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Leveraging Swarm Optimization with Deep Learning Driven Nutrients Deficiency Diagnosis in Rice Crop Management

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Abstract: Rice (Oryza sativa L.) is the fourth main food crop globally and is crucial for food security worldwide. Fertilization plays a significant part in rice yield and excellence and is a major portion of rice field management. Nutrient deficiency in the soil is considered as the main factor. Fundamentally, macronutrients are nutrients that contain more attention than micronutrients and are vital for tissue growth and plant cells. The most essential nutrients for plants are nitrogen (N), phosphorus (P), and potassium (K). A computer vision-based automated nutrition position of rice recognition model has occurred in agriculture. Deep convolutional neural network (DCNN) learning depends upon an artificial neural network (ANN) that can absorb and create intelligent forecasts using techniques. This objective focuses on the design of the Rhinopithecus Swarm Optimization Algorithm for Diagnosing Nutrient Deficiency Rice Crop (RSOA-NDRC) technique for the identification of nutrient deficiency in rice crops using a parameter-tuned Deep Learning (DL) model. Several stages of the RSOA-NDRC technique achieve this. In pre-processing, RGB images are converted into HSV images to remove the background. Binary images are produced based on hue and saturation to separate the diseased from the non-diseased areas. In addition, Feature extraction is performed using the ShuffleNet method. The deep fuzzy neural network (DFNN) approach was applied to identify nutrient deficiencies. Finally, the rhinopithecus swarm optimization (RSO) model-based hyperparameter selection procedure is used to enhance the recognition outcomes of the DFNN approach. A comprehensive set of experimentations was performed to establish the improved performance of the RSOA-NDRC technique. The performance validation of the RSOA-NDRC technique portrayed a superior accuracy value of 98.85% over existing models.

Keywords: Nutrient deficiency, Rhinopithecus swarm optimization, Rice crop, Classification, RGB images, ShuffleNet, Deep learning.

1. Introduction

Rice is the most significant crop worldwide, subsidizing 45% of the edible energy and 30% of the entire protein, and substantially contributes to feeding livestock [1]. Rice and its producing methods have advanced, with their photothermal needs for development and growth, with distinctive geographical allocations [2]. However, the highest rice harvests are attained from the moderate regions of Japan, Australia, the USA, and China; rice is the main crop of the subtropics and tropics. For employment, about 80% of the people depend on agriculture or its by-products as their primary income [3]. Since the rapid growth of the population, government officials need to support smart farming for profitable and sustainable agriculture, so it is essential to quicken the incorporation of advanced technologies to improve the agricultural sector, particularly in emerging countries like India. Health status and crop estimation have traditionally been supervised in India over crop cutting and physical observations [4]. Based on this, farmers apply fertilizer, pesticides, herbicides, and irrigating to their farms to improve the production of crops. However, this process can be either resource-intensive or time-consuming, resulting in augmented input costs in agriculture [5]. To overcome this persistent problem, real-time crop growing monitoring across various locations and under variable environmental conditions is imperative. Real-time crop monitoring not only improves management techniques and saves time but also allows managers to efficiently respond to intense climatic events and reduce their impacts on the global food system [6].

The production performance of important crops in many areas, together with the area's circumstances for the production of crops, economic outcome, and environmental impact, were evaluated utilizing the methods of DL and machine learning (ML) [7]. DL allows computing methods with various processing layers to specify the data at different abstraction levels. The foremost applications of DL in the agriculture field are creating methods for deriving significant perceptions from agriculture data, image studies containing object detection and classification, like plant disease detection, detection of pests, weed identification, soil analysis, etc [8]. The rise of novel recognizing abilities and radical ML and DL methods are the best technologies, and they also affect soil fertility management to overcome the difficulties related to conventional fertility monitoring and mapping. The growing global population demands more effectual agricultural practices to ensure food security, specifically in staple crops like rice [9]. As conventional farming methods face limitations in productivity and sustainability, there is a pressing need for innovative technologies that can improve nutrient management and crop health. By incorporating advanced models, namely swarm optimization and DL, smarter solutions can be developed to diagnose nutrient deficiencies in rice. This approach aims to boost yields and promote sustainable farming practices, benefiting farmers and the environment. Embracing such improvements is significant for meeting the threats of modern agriculture, especially in developing regions [10].

This objective focuses on designing the Rhinopithecus Swarm Optimization Algorithm for Diagnosing Nutrient Deficiency in Rice Crop (RSOA-NDRC) technique. To achieve this, the RSOA-NDRC technique employs pre-processing to remove noise. In addition, the feature extraction procedure occurs by a ShuffleNet method. The deep fuzzy neural network (DFNN) approach was applied to identify the rice crop's nutrient deficiency. At last, the rhinopithecus swarm optimization (RSO) method-based hyperparameter selection method is carried out to augment the recognition outcomes of the DFNN method. A comprehensive set of simulations was performed to establish the heightened performance of the RSOA-NDRC approach. The major contribution of the RSOA-NDRC approach is listed below.

- The RSOA-NDRC technique improves data quality by integrating a pre-processing step that effectively removes noise. This noise reduction is crucial for improving the accuracy of subsequent analyses. By ensuring cleaner input data, the approach lays a robust foundation for more reliable outcomes in detecting nutrient deficiencies.
- The ShuffleNet methodology for feature extraction substantially optimizes the process, improving computational effectualness while conserving accuracy. This advanced method confirms that critical features are efficiently captured, facilitating enhanced performance in detecting nutrient deficiencies. By streamlining feature extraction, the technique enables quicker and more reliable analyses.
- The DFNN model is specifically constructed for precisely detecting nutrient deficiencies in rice crops, enabling more complex evaluation. This methodology improves the capability of the technique to interpret complex data patterns related to crop health. By enhancing accuracy in deficiency detection, the method assists improved decision-making for agricultural management.
- The RSO method is used for hyperparameter selection, crucially enhancing the performance of the DFNN model. This approach optimizes parameter tuning, enhancing recognition outcomes for nutrient deficiency detection. Refining the model's settings confirms more accurate and reliable assessments in agricultural contexts.
- Incorporating ShuffleNet for feature extraction with RSO for hyperparameter tuning in rice crop nutrient deficiency detection presents a novel approach that enhances both effectualness and detection accuracy. This integration allows for rapid processing of complex data while ensuring precise evaluations. By employing these advanced models, the methodology stands out as an innovative solution in agricultural technology.

The article is structured as follows: Section 2 presents the literature review, Section 3 outlines the proposed method, Section 4 details the results evaluation, and Section 5 concludes the study.

2. Related works

Zhe Xu et al. [11] proposed using DCNNs to classify nutrient deficiencies in rice plants. Leaf images from hydroponically grown rice plants were acquired to induce N, P, K, and other elements' deficiencies. Then, four models of DCNNs—Inception-v3, ResNet-50, NasNet-Large, and DenseNet-121—are used to classify the leaves based on their specific visual signs of damage. The study demonstrated that DCNNs can easily overcome the challenge of automated nutrient deficiency diagnosis and, therefore, can be used in real-time precision agriculture applications. Shaik Salma Begum et al. [12] used block-wise crop nutrient deficiency detection, suggesting a custom CNN approach. In this method, leaf images are divided into many smaller blocks and further researched to classify some specific nutrient deficiencies. The overall leaf classification is then obtained using the winner-takes-all strategy from the block-wise classifications with the MLP outcome. Considering this, the model efficiently detected deficiencies such as nitrogen and phosphorus. Plant health monitoring is thus more automatic than traditional methods. Shauryavir Singh Manhas et al. [13] developed a deep-learning-based system to detect nutrient deficiencies in plant leaves. Based on ResNet, VGGNet, and GoogleNet, this system classifies the leaves' images to detect such deficiencies as nitrogen (N) and phosphorus (P). The study addresses some shortcomings of conventional soil-testing methods by proposing a more direct automated method for identifying plant nutrient shortages. The proposed research argued that methods such as neural networks could significantly impact how large-scale farming manages crop nutrition. Borja Espejo-Garcia et al. [14] used deep learning methods, specifically the implementation of EfficientNet with transfer learning, to diagnose nutrient deficiencies in sugar beet and orange tree crops. Two datasets were involved; one regarding sugar beet was related to N, P, and K deficiencies, and the other was for orange trees, but it considered Fe, Mg, and Mn deficiencies, among others. In other words, this paper proved how deep learning models could potentially predict nutrient deficiencies using RGB images, an application for early diagnosis and efficient nutrient management in agriculture.

Anu Jose et al. [15] have developed an ANN to classify nutrient deficiency in tomatoes by nutrients: N, P, K, Mg, Ca, and S. The model uses hue-based segmentation, thresholding, and feature extraction using the Color Co-occurrence Method. Many approaches toward image pre-processing in improving detection accuracy have been adopted in this study, including resizing, noise elimination, and contrast stretching. The ANN-based approach resolved the issue by optimizing crop health and yield management abilities so farmers could monitor nutrient deficiency in real-time. Md. Simul Hasan Talukder et al. [16] proposed the DECNN to detect nutrient deficiencies in rice crops. In addition, the weighted ensemble learning strategy was developed to fuse those pre-trained architectures—DenseNet169, DenseNet201, and InceptionV3. Furthermore, data augmentation and its amount were also improved to increase the robustness of the model and improve the diagnosis of N, P, and K deficiencies in rice crops. This is to say that ensemble learning could be an effective strategy for enhancing the correctness and reliability of deficiency diagnosis. To get around the problems of underfitting, Sherline Jesie R et al. [17] created a hybrid convolutional neural network (HCNN) to help classify nutrient deficiencies in rice crops toward NPK classification. CLAHE, also known as Contrast Limited Adaptive Histogram Equalization, serves as the enhancement technique, while GLCM, also known as Gray Level Co-occurrence Matrix, is used for feature extraction. All these hybrid architectures with data augmentation techniques will overcome the problems of underfitting. The experiment proved the HCNN's potential use of nutrient deficiency in paddy crops for automated detection, and as a result, it was a scalable solution for precision agriculture.

Despite the promising results of these studies, a few constraints were identified. As noted by Zhe Xu et al. and Borja Espejo-Garcia et al., the biggest constraint is the lack of readily available, relatively large, and diverse datasets. If comprehensive datasets are lacking, then the models will fail to generalize appropriately to new conditions or unseen data. With these problems come the overfitting and underfitting difficulties, which are also exposed by the studies of Sherline Jesie R et al. and Shaik Salma Begum et al. with the scarcity of data and advanced image segmentation techniques. Another problem arises when deploying these models in agriculture in real-time, as lighting conditions and noise will affect the accuracy of predictions, according to the author Anu Jose et al. Furthermore, while Md. Simul Hasan Talukder et al. used ensemble models to improve prediction accuracy; they face significant challenges in selecting weights that do not amplify the errors within individual models. The challenges in using these models in large-scale farming stem from the early stage of model integration into farm management systems.

3. Materials and methods

This paper presents the RSOA-NDRC technique. The technique's purpose is to precisely and proficiently identify rice crop nutrient deficiency using a parameter-tuned DL model.

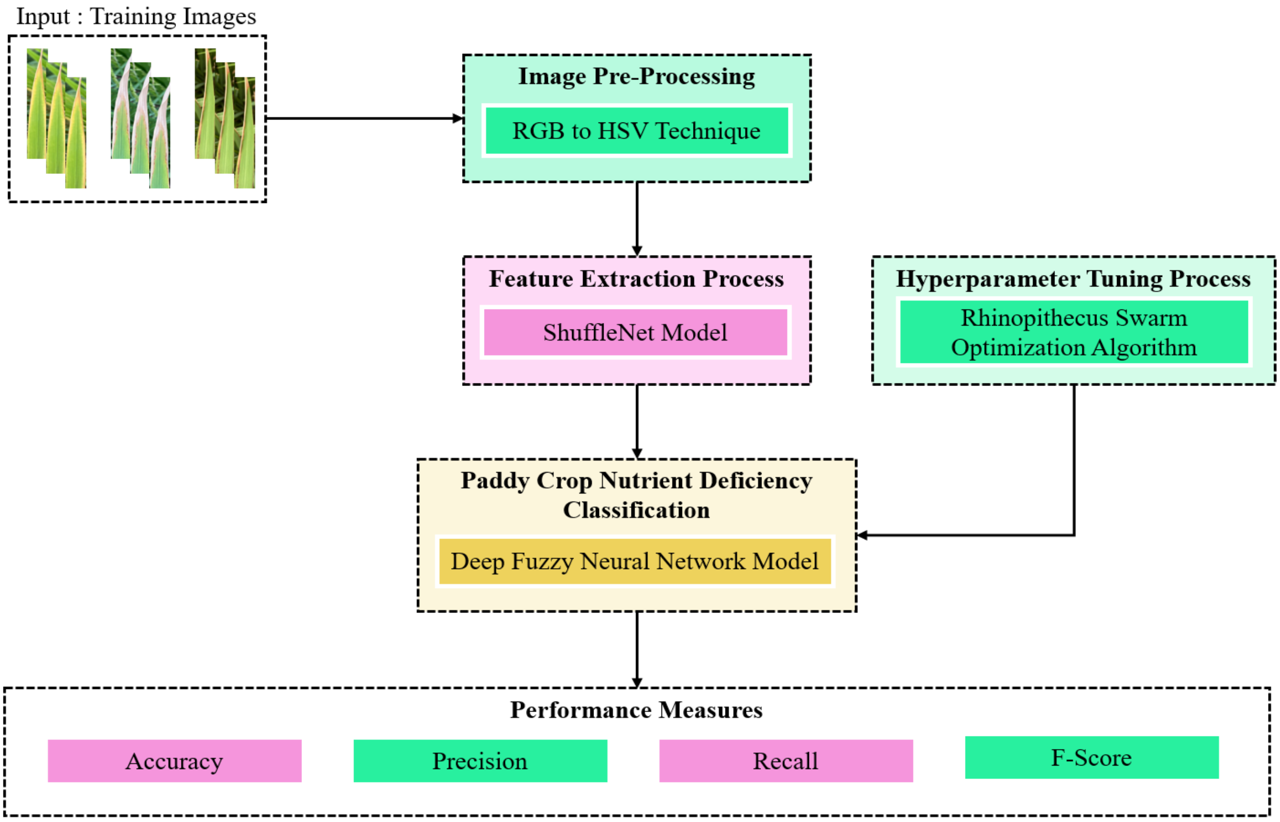

Figure. 1 Workflow of RSOA-NDRC technique

To accomplish this, the technique uses image pre-processing, feature extractor, classification, and parameter optimizer systems. Fig. 1 depicts the workflow of the RSOA-NDRC technique.

3.1 Image pre-processing

The RSOA-NDRC technique primarily utilizes the image pre-processing method for noise removal. During pre-processing, images of the dataset are resized and cropped to 300 x 450 pixels to reduce memory requirements and computational power. In this stage, the primary task is to remove the background from images based on hue value integration. In the initial stage, RGB images are converted into HSV format [18]. Taking the value for the process from the HSV model first, since it conceals whiteness, the S value is considered a binary image based on a threshold value of 90. This binary image is merged with the original RGB image to form a mask. The threshold value requires numerous tries. During fusing, the background gets removed by assigning pixel values as 0's. In the RGB model, the value 0 from any pixel represents a black colour. After removing the background, only a part of the leaf containing the diseased portion is visible in the image.

3.2 ShuffleNet model

Next, the feature method is extracted using a ShuffleNet method. ShuffleNet employs group convolution as an alternative to point convolution for raising accuracy [19]. In group convolution, every group's output relies only on its input, separating details between clusters. ShuffleNet uses shuffling, depth-wise convolution, and pointwise group convolution devices to enhance efficacy. This simplifies superior learning rates and allows more minor dropouts to be used. To achieve normalization, every size of d-dimensional data $Y = Y^{(1)}, Y^{(2)}, \dots, Y^{(P)}$ is regularized by employing Eq. (1). This calculation combines per-extent variance, and the mean of data is denoted as g and var. The BN function, Eq. (2), declares the $ReLU$ activation function.

$$\tilde{Y}^{(k)} = \frac{Y^{(K)} - g[Y^{(K)}]}{\sqrt{var[Y^{(K)}]}} \tag{1}$$

$$\mathrm{Re}LU(Y) = \begin{cases} 0, if\ Y \le 0 \\ Y\ otherwise \end{cases} \tag{2}$$

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In Eq. (2), Y represents input, and its output is Y for positive value and 0 for negative rate. Assume X_1 is an output produced by AlexNet, specified as $softmax(x)_I$ and X_2 output got from ShuffleNet, which is expressed as

$$X_2 = \sum \sum Y^{(K)_*} Q_i^* X_i \quad (3)$$

Computed output layer achieved from uniting layer,

$$X_3 = \sum_d \sum_z Z_{t+1}^* X_2^* \vartheta \quad (4)$$

Whereas θ definite weight ranges from (0-1), Z_{t+1} signifies the amplified images, measured as the feature.

3.3 Classification using DFNN model

The DFNN approach was applied to the rice crop classification process. The DFNN model mainly depends upon the FNN technique that unites a fuzzy inference system (FIS) with ANNs [20]. The Takagi-Sugeno kind of FIS has been employed to recover computational efficacy by neglecting the defuzzification method at an output phase. For the Takagi-Sugeno kind of FIS, the fuzzy rules are stated in Eq. (5) and indicate the outcome of *each* fuzzy rule for the *sth* data instance.

$$\text{When } x_1(s) \text{ is } M_{i1}(s), \cdots, x_m(s) \text{ is } M_{im}(s), \\ then\ \hat{y}_i(s) is\ f_i(x_1(s), \cdots, x_m(s)) \quad (5)$$

whereas χ_1, χ_m denotes an input variable in the FNN model, m refers to an input variable counts, $M_{i1} \cdots, M_{im}$ indicates a fuzzy set of ith fuzzy rule, and $\hat{y}$ signifies an output variable. The FNN model's six layers are mentioned below:

Layer 1: Input: $x_1(s), \cdots, x_m(s)$
Layer 2: Membership function: $M_{i1}, \ldots, M_{im}$
Layer 3: Weight: $w_1, \ldots, w_n$
Layer 4: Normalization: $\overline{w}_1, \ldots, \overline{w}_n$
Layer 5: Multiplication: $\overline{w}_1 f_1(x_1(s), x_m(s)), \ldots, \overline{w}_n f_n(x_1(s), \ldots, x_m(s))$
Layer 6: Output layer: y

At first, the input layer is liable for grabbing $x_1(s), \ldots, x_m(s)$ and taking place in the subsequent layer. Then, the layer of membership function obtains the values from a layer of input and computes utilizing Eq. (6). Depending upon Eq. (6), the layer of membership function computes the value and conveys it to the subsequent layer.

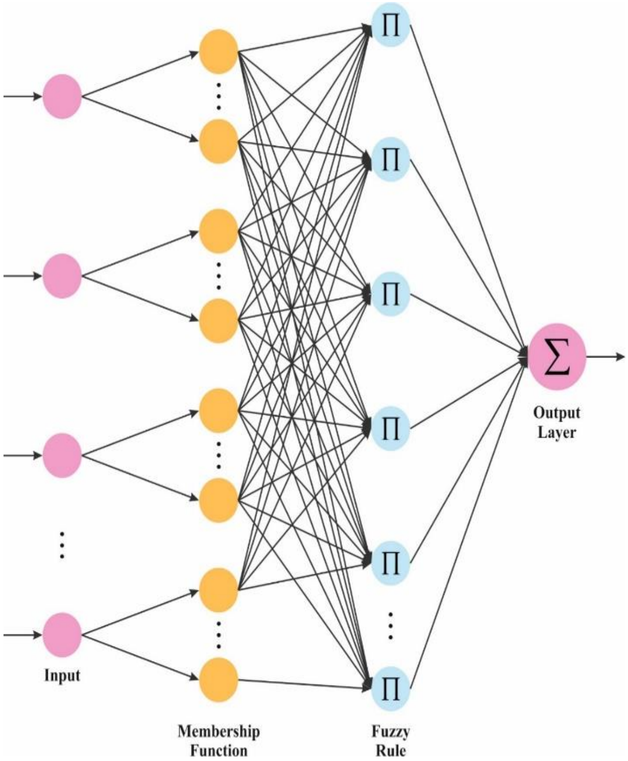


Figure. 2 Structure of DFNN

$$M_{ij}\left(x_j(s)\right) = e^{-(x_j(s)-c_{ij})^2/2d_{ij}^2}, \quad (6)$$

Meanwhile, c_{ij} denotes a midpoint point, and d_{ij} refers to the breadth value of the symmetric Gaussian function.

Next, the layer of weight multiplies every value of membership from the preceding layer intended for all fuzzy rules and exposed in Eq. (7).

$$w_i(s) = \prod_{j=1}^{m} M_{ij}\left(x_j(s)\right) \quad (7)$$

In the 4th layer, the normalization layer captures the value from the preceding layer and regularizes them, as revealed in Eq. (8).

$$\overline{w}_i(s) = \frac{w_i(s)}{\sum_{i=1}^{n} w_i(s)} \quad (8)$$

Fifth, the multiplication layer is used to multiply every weight regularized by the output of fuzzy rules, which leads to the following layer. Lastly, the output layer sums up every outcome from the preceding layer to deliver a value of output, as revealed in Eq. (9).

$$\hat{y}(s) = \sum_{i=1}^{n} \overline{w}_i(s) y_i(s) = \\ \sum_{i=1}^{n} \overline{w}_i(s) f_i(x_{1)}) x_m) \quad (9)$$

The DFNN model reflects the stacked architecture of the FNN module, which is parallel to DL models. On the other hand, the DFNN technique places the FNN components repeatedly. Eqs give the FIS at an initial and $g\text{-}th$ FNN module. (5) and (10), respectively

If $x_1(s)$ is $M_{i1}^{(g)}(s), \ldots, x_m(s)$ is $M_{im}^{(g)}(s)$,
$and\ \hat{y}_{(g-1)}(s) is\ M_{i(m+1)}^{(g)}(s),$
then $\hat{y}(s)$ is $f_g\left(x_1(s), \cdots, x_m(s), y_{(g-1)}(s)\right)$ (10)

where g denotes the number of FNN modules. The structural features of the DFNN technique permit superior valuation performance, but the risk of overfitting happens due to the structural difficulty. The DFNN technique employs a rule-dropout model and a genetic algorithm to avert overfitting. Fig. 2 depicts the structure of DFNN.

3.4 Parameter tuning process

Additionally, the RSO model-based hyperparameter selection method is performed to enhance the recognition outcomes of the DFNN method [21]. The RSO technique is an efficient choice for hyperparameter tuning due to its unique approach that duplicates the social behaviour and interactions of rhinopithecus monkeys. This model outperforms in exploring the search space effectually, balancing exploration and exploitation to avert local optima. Unlike conventional methodologies, RSO can dynamically adapt its search strategies based on population behaviours, resulting in more robust solutions. Its capability to handle complex optimization issues makes it superior to conventional models, namely grid search or random search, which may be less effective. Moreover, the flexibility of the RSO model allows it to be applied across diverse ML frameworks, improving its applicability in various scenarios. Overall, RSO presents a novel, biologically inspired alternative that enhances tuning accuracy and convergence speed. Fig. 3 illustrates the steps involved in the RSO method. The migration behaviour of rhinopithecus groups stimulated a new RSO approach. The groups of rhinopithecus hunt for migration positions deliver a novel hunt tactic for the optimization technique that will well balance exploitation and exploration ability. The highest 40% of individuals are named as mature rhinopithecus, those placed among 40 to 70 percent are termed adolescent rhinopithecus, and the leftover individuals are called infancy rhinopithecus depending upon their fluctuating grades of existence dominance. The distinct with the poorest locale position is king

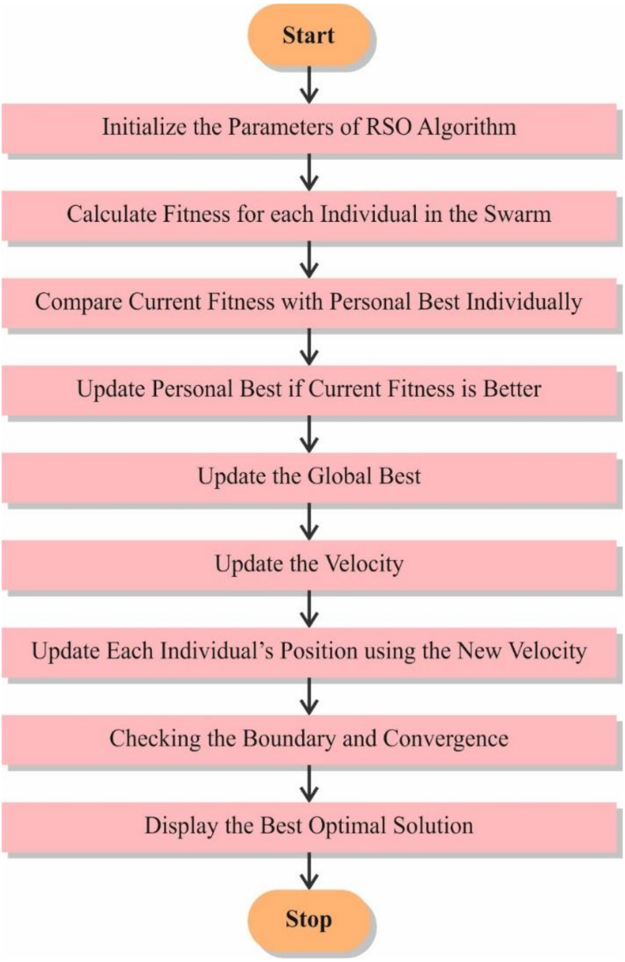


Figure. 3 Steps involved in the RSO model

rhinopithecus, which generally arises from mature individuals. The mature and king rhinopithecuses together main the migration of the cluster.

3.4.1. Vertical migration

Vertical migration action of rhinopithecus plays a vital part in the existence of clusters. Generally, rhinopithecus groups sometimes travel among higher and lower altitudes dependent on climatic conditions and food distribution. At lower temperatures, rhinopithecus choose to be dynamic, whereas the lower altitude position decreases the physical pressure of low temperature, and the nutrition was moderately more ample. In other temperatures, the rhinopithecus groups show the reverse migrant tendency and prefer to use greater altitude regions where food is comparatively higher quality. King and mature rhinopithecus generally have spatial cognition and richer knowledge of the migration procedure. They used to remember the perception of the optimum position for dual temperature conditions. The search tactics depend upon spatial cognition and aid rhinopithecus swarms in picking appropriate migration positions more effectively for dissimilar food resources and climatic conditions.

$$KingR = [KingR, KingR_{c1}, KingR_{c2}]$$
$$MR = [MR, MR_{c1}, MR_{c2}] \tag{11}$$

Here, $KingR$ and MR stand for king and mature rhinopithecuses, respectively. Eq. (13) demonstrates their candidate solution.

$$\alpha = \frac{KingR_a + MR_b}{2}$$
$$\beta = |KingR_a - MR_b| \quad a, b\epsilon[0.2] \tag{12}$$

$$CandiMR = Gausi(\alpha, \beta) \tag{13}$$

Meanwhile, $KingR_a$ and MR_b stand for the positions of king and mature rhinopithecuses. $Gausi$ (α, β) denotes a function value produced randomly from a Gaussian distribution with a variance of β and an expectation of α.

3.4.2. Concerted search

In a group of rhinopithecus, adolescent rhinopithecus are in the development phase. Even though they have a definite grade of searchability while examining migration positions, they must be more knowledgeable when equated to king and mature rhinopithecuses. So, adolescent rhinopithecus generally show comparative uncertainty in selecting hunt routes and migration positions. In this situation, adolescent rhinopithecus would energetically search for help from mature and king rhinopithecuses, trusting their perception of the atmosphere and employing search knowledge to aid in making decisions. Naturally, adolescent rhinopithecus share information regarding their past position to mature and king rhinopithecuses. Then, they utilize their knowledge to show the adolescents how to make decisions. In RSO, the adolescent rhinopithecus is used to converse dual past locations to the mature and king rhinopithecuses, respectively.

$$AR = [AR_{h1}, AR_{h2}]$$

where AR refers to an adolescent rhinopithecus, who will consider both proposals equally and create their thoughts to generate a candidate solution that is computed by Eq. (15). The decision-making tactic depends upon data distribution and group collaboration, which can efficiently increase the efficacy and precision of rhinopithecus groups in migration.

$$\gamma = \frac{KingR_a + AR_c}{2}$$

$$\epsilon = \frac{MR_b + AR_c}{2} \quad a, b \in [0,2] \tag{14}$$

$$c \in [0,1]$$

$$\delta = |KingR_a - AR|$$

$$\zeta = |MR_b - AR|$$

$$CandiAR = \frac{Gausi(\gamma,\delta) + Gausi\ (\varepsilon,\zeta)}{2} \tag{15}$$

$KingR_a$, MR_b, and AR_c standard king, mature, and adolescent rhinopithecuses locations. $Gausi(\gamma, \delta)$ denotes a value of the function that makes at random from a distribution of Gaussian with a variance of δ and an expectation of γ. $Gausi(\varepsilon, \zeta)$ was a value of a function that produces randomly with an expectation of ε and a variance of ζ.

3.4.3. Mimicry

Infancy rhinopithecus is generally in the initial steps of growth and learning. So, discovering an appropriate position for migration is highly challenging for infancy rhinopithecus. In this growing phase, infancy rhinopithecus rely on other followers of the swarm, exceptionally mature and adolescent rhinopithecuses, to help them in their voyage. In the migration procedure, infant individuals share information regarding their position with the grownup rhinopithecuses in many ways. Mature and adolescent rhinopithecuses will get the behaviours of the infancy rhinopithecus, like consumption habits and way of life, depending upon the position data. Therefore, they will mix their knowledge well to direct young individuals to travel. After receiving direction, the infant individuals will implement the proposals from both of them distinctly. Their candidate solutions were formulated by Eq. (17). The group-assistance-based tactic aids infancy rhinopithecus to pass over the development stage effortlessly. They can efficiently study existence abilities by copying the exploration tactics of older rhinopithecus.

$$\eta = \frac{MR_b + IR}{2}$$

$$\iota = \frac{AR_c + IR}{2} \quad b \in [0,2] \tag{16}$$

$$c \in [0,1]$$

$$\theta = |MR_b - IR|$$

$$\kappa = |AR_c - IR|$$

$$CandiAR = \frac{Gausi(\eta,\theta)+Gausi(\iota,\kappa)}{2} \quad (17)$$

MR_b, AR_c and IR refer to the locations of matured, infancy, and adolescent rhinopithecuses. $Gausi(\eta,\theta)$ refers to the value of a function that produces randomly with an expectation of η and a variance of θ. $Gausi(\iota,\kappa)$ denotes a function value that generates at random with an expectation of ι and a variance of κ. Fitness selection is a substantial factor in manipulating the efficiency of the RSO model. The hyperparameter selection procedure includes the solution-encoded system to assess the effectiveness of the candidate solutions. In this paper, the RSO technique reflects precision as the foremost standard for projecting the fitness function, expressed below.

$$Fitness = \max(P) \quad (18)$$

$$P = \frac{TP}{TP+FP} \quad (19)$$

Here, TP and FP correspondingly signify the true positive and false positive values.

4. Experimental results and analysis

In this section, the investigational validation of the RSOA-NDRC approach is performed using the Kaggle dataset [22], which contains 1156 samples under three classes. Table 1 demonstrates this. Fig. 4 illustrates the sample images of three classes.

Fig. 5 establishes the confusion matrices formed by the RSOA-NDRC model under 80:20 of TRAP/TESP. The results state that the RSOA-NDRC technique efficiently recognizes and identifies all classes.

Table 2 and Fig. 6 represent the classifier results of the RSOA-NDRC technique under 80% TRAP and 20% TESP. The results specify that the RSOA-NDRC approach correctly identified the samples. With 80% TRAS, the RSOA-NDRC method provides average $accu_y$, $prec_n$, $reca_l$, and F_{score}, of 98.48%, 97.78%, 97.80%, and 97.78%, correspondingly. Simultaneously, with 20% TESP, the RSOA-NDRC model provides an average $accu_y$, $prec_n$, $reca_l$, and F_{score} of 98.85%, 98.31%, 98.47%, and 98.37%, respectively.

Fig. 7 establishes the training (TRA) and validation (VLA) accuracy results of the RSOA-NDRC technique under 80% TRAP and 20% TESP.

(a) (b) (c)

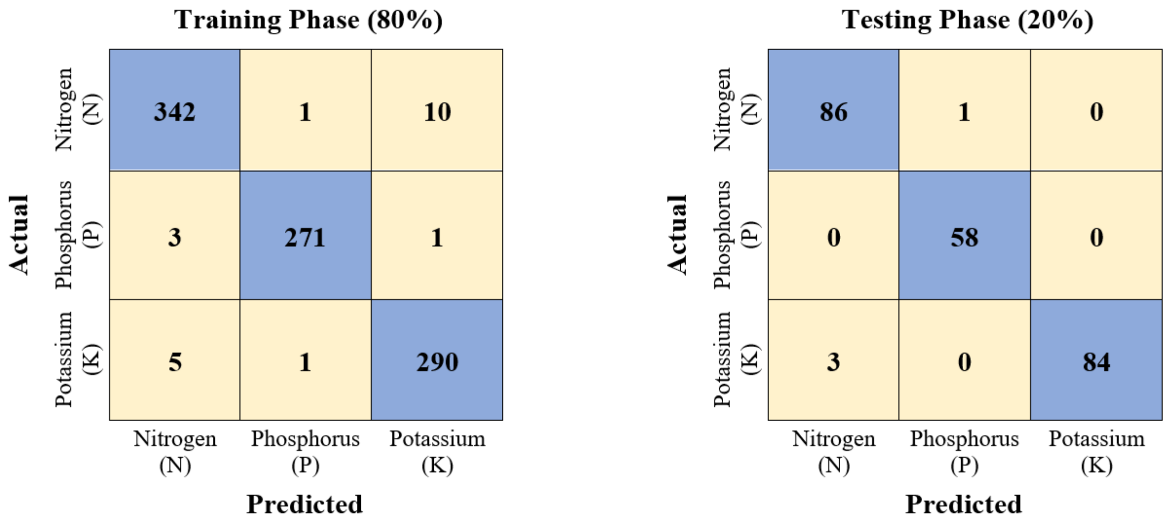
Figure. 4 Sample images: (a)Nitrogen, (b)Phosphorus, and (c)Potassium

Table 1. Details on dataset

Nutrients	No. of Samples
Nitrogen (N)	440
Phosphorus (P)	333
Potassium (K)	383
Total Samples	1156

Table 2. Classifier outcome of RSOA-NDRC method under 80% TRAP and 20% TESP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
TRAP (80%)				
Nitrogen (N)	97.94	97.71	96.88	97.30
Phosphorus (P)	99.35	99.27	98.55	98.91
Potassium (K)	98.16	96.35	97.97	97.15
Average	**98.48**	**97.78**	**97.80**	**97.78**
TESP (20%)				
Nitrogen (N)	98.28	96.63	98.85	97.73
Phosphorus (P)	99.57	98.31	100.00	99.15
Potassium (K)	98.71	100.00	96.55	98.25
Average	**98.85**	**98.31**	**98.47**	**98.37**



(a) (b)

Figure. 5 Confusion matrices: (a)80% TRAP and (b)20% TESP

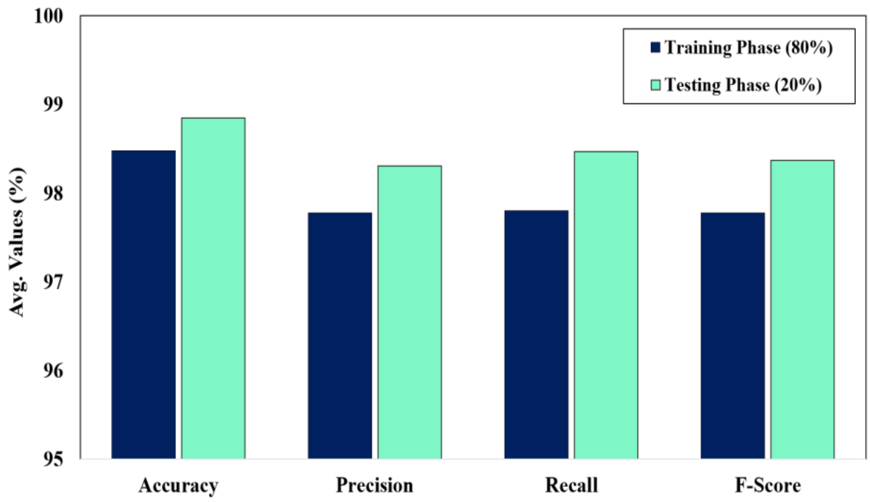


Figure. 6 Average of RSOA-NDRC method under 80% TRAP and 20% TESP

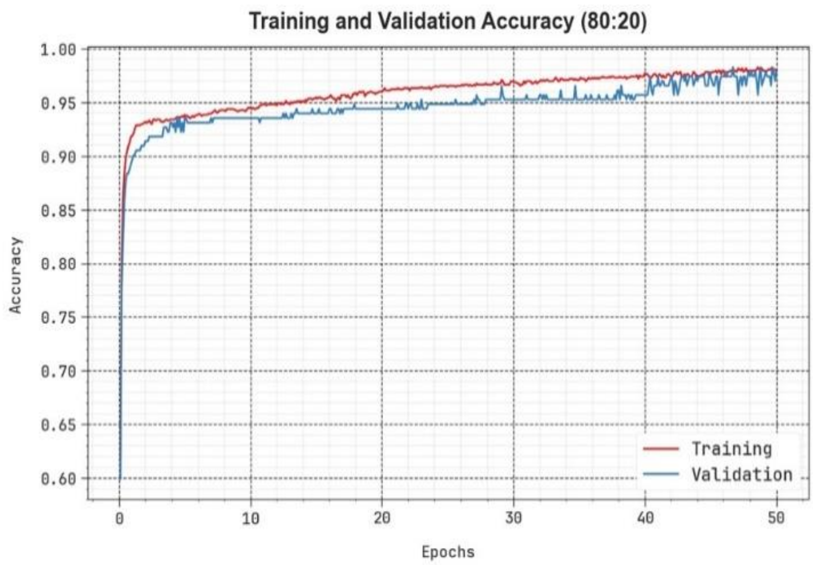


Figure. 7 $Accu_y$ curve of RSOA-NDRC technique under 80% TRAP and 20% TESP

Table 3. Comparative analysis of RSOA-NDRC method with recent models [23-26]

Classifiers	$accu_y$	$prec_n$	$reca_l$	F_{score}
InceptionResNetV2	90.00	90.00	90.00	89.67
InceptionResNetV2 + DenseNet	92.00	92.67	92.00	92.33
Inception-V3	93.00	93.00	93.00	93.00
Finetuned MobileNet	93.10	93.11	93.10	93.09
Xception Model	95.14	95.26	94.40	94.93
RSOA-NDRC	98.85	98.31	98.47	98.37

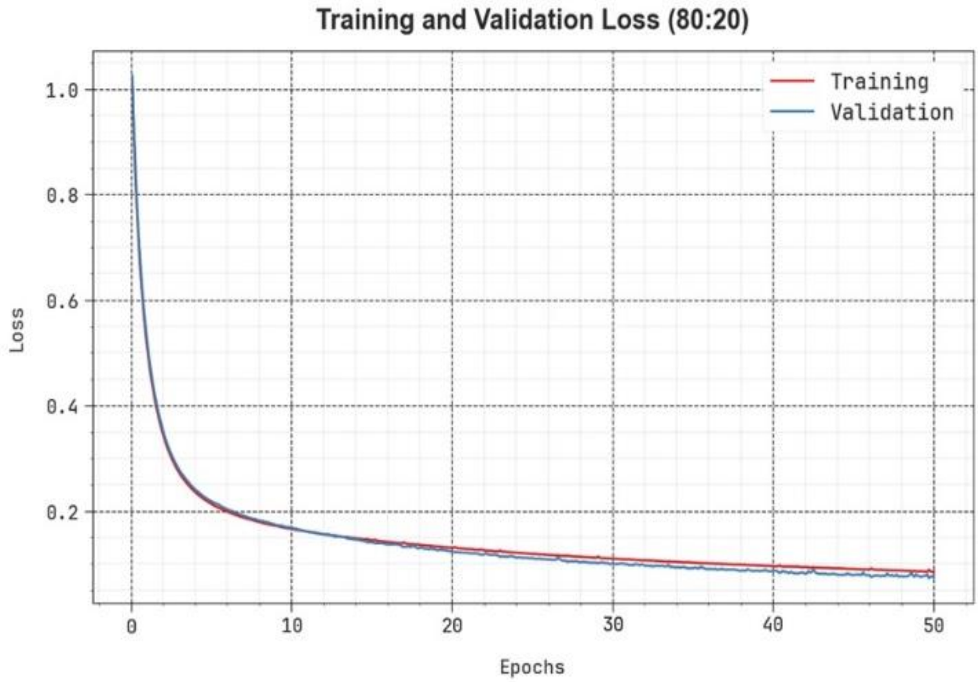


Figure. 8 Loss curve of RSOA-NDRC method under 80% TRAP and 20% TESP

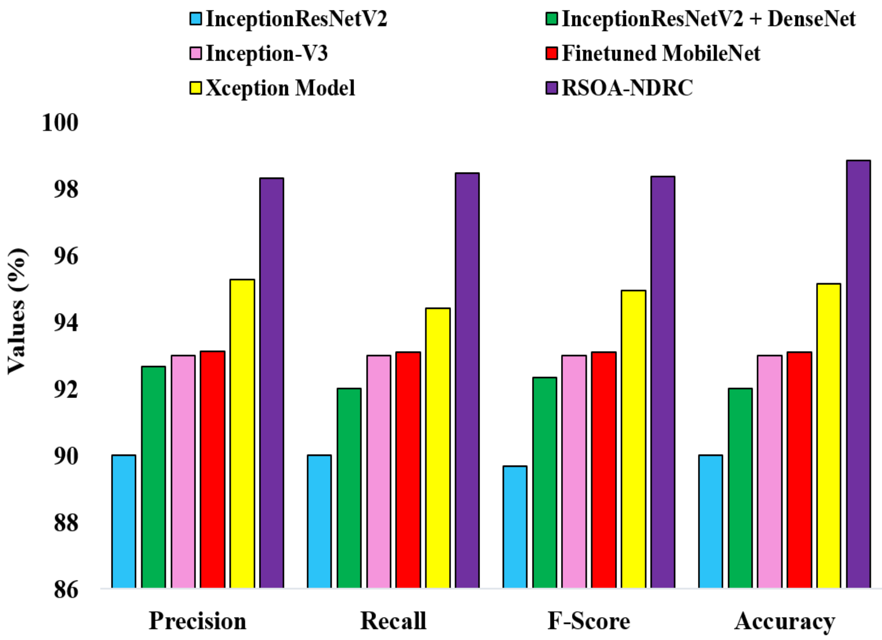


Figure. 9 Comparative analysis of RSOA-NDRC method with recent models

The accuracy values are calculated over a range of 0-50 epochs.

The outcome emphasized that the TRA and VLA accuracy values exhibit a rising trend, which indicates the ability of the RSOA-NDRC model to perform heightenedly over numerous iterations. Also, the TRA and VLA accuracy remains quicker over the epochs that label the lowest insignificant overfitting and display the heightened efficiency of the RSOA-NDRC model, assuring a steady forecast on hidden samples.

Fig. 8 shows the TRA and VLA loss graph of the RSOA-NDRC model under 80% TRAP and 20% TESP. The loss values are calculated throughout 0-50 epochs. It is signified that the TRA and VLA accuracy values validate a decreasing tendency, alerting the ability of the RSOA-NDRC model to harmonize a trade-off between generalize and data fitting. The continual reduction in loss values similarly ensures the heightened performance of the RSOA-NDRC technique and tunes the prediction results over time.

Table 3 and Fig. 9 inspect the comparison results of the RSOA-NDRC model with the existing techniques InceptionResNetV2 [23], InceptionResNetV2 + DenseNet [23], Inception-V3 [24], Finetuned MobileNet [25], and Xception model [26]. The performance of various classifiers reveals notable differences in their efficiency. The inceptionResNetV2 model attained an accuracy of 90.00% while integrating InceptionResNetV2 and DenseNet methods, which improved this to 92.00%. Inception-V3 and Finetuned MobileNet demonstrated similar performance, with an accuracy of 93.00% and 93.10%, respectively. The Xception Model showed significant improvement, reaching an accuracy of 95.14%. On the contrary, the RSOA-NDRC approach outperformed all others with an impressive accuracy of 98.85%, along with precision, recall, and F-score values of 98.31%, 98.47%, and 98.37%, respectively.

5. Conclusion

In this paper, the RSOA-NDRC technique is presented. The purpose of the RSOA-NDRC technique rests in the precise and expert identification of rice crops using a parameter-tuned DL model. To achieve this, the RSOA-NDRC technique employs pre-processing to remove noise. In addition, the feature extraction procedure occurs by a ShuffleNet method. For the rice crop nutrient deficiency identification process, the DFNN technique was deployed. At last, the RSO technique-based hyperparameter selection method is carried out to enhance the recognition outcomes of the DFNN method. A comprehensive set of simulations was carried out to establish the heightened performance of the RSOA-NDRC technique. The extensive results show the improved performance of the RSOA-NDRC technique over other models. The performance validation of the RSOA-NDRC technique portrayed a superior accuracy value of 98.85% over existing models. The limitations of the RSOA-NDRC technique encompass its dependency on the quality and completeness of input data, which can affect the accuracy of nutrient deficiency predictions. Furthermore, the model may need help with intrinsic interactions between diverse nutrients and environmental factors, resulting in oversimplified recommendations.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by Hussain. A. The supervision and project administration, have been done by Balaji Srikaanth. P.

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