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Zooming Algorithm Based Edge Detection Techniques for Plant Leaf Disease Identification using Convolutional Neural Networks optimized with Battle Royale Optimization

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Abstract— Agriculture is a very important sources for every living things but it is affected with various issues like plant diseases. To predict the plant leaf diseases in an early stage is very necessary in the agriculture field, which improve the productivity. Thus, to improve the effectiveness of the plant leaf disease identification process and classification, a Deep Learning (DL) based optimization approach was developed. In this manuscript, a Zooming Algorithm based edge detection model is used for identification and Convolutional Neural Networks optimized with Battle Royale Optimization (CNN-BRO) is proposed for classification. The implementation of this work is done by MATLAB and the parameters are calculated. Thus, the proposed CNN-BRO approach was attained 25.34% ,15.45% high accuracy, 28.5% , 11.46% high specificity, 27.97% ,10.25% high sensitivity, 30.22% ,13.95% high recall, 16.38% , 9.1%% high precision, 25.27%, 13.21% high F-score and 59.99%, 42.86% lower system error than other existing methods like Support Vector machine with exponential spider monkey optimization (SVM-SMO) and Bacterial Foraging optimization based Radial Basis Function Neural Network (BRBFNN-BFO).

Index Terms— Convolutional Neural Network, Zooming algorithm, Battle Royale Optimization, Plant Leaf Disease Identification, Support Vector machine, Bacterial Foraging optimization

I. Introduction

Harvesting various varieties of food plants is based on the needs and environmental conditions of land [1]. Moreover, the farmers facing more issues and risks such as lack of water, 5 disasters occurring naturally, plant diseases, so on [2]. Here, few problems less by providing technical facilities to the farmers [3]. The automated plant disease identification and prevention system is one of the solutions that benefit the farmers [4]. To overcome these type of problems like lack of plant disease knowledge. There is no experts there to tell about this disease and the prevention methods [5] So, this increases the food productivity to perform on time prevention from the ten diseases [6]. Using that automated system will be useful for consuming the time and cost efficient [7]. Usually, to detect most of the disease of plants consider leaves of the plants as the 1st source [8]. Using efficient image processing techniques 15 can be detected automatically through, the yellow and brown spots, primary and late blister, and other ailments caused by bacteria, virus and fungus [9-11]. Identification of plant disease uses only the properties of leaves [12]. Though, identification of plant disease through image processing is not very easy because of the huge disparities available in the leaves of different and similar plants, for example, size, texture, color, shape, etc [13]. Numerous image processing schemes are expected for overcoming such problems and normally 20 all methods have two steps [14]. Firstly, prominent features are extracted from the leaves input images [15] and secondly, particular classifiers are used to categorise the images into healthy/diseased images [16]. k-Nearest Neighbour (k-NN), SVM [6], Fisher Linear Discriminant (FLD), neural network, Random Forest (RF), etc [17, 18] are the main classification methods used popularly for disease identification in plants.

Main contribution of this manuscript is as follows,

- In this manuscript Convolutional Neural Networks optimized with Battle Royale Optimization (CNN-BRO) is proposed for identifying diseases in plants.
- Initially, the attained images are pre-processed using the zooming algorithm [19], which is effectively detecting the edges of images. Additionally, the feature extraction method is supports the image by using the image classification.
- After that, the convolution neural network [18] model is developed for classifying the plant leaf images.
- At last, efficacy of proposed approach are enhanced using Battle Royale Optimization (BRO) optimization [20], which has optimize the parameters while classification.
- Moreover, the simulation of this model is done in MATLAB and the performance metrics are examined.
- Here, calculate the performance metrics like accuracy, precision, recall, sensitivity, specificity, f-score are compared with existing approaches like Support Vector machine with exponential spider monkey optimization (SVM-SMO) and BRBFNN-BFO.

This manuscript is arranged as following sections. The work related to the developed model is described in section 2. Section 3 shows the detailed developed method and section 4 illustrates the outcomes. Section 5 concludes present work.

II. LITERATURE SURVEY

In 2020, Kumar, S, et.al., [21] have presented Plant Leaf Disease Identification using Exponential SMO. Here, the selected features were feed to SVM for classifying about the diseased and vigorous plants by using few significant features of leaves. Experimental results demonstrate the particular types by using Exponential spider monkey optimization efficiently to enhance the classification consistency of classifier in comparison with the existing methods.

In 2018, Chouhan, et.al., [22] have presented a method called BRBFNN to automatically identify and classify the diseases of plant leaf. To allocate the optimal weight to radial basis function neural network using BFO to enhance the speed and accuracy of the network used to detect and classify the regions that were contaminated with various plant leaf disease. The region growing algorithm improves efficacy of the network using the feature extraction process.

In 2020, Gadekallu, T.R, et.al., [23] have presented PCA whale optimization based deep neural network method for classifies the tomato plant diseases using GPU. Here, hybrid principal component analysis of whale optimization algorithm was utilised for extracting the features from the dataset. Then the extracted data were sending into a deep neural network to classify tomato diseases. This method was estimated with classical machine learning methods for establishing the advantage in terms of accuracy and loss of rate metrics.

In 2020, Ramesh, S, et.al., [24] have presented Recognition and Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya algorithm. Initially the pre-processing stages, for background elimination of RGB images were changed into HSV images. For the segmentation of diseased portion, non-diseased portion and background, a clustering technique was used. The optimized Deep Neural Network with Jaya Optimization Algorithm (DNN_JOA) was used for classifying the diseases. This method accomplish the high accuracy of 98.9% for the blast affected, 95.78% for the bacterial blight, 92% for the sheath rot, 94% for the brown spot and 90.57% for the normal leaf image.

In 2020, Darwish, A, et.al., [25] have presented An Optimized Model based on CNN and Orthogonal Learning PSO Algorithm for Diagnosing plant disease. The CNNs bear from a big selection of hyper parameters with exact architectures which was regard as confront to recognize manually the optimal hyper parameters. So, the orthogonal learning particle swarm optimization (OLPSO) procedure was used for optimizing a number of hyper parameters. Here, to prevent convolutional neural network descending into local minimum and to train efficiently and an exponentially decaying learning rate (EDLR) modal was utilised. Evaluation results for this approach gives accuracy of this model were very competitive.

III. PROPOSED CNN-BRO METHODOLOGY FOR CLASSIFYING PLANT LEAF DISEASE IMAGES

In general, the deep learning based methodologies are developed to identify the plant leaf diseases. However, these methods are providing very low efficiency in the classification results. Thus, the new DL technique is developed to identify the plant disease. This research work consist of zooming algorithm based edge detection technique for Plant Leaf Disease Identification using Convolutional Neural Networks optimized with Battle Royale Optimization (CNN-BRO) is proposed for accurately identifies and classify the plant disease. At first the captured images are pre-processed by zooming algorithm that is used for edge detection of the plant leaf images. After pre-processing, the spot is segmented, and the recognition features of colour, shape and texture are extracted.

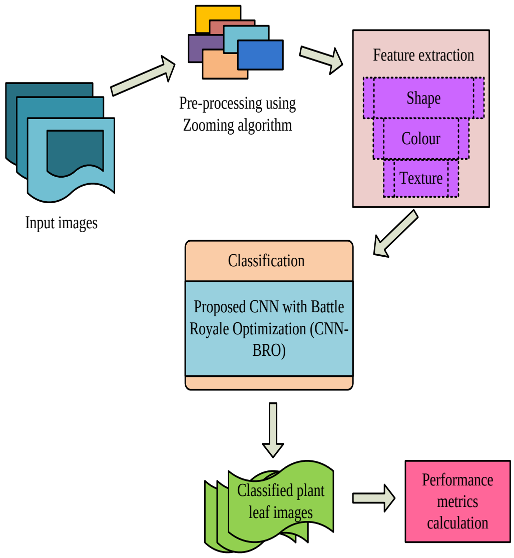

Figure.1 Process of the proposed methodology

Then, the extracted features of plant leaf images is classified using CNN and the weight parameters of the CNN are tuned using Battle Royale Optimization algorithm. At last, proposed technique identifies the plant leaf disease very accurately. Simulation process is implemented on MATLAB environment.Here the efficacy metrics like accuracy, sensitivity, specificity, recall, F-Score, and precision are measured. Figure 1 explains the proposed method process.

A. Pre-processing using Zooming algorithm

Image pre-processing is necessary for input images for reducing the unwanted noise and artifacts in an image, which are used for training process. Moreover, the unwanted effects and noises are removed from the input images by pre-processing process. In this, zooming algorithm is used for preprocessing and edge detection process. Here, zooming algorithm is used the input image as RGB picture that provides the output as a greater size by zooming technique. Subsequently, the input images are enlarged using the pixel size of the images. The zooming process is defined in eqn.(1)

$$E[S(m,n)] = z(2m-1, 2n-1); m,n = 1,2,.....l \qquad (1)$$

Where, $[S(m,n)]$ represents the pixel value of input image in row m and column n, E defined the leaves undefined the range of every image pixels and z is the zooming function. Also, the edge detection process is carried out based on the pixels of input images. Here, the pixel values of the images are considered as $[m,n]$

- (m) or (n) are have not been assigned a value

The algorithm verifies the condition as $|a-b| < T$ where, a, b denotes the luminious value of pixels and T denotes the threshold value. If the condition is satisfied then the pixel value is equal to $(a+b)/2$ otherwise the pixel value is undefined.

- (m) and (n) are have been assigned a value

In this condition the proposed algorithm verifies a presents of horizontal and vertical edges. Thus, the edges are detected in the direction $[m,n.|a-b|]>T$ and $|a-b|>|m-n|$. In this, the value of $(m-n)/2$ is allocated to pixels. Thus, the edge detection process is carried out on every pre-processed image in the dataset. Also, the segmentation process utilised for simplify the representation images that can used for easy to evaluate and understandable format. For segmentation process, the input images are separated in various segments. In this, the input dataset is considered as $K=\{k_1,k_2,.......k_i\}$ with i-number of images. Thus, the segmentation process is done using eqn.(2),

$$S=\{s_i^1,s_i^2,..........s_i^{\alpha}........s_g^i\} \qquad (2)$$

Where, s_i^{α} represents the α^{th} segment of i^{th} image, total numbers of segments are denoted as s_g^i. Thus, the segmented images are utilized in the process of feature extraction, which is used for enhancing the classification of images.

B. Feature extraction

The feature extraction process utilized for extracting the feature images like leaf colour, shape and texture are all used in the proposed approach.

C. Shape features

This type of features is utilized for identifying the particular leaves are slimness and roundness. In this, the slimness (S) of the leaves are calculated using eqn.(3), which is also called as aspect ratio.

$$S=\left(\frac{L_1}{L_2}\right) \qquad (3)$$

Where, L_1 is represents the width of the particular leaf and L_2 represents the length of the particular leaf. Moreover, the roundness (R) of leaves are calculated using eqn.(4),

$$R=\left(\frac{4\pi A}{P^2}\right) \qquad (4)$$

Where, P represent the perimeter value of the leaves contour and A denotes the area of leaf images.

D. Colour features

The colour moments of the images are represented the colour features that can able to describe a colour images. This type of features are indicates mean, skewness, standard deviation, and kurtosis. In this, features are extracted from every plane for RGB colour space. The calculation of mean value (μ) is done using eqn.(5),

$$\mu = 1/mn\left(\sum_{x=1}^{m}\sum_{y=1}^{n} K_{xy}\right) \qquad (5)$$

Where, the dimension of the images are represented as $m \& n$. Also, K_{xy} is representing the colour value on (x) column and (y) row. The calculation of standard deviation value is done using eqn.(6),

$$\sigma = \sqrt{1/mn\left[\sum_{x=1}^{m}\sum_{y=1}^{n}\left(K_{xy} - \mu\right)^2\right]} \qquad (6)$$

The calculation of skewness value is done using eqn.(7),

$$\theta = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\left(K_{xy} - \mu\right)^3}{mn\sigma^3} \qquad (7)$$

The calculation of skewness value is done using eqn.(8),

$$\gamma = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\left(K_{xy} - \mu\right)^4}{mn\sigma^4} \qquad (8)$$

F. Texture features

Normally, the input images are not providing the similar structure with all scale value thus the images are not a fractals. In this, the fractal measures of the images are called lacunarity that is utilized for differentiating the fractals through equal fractal dimension. Thus, the calculation of the above parameters are given in eqn.(9),

$$L_s = \frac{1/mn\sum_{x=1}^{m}\sum_{y=1}^{n} K_{xy}^2}{\left(1/mn\sum_{x=1}^{m}\sum_{y=1}^{n} K_{xy}\right)^2} - 1 \qquad (9)$$

This formula applies to extract the features of the gray scale images. Here, K_{xy} is represents the gray value with coordinates (x, y). Thus, it indicates the colour value of the RGB image and intensity of the gray scale images. Here, the extracted features are represents the texture features.

G. Feature Normalization

The normalization process is necessary for the extracted features for classification because it does not vary the dynamic ranges of the images. The dynamic ranges of the feature are predetermined by the normalization process. Thus, the calculation of normalization is given in eqn.(10),

$$F_x = \frac{f_x - f_{\min}}{f_{\max} - f_{\min}} \qquad (10)$$

Where, the new value of the feature is defined as F_x, original value of the feature is defined as f_x, $f_{\min}$ represent the smaller value of the original feature, and $f_{\max}$ denotes the highest value of the original feature.

H. Classification using Convolution Neural Network

In this research, convolution neural network is utilized for classifying the leaf disease images using leaf samples. The CNN layers are utilized in processing the leaf samples for identifying and classifying the leaf diseases. Here, the layers are convolution, pooling, fully connected, output layer, which are classified using leaf images. The CNN model has effectively classifies the images with high computation level. Convolution layer is utilized for convoluting every raw pixel of the input images through the dot product among the pixels for kernel and input. In this, every pixel value of the sample images are represents the neurons that are locally connected by convolution layer. The overall procedure of the proposed CNN-BRO methodology is detailed in figure.2.

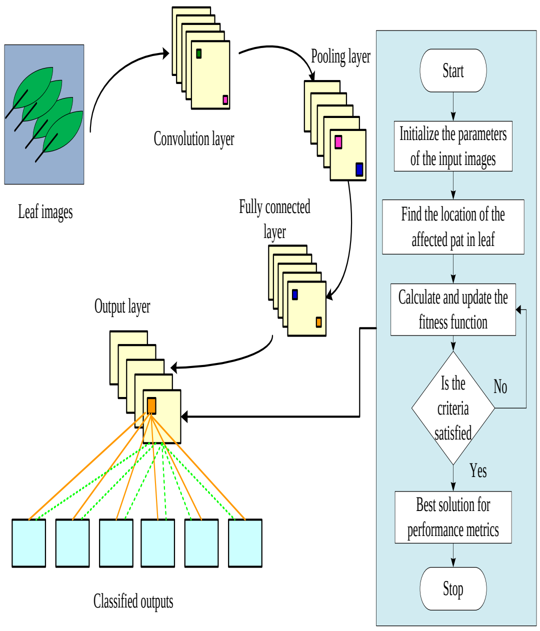

Figure:2 Flow diagram of the proposed CNN-BRO methodology

Here, the value of the k^{th} convolution layer with output of p^{th} layer is convolved by weights, which are computed using eqn.(11),

$$z_p^k = \sum_{i \in m} x_i^{k-1} * W_{ip}^k + b_p^k \qquad (11)$$

Where, k represents the network layer, p denotes the kernel, z_p^k represents the out value of the neurons in the convolution layer, W_{ip}^k is the weight value of the samples in the layer and b_p^k

represents the additive bias. Moreover, the activation function is utilized for identifying the extracted features of the input images that is given in eqn.(12),

$$x_p^k = f\left(z_p^k\right) \tag{12}$$

Where, $\left(z_p^k\right)$ represents the non-linearity of the layer and f represents the activation function. Thus, it is processed on every layer of the CNN and finally, the classified output has attained from the classification layer. The output layer of the CNN is also called as classification layer. The output layers with the softmax function are developed by feature vector of fully connected layer are used for classifying the input sample images to pre-defined class. The probability of the classification result are given in eqn.(13),

$$P_p^i = \frac{\exp\left(W_p^T x^i + a_p\right)}{\sum_{n=1}^{C} \exp\left(W_n^T x^i + a_n\right)} \tag{13}$$

Where, the probability of the input sample x^i denoted as P_p^i belongs to the p^{th} class image, the classifier parameter is represented as W_p and a_p. The quantity of final classified images is mentioned as C. Finally, the virus/disease affected by leaf and the normal leaf types are classified and the output is attained from the CNN output layer. Moreover, the performance metrics like accuracy, precision, recall, and sensitivity are calculated. Additionally, to enhance the efficiency of the classifier parameters a novel BRO method is used in this work.

I. Parameter optimization using Battle Royale Optimization (BRO)

In this manuscript, the Battle Royale Optimization (BRO) mechanism is proposed for enhancing the efficiency of the parameters for attaining efficient results. Initially, the total numbers of input samples are initiated for the population process. Here, the damage location of the soldier is identified by the updating the population. Thus, the position was changed by the soldier and the best location was identified. These procedure is applied for input sample images and the fitness function BRO is identified the affected location and classifies the images for improving the efficiency of the parameters. Thus, the fitness function of the BRO is calculated for enhancing the parameters of the classified images are mentioned as eqn.(14), Also, the classifier parameter W_p and a_p is initiated in BRO fitness function, which optimized by BRO mechanism.

$$X_{dam,d} = W_p X_{dam,d} + a_p r\left(X_{b,d} - X_{dam,d}\right) \tag{14}$$

Where, (r) denotes the randomly generated number that is equally distributed in the range of [0,1], $X_{dam,d}$ represents the location of disease in the leaf with dimension (d) and $X_{b,d}$ represents the best value of parameters. Thus, the best value of the performance parameters are attained using eqn.(15),

$$P_{best} = X_{best,d}(W_p.a_p) - R(\overline{X}_d) \tag{15}$$

The parameter for improving the performance metrics is represented as R with dimension (d), and finally, the performance of the classifier parameter is optimized by BRO mechanism. Lastly, the metrics like accuracy, precision, recall, F-score, sensitivity, specificity are computed.

IV. RESULTS AND DISCUSSION

In this paper, the result and discussion is described. Here, theConvolutional Neural Networks optimized with Battle Royale Optimization (CNN-BRO) is implemented for Plant Leaf Disease Identification. The proposed approach is implemented on MATLABand the efficacy is examined by calculation metrics like accuracy, precision, recall, F-score, sensitivity,specificity. Simulation parameter for the proposed methodology is detailed in table 1. Also, the output of the proposed model obtained from implementation is detailed in fig.3.

Table 1: Simulation parameter

Parameter	Value
Total number of images	54303
Iteration	1000
Iterations per epoch	150
Elapsed time	10 minutes 45 seconds
Hardware resource	Single CPU
Learning rate	0.001

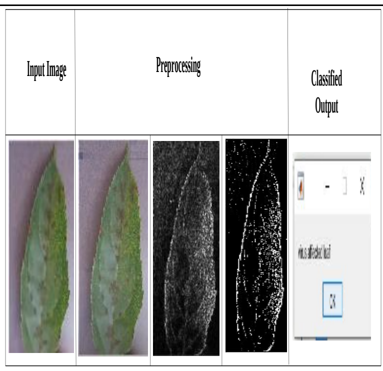

Figure:3 Output results of images

The comparison of evaluation metrics is examined by the existing methods such as Plant leaf disease identification using support vector machine with exponential spider monkey optimization (PLDI-SVM-SMO) [21] and Plant leaf disease identification using PLDI-BRBFNN–BFO [22].

A. Dataset Description

This manuscript contains images of plant leaf that are taken from the standard dataset as Plant Village dataset [26]. This dataset consists of 54303 totals healthy and unhealthy images are used for training and testing process.

B. Performance Metrics

Measuring the performance metrics such as accuracy, precision, recall, F-score, sensitivity, specificity that confusion matrix is needed. For measuring the confusing matrix like True Negative, True Positive, False Negative, False Positive values are necessary.

- True Positive (tp): Disease is correctly classified as disease
- True Negative (tn): Non- disease is correctly classified as Non- disease
- False Positive (fp): Non- disease is correctly classified as disease
- False Negative (fn): Disease is correctly classified as Non- disease.

C.Calculation of Accuracy

It is defined as the total count of values needed for classification results can be determined and its equation is given below,

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \times 100 \tag{16}$$

D.Calculation of Precision

It consist of positive predictive value and is denoted below,

$$\Pr ecision = \frac{tn}{tn + fn} \times 100 \tag{17}$$

E.Calculation of Recall

It contains number of records which are correctly categorised using the number of every corrected events. It is given by the equation (18),

$$\operatorname{Re} call = \frac{tp}{tp + fn} \tag{18}$$

F. Calculation of F-Score

It consist of harmonic mean of recall and precision . It is mentioned below,

$$F - Score = \frac{2tp}{2tp + fp + fn} \tag{19}$$

G. Calculation of Sensitivity

It calculates the quantity of actual positives which is predicted correctly and is calculated below,

$$Sensitivity = \frac{tn}{fp + fn} \qquad (20)$$

H.Calculation of Specificity

Specificity is known as true negative rate. It is denoted using equation (21).

$$Specificity = \frac{fn}{fp + fn} \qquad (21)$$

I. Comparison of performance analysis for plant leaf disease identification

Here, the efficacy metrics such as accuracy, precision, recall, F-score, sensitivity, specificity, system error are analysed for Skin cancerclassification. Then the proposed PLDI-CNN-BRO technique compared with the existing approaches such as PLDI-SVM-SMO, PLDI-BRBFNN–BFO.

Table 2: Comparison of performance metrics

Performance Metrics	**PLDI-SVM-SMO [21]**	**PLDI-BRBFNN–BFO [22]**	**PLDI-CNN-BRO (Proposed)**
Accuracy (%)	77.78	84.44	97.49
Precision (%)	83.33	88.89	96.98
Recall (%)	71.43	81.63	93.02
F-Score (%)	76.92	85.11	96.36
System Error (%)	22.22	15.56	8.89
Sensitivity (%)	74.75	86.76	95.66
Specificity (%)	72.56	83.65	93.24

Table 2 shows the comparison of efficacy metrics of accuracy, precision, recall, F-score, sensitivity, specificity ,system error. Performance metrics of proposed method PLDI-CNN-BRO for plant leaf disease identification is calculated and efficacy is compared with numerous existing techniques such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO. Here, accuracy of proposed method PLDI-CNN-BRO shows 25.34% and 15.45% higher than the existing approaches such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO. Precision of PLDI-CNN-BRO shows 16.38% and 9.1% higher than the existing methods such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO. The recall of PLDI-CNN-BRO shows 30.22% and 13.95% higher than the existing approaches like PLDI-SVM-SMO and PLDI-BRBFNN–BFO. The F-score of PLDI-CNN-BRO illustrations 25.27% and 13.21% higher than the existing approaches such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO. The system errors of PLDI-CNN-BRO illustrations 59.99% and 42.86% lower than the existing approaches like PLDI-SVM-SMO and PLDI-BRBFNN–BFO. The sensitivity of proposed method PLDI-CNN-BRO shows 27.97% and 10.25% higher than the existing approaches such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO. The specificity of PLDI-CNN-BRO illustrations 28.5% and 11.46% higher than the existing approaches such as PLDI-SVM-SMO and PLDI-BRBFNN–BFO.

V. CONCLUSION

In this manuscript, Zooming Algorithm based edge detection and Convolutional Neural Networks optimized with Battle Royale Optimization (CNN-BRO) is proposed for plant leaf disease classification. Initially, input images are attained from standard dataset and pre-processed using zooming algorithm. Moreover, the classifications of affected leaf images are done with the use of CNN and the parameters are optimized using BRO mechanism. Thus, the proposed CNN-BRO approach was attained 25.34% &15.45% high accuracy and59.99%, 42.86% low system error than other existing methods like SVM-SMO and BRBFNN-BFO.

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