Soft Computing
https://doi.org/10.1007/s00500-023-07936-0

FOCUS

Deep learning-based automated disease detection and classification model for precision agriculture

A. Pavithra[1] · G. Kalpana[1] · T. Vigneswaran[2]

Accepted: 16 February 2023

Abstract
Plant phenotyping and Precision agriculture are information- and technology-oriented fields with specific challenges and demands for the detection and diagnosis of plant disease. Precision agriculture can be referred as a crop management method related to the spatial and temporal variability in soil and crop factors within a field. Accurate and early diagnosis and detection of plant diseases were major factors in plant production and the reduction in quantitative and qualitative losses in crop yield. Advancement of automatic disease detection and classification system is significantly explored in precision agriculture. In recent times, research workers have investigated numerous cultures leveraging dissimilar parts of a plant. This article develops a new Deep Learning-based Automated Plant Disease Detection and Classification (DL-APDDC) Model for Precision Agriculture. The presented DL-APDDC algorithm concentrates on the recognition and classification of plant diseases in leaf and fruit regions. In the initial stage, the leaf and fruit regions are extracted by the use of U2Net-based background removal. Next, the Adam optimizer with SqueezeNet model is exploited as feature extractor, and the hyperparameters are tuned by Adam optimizer. Finally, the extreme gradient boosting (XGBoost) classifier performs classification of plant diseases. The experimental validation of the DL-APDDC technique is tested on benchmark plant disease dataset. The simulation values indicated the enhanced outcomes of the DL-APDDC approach over other models.

Keywords Smart farming · Agriculture · Plant disease detection · Computer vision · Adam optimizer

1 Introduction

Precision agriculture is a concept of farm management based on measuring, responding, and monitoring crop variability (Li et al. 2021). The study aims to determine the decision support system (DSS) for farming management by improving the returns on input when maintaining resources. MPlant disease was a threat to food security around the world but has disastrous consequences for smallholder farmers whose livelihood depends on healthy crops (Ramesh and Vydeki 2018). In the developing world, around 80% of agriculture production is produced by smallholder farmers (UNEP, 2013), and reports of crop loss of above 50% due to diseases and pests are prevalent. Moreover, a larger fraction of hungry people lives in smallholder agricultural households, which makes the smallholder farmer a group that is mainly susceptible to pathogen-derived disruption in food supplies (Jasim and Al-Tuwaijari 2020). Due to crop diseases, numerous efforts are being made to prevent these losses.

Machine vision was extensively applied to assist precision agriculture by giving automatic solutions to tasks that are performed conventionally (Sambasivam and Opiyo 2021). Manual method tends to be error prone and tedious. Plant disease detection using visual means is less accurate, more time-consuming, and only possible in restricted areas. Where automated detection methods are used, accuracy

✉ G. Kalpana
kalpanag@srmist.edu.in

A. Pavithra
pa6635@srmist.edu.in

T. Vigneswaran
vigneswaran.t@vit.ac.in

1 College of Science and Humanities, SRM Institute of Science Technology, Chennai, India

2 School of Electronics Engineering, Vellore Institute of Technology, Chennai, India

may increase with less effort and time expended. Image processing is used to measure diseased regions that are infected and to calculate the variations in the colors of those regions (Too et al. 2019). Machine vision provides efficient and accurate solutions to assist agricultural activity. Furthermore, ML algorithm enabled the analysis of great amounts of information precisely and rapidly, providing a means for the application of machine vision in agriculture (Panigrahi et al. 2020). ML algorithm enables to analyze huge amounts of information, irrespective of complexity, accurately, and quickly. Its use is already common in several fields namely credit analysis, fraud detection, image recognition patterns, fault prediction models, product quality analysis, and intelligent spam filters (Shruthi et al. 2019). But considering the different alternatives, it is crucial to know the individual features of every technique and the better scenario for its usage.

The wide usage of precision farming worldwide is due to the existence of advanced machine learning (ML) and deep learning (DL) approaches (Patidar et al. 2020), efficient computational devices, and high-speed internet access. DL architecture tackles crucial problems by using different feature extraction techniques (Saleem et al. 2019). Training models from scratch can be computationally expensive, especially for large and complex models like SVM, GoogleNet, and VGG. Therefore, it is common to use pre-trained models where their weights and biases have been optimized to recognize certain patterns in the data. Pre-trained network provides fast convergence and is utilized in advanced techniques to tasks such as activity recognition, object detection, and segmentation (Sharma et al. 2020). DL network achieves advanced performance in other fields of study are not applicable for agricultural tasks of crop management namely fertilization, irrigation, picking, and pesticide spraying. This situation demonstrates the requirement to create proper crop dataset by using different devices for wider and deeper networks to produce best outcomes (Mosavi et al. 2022).

This article develops a new Deep Learning-based Automated Plant Disease Detection and Classification (DL-APDDC) Model for Precision Agriculture. The presented DL-APDDC approach concentrates on the recognition and classification of plant diseases in leaf and fruit regions. In the initial stage, the leaf and fruit regions are extracted by the use of U2Net-based background removal. Next, the Adam optimizer with SqueezeNet model is exploited as feature extractor, and the hyperparameters are tuned by Adam optimizer. Finally, the extreme gradient boosting (XGBoost) classifier performs classification of plant diseases. The experimental validation of the DL-APDDC technique is tested on benchmark plant disease dataset.

2 Related works

Venkataramanan et al. (2019) modeled a DL algorithm for classifying and detecting plant diseases by analyzing the leaf of a given plant. In this study, the classification can be accomplished in many stages for eradicating possibilities at every stage, thereby rendering higher accuracy levels during estimations. To extract a leaf from the input image, a method named YOLOv3 object detector was employed. This extracted leaf will be examined by a sequence of ResNet18 techniques. Such ResNet18 techniques have been trained by utilizing TL. Image segmentation combined with machine learning or deep learning models improves the identification of leaf diseases. Image segmentation can be used to divide up a large data set, and the results are then fed into AI systems for spotting diseases (Sungheetha 2022). When compared to fine-tuning with cyclical learning rates, discriminative fine-tuning is more effective for CNN architectures in image classification of rice leaf diseases (Bhujel and Shakya 2022).

Hossain et al. (2019) modeled that a method uses the KNN algorithm for detecting and classifying plant leaf diseases. The texture features can be derived from leaf disease images for classifying purposes. In this study, the diseases such as leaf spot, alternaria, canker, bacterial blight, alternata, and anthracnose of many plant species will be classified by KNN classifier.

Sardogan et al. (2018) devised a Learning Vector Quantization (LVQ) algorithm-oriented approach and CNN method for classifying and detecting tomato leaf diseases. The author has devised a CNN for automatic classification and feature extraction. In plant leaf disease research, color information is actively used. In this method, based on RGB elements, the filters were implemented to 3 channels. The LVQ was given to the output feature vector of convolution part to train the network. In (Upadhyay and Kumar 2022), the author formulated an effective rice plant disease detection approach related to CNN method. This study had a focus toward 3 renowned rice diseases; they are bacterial leaf blight caused by bacteria, brown spots, and leaf smut caused by fungus. This presented method would apply Otsu’s global thresholding approach for performing image binarization to eliminate background noise of images.

Ashwinkumar et al. (2022) present an automated method for classifying and detecting plant leaf diseases with the use of an optimal mobile network-oriented CNNs (OMNCNNs). It encompasses Kapur’s thresholding-oriented image segmentation and bilateral filtering (BF) oriented pre-processing for identifying the affected areas of the leaf image. Likewise, the MobileNet technique was enforced as a feature extracting method where the hyperparameters will be optimized through the emperor penguin optimizer (EPO) technique for improving the plant disease recognition rate. At last, ELM related method was employed for allocating suitable class labels to the applied plant leaf images. Guo et al. (2020) presented a mathematical technique of plant disease recognition and detection relies upon DL, which will improve training efficiency, precision, and generality. Firstly, the region proposal networks (RPNs) are leveraged for localizing and recognizing the leaves in complex surroundings. Next, images segmented on the basis of the outcomes of RPN method have the feature of symptoms by utilizing Chan–Vese (CV) method.

3 The proposed model

In this article, we have introduced an automated plant disease classification model, named DL-APDDC technique. It mainly focuses on the categorization of different plant diseases affected in the leaf and fruit regions. The presented DL-APDDC technique encompasses U2Net-based background removal, SqueezeNet feature extraction, Adam optimizer, and XGBoost-based classification. Figure 1 represents the working process of DL-APDDC system.

In the initial stage, the leaf and fruit regions are extracted by the use of U2Net-based background removal. Next, the Adam optimizer with SqueezeNet model is exploited as feature extractor, and the hyperparameters are tuned by Adam optimizer. Finally, the extreme gradient boosting (XGBoost) classifier performs classification of plant diseases.

3.1 U2Net-based background removal

Primarily, the leaf and fruit regions are extracted by the use of U2Net-based background removal. The U2-net is a two-level nested U-architecture (Qin et al. 2020). The outer layer is the largest U-architecture comprising 11 stages. Every phase is populated through a residual U-block (RSU) (inner layer). The neural network-based background removal tool utilizes static visual formats and analyses the image to distinguish between the main and supporting objects before cropping the image as necessary. Ideally, the nested U-architecture enables the extraction of multiscale and multilevel features most effectively. It comprises three parts: (1) map fusion module, (2) encoder, and (3) decoder. (1) There are 6 phases in the encoder phase. Every phase is comprised of RSU. The feature map can be decreased for increasing the receptive field and to attain more largescale data. In the next two phases, dilated convolution is utilized for replacing the pooling function. This phase is needed for preventing context data loss. Note that the receptive field is improved while the feature map is not decreased. (2) The decoder stage has structure same as the encoder stage. Every decoder phase concatenates the up-sampled feature map from its preceding phase and those from symmetrical encoder phase as the input. (3) Feature map combination with the deep supervision approach is the final phase used to produce a probability map. The model generates six side

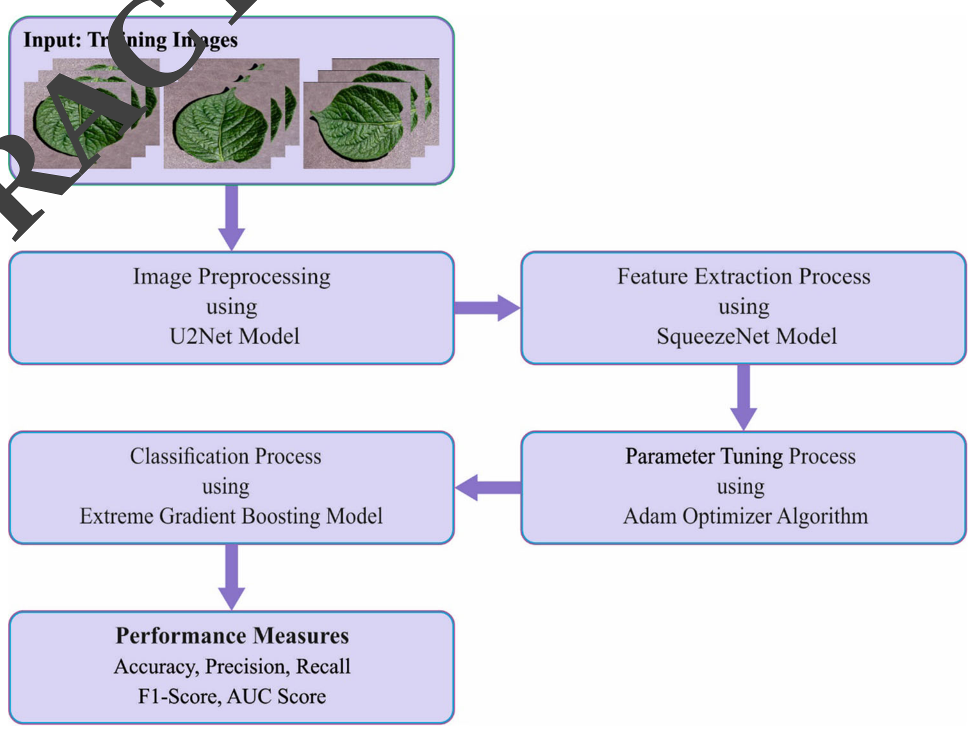
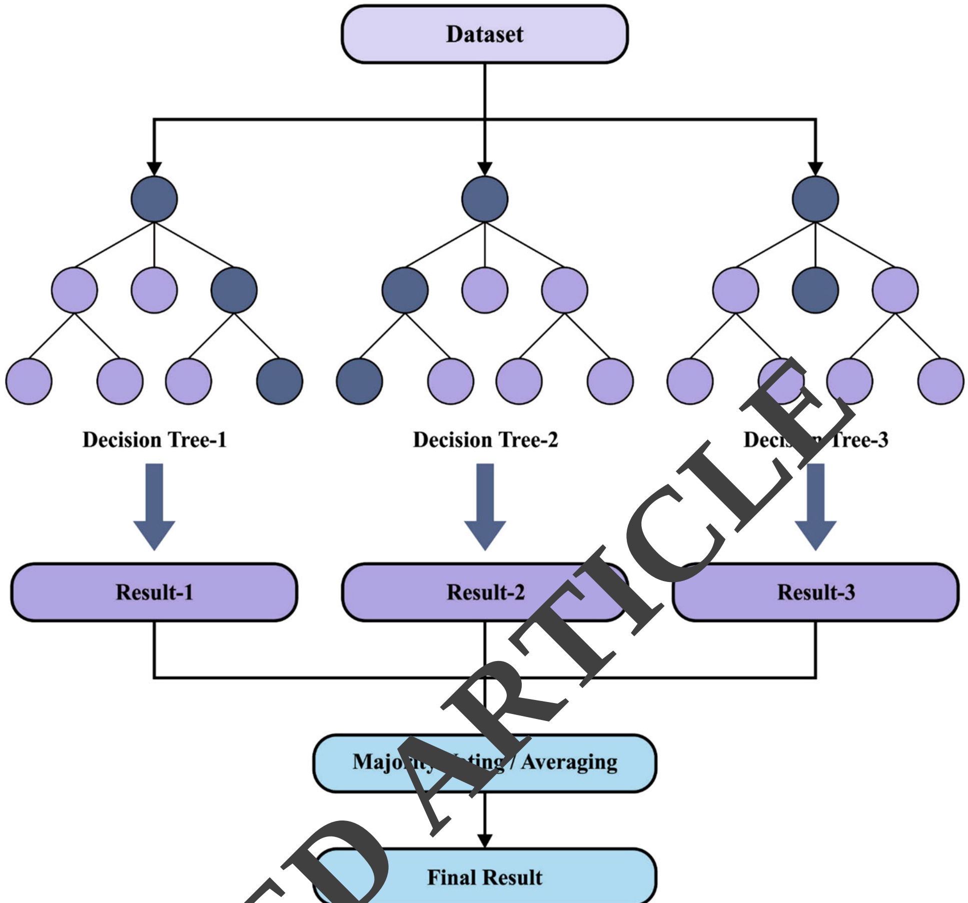


Fig. 1 Working process of DL-APDDC system

Fig. 2 Framework of XGBoost



outputs. Then, this output is up-sampled to the size of input images and merged with a concatenation function. To summarize, the U2-net design has a deeper structure with rich multiscale features, low memory, and computing costs. Furthermore, the U2-net structure is based on the RSU block and does not utilize pre-trained backbone; it is easy and flexible *t*.

3.2 Feature extraction model

In this study, the SqueezeNet model is exploited as feature extractor. The feature map can be decreased for increasing the receptive field and to attain more largescale data. In the next two phases, dilated convolution is utilized for replacing the pooling function. This phase is needed for preventing context data loss. Note that the receptive field is improved while the feature map is not decreased. The most important benefit of CNN over traditional classification algorithms is that, in CNN, the classifier and the representation of the features are deployed in a similar network, which eliminates the requirement for them to be reliant on each other (Lee et al. 2019). Convolution layer is comprised that a fixed set of learnable filters is considered the significant layers in CNN. 2D activation maps are made by sliding the filter over input visual dataset during the forward pass. The strength and location of the recognized visual feature of the input images are characterized by the activation maps. The significant feature of CNN is the pooling layer, which is mainly applied between consecutive convolutional layers to gradually decrease the spatial presentation size concurrently maintaining the relevant data. This assists in controlling the over-fitting during the learning procedure. Regularization is a common methodology in CNN to prevent the over-fitting consequence by adding a significant amount of penalty to the loss function. The neuron of the FC layers is coupled with each activation of the previous layer in the final section of CNN architecture to minimalize feature dimension. CNN has a last pooling layer that smooth the convolution layer that is afterward transferred to the node of network that is connected wholly. In the next phase, the activation is calculated using matrix multiplication that is followed by the implementation of bias factor.

A CNN is a FFNN that mainly comprises pooling and convolutional layers. In comparison with the designed image feature artificially in conventional computer vision, the image feature extracted through the CNN could better reflect the real characteristics of an image and is very

Table 1 Dataset details

Potato dataset				Citrus fruits dataset			
Class	No. of images	Training	Testing	Class	No. of images	Training	Testing
Early_Blight	1939	1455	484	Black Spot	11	7	4
Healthy	1824	1404	420	Canker	34	22	12
Late_Blight	1939	1375	564	Greening	8	5	3
Total images	5702			Healthy	5	3	2
				Scab	15	9	6
				Total images	73		

Fig. 3 Sample Images—Potato

efficient when compared to conventional computer vision method in the fields of image recognition and classification. Thus, CNN is utilized rather than the conventional bag-of-words (BoW) to implement loopback recognition. SqueezeNet was intended by UC Berkeley and Stanford researchers, not to accomplish better CNN detection performance, however, to simplify the difficulty of the network and accomplish the detection performance of public networks. The major configuration of SqueezeNet is the Fire model.

SqueezeNet comprises 8 Fire models from fire2 to fire9, whereas the architecture of fire2, whereby H and W denote the height and width of feature maps, correspondingly, and e3 shows the channel count. SqueezeNet decreases the number of flops and parameters in the network through Fire module that comprises expand and squeeze models. The squeeze model makes use of e1 1×1 convolution kernel to decrease the dimensionality of feature maps, and the feature maps are $H \times W \times e1$ afterward ReLU activation. The feature map is $H \times W \times e2$; afterward, the two taps of expanding (with 1×1 and 3×3 convolution kernels, correspondingly) are separately calculated, and later the feature map of the two taps is stitched together by the concat layer to produce $H \times W \times e3$. Only the number of channels varies; meanwhile, the convolution kernel of the fire network is similar in size. The fire module can be labeled with the number of channels of the fire model output e3. Once the network input is $224 \times 224 \times 3$ RGB images, the computation of network is 837 MFlops; hence, the network architecture is very applicable for lightweight devices like intelligent mobile robots.

The hyperparameter tuning process is carried out by the use of Adam optimizer. The Adam optimizer was broadly applied in the DL fields by virtue of its relatively fast convergence speed and self-adaptive learning rate (Liu 2021). Thus, the study adopts the Adam model to upgrade

Fig. 4 Sample Images—Citrus

the SqueezeNet model parameter. The training step is defined in the following:

$$m_\tau = u_1 * m_{\tau-1} + (1 - u_1) * g_T \quad (1)$$

$$n_t = u_2 * m_{t-1} + (1 - u_2) * g_T^2 \quad (2)$$

wherein, m_τ signifies the average value of gradient index at t time, and n_t signifies the squared gradient at t time. $m_{\tau-1}$ denotes average value of gradient index at preceding time, and n_{t-1} denotes squared gradient at preceding duration. $u_1 = 0.9$, and $u_2 = 0.999$. This two values were hyperparameter that controls attenuation of moving average. u_2 Then, evaluate the updating bias: $\tilde{m}_t = \frac{m_t}{1-u_1^t}, \tilde{n}_t = \frac{n_t}{1-u_2^t}$ later obtain the final value of the updating variable: $\theta_t = \theta_{t-1} - \eta * \frac{\tilde{m}_t}{\varepsilon + \sqrt{\tilde{\tilde{n}}_t}}$, whereas the first value of update learning rate was $r1 = 0.01$, and in sampling training procedure, it is noted that:

The convergence tendency is closer to power exponential function. Thus, this study adds a power exponent correction term to learning rate at t time $\eta_t = \frac{\eta_{t-1}}{\sqrt{k+L_t}}$

$$\eta_{t-1} = \eta_0 * \left(1 + \frac{t}{R}\right)^{-K} \quad (3)$$

$$k = \sum_{i=1}^{n} \lambda_i + q \quad (4)$$

$$L_t = \varepsilon g_{t-1}^2 + g_t^2 \quad (5)$$

From the expression: R indicates the maximal iteration count; ξj denotes the attenuation factor, within the value of

Fig. 5 Pre-processed Images

0.99; it is viewed that development of learning rate depending on the value of the rate of learning in the preceding phase and gradient value of present phase was utilized for adaptive adjustment. Afterward, the time t is accelerated, which improves the possibility to prevent the oscillation zone.

3.3 Plant disease detection model

At the final stage, the XGBoost classifier performs classification of plant diseases. Gradient boosting is the name of a group of ensemble machine learning algorithms that can be applied to classification or regression predictive modeling issues. XGBoost was an ensemble model depends on gradient boosted tree (Zhang et al. 2018). The outcome of prediction was the sum of the score forecasted by K trees, as follows:

$$\hat{y}_j = \sum_{k=1}^{K} f_k(x_j), f_k \in F, \tag{6}$$

In Eq. (6), x_j denotes $i-th$ of the training samples, $f_k(x_i)$ represents the score for $k-th$ tree, and F indicates space of function comprising each gradient boosted tree, and it can be attained as follows:

$$\mathrm{obj}(\theta) = \sum_{i=1}^{n} l\left(y_j, y_j\right) + \sum_{k=1}^{K} \Omega(f_k), \tag{7}$$

In Eq. (7), the previous $\sum_{i=1}^{n} l(y_j, \hat{y}_i)$ refers to a differentiable loss function which measures fitness of module prediction $\hat{y}_j$ and sample of trained data y_j, whereas the latter $\sum_{k=1}^{K} \Omega(f_k)$ characterizes an standardization item which punishes the model complexity to prevent over-fitting. Figure 2 depicts the architecture of XGBoost.

4 Results and discussion

The experimental validation of the DL-APDDC method is tested using two plant disease datasets: potato leaf disease dataset (Potato Dataset Source 2018) and citrus fruit dataset (Rauf et al. 2019). The potato dataset has 5702 samples with three classes, and the citrus fruit dataset comprises 73 samples with five classes as defined in Table 1.

Figure 3 demonstrates some sample images of potatoes. Figure 4 depicts some sample images of Citrus.

Figure 5 illustrates some sample pre-processing images. Figure 6 shows the classifier outcomes of the DL-APDDC methodology under Potato dataset. Figure 6a exhibits the confusion matrix rendered by the DL-APDDC approach under training set. The figure signified the DL-APDDC technique has identified 1333 instances under EB, 1231 instances under HY, and 1285 instances under LB. Also, Fig. 6b shows the confusion matrix presented by the DL-APDDC technique under testing set. The figure exhibited the DL-APDDC approach has identified 589 instances under EB, 506 instances under HY, and 541 instances under LB. Likewise, Fig. 6c, d demonstrates the precision-

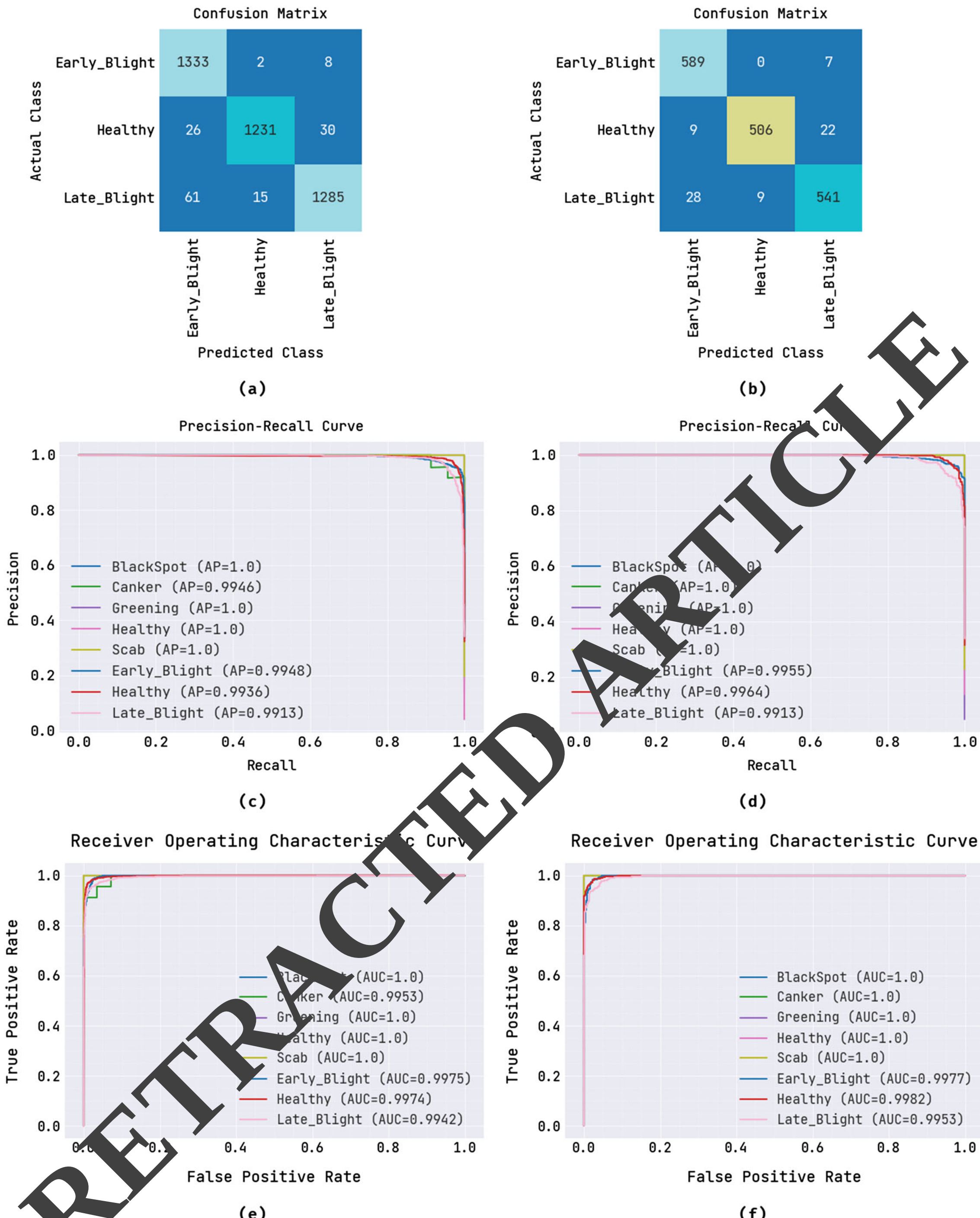


Fig. 6 Potato Dataset **a** Confusion Matrix Training Set, **b** Confusion Matrix Testing Set, **c** PR-Curve Training Set, **d** PR-Curve Training Set, **e** ROC Training Set, and **f** ROC Testing Set

recall analysis of the DL-APDDC model under training and testing sets. The figures reported that the DL-APDDC technique has acquired maximum precision-recall performance under all classes. Lastly, Fig. 6e, f demonstrates the ROC study of the DL-APDDC technique under training and testing sets. The figure exhibited that the DL-APDDC approach has resulted in proficient results with maximum ROC values in different class labels.

In Table 2 and Fig. 7, an overall plant disease classification results of the DL-APDDC model on potato dataset are given. The outcomes exhibited the DL-APDDC method have attained effectual outcomes under both TR and TS datasets. For instance, on TR set, the DL-APDDC model

Table 2 Result analysis of DL-APDDC system with distinct measures under Potato dataset

Potato dataset		
Metrics	Training set	Testing set
Accuracy	96.44	95.62
Precision	96.55	95.75
Recall	96.44	95.55
F1-score	96.45	95.62
ROC AUC score	99.64	99.71

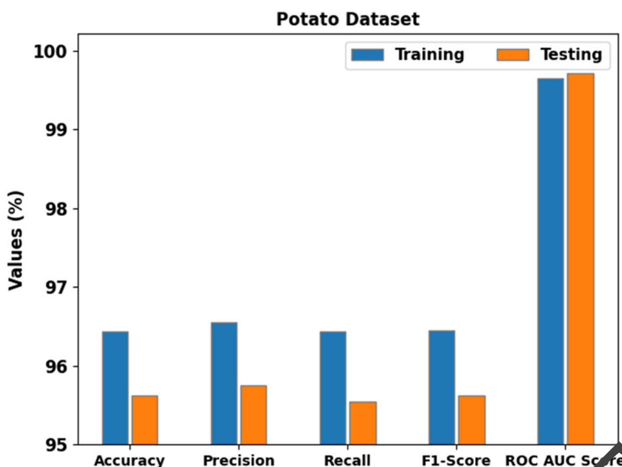


Fig. 7 Result analysis of DL-APDDC system under Potato dataset

Table 3 Comparative analysis of DL-APDDC system with other approaches under Potato dataset

Potato dataset	
Methods	Accuracy (%)
DL-APDDC	96.44
CNN-SVM	84.00
CNN-RF	79.00
CNN-ANN	92.00
GoogLeNet	86.00
VGGNet	86.00

has attained $accu_y$ of 96.44%, $prec_n$ of 96.55%, $reca_l$ of 96.44%, $F1_{score}$ of 96.45%, and $ROCAUC_{score}$ of 96.64%. Meanwhile, on TS set, the DL-APDDC technique has achieved $accu_y$ of 95.62%, $prec_n$ of 95.75%, $reca_l$ of 95.55%, $F1_{score}$ of 95.62%, and $ROCAUC_{score}$ of 99.71%.

Table 3 and Fig. 8 highlight an overall $accu_y$ examination of the DL-APDDC model on potato dataset. The outcomes signified that the CNN-RF method has attained least $accu_y$ of 79%. Simultaneously, the CNN-SVM, GoogLeNet, and VGGNet techniques have reported moderately closer $accu_y$ values of 84%, 86%, and 86%,

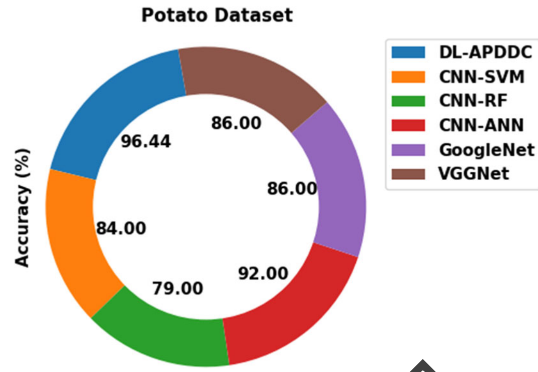


Fig. 8 Comparative analysis of DL-APDDC system under Potato dataset

respectively. Contrastingly, the CNN-ANN model has managed to portray considerable $accu_y$ of 92%. But the DL-APDDC model has shown maximum classification performance with $accu_y$ of 96.44%.

Figure 9 portrays the classifier results of the DL-APDDC approach under Citrus dataset. Figure 9a represents the confusion matrix rendered by the DL-APDDC technique under training set. The figure exhibited that the DL-APDDC approach has identified 8 instances under BS, 23 instances under CR, 6 instances under GR, 2 instances under HY, and 10 instances under SB. Similarly, Fig. 9b portrays the confusion matrix presented by the DL-APDDC technique under testing set. The figure exhibited the DL-APDDC technique has identified 1 instance under BS, 11 instances under CR, 1 instance under GR, 3 instances under HY, and 5 instances under SB. Also, Fig. 9c, d exhibits the precision-recall study of the DL-APDDC approach under training and testing sets. The figures stated that the DL-APDDC technique has attained maximum precision-recall performance under all classes. Lastly, Fig. 9e, f exemplifies the ROC study of the DL-APDDC technique under training and testing sets. The figure depicted that the DL-APDDC technique has resulted in proficient outcomes with maximal ROC values in different class labels.

In Table 4 and Fig. 10, an overall plant disease classification outcomes of the DL-APDDC approach on citrus dataset are given. The outcomes designated the DL-APDDC approach has acquired effectual outcome under both TR and TS datasets. For example, on TR set, the DL-APDDC approach has accomplished $accu_y$ of 96.08%, $prec_n$ of 98.40%, $reca_l$ of 94.92%, $F1_{score}$ of 96.45%, and $ROCAUC_{score}$ of 99.91%. In the meantime, on TS set, the DL-APDDC technique has reached $accu_y$ of 95.45%, $prec_n$ of 98.33%, $reca_l$ of 90%, $F1_{score}$ of 92.46%, and $ROCAUC_{score}$ of 100%.

Table 5 and Fig. 11 exhibit an overall $accu_y$ inspection of the DL-APDDC technique on citrus dataset. The results exhibited the Linear SVM technique has achieved least

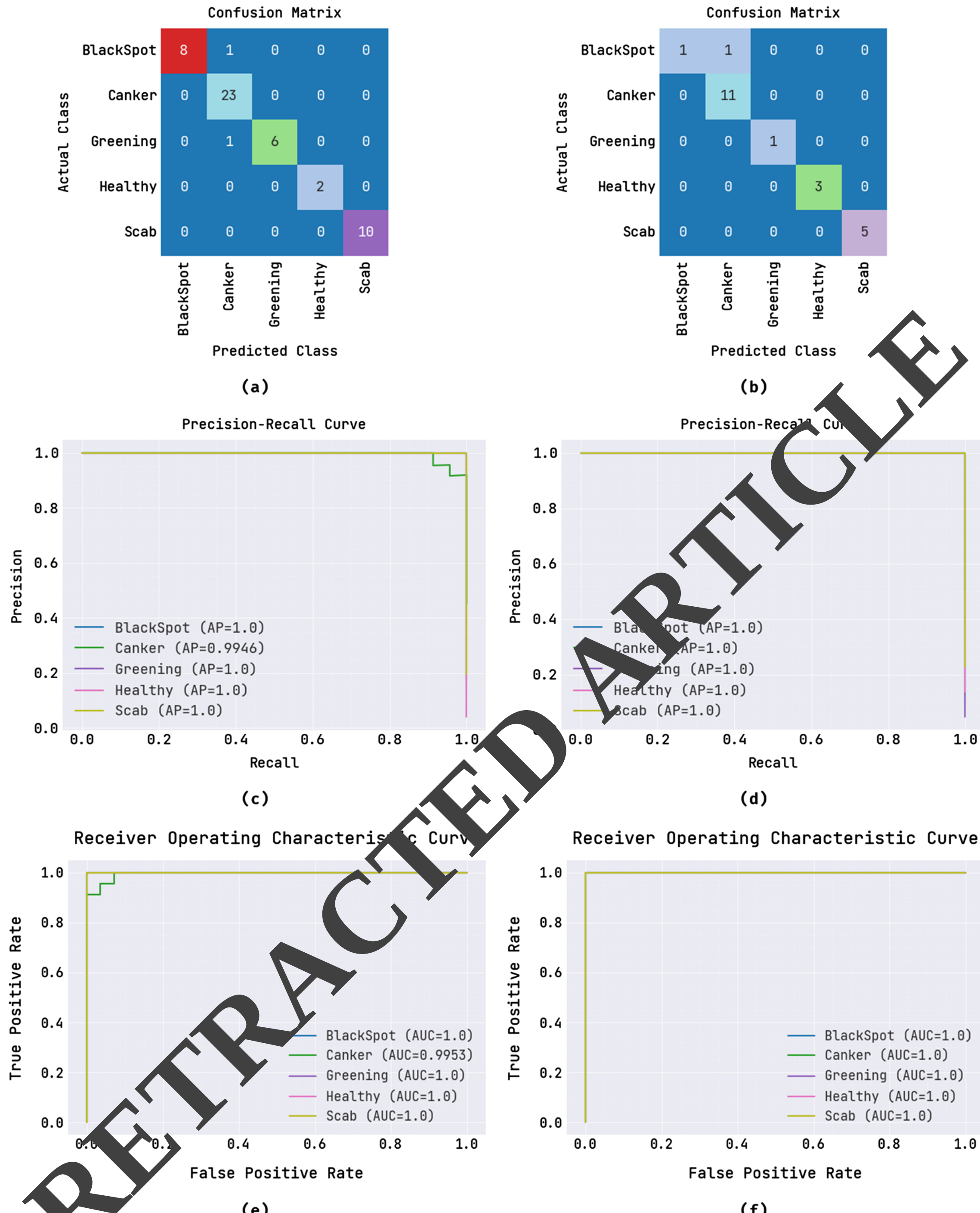


Fig. 9 Citrus Dataset **a** Confusion Matrix Training Set, **b** Confusion Matrix Testing Set, **c** PR-Curve Training Set, **d** PR-Curve Training Set, **e** ROC Training Set, and **f** ROC Testing Set

$accu_y$ of 74%. Simultaneously, the linear discriminant, Quadratic SVM, and Cubic SVM techniques have reported moderately closer $accu_y$ values of 74.09%, 77.15%, and 78.82% correspondingly.

Contrastingly, the Otsu method has managed to portray considerable $accu_y$ of 83.95%. But the DL-APDDC technique has shown maximal classification performance with $accu_y$ of 96.08%. By observing the results and discussion, it is confirmed that the DL-APDDC model has gained maximum plant disease classification performance.

Table 4 Result analysis of DL-APDDC system with distinct measures under Citrus dataset

Citrus dataset		
Metrics	Training set	Testing set
Accuracy	96.08	95.45
Precision	98.40	98.33
Recall	94.92	90.00
F1-score	96.45	92.46
ROC AUC score	99.91	100.00

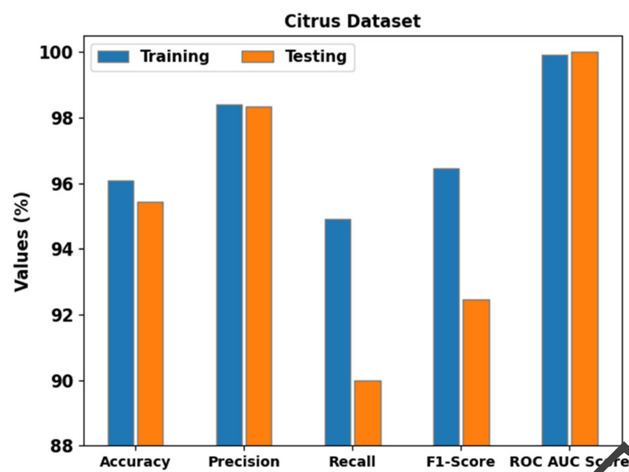


Fig. 10 Result analysis of DL-APDDC system under Citrus dataset

Table 5 Comparative analysis of DL-APDDC system with other approaches under Citrus dataset

Citrus dataset	
Methods	Accuracy (%)
DL-APDDC	96.08
Linear SVM	74.00
Quadratic SVM	77.15
Cubic SVM	78.82
Linear discriminant	74.09
Otsu algorithm	83.95

5 Conclusion

In this article, we have introduced an automated plant disease classification model, named DL-APDDC technique. It mainly focuses on the categorization of different plant diseases affected in the leaf and fruit regions. At the initial stage, the leaf and fruit regions are extracted by the use of U2Net-based background removal. Next, the Adam optimizer with SqueezeNet model is exploited as feature extractor, and the hyperparameters are tuned by Adam optimizer. Finally, the XGBoost classifier performs classification of plant diseases. The experimental validation of the DL-APDDC technique is tested on benchmark plant disease dataset. The simulation values indicated the enhanced outcomes of the DL-APDDC approach over other models. In future, the classification accuracy of the DL-APDDC algorithm can be boosted by the DL classification techniques.

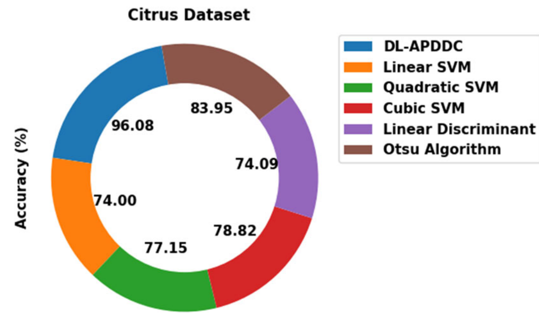


Fig. 11 Comparative analysis of DL-APDDC system under Citrus dataset

Funding The authors received no specific funding for this study.

Data availability Source—leaves: https://www.kaggle.com/vipoooo/new-plant-diseases-dataset/data#. Source—fruit: https://data.mendeley.com/datasets/3f83gxmv57/2.

Declarations

Conflict of interest The author declare that they have no conflicts of interest for the following title "Deep Learning-based Automated Disease Detection and Classification Model for Precision Agriculture".

Ethical approval Not Applicable.

References

Ashwinkumar S, Rajagopal S, Manimaran V, Jegajothi B (2022) Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks. Mater Today Proc 51:480–487

Bhujel S, Shakya S (2022) Rice leaf diseases classification using discriminative fine tuning and CLR on EfficientNet. J Soft Comput Paradig 4(3):172–187

Guo Y, Zhang J, Yin C, Hu X, Zou Y, Xue Z, Wang W (2020) Plant disease identification based on deep learning algorithm in smart farming. Discret Dyn Nat Soc

Hossain E, Hossain MF, Rahaman MA (2019) A color and texture based approach for the detection and classification of plant leaf disease using KNN classifier. In: 2019 International conference on electrical, computer and communication engineering (ECCE), IEEE, pp 1–6

Jasim MA, Al-Tuwaijari JM (2020) Plant leaf diseases detection and classification using image processing and deep learning techniques. In: 2020 international conference on computer science and software engineering (CSASE), IEEE, pp 259–265

Lee HJ, Ullah I, Wan W, Gao Y, Fang Z (2019) Real-time vehicle make and model recognition with the residual SqueezeNet architecture. Sensors 19(5):982

Li L, Zhang S, Wang B (2021) Plant disease detection and classification by deep learning—a review. IEEE Access 9:56683–56698

Liu X (2021) Research on the forecast of coal price based on LSTM with improved adam optimizer. J Phys Conf Ser 1941(1):012069

Panigrahi KP, Das H, Sahoo AK, Moharana SC (2020) Maize leaf disease detection and classification using machine learning algorithms. In: Progress in computing, analytics and networking, Springer, Singapore, pp 659–669

Patidar S, Pandey A, Shirish BA, Sriram A (2020) Rice plant disease detection and classification using deep residual learning. In: International conference on machine learning, image processing, network security and data sciences, Springer, Singapore, pp 278–293

Potato Dataset Source (2018). https://www.kaggle.com/vipoooool/new-plant-diseases-dataset/data#

Qin X, Zhang Z, Huang C, Dehghan M, Zaiane OR, Jagersand M (2020) U2-Net: Going deeper with nested U-structure for salient object detection. Pattern Recogn 106:107404

Ramesh S, Vydeki D (2018) Rice blast disease detection and classification using machine learning algorithm. In: 2018 2nd international conference on micro-electronics and telecommunication engineering (ICMETE), IEEE, pp 255–259

Rauf HT, Saleem BA, Lali MIU, Khan MA, Sharif M, Bukhari SAC (2019) A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning. Data Brief 26:104340

Saleem MH, Potgieter J, Arif KM (2019) Plant disease detection and classification by deep learning. Plants 8(11):468

Sambasivam G, Opiyo GD (2021) A predictive machine learning application in agriculture: cassava disease detection and classification with imbalanced dataset using convolutional neural networks. Egypt Inform J 22(1):27–34

Sardogan M, Tuncer A, Ozen Y (2018) Plant leaf disease detection and classification based on CNN with LVQ algorithm. In: 2018 3rd international conference on computer science and engineering (UBMK), IEEE, pp 382–385

Sharma P, Hans P, Gupta SC (2020) Classification of plant leaf diseases using machine learning and image preprocessing techniques. In: 2020 10th international conference on cloud computing, data science & engineering (Confluence), IEEE, pp 480–484

Shruthi U, Nagaveni V, Raghavendra BK (2019) A review on machine learning classification techniques for plant disease detection. In: 2019 5th international conference on advanced computing & communication systems (ICACCS), IEEE, pp 281–284

Sungheetha A (2022) State of art survey on plant leaf disease detection. J Innov Image Process 4(2):93–102

Too EC, Yujian L, Njuki S, Yingchun L (2019) A comparative study of fine-tuning deep learning models for plant disease identification. Comput Electron Agric 161:272–279

Upadhyay SK, Kumar A (2022) A novel approach for rice plant diseases classification with deep convolutional neural network. Int J Inf Technol 14(1):185–199

Vasavi P, Punitha A, Rao TVN (2022) Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review. Int J Electr Comput Eng 12(2):2079

Venkataramanan A, Honakeri DKP, Agarwal P (2019) Plant disease detection and classification using deep neural networks. Int J Comput Sci Eng 11(9):40–46

Zhong J, Sun Y, Peng W, Xie M, Yang J, Tang X (2018) XGBFEMF: an XGBoost-based framework for essential protein prediction. IEEE Trans Nanobiosci 17(3):243–250

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.