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ARTIFICIAL BEE COLONY OPTIMIZATION WITH FEATURE FUSION BASED AGRICULTURAL PLANT DISEASE DETECTION AND CLASSIFICATION MODEL

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ABSTRACT

Agricultural plant disease detection and classification is a critical task to ensure productivity and health of the crops. Laboratory testing, visual inspection, and the use of technology such as imaging and machine learning (ML) are different methodologies used for the detection and classification of plant disease in agriculture. Visual inspection includes inspecting the appearance of the plant and symptoms like wilting, abnormal growth, and discolouration. The ML algorithm can be used for the classification of various plant diseases and trained to identify patterns in an image of diseased plants. This method could help researchers and farmers to accurately and quickly recognize plant diseases and take necessary measures to control or prevent them. This study develops an Artificial Bee Colony Optimization with Feature Fusion based Agricultural Plant Disease Detection and Classification (ABCFF-PDDC) model. The presented ABCFF-PDDC technique focuses on the detection of plant diseases via computer vision and feature fusion concepts. In the presented ABCFF-PDDC technique, NestNet model is initially used for the background removal process, i.e. segmenting the leaf regions in the image. Next, deep instance segmentation (DIS) is applied for the segmentation of diseased leaf regions. For feature extraction, a fusion based feature extraction comprising EfficientNet and residual network (ResNet101) model with Nadam optimizer is used. Finally, the ABC algorithm with 1D convolutional neural network (1D-CNN) is used. The experimental analysis of the ABCFF-PDDC model on benchmark plant disease dataset reported the betterment of the ABCFF-PDDC technique in terms of different measures.

Keywords: *Agriculture; Feature fusion, Computer vision, Deep instance segmentation, Parameter tuning, Plant disease detection*

1. INTRODUCTION

Agriculture plays a significant role, and, it is a major source of income for many individuals in different nations [1]. Agriculture is a fundamental necessity for survival of mankind. Hence, it becomes crucial to increase productivity of the crops, vegetables, and fruits in developing nations like India [2]. On top of that, the quality of production must be higher enough to have good health conditions. But, the productivity and quality of food get fraught with various elements such as disease spread which could be evaded with initial diagnosis. Many diseases were transmissible, which resulted in the loss of crop yield [3]. Many varieties of food plants were harvested through environmental conditions of land, but concurrently several problems were confronted by the agronomists some of them are natural disasters, water shortages, and plant diseases [4]. But many problems can be diminished by providing technical amenities to the agriculturalists. This is called an automated plant disease detection system, which aids the farmers to offer technical facilities. Such mechanism can conquer the issues by the specialists using their prior knowledge [5]. In agriculture, an automatic related mechanized approach can be used to detect the plant diseases. So, disease recognition is becoming a significant research topic in mitigating, controlling, detecting, and monitoring automatically the plant disease [6]. Such mechanism is developed and used in the proposed model.

Conventional disease detection approaches depend upon agricultural organizations, but such techniques are limited because of lack of human resources [7]. An automated plant disease detection technique is used which does not require human frequent interactions. UAVs and mobile phones leverage technologies for increasing internet access and have innovative tools for detecting diseases that depend on automated image recognition to help in largescale identification. With the advent of AI, CV, and ML technologies, development was attained in framing automatic methods that allow the timely and

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accurate detection of plant disease [8]. In the earlier decade, with high performance computer devices and processors, ML and AI technologies have grabbed interest. DL is commonly known as it is primarily used in agriculture [9]. This concept looks critical for sustaining, regulating, establishing, and increasing crop production. It is at the core of the intellectual farming approach, which can be detected for incorporating novel technology, gadgets, and algorithms into farming [10]. DL utilizing Neural Network was a part of ML. The progression of these computer technologies will be helpful to the farmers in controlling and monitoring plant diseases.

This study develops an Artificial Bee Colony Optimization with Feature Fusion based Agricultural Plant Disease Detection and Classification (ABCFF-PDDC) model. In the presented ABCFF-PDDC technique, NestNet model is initially used for the background removal process, i.e. segmenting the leaf regions in the image. Next, deep instance segmentation (DIS) is applied for the segmentation of diseased leaf regions. For feature extraction, a fusion based feature extraction comprising EfficientNet and residual network (ResNet101) model with Nadam optimizer is used. Finally, the ABC algorithm with 1D convolutional neural network (1D-CNN) model is used. The experimental analysis of the ABCFF-PDDC algorithm takes place on benchmark plant disease dataset.

2. RELATED WORKS

Reddy et al. [11] presented a customized PDICNet method for plant leaf disease classification and identification. Primarily, ResNet-50 has been utilized in the process of extracting various features from plant leaf imageries with texture and colour properties. Also, the modified Red Deer optimization algorithm (MRDOA) was applied as the best feature selection technique for acquiring better and more significant features with minimized size of the MRDOA. In addition, a DL-CNN classifier method was leveraged for gaining enhanced classifier performance. In [12], an attempt was executed towards automated disease identification from the plant leaf. For this a new framework, an approach termed IoT_FBFN leveraging Fuzzy Based Function Network (FBFN) enabled with IoT has been presented. In the beginning, the leaf images were gained. After these imageries were preprocessed and attributes can be derived over the Scale-invariant feature transform approach.

Kumar et al. [13] designed a new exponential spider monkey optimization which can be used to set the important features from higher dimensional set of attributes produced by SPAM. Moreover, the selective features were given to SVM for plant classification into healthy and diseased plants utilizing certain significant features of the leaves. Venu et al. [14] devised DL related CNN to detect the diseases in the images precisely with the help of image classifier approaches. In this work, CNN was distributed with the input images. In every convolution layer of CNNs, relevant feature was mined and sent to the next pooling layer. At last, every feature which was derived from convolutional layers was formed and concatenated as input to the FC layer of existing architecture and after output class will be estimated by the model.

Chouhan et al. [15] modelled a technique called bacterial foraging optimization (BFO) related to radial basis function NN (BRBFNN) for classification and identification of plant leaf disease mechanically. To assign best weight to BRBFNN the author has used BFO which further rises the accuracy and speed of the networks to categorize and detect the regions infected with various diseases on the plant leaves. Mohapatra et al. [16] devise a CNN-related metaheuristic method for disease detection and diagnosis. Initially, the image of mango leaves will be improvised through contrast enhancement and histogram equalization. After, a geometric mean-related neutrosophic with the fuzzy c-means technique was employed for segmenting process. Then, the vital attributes were retrieved from imageries which have been segmented, including the Upgraded LBP (ULBP), color, and pixel features. At last, such attributes were presented in the disease identification stage, which can be devised through a CNN-DL method. M.J.Bradshaw et al. [17] suggested the ways to avoid the spread of Powderly mildew Pathogens discerning the geographic spread and host range of economically significant plant pathogens, is vital for biosecurity measures and identifying the origins and expansion of potentially harmful pathogens. O.Carisse et al. [18] suggested the important role of leaf removal in managing grape anthracnose. Which requires a continuous monitoring that can be accomplished by using the proposed model.

3. THE PROPOSED MODEL

In this study, a new ABCFF-PDDC technique has been introduced for plant disease detection and classification using CV and feature fusion concepts. The ABCFF-PDDC technique comprises NestNet based background removal, DIS based segmentation, feature fusion-based extraction, Nadam optimizer, 1D-CNN classification, and ABC based hyperparameter tuning. Fig. 1 illustrates the working flow of ABCFF-PDDC methodology.

3.1. Background Removal Process

In the presented ABCFF-PDDC technique, NestNet model is initially used for segmenting the leaf regions in the image. NestNet is a DL-based technique for removing background in an image [19]. It is based on top of NN structure named U-Net which is frequently used for image segmentation tasks. NestNet is trained for segmenting the foreground object from the background through fully connected and convolutional layers. Also, it exploits a nested structure that enables the network to learn more complicated representations of an image. NestNet is capable of handling images with complex backgrounds like images with more than one object and used for background removal in an image for variety of applications namely video production, object recognition, and image editing. The NestNet integrates a pair of parallel modules for image processing at different time intervals. The NestNet model consists of encoding and decoding units. The encoding unit has four hierarchical ranks and generates feature vector. An increase in channel count results in higher computational difficulty to derive image features. The parallel processing block in the NestNet could remove it. Next, decoding unit combines the feature data and performs feature upsampling to the image of similar width and height.

3.2. Segmentation Process

At this stage, the DIS is applied for the segmentation of diseased leaf regions. Fast RCNN accomplishes promising performance on pattern analysis, statistical modeling and computational learning visual object classes (PASCAL VOC) dataset [20]. But Faster RCNN and RCNN need additional steps like selective search (SS) 25, Edge boxes for generating object proposals. With Edge or SS boxes, which extract each proposal from the image with CPU needs approximately 2s. From the end-to-end perspective, the time-consuming is a noticeable bottleneck for Fast RCNN and RCNN. Using robust feature extraction ability of NN, Fast RCNN combines Region Proposal Network (RPN) into Faster RCNN for extracting proposals.

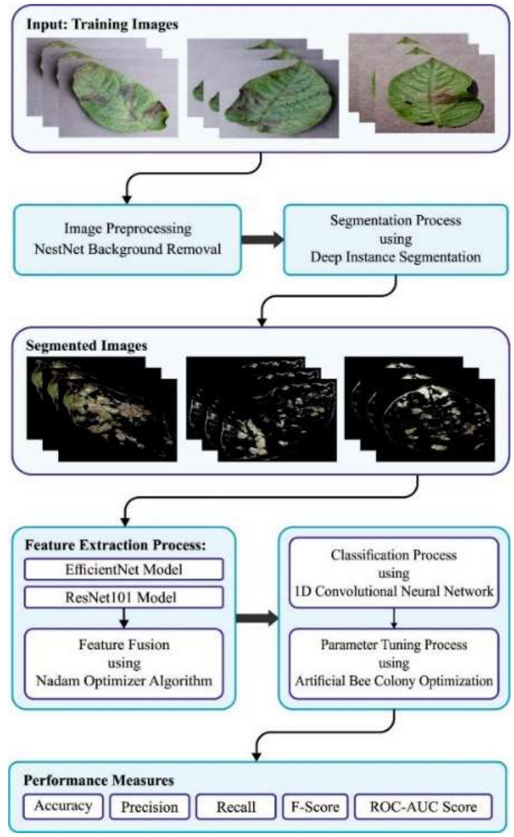

Figure.1.Overall flow of ABCFF-PDDC approach

RPN is a Fully Convolutional Network (FCN), where it produces higher quality region proposals, and all of them have a confidence score. Simultaneously, it forecasts object scores and object bounds at every location. A smaller network slide over the convolution feature map output by the top convolution Layer to generate region proposals. As compared with the additional step Edge or SS boxes, RPN shares full-image convolution features with the Faster RCNN, which enables almost cost-free region proposal. Simultaneously, it forecasts confidence score and object bound at every position.

3.3. Fusion based Feature Extraction Process

At this stage, a fusion based feature extraction comprising EfficientNet and ResNet101 model. Data fusion method was utilized in many ML and CV applications. Feature fusion is a critical task that integrates different feature vectors [21]. The suggested technique is based on feature fusion using entropy. The feature extraction and feature selection methods are represented as follows:

The two feature vectors are described by:

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$$f_{EfficientNet \times n} = \{EfficientNet_{1\times 1} \cdots , EfficientNet_{1\times n}\} \quad (1)$$

$$f_{ResNet \times m} = \{ResNet_{1\times 1}, \cdots , ResNet_{1\times n}\} \quad (2)$$

Moreover, feature extracted was fused in a single vector.

$$Fused(features\ vector)_{1\times q} = \sum_{i=1}^{2} \{fEfficientNet_{1\times n}, f\mathrm{ResNet}_{1\times m}\} \quad (3)$$

Where f represent the fused vector (1x1186). The entropy is used on feature vector for selecting optimal feature based on the score. The mathematical expression of feature selection method is shown in Eqs. (1) and (3).

$$B_{He} = -NHe_b \sum_{i=1}^{n} p\,(f_i) \quad (4)$$

$$F_{select} = B_{He}\big(\,max\ \ (f_i, 1186)\big) \quad (5)$$

Where p symbolizes feature probability and He specifies the entropy. Lastly, the feature selected was given to the classifier for distinguishing the healthy and glioma images.

3.3.1. EfficientNet Model

EfficientNet is a deep learning network structure proposed in 2019 [22]. This structure provides the relation between three terms that considerably affect the performance of deep network architecture. They are depth, width, and resolution. Such architecture is based on the decompound scaling technique. At first, a grid search technique is utilized. This model enables the network to establish the relationships between the scaling dimensions. The target deep learning network is started with the specified scaling dimension. The composite scaling method can be mathematically expressed as follows:

$$\alpha^{\phi}, w = \beta^{\phi}, r = \gamma\string^\phi \quad (6)$$

$$\alpha.\beta\string^2.\gamma\string^2 \approx 2 \quad (7)$$

$$\alpha \geq 1, \beta \geq 1, \gamma > 1 \quad (8)$$

Where the ϕ parameter represents a user-defined coefficient. α, β, γ are the parameters used for depth, width and resolution, correspondingly. Depth is related to the number of layers of a DL network architecture. A deep network could get complex features by going into further detail. But increasing the depth of the network is not often desirable since the depth might increase the cost and loss of time. As well, improved accuracy gain might not be often predicted. Width is related to the size of the layer of deep network structure. The increase of neurons in the layers causes the extension of the network. Resolution is related to the aspect ratio of the input data of a DL network structure. The high resolution of the input image has fine details in the image.

3.3.2. ResNet101 Model

ResNet-101 is a deep CNN (DCNN) [23]. It is a variation of Residual Network (ResNet) structure, and is also known for its capability to train DCNN with hundreds or thousands of layers while still being able to accomplish better performance. ResNet-101 has 101 layers, with an enormous amount of filters in the convolutional layers that enable the network to learn complicated representation of the input dataset.

The primary concept behind ResNet is to apply residual connection that allows the network to learn the residual mapping between the input and output, rather than the original mapping. This assist to alleviate the gradient disappearing problems, which is a common issue while training deep networks, and enables the network to learn more easily. ResNet-101 was trained on the ImageNet data and used for different image classification tasks. It was demonstrated to accomplish outstanding performance on numerous benchmarks and is extensively used as a feature extractor in other computer vision tasks like facial recognition, semantic segmentation, and object detection. Generally, ResNet-101 is a widely used and powerful architecture that has been demonstrated to accomplish better performance on a large number of image classification tasks and is frequently used as a feature extractor in other CV tasks.

3.3.3. Nadam Optimizer

The Nadam optimizer is used for selecting the hyperparameters of the EfficientNet and ResNet101 models. Nadam (Nesterov-Accelerated Adaptive Moment Estimation) is an optimization technique that combines the concepts of Adam and Nesterov momentum optimization. It is an extension of Adam [24], which employs the adaptive learning rate to update the parameter of the neural network. Similar to Adam, Nadam uses the concept of the first and second moments of the gradient for adapting the learning rate for all the parameters. The first moment, a.k.a. the mean, estimates the existing direction of the gradient, whereas the second moment, a.k.a. the variance, estimates the present curvature of the loss function. Nadam uses a similar formula as Adam to update the parameter with the gradient, however, it also exploits a Nesterov-style acceleration term to increase the optimization technique. The Nesterov-style acceleration term uses the gradient of the future location of the parameter,

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instead of the existing location, to update the parameter. This enables Nadam to make more accurate updates to the parameters and take into account the future direction of the gradient. Nadam is a newly developed optimization approach that has been demonstrated to function effectively for different DL tasks, like image classification, reinforcement learning, and natural language processing. It was noted to achieve better results and converge faster than other optimizers, like RMSprop, Adagrad and Adam, in some cases.

3.4. Image Classification using 1D-CNN

The 1D-CNN model is used to classify plant diseases. The CNN model can be effectively extracting the features of 1D complex images, and it excellently extracts temporal features with less network parameters, thereby preventing over fitting and enhancing the speed of model detection [25]. The 1D-CNN improves the detection rate of an image, and its proposed model comprises the convolutional, pooling and FC layers. Fig. 2 represents the framework of 1D-CNN. The convolution layer aims to effectively implement a feature extraction of the input specific image that implements a local convolution function on the target input.

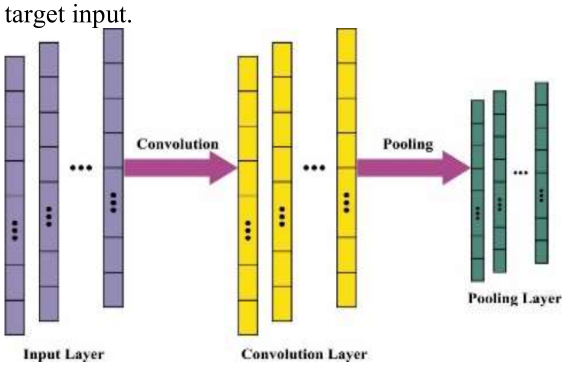

Figure. 2 *Structure of 1D-CNN*

For one spatial dimension, the convolution method is given by:

$$X_j^l = f\left(\sum_{i \in N} X_i^{l-1} W_{ij}^l + b_j\right), \tag{9}$$

In Eq. (9), f denotes the activation function, M_j represent the target of input operation, is the length of the input, X_i^{l-1} indicates the region of targeted input to be convoluted, W_{ij}^l shows the convolutional kernel, a.k.a. the weights, and b_j represent the bias parameter. Meanwhile, the $Tanh$ function is an output zero mean function, where it converges faster and achieves good performance than Sigmoid function.

Generally, the pooling layer follows the convolution layer same as convolution function. The computation speed of the network can be improved, and the dimensionality of input dataset can be decreased by sampling the convolution layer, as follows.

$$X_j^l = f\left(\beta_j^l \, down\left(x_j^{l-1}\right) + b_j^l\right), \tag{10}$$

Where β represent the weight, l denotes the existing layer of the network, and down 0 denotes the pooling function.

The equation for the FC layer is represented as follows:

$$h(x^l) = f(\omega_1 x^{l-1} + b_1), \tag{11}$$

Where $h(x)$ denotes the FC output of layer L, Ω_1 and b_1 indicates the weight parameter and offset of the neuron node. $Softmax$ is generally applied as an activation function to resolve the problem with various classifications and the output is

$$Y = S(\omega_2 h + b_2), \tag{12}$$

In Eq. (12), Y denotes the output and S indicates the Softmax function that is formulated by:

$$S_j = \frac{e^{a^j}}{\sum_{p=1}^{k} e^{a_p}}, \tag{13}$$

In Eq. (13), a_j specifies the outcome of j^{th} output of the FC layer, and S_j specifies the probability that the classification outcome is the j^{th} class.

3.5. Hyperparameter Optimization

At last, the ABC algorithm takes place for the optimal hyperparameter selection of the 1D-CNN architecture. The ABC algorithm is based on the foraging behaviours of honey bees [26] which makes some assumptions different from the behaviors of real bees. The proposed model consists of three types of bees, namely scout bees, employed bees and onlooker bees. Half of the colony has employed bees. The remaining half has onlooker bees. The nectar quantity of a food source is the solution quality. The location of food sources is a candidate solution to the problem. The proposed method comprises three fundamental control parameters. They are maximum number of generations, colony size, and limit.

In this work, the algorithm begins with randomly determining the position of the food source based on (14). $x_j^{\min}$ and $x_j^{\max}$ denotes the minimum and the maximum limitations. x_i corresponds to the i-th solution. The solution generation mechanism shown in (15) is utilized to generate new solution. Now, $\emptyset_{ij}$ denotes the randomly generated value within [1, 1] and k indicates the integer number within [1, amount of employed bees].

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31st March 2024. Vol.102. No 6

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$$\chi_{ij} = x_j^{\min} + rand(0,1)\left(x_j^{\max} - x_j^{\min}\right) \quad (14)$$

$$v_{ij} = x_{ij} + \emptyset_{ij}\left(x_{ij} - x_{kj}\right) \quad (15)$$

$$P_i = \frac{fitness_i}{\Sigma_{j=1}^{SN} fitness_j} \quad (16)$$

The nectar amount of candidate source is compared to whether it is better than the earlier one. The data of the preceding source is removed from the memory and the data of candidate solution is written, when the nectar amount of the candidate solution is better. In this work, a selection method can be done by using roulette wheel algorithm. The selection probability of source is calculated using (16). Now, $fitness_i$ characterizes the quality of $i\text{-}th$ sources. SN indicates the number of employed bees.

The proposed algorithm has a failure counter. A newest solution is generated randomly by the scout bees based on Eq. (14) when the value of failure counter obtains the limit value. This procedure is reiterated until the maximum amount of generations is attained.

The ABC algorithm not only derives a fitness function to attain better outcome of classification and also determines the positive integer to characterize the superior performance of the candidate solution. The reduction of the classification error rate is regarded as a fitness function.

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 10 \quad (17)$$

4. Experimental Validation

In this section, the plant disease detection results can be investigated on two datasets: citrus fruit dataset [27] and potato dataset [28]. The citrus dataset comprises 73 samples and the potato dataset holds 5702 samples. Figure. 3 illustrates the sample images of potatoes.

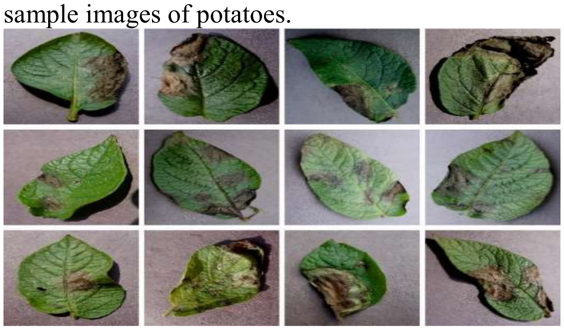

***Figure.* 3** *Few test potato images*

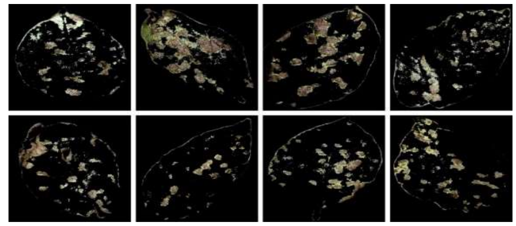

***Figure.* 4** *Segmentation outcomes*

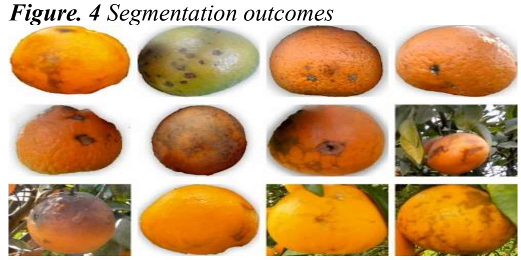

***Figure.* 5** *Few test citrus images*

Fig. 6 demonstrates the classification output of the ABCFF-PDDC technique on potato database. Fig. 6a depicts the CM offered by the ABCFF-PDDC method under TRS. The result that the ABCFF-PDDC method has identified 1327 samples to EB, 1265 samples to HY, and 1353 samples to LB. In addition, Fig. 6b depicts the CM offered using the ABCFF-PDDC method to TSS. The figure denoted that the ABCFF-PDDC method has identified 591 samples to EB, 527 samples to HY, and 574 samples to LB. Similarly, Figs. 6c-6d demonstrates the PR examination of the ABCFF-PDDC method to TRS and TSS. The figures show that the ABCFF-PDDC method has obtained highest PR performance to every individual class. Finally, Figs. 6e-6f illustrates the ROC investigation of the ABCFF-PDDC method to TRS and TSS. The results indicate that the ABCFF-PDDC method has led to superior output with highest ROC values to every individual class.

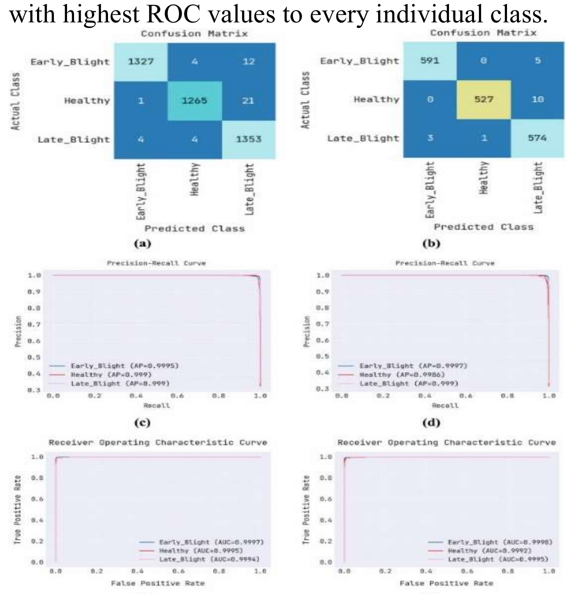

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Figure. 6 Results on Potato Dataset a) CM TRS b) CM TSS c) PR Curve TRS d) PR Curve TRS e) ROC TRS f) ROC TRS

In Table 1 and Fig. 7, the entire potato disease classifier outcome of the ABCFF-PDDC technique is demonstrated. The ABCFF-PDDC technique has identified potato plant diseases accurately. For instance, on TRS, the ABCFF-PDDC technique reachesaccu_y, prec_n, reca_l, F_score, and ROC AUC score of 98.85%, 98.87%, 98.84%, 98.85%, and 99.95% respectively. On the other hand, on TSS, the ABCFF-PDDC technique reaches accu_y, prec_n, reca_l, F_score, and ROC AUC score of 98.89%, 98.92%, 98.87%, 98.89%, and 99.95% respectively.

Table 1 Classifier outcome of ABCFF-PDDC approach under potato database

Potato Database		
Measure	*TRS*	*TSS*
Accuracy	98.85	98.89
Precision	98.87	98.92
Recall	98.84	98.87
F1-Score	98.85	98.89
ROC AUC Score	99.95	99.95

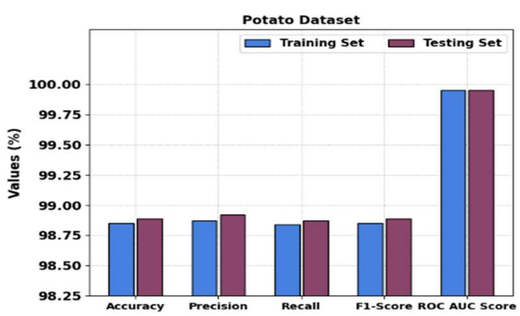

***Figure.** 7 Classifier outcome of ABCFF-PDDC approach under potato dataset*

The TACY and VACY of the ABCFF-PDDC model under potato database are represented in Fig. 8. The figure inferred the ability of ABCFF-PDDC model in attaining superior results with increasing values of TACY and VACY. It is visible that the ABCFF-PDDC method has obtained highest TACY outcome.

The TLOS and VLOS of the ABCFF-PDDC model under potato dataset are represented in Fig. 9. The figure inferred that the ABCFF-PDDC model has demonstrated improvised output with least values of TLOS and VLOS. It is visible that the ABCFF-PDDC model has resulted in reduced VLOS outcomes.

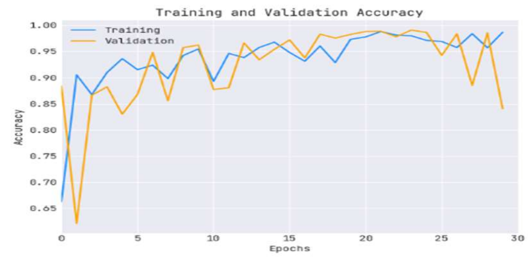

***Figure. 8.** TACY and VACY outcome of ABCFF-PDDC approach under potato dataset*

***Figure. 9.** TLOS and VLOS outcome of ABCFF-PDDC approach under potato database*

In Fig. 10, a $accu_y$ inspection of the ABCFF-PDDC approach with other DL models on potato database is given. The results indicate that the CNN-RF model results in decreasing $accu_y$ of 79%. Meanwhile, the CNN-SVM, GoogleNet, and VGGNet models accomplish closer $accu_y$ of 84%, 86%, and 86% correspondingly. Although the CNN-ANN models obtain reasonable $accu_y$ of 92%, the ABCFF-PDDC technique outperformed other models with higher $accu_y$ of 98.89%.

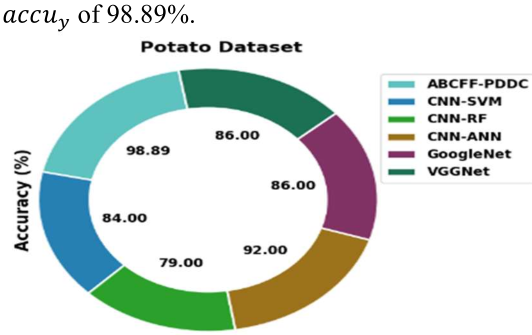

***Figure. 10** Comparison study of ABCFF-PDDC approach on potato database*

Fig. 11 demonstrates the entire outcomes of the ABCFF-PDDC technique on citrus database. Fig. 11a depicts the CM offered by the ABCFF-PDDC method on TRS. The output represented that the ABCFF-PDDC model has recognized 9 samples on BS, 22 samples on CK, 7 samples on GR, 2 samples on HY, and 10 samples on SB. Also, Fig. 11b depicts the CM offered by the ABCFF-PDDC method on TSS. The output denoted that the ABCFF-PDDC method has identified 2 samples on BS, 11 samples on CK, 1 sample on GR, 3 samples

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on HY, and 5 samples on SB. Similarly, Figs. 11c-11d demonstrates the PR analysis of the ABCFF-PDDC method on training and TSS. The outputs reported that the ABCFF-PDDC method has obtained maximum PR performance on every individual class. Finally, Figs. 11e-12f illustrates the ROC investigation of the ABCFF-PDDC model on TRS and TSS. The output portrayed that the ABCFF-PDDC method has resulted in proficient results with maximum ROC values on distinct class labels.

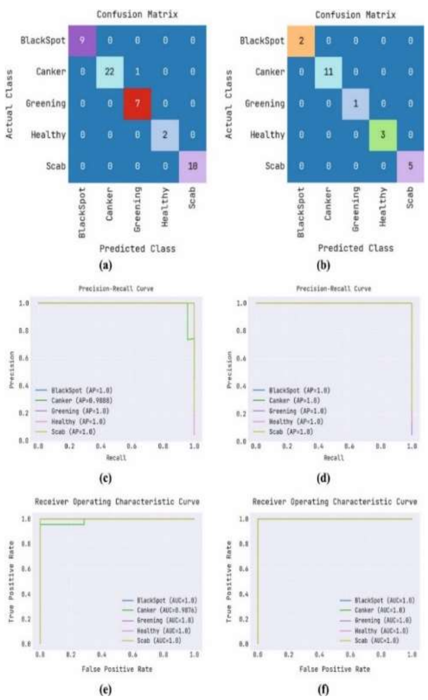

Figure. 11 *Results on Citrus Database a) CM TRS b) CM TSS c) PR-Curve TRS d) PR-Curve TRS e) ROC TRS f) ROC TSS*

In Table 2 Fig. 12, the entire potato disease classification outcome of the ABCFF-PDDC technique is demonstrated. The ABCFF-PDDC technique has recognized the citrus plant diseases accurately. For example, on TRS, the ABCFF-PDDC technique reaches $accu_y$, $prec_n$, $reca_l$, F_{score}, and ROC AUC score of 98.04%, 97.50%, 99.13%, 98.22%, and 99.75% respectively. On the other hand, on TSS, the ABCFF-PDDC technique reaches $accu_y$, $prec_n$, $reca_l$, F_{score}, and ROC AUC score of 100%, 100%, 100%, 100%, and 100% correspondingly.

Table 2 *Comparative examination of ABCFF-PDDC approach with other DL systems under citrus database*

Citrus Dataset		
Metrics	*Training Set*	*Testing Set*
Accuracy	98.04	100
Precision	97.50	100
Recall	99.13	100
F1-Score	98.22	100
ROC AUC Score	99.75	100

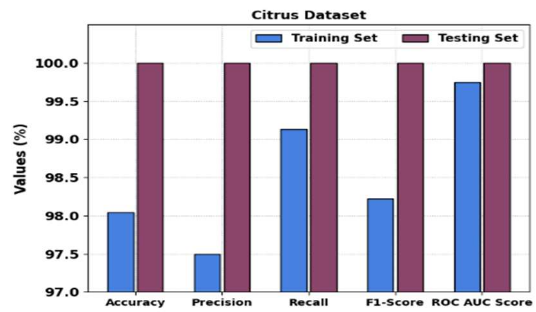

Figure. 12 *Classifier outcome of ABCFF-PDDC approach under citrus database*

The TACY and VACY of the ABCFF-PDDC method under citrus database are represented in Fig. 13. The ABCFF-PDDC approach gains highest values of TACY and VACY. It is visible that the ABCFF-PDDC method has reaches superior TACY outcomes.

The TLOS and VLOS of the ABCFF-PDDC method under citrus database are represented in Fig. 14. The outcome inferred that the ABCFF-PDDC method has attain better performance with least values of TLOS and VLOS. It is visible that the ABCFF-PDDC method has resulted in reduced VLOS outcomes.

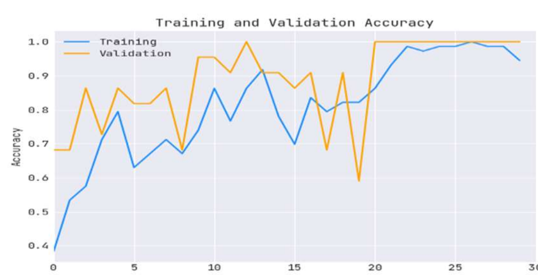

Figure. 13 *TACY and VACY outcome of ABCFF-PDDC approach under citrus database*

***Figure. 14** TLOS and VLOS outcome of ABCFF-PDDC approach under citrus database*

In Fig. 15, a comprehensive $accu_y$ examination of the ABCFF-PDDC technique with other DL models on citrus database is given. The outcomes indicate that the Linear SVM method results in decreasing $accu_y$ of 74%. Meanwhile, the Linear Discriminant, Quadratic SVM, and Cubic SVM methods accomplishes closer $accu_y$ of 74.01%, 77.15%, and 78% respectively. Although the Otsu method obtains reasonable $accu_y$ of 83.95%, the ABCFF-PDDC technique outperformed other models with higher $accu_y$ of 100%.

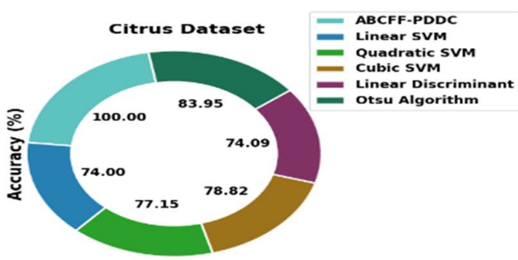

***Figure. 15** Comparative analysis of ABCFF-PDDC approach under citrus database*

The extensive results highlighted the betterment of the ABCFF-PDDC technique over other existing models.

5. CONCLUSION

In this study, a new ABCFF-PDDC technique has been introduced for plant disease detection and classification using CV and feature fusion concepts. The ABCFF-PDDC technique comprises NestNet based background removal, DIS based segmentation, feature fusion based extraction, Nadam optimizer, 1D-CNN classification, and ABC based hyperparameter tuning. In the presented ABCFF-PDDC technique, NestNet model is initially used for the background removal process, i.e. segmenting the leaf regions in the image. Moreover, the DIS is applied for the segmentation of diseased leaf regions. Meanwhile, a fusion based feature extraction comprising EfficientNet and ResNet101 model with Nadam optimizer is used. Lastly, the ABC algorithm with 1D-CNN model is used. The experimental analysis of the ABCFF-PDDC model on benchmark plant disease database reported the betterment of the ABCFF-PDDC technique in terms of various measures. In future, ensemble voting based classifier can be designed to enhance the performance of the ABCFF-PDDC technique.

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