision = \frac{T_a}{T_a + P_b} \quad (9)$$

Where, false-positive is determined asP_b, True-negative is determined asT_b, true-positive is represented as T_a, and N_a determines false-negative. In addition, it is the metric that has been utilized to find the stability performance of the proposed system. Hence, the precision validation functions in Eqn. (9)

Recall

The metric recall is validated to measure the segmentation sensitivity score; it is measured to find the exact segmentation rate from the total predicted leaves disease features. Moreover, recall is the crucial parameter in image processing applications to value the designed methodology's working rate. Hence, the recall calculation is performed using eqn. (10)

$$Recall = \frac{T_b}{T_b + P_b} \quad (10)$$

The overall performance score in segmenting and classifying the affected area is graphically illustrated in fig.16. Moreover, the parameters analyzed to find the robustness score are F-measure, precision, recall, and accuracy, which is described in fig.16.

The disease classification performance is described in fig.17. here, three classes have specified EB, LB, and healthy.

F-measure

The purpose of calculating the F-score is to find the mean difference between precision and recall metrics. Moreover, the F-score is valued by Eqn. (11).

$$F - value = \frac{T_a}{T_a + \frac{1}{2}\ (P_b + N_a)} \quad (11)$$

Moreover, the F-score measurement has given every case the maximum possible test accuracy. To measure the exactness score of the testing data, the metric F-measure was calculated.

5.3. Comparison Assessment

Several classification frameworks have been implemented in the past to address this problem, which is called disease prediction and segmentation. The present reach has designed a novel solution called ALHTCNA to segment and specify the disease-affected region in leaves. Hence, the segmentation and classification improvement score is found by comparing the merits with the existing models. To find the improvement score of the proposed approach, some other works have been taken such as Support-Vector-Machine (SVM) [24], Decision-Tree(DT) [24], K-nearest-neighbouring (KNN) [24], Naive-Bayes (NB) [24], Random-Forest (RF) [24] and Non-Dominated-Genetic-Algorithm (NDGA) [25].

The model SVM has obtained the accuracy in leaf disease forecasting is 77.56% and precision76%; NB has scored the exactness range of segmentation as 77.46% and precision of 77%, DT has reported the exactness value as 74.355 and precision as 74%, KNN has illustrated the tested accuracy as 76.16% and 75% precision, NDGA has recorded the exactness value as 83% and 77% precision. The proposed novel ALHTCNA has obtained 95% precision and accuracy considering all these validation scores. The graphical representation of accuracy and precision status is described in fig.18.

SVM's reported recall and F-score value is 78% and 79% for the segmentation process. Moreover, the model KNN obtained a recall value of 75% and F-score of 76%, the NB gained an f-score of 75% and recalled 77%, and the approach DT obtained a recall value of 74% and an F-score of 75%. The recall score and f-score for the technique RF were reported as 80% and 79%, respectively. The NDGA technique recorded a recall score of 84% and f-measure of 78%. Considering all these validations, the proposed novel ALHTCNA has gained the maximum recall and F-score of 95%. The graphical representation of recall and F-measure status is described in fig.19. Moreover, the overall comparison statistics are described in table.2.

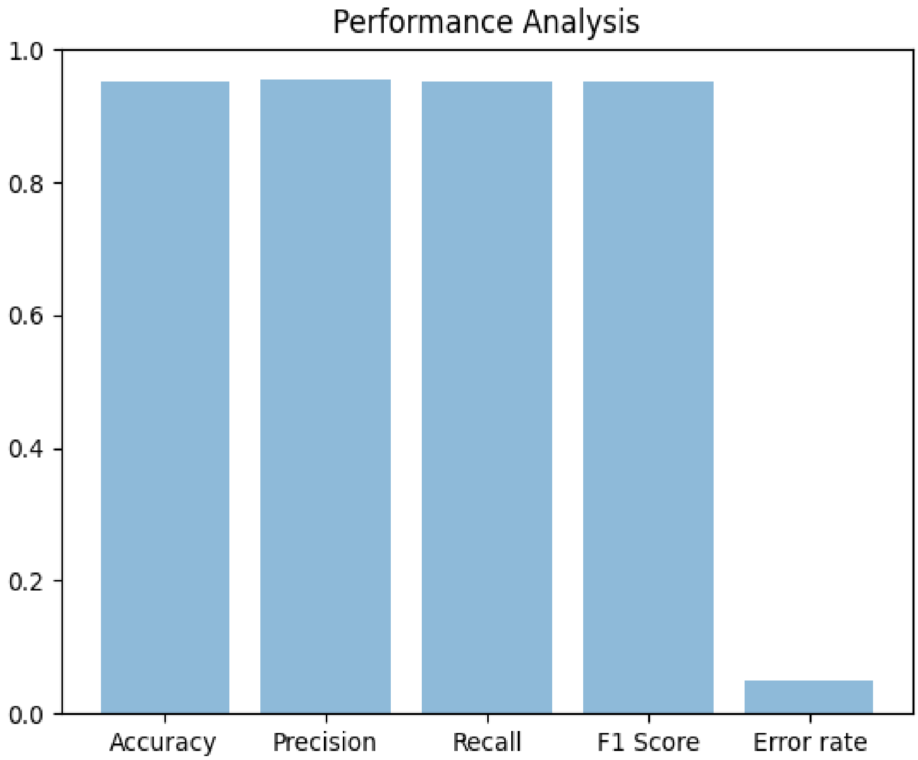


Fig. 16 Performance statistics

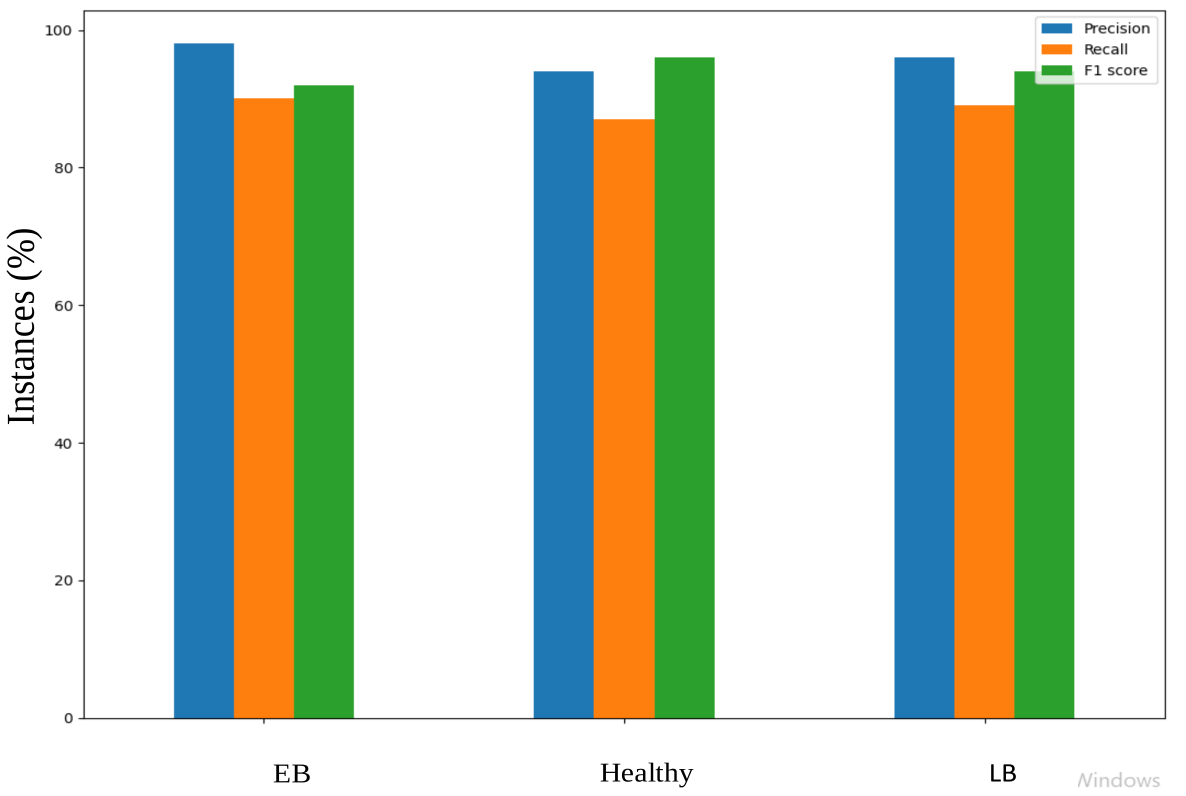


Fig. 17 Classification performance

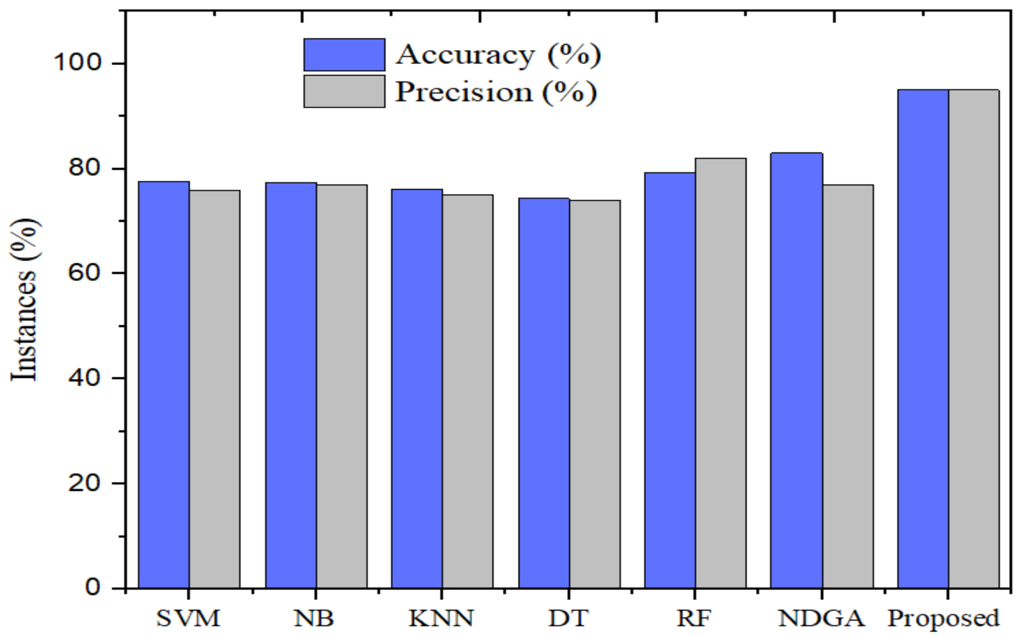


Fig. 18 Accuracy and precision assessment

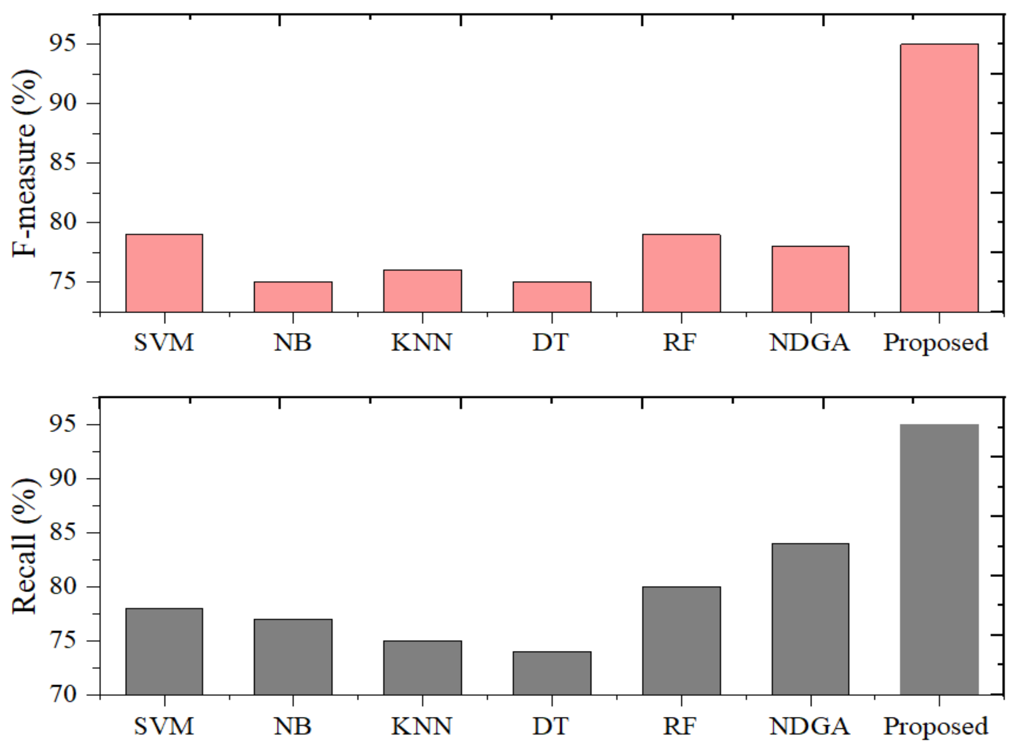


Fig. 19 Recall and F-measure validation

5.4. Discussion

Several metrics have been measured above to prove the robustness of the developed novel ALHTCNA. The proposed scheme has observed the finest outcome in all metrics and forms, like segmentation and classification for different diseases. The overall robustness of the novel ALHTCNA in both the classification and segmentation process is detailed in table.3. The error metric has also been validated to find the miss-segmentation and classification score. The novel ALHTCNA has observed the minimum error score as 0.04%. It has been verified that the

The proposed approach efficiently segments and classifies the affected area and disease types.

Table 2. Comparison statistics

Overall comparison statistics				
Methods	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
SVM	77.56	76	78	79
NB	77.46	77	77	75
KNN	76.16	75	75	76
DT	74.35	74	74	75
RF	79.23	82	80	79
NDGA	83	77	84	78
Proposed	95	95	95	95

Table 3. Overall performance assessment

Performance validation of ALHTCNA						
	Classification Performance			**Segmentation performance**		
	Precision	**Recall**	**F-measure**	**EB, LB, Healthy**	**Accuracy**	95%
EB	0.98	0.94	0.96		**precision**	95%
Healthy	0.90	0.87	0.89		**Recall**	95%
LB	0.92	0.96	0.94		**F-measure**	95%

6. Conclusion

The proposed work has aimed to forecast and segment the affected region of the potato leaves. For that, a novel ALHTCNA has been executed in the python framework then the stability score of the designed model is analysed in three cases: healthy leaves, EB, and LB. The presented model has gained the exactness score of affected region segmentation is 95%; by comparing other schemes, it has maximized the segmentation performance by up to 15%. In addition, it has been recorded that the maximum classification sensitivity score is an average of 95%. The time required to execute this potato leaf disease segmentation process is 8.3s, and the observed error rate is 0.04%. Moreover, the present model has maintained the stability range in all sectors, verifying that the novel ALHTCNA has attained the same performance score of all metrics, 95%. Hence, the designed novel ALHTCNA is suitable for image processing applications, especially for the leaf data segmenting of the training images' affected regions.

References

[1] Md. Al-Amin, Dewan Ziaul Karim, and Tasfia Anika Bushra, "Prediction of Rice Disease from Leaves Using Deep Convolution Neural Network Towards a Digital Agricultural System," *22nd International Conference on Computer and Information Technology, IEEE*, pp. 1-5, 2019. [CrossRef]

[2] Sk Mahmudul Hassan et al., "Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach," *Electronics*, vol. 10, no. 12, p. 1388, 2021. [CrossRef]

[3] K. S. Chethan et al., "Mobile Application for Classification of Plant Leaf Diseases Using Image Processing and Neural Networks," *Data Intelligence and Cognitive Informatics, Springer*, Singapore, pp. 287-306, 2021. [CrossRef]

[4] Ruchi Gajjar et al., "Real-Time Detection and Identification of Plant Leaf Diseases Using Convolutional Neural Networks on an Embedded Platform," *The Visual Computer*, pp. 2923-2938, 2022. [CrossRef]

[5] Ravindra Namdeorao Jogekar, and Tiwari Nandita, "A Review of Deep Learning Techniques for Identification and Diagnosis of Plant Leaf Disease," *Smart Trends in Computing and Communications: Proceedings of SmartCom*, vol. 182, pp. 435-441, 2021. [CrossRef]

[6] M. Karthick et al., "Machine Learning Approaches for Automatic Disease Detection from Paddy Crops - A Review," *International Journal of Engineering Trends and Technology*, vol. 70, no. 12, pp. 392-405, 2022. [CrossRef]

[7] Mohamed Loey, "Big Data and Deep Learning in Plant Leaf Diseases Classification for Agriculture," *Enabling AI Applications in Data Science*, *Springer*, *Cham*, pp. 185-200, 2021. [CrossRef]

[8] A. Lakshmanarao, M. Raja Babu, and T. Srinivasa Ravi Kiran, "Plant Disease Prediction and Classification using Deep Learning ConvNets," *International Conference on Artificial Intelligence and Machine Vision, IEEE*, pp. 1-6, 2021. [CrossRef]

[9] Man Gong et al., "Mechanism by Which Eucommiaulmoides Leaves Regulate Nonalcoholic Fatty Liver Disease Based on System Pharmacology," *Journal of Ethnopharmacology*, vol. 282, p. 114603, 2022. [CrossRef]

[10] Ravindra Jogekar, and Nandita Tiwari, "Enhanced Adaptive Creation of Visualisation Network by Detection of Leaves," *Materials Today: Proceedings*, 2021. [CrossRef]

[11] Tahmina Tashrif Mim et al., "Leaves Diseases Detection of Tomato Uusing Image Processing," *8th International Conference System Modeling and Advancement in Research Trends, IEEE*, pp. 244-249, 2019. [CrossRef]

[12] D. Sheema et al., "The Detection and Identification of Pest-FAW Infestation in Maize Crops Using Iot-Based Deep-Learning Algorithm," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 180-188, 2022. [CrossRef]

[13] H. Suheri, and T. V. Price, "Infection of Onion Leaves by Alternariaporri and Stemphyliumvesicarium and Disease Development in Controlled Environments," *Plant Pathology*, vol. 49, no. 3, pp. 375-382, 2000. [CrossRef]

[14] G. Geetharamani, and J. Arun Pandian, "Identification of Plant Leaf Diseases using a Nine-Layer Deep Convolutional Neural Network," *Computers & Electrical Engineering*, vol. 76, pp. 323-338, 2019. [CrossRef]

[15] Rina Mahakud, Binod Kumar Pattanayak, and Bibudhendu Pati, "A Hybrid Multi-class Classification Model for the Detection of Leaf Disease using XGBoost and SVM," *International Journal of Engineering Trends and Technology*, vol. 70, no. 10, pp. 298-306, 2022. [CrossRef]

[16] S. Ramesh, and D. Vydeki, "Recognition and Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya Algorithm," *Information Processing in Agriculture*, vol. 7, no. 2, pp. 249-260, 2020. [CrossRef]

[17] Sammy V. Militante, Bobby D. Gerardo, and Nanette V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," *IEEE Eurasia Conference on IOT, Communication and Engineering, IEEE*, pp. 579-582, 2019. [CrossRef]

[18] Santosh Kumar Upadhyay, and Avadhesh Kumar, "A Novel Approach for Rice Plant Diseases Classification with Deep Convolutional Neural Network," *International Journal of Information Technology*, pp. 185-199, 2022. [CrossRef]

[19] Gargi Sharma, and Gourav Shrivastava, "Crop Disease Prediction using Deep Learning Techniques - A Review," *SSRG International Journal of Computer Science and Engineering*, vol. 9, no. 4, pp. 23-28, 2022. [CrossRef]

[20] R. Sujatha et al., "Performance of Deep Learning vs Machine Learning in Plant Leaf Disease Detection," *Microprocessors and Microsystems*, vol. 80, p. 103615, 2021. [CrossRef]

[21] Zhencun Jiang et al., "Recognition of Rice Leaf Diseases and Wheat Leaf Diseases Based on Multi-Task Deep Transfer Learning," *Computers and Electronics in Agriculture*, vol. 186, no. 1, p. 106184, 2021. [CrossRef]

[22] N. Krishnamoorthy et al., "Rice Leaf Diseases Prediction Using Deep Neural Networks with Transfer Learning," *Environmental Research*, vol. 198, p. 111275, 2021. [CrossRef]

[23] Reem Issa, Mitiady Boras, and Riad Zidan, "Effect of Seaweed Extract on the Growth and Productivity of Potato Plants," *SSRG International Journal of Agriculture & Environmental Science*, vol. 6, no. 2, pp. 83-89, 2019. [CrossRef]

[24] Kshyanaprava Panda Panigrahi et al., "Maize Leaf Disease Detection and Classification Using Machine Learning Algorithms," *Progress in Computing, Analytics and Networking, Springer*, Singapore, pp. 659-669, 2020. [CrossRef]

[25] Somnath Mukhopadhyay et al., "Tea Leaf Disease Detection Using Multi-Objective Image Segmentation," *Multimedia Tools and Applications*, vol. 80, no. 1, pp. 753-771, 2021. [CrossRef]

[26] T. Nagarathinam, and Dr. K. Rameshkumar, "A Survey on Cluster Analysis Techniques for Plant Disease Diagnosis," *SSRG International Journal of Computer Science and Engineering*, vol. 3, no. 6, pp. 11-17, 2016. [CrossRef]

[27] Dalwinder Singh, and Birmohan Singh, "Effective and Efficient Classification of Gastrointestinal Lesions: Combining Data Preprocessing, Feature Weighting, and Improved Ant Lion Optimization," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 9, pp. 8683-8698, 2021. [CrossRef]

[28] R. Tamilaruvi et al., "Brain Tumor Detection in MRI Images using Convolutional Neural Network Technique," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 198-208, 2022. [CrossRef]

[29] Chandrasen Pandey et al., "Machine Learning Approach for Automatic Diagnosis of Chlorosis in Vignamungo Leaves," *Multimedia Tools and Applications*, vol. 80, no. 9, pp. 13407-13427, 2021. [CrossRef]

[30] Ümit Atila et al., "Plant Leaf Disease Classification Using Efficientnet Deep Learning Model," *Ecological Informatics*, vol. 61, p. 101182, 2021. [CrossRef]

[31] Siddharth Singh Chouhan et al., "Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach towards Plant Pathology," *IEEE Access*, vol. 6, pp. 8852-8863, 2018. [CrossRef]

[32] Nour Eldeen M. Khalifa et al., "Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach," *Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges, Springer, Cham*, pp. 63-79, 2021. [CrossRef]

[33] Henan Sun et al., "MEAN-SSD: A Novel Real-Time Detector for Apple Leaf Diseases using Improved Light-Weight Convolutional Neural Networks," *Computers and Electronics in Agriculture*, vol. 189, p. 106379, 2021. [CrossRef]