

# SAILFISH OPTIMIZATION ALGORITHM WITH DEEP CONVOLUTIONAL NEURAL NETWORK FOR NUTRIENT DEFICIENCY DETECTION IN RICE PLANTS

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## Abstract

Computer vision (CV)-based automation has gained popularity in monitoring and detecting plants' nutrient deficiency. The prediction method formulated by several authors can be utilized in an embedded mechanism, considering the accessibility of computational resources. Yet, the huge popularity of smartphone technology paved the way for common agronomists to have access to high computational resources. Therefore, this study presents a Sailfish Optimization with deep learning for Nutrient Deficiency Detection (SFODL-NDD) in Rice Plants. The presented SFODL-NDD technique focuses on the identification of nutrients using DL and computer vision approaches. Initially, the SFODL-NDD technique employs median filtering (MF) approach for noise elimination process. Next, the SFODL-NDD technique uses Xception model for feature extraction with SFO algorithm as hyperparameter optimizer. At last, the nutrient deficiencies can be recognized by extreme gradient boosting (XGBoost) classifier. The experimental evaluation of the SFODL-NDD technique is tested using rice plant dataset from Kaggle repository. The experimental outcomes stated the better superior performance of the SFODL-NDD technique over other approaches in terms of different measures.

**Keywords:** Nutrient deficiency; Rice plants; Deep learning; Computer vision; Sailfish optimizer

## 1. Introduction

Nutrient deficiency frequently occurs in rice plants, therefore affecting the rice quality and production level [1]. Nutrient deficiency is noticed from the shape and color of sick leaves; thus, it is identified early for minimizing the indications of nutritional deficiencies in rice plants. Signs of nutrient deficiency in rice plants frequently appeared on leaves [2]. The leaf shape and color, so, can be utilized for diagnosing nutrient deficiency in rice. Image classification becomes a fast and potential method for this diagnosing process. Deep convolutional neural network (DCNN) is been a potential one in image classification, butt their use to find nutrient deficiency in rice are of little notice [3]. Fertilizer is vital to global food production, predominantly by guaranteeing stable and high yields of rice. The finest outcomes will be received if some fertilizers were implemented in the required amounts on time [4]. Recently, blind fertilization occurs regularly. So, ever greater quantities of fertilizers will be implemented for attaining just limited increases in rice yield, and standard of resulting rice deterioration [5]. This

makes smallholder farmers who cultivate most of China's rice—not realise achievable surges in income.

Analysis of nutrient deficiency in paddy was a core area of scientific fertilization since soils frequently failed to wholly address nutrient stresses of growing plants [6]. The automatic detection of nutrition deficiencies is comparable to the detection of diseases since the purpose was to find the visual signs that characterized the disorder of interest [7]. 3 major issues should be managed: classification is done to properly find the source of an unknown symptom or sign; detection [8], which intends to specify the occurrence of a target disorder by identifying its symptoms; quantification, which forecasts the targeted disorder severity. All 3 issues were widely sightseen in the case of diseases; in the case of received nutrition deficiencies, there were just studies dedicated to classification [9]. Therefore, generally, the objective was to find or roughly quantify one of related deficiencies, and signs and symptoms that were not linked to those target disorders are simply unnoticed [10]. There were some practical issues linked with these “non-systemic” methods, as deficiency signs rarely appear isolated in uncontrolled situations.

This study presents a Sailfish Optimization with deep learning for Nutrient Deficiency Detection (SFODL-NDD) in Rice Plants. The presented SFODL-NDD technique focuses on the identification of nutrients using DL and computer vision approaches. Initially, the SFODL-NDD technique employs median filtering (MF) approach for noise elimination process. Next, the SFODL-NDD technique uses Xception model for feature extraction with SFO algorithm as hyperparameter optimizer. At last, the nutrient deficiencies can be recognized by extreme gradient boosting (XGBoost) classifier. The experimental evaluation of the SFODL-NDD technique is tested using rice plant dataset from Kaggle repository. The experimental outcomes stated the better performance of the SFODL-NDD method over other approaches in terms of different measures.

## 2. Related Works

Sharma et al. [11] concentrated on implementing CNN-related DL structures, which include TL methods in agricultural studies. Ensembling numerous TL structures have the ability to enrich the outcome of prediction methods to a great extent. In this study, 6 TL architectures viz. InceptionResNetV2, InceptionV3, Xception, DenseNet201, VGG19, and ResNet152V2 were taken into account, and numerous ensemble methods were utilized to execute deficiency analysis in rice plants. Bishwas et al. [12] offered study goals to classify and identify the potassium, nitrogen, and phosphorus nutrient deficiency in paddy leaves images. The experimentation has been held with a k-means clustering technique and CNN. At first, the paddy leaf images will be segmented with many K values by k-means clustering method thereby defective leaves were precisely detected for classifying purposes. Then, the diverse segmented imageries were used by a classifier called CNN.

Sethy et al. [13] recommended a setup containing IoT and DL to monitor rice fields remotely. The vgg16 pre-trained network was taken into account for identifying nitrogen status estimation and paddy leaf diseases. The deep feature extraction method was integrated with an SVM for image classification. Sharma et al. [14] considered several ML and DL methods (TL) for rice disease recognition. A detailed comparative study of the outcomes specifies the superiority of TL methods on orthodox ML methods. It is noted that InceptionResNetV2 attains the best outcome followed by XceptionNet.

Kukana [15] research technique presents MSVM Classification method, paddy leaves image Acquisition and paddy leaf disease pre-processing, Segmentation of rice Leave diseases. Using the OMSVM classifier technique, the Paddy Leave Disease imageries were computed and reduced the error rates like TNR and FDR variables. In [16], an attempt was made to pre-process the imageries for preparing feature-set for techniques and after feature extracting techniques were employed for deriving related features from processed images. The use of cascaded classifiers was explored to distinguish diseases of paddy leaves. An effort was made to leverage GA with NN method for identifying diseases of paddy leaves.

### 3. The Proposed Model

In this study, we have presented a new SFODL-NDD technique for the identification of nutrient deficiencies in rice plants. The presented SFODL-NDD technique focuses on the identification of nutrients using DL and computer vision approaches. It has four processes namely MF based noise elimination, Xception feature extraction, SFO based hyperparameter tuning, and XGBoost classifier. Fig. 1 represents the block diagram of SFODL-NDD system.

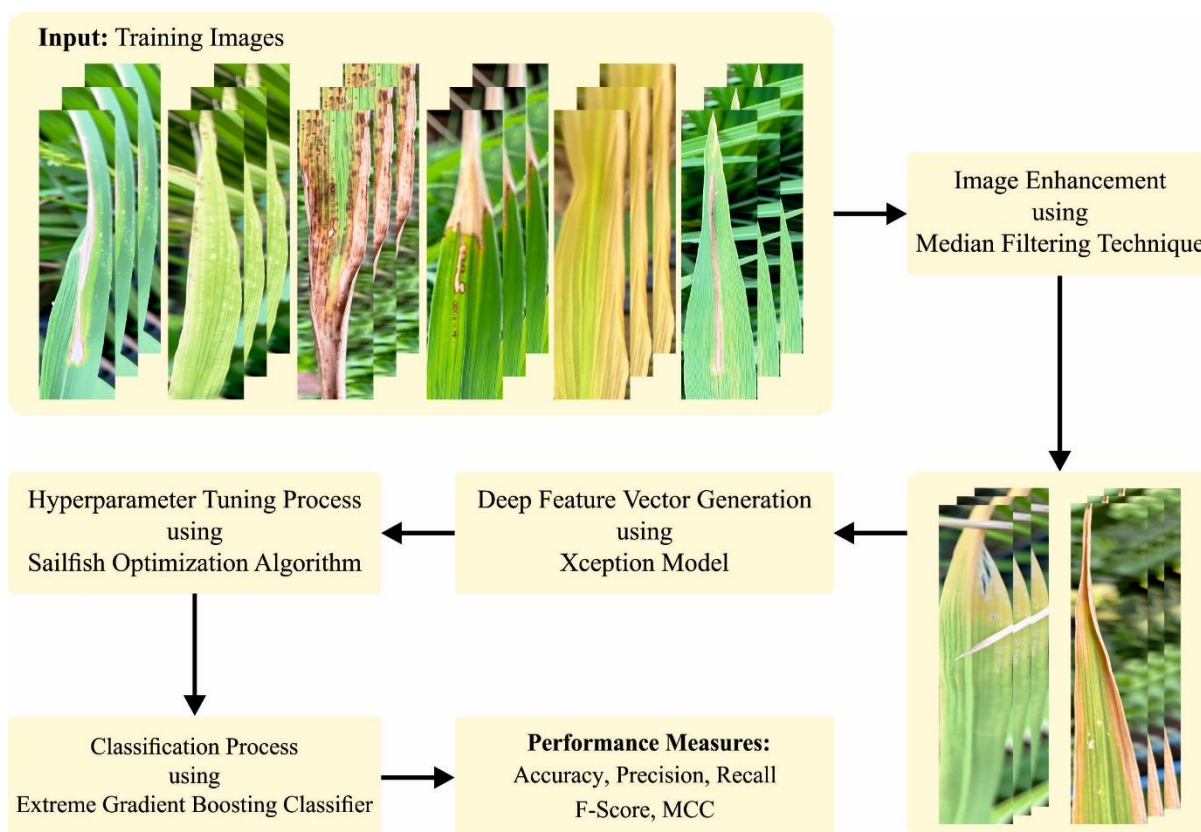
#### 3.1. Image Enhancement

Initially, the SFODL-NDD technique employed MF approach for noise elimination process. Order-statistics otherwise called MF, which interchanges the prediction of a pixel by middle of gray levels in zone of that pixel [17]. The median can be a rank command statistic and, in, an AI the main stream of the pixel values invoke determinate d 000the rcskirt result. The expression of MF,

$$f'(x, y) = \underset{(s,t) \in S_{xy}}{\text{median}}\{g(s, t)\} \quad (1)$$

The initial prediction of the pix was integrated into computation of median. MFs can be very standard for assured sorts of arbitrary noises. They present astonishing noise diminish capability, with strikingly less clouding than linear smoothing filters of comparative size.

Fig. 1. Block diagram of SFODL-NDD approach



#### 3.2. Feature Vector Generation

In this work, the SFODL-NDD technique uses Xception model for feature extraction. The Xception architecture is employed for producing feature vectors. In the presented method, the Xception network with the depthwise

separable convolution method was adopted as a CNN for the driver emotion classification [18]. Xception model was proposed to completely separate cross-channel and spatial correlations. Thereby, it used Depthwise separable convolution encompassing depthwise and pointwise layers. The depthwise part separates the channel and implements the size of 3x3 convolution. This process produces one feature map for all the channels. The computational amount can be reduced in the convolutional of 3x3 size that requires considerable computation, thus avoiding the bottleneck phenomenon. The point-wise layer performs a 1x1 convolution on all the channels of the depthwise output. Extracting features was effectively implemented by the depthwise separable convolution layer and the computation amount is minimized. Moreover, a deep network was constructed by using techniques such as batch normalization to skip connection and Xception of ResNet.

At this stage, the SFO algorithm is used as hyperparameter optimizer. The SFO is a new metaheuristic method stimulated by the set of hunting sailfish [19]. In this work, sailfish are considered as candidate solutions and the place of sailfish under searching space represents variable of problem. The location of  $i^{th}$  sailfish from  $k^{th}$  search round was characterized by the  $SF_{i,k}$ , and corresponding fitness was assessed using  $f(SF_{i,k})$ . The sardine is another significant participant in the SFO algorithm. The location of  $i^{th}$  sardine has illustrated by the  $S_i$ , and their corresponding fitness was evaluated using  $f(S_i)$ . In the SFO approach, the sailfish that take an optimal location was selected by the elite sailfish that affected the acceleration and manoeuvrability of sardines under attack. As well, the location of the injured sardines from every round is chosen as best place for collaborative hunting with sailfish. This procedure aims to prevent the earlier discarded solution from being selected again. The elite sailfish and injured sardine was characterized by  $Y_{eliteSF}^i$  and  $Y_{injuredS}^i$  at  $i^{th}$  iteration. In the process of hunting, sailfish's attack alternation technique was often applied to enrich the achievement of hunt. A novel location of sailfish  $Y_{newSF}^i$  was upgraded based on the following expression:

$$Y_{newSF}^i = Y_{eliteSF}^i - \lambda_i \times \left( random(0,1) \times \left( \frac{Y_{eliteSF}^i - Y_{injuredS}^i}{2} \right) - Y_{currentSF}^i \right), \quad (2)$$

In Eq. (2),  $Y_{currentSF}^i$  represent the existing location of sailfish and  $random(0,1)$  denotes the arbitrary value within [0,1].

The parameter  $\lambda_i$  represent the coefficient from  $i^{th}$  iteration and the value was given by:

$$\lambda_i = 2 \times rand(0,1) \times SD - SD, \quad (3)$$

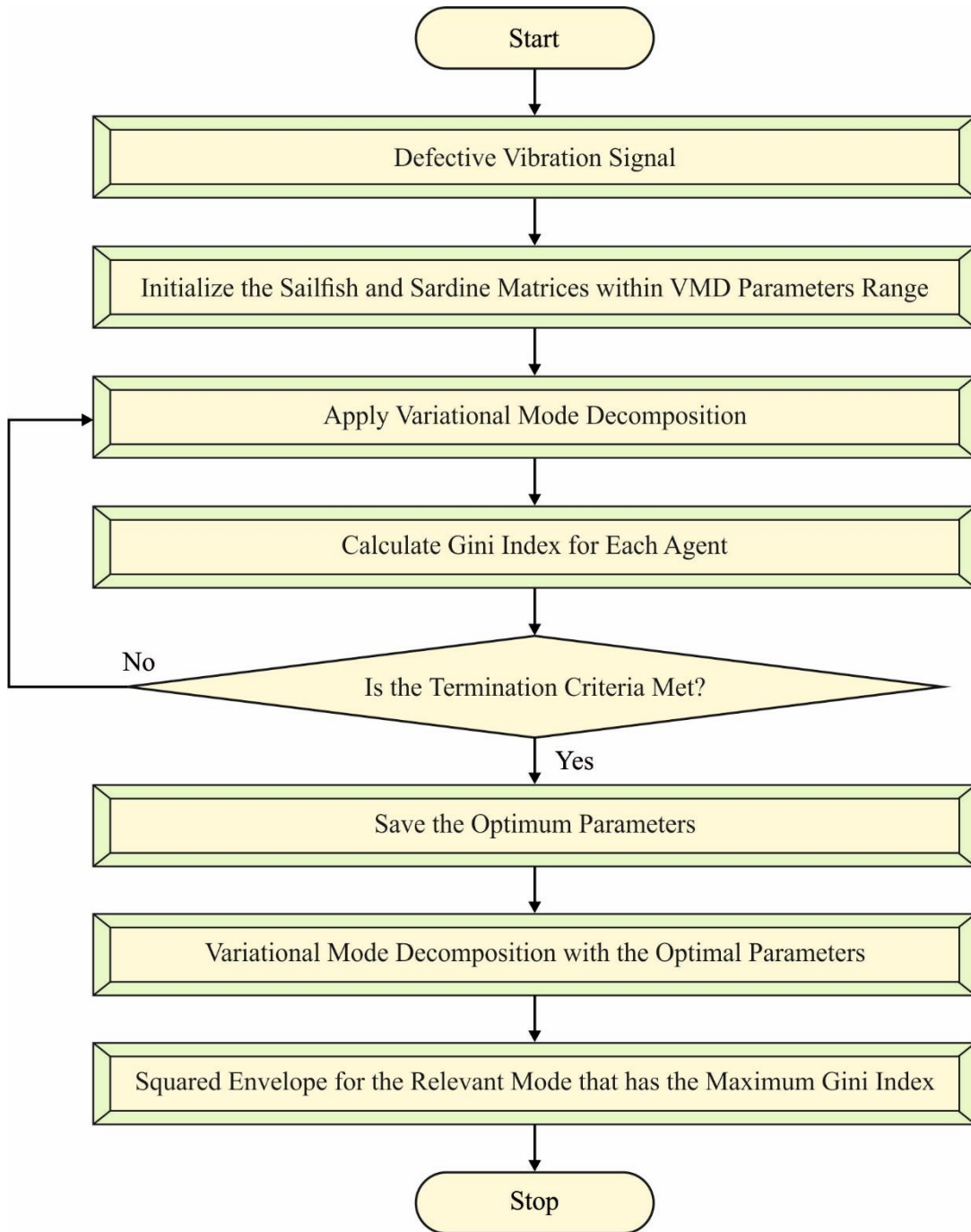
In Eq. (3),  $SD$  shows the sardine density that represents the quantity of sardines from every iteration.

The parameter  $SD$  is given by:

$$SD = 1 - \left( \frac{N_{SF}}{N_{SF} + N_S} \right), \quad (4)$$

In Eq. (4),  $N_{SF}$  and  $N_S$  represent the quantity of sailfish and sardines correspondingly. Fig. 2 illustrates the flowchart of SFO technique.

Fig. 2. Flowchart of SFO



At first, sailfish was energetic, and sardine was not injured or tired. The sardine was quickly escape. However, with continued hunting, control of sailfish attack is decreased gradually. Meanwhile, the sardine is tired, and the awareness of sailfish location is also decreased. Thereby, the sardine was hunted. Depends on algorithmic process, a new location of sardine  $Y_{newS}^i$  has upgraded based on the following expression:

$$Y_{newS}^i = random(0,1) \times (Y_{eliteSF}^i - Y_{oldS}^i + ATP), \quad (5)$$

In Eq. (5),  $Y_{oldS}^i$  represent the older place of sardine and  $random(0,1)$  shows arbitrary integer ranges within [0,1].  $ATP$  represent sailfish attack power.

The parameter  $ATP$  has evaluated by:

$$ATP = B \times (1 - (2 \times Itr \times \varepsilon)) \quad (6)$$

In Eq. (6),  $B$  and  $\varepsilon$  denotes the coefficient that is exploited to reduce the attack power linearly in  $B$  to 0 and  $Itr$  indicates the iteration count. When  $ATP$  has maximal, for example, better than 0.5, the location of all the sardines was upgraded. On the other hand,  $\alpha$  sardine with  $\beta$  variable upgrades its place:

$$\alpha = N_S \times ATP, \quad (7)$$

In Eq. (7),  $N_S$  represent the amount of sardines from every iteration. The amount of parameters of the sardine that upgrade the place was accomplished by:

$$\beta = d_i \times ATP, \quad (8)$$

In Eq. (8),  $d_i$  represent the amount of parameters from  $i^{th}$  iteration. Once the sardine was hunted, the fitness is better than sailfish. In this case, the sailfish place  $Y_{SF}^i$  has upgraded with newest place for hunted sardine  $Y_S^i$  to promote the hunted of newest sardine and it can be expressed in the following:

$$Y_{SF}^i = Y_S^i \text{ if } f(S_i) < f(SF_i). \quad (9)$$

**Algorithm 1:** Pseudocode for the SFO algorithm

Initialized the population of sardine and sailfish arbitrarily

Initialized parameters ( $A = 4, \varepsilon = 0.001$ ) .

Calculated the fitness of sardines and sailfish.

Identify the optimal sardine and sailfish and assume that they are as elite sailfish and injured sardine correspondingly.

While the termination conditions are not satisfied

for all sailfishes

Compute  $\lambda_i$ .

Upgrade the sailfish position.

end for

Compute AttackPower.

If AttackPower < 0.5

Compute  $\alpha$ .

Compute  $\beta$ .

Choose a set of sardine base on the value of  $\alpha$  and  $\beta$

Upgrade the location of selective sardine.

else

Upgrade the location of each sardine.

end if

Compute the fitness of all sardine

```

If there is a better solution in sardine population
Replaced a sailfish with injured Sardine.
Removed the hunted sardine from population
Upgraded the optimal sardine and optimal sailfish
end if
end while
Return best sailfish

```

### 3.3. Image Classification

To classify nutrient deficiencies, the XGBoost model is used. The XGBoost architecture used adaptive training technique for objective function optimization [20]. Without doubt, each step in the optimization technique relies on the preceding step. The objective function of XGBoost model can be mathematically expressed as follows:

$$F_0^i = \sum_{k=1}^n l(y_k, \hat{y}_k^{i-1} + f_i(\chi_k)) + R(f_i) + C, \quad (10)$$

In Eq. (10),  $l$  represents the  $t$ -th iteration loss term,  $C$  denotes the constant term, and  $R$  is the regularization parameter of the model defined in the following:

$$R(f_i) = \gamma T_i + \frac{\lambda}{2} \sum_{j=1}^T w_j^2 \quad (11)$$

Now, the simplicity of tree structure is proportional to the values of  $\gamma$  and  $\lambda$  customization parameters. The large value of parameter is, the simple the tree structure. The 1<sup>st</sup> and 2<sup>nd</sup> derivatives of the model,  $g$  and  $h$ , correspondingly are shown below:

$$g_j = \partial_{y^{i-1}} l(y_j, \hat{y}_k^{i-1}) \quad (12)$$

$$h_j = \partial_{y_k}^2 l(y_j, \hat{y}_k^{i-1}) \quad (13)$$

The subsequent equation is used for obtaining the solution:

$$w_j^* = -\frac{\sum g_t}{\sum h_t + \lambda} \quad (14)$$

$$F_0^* = -\frac{1}{2} \sum_{j=1}^T \frac{(\sum g)^2}{\sum h + \lambda} + \gamma T, \quad (15)$$

From the above equations,  $F_0^*$  denotes the loss function score, and  $w_j^*$  represents the solution weight.

## 4. Results and Discussion

In this study, the rice plant nutrient deficiency recognition of the SFODL-NDD model is elaborated on Kaggle dataset [21]. The dataset comprises 1156 samples with three classes as shown in Table 1. Fig. 3 demonstrates the sample images.

Table 1 Details of dataset

Kaggle Deficiency Rice Dataset	
Class	No. of Images
N	440
P	333
K	383
<b>Total Number of Images</b>	<b>1156</b>

Fig. 3. Sample Images



Fig. 4 portray the classifier results of the SFODL-NDD method under test dataset. Fig. 4a shows the confusion matrix offered by the SFODL-NDD approach on 70% of TR database. The figure signified that the SFODL-NDD

method has identified 301 instances under class N, 199 instances under class P, and 262 instances under class K. Similarly, Fig. 4b represents the confusion matrix offered by the SFODL-NDD approach on 30% of TS database. The figure denoted that the SFODL-NDD approach has identified 119 instances under class N, 95 instances under class P, and 115 instances under class K. Also, Fig. 4c demonstrates the PR analysis of the SFODL-NDD method. The figures reported that the SFODL-NDD model has gained maximum PR performance under all classes. At last, Fig. 4d exemplifies the ROC investigation of the SFODL-NDD approach. The figure represented that the SFODL-NDD technique has proficient results with maximal ROC values in different class labels.

Fig. 4. Classifier outcome of SFODL-NDD approach (a-b) 70:30 of TR/TS data, (c) PR curve (d) ROC

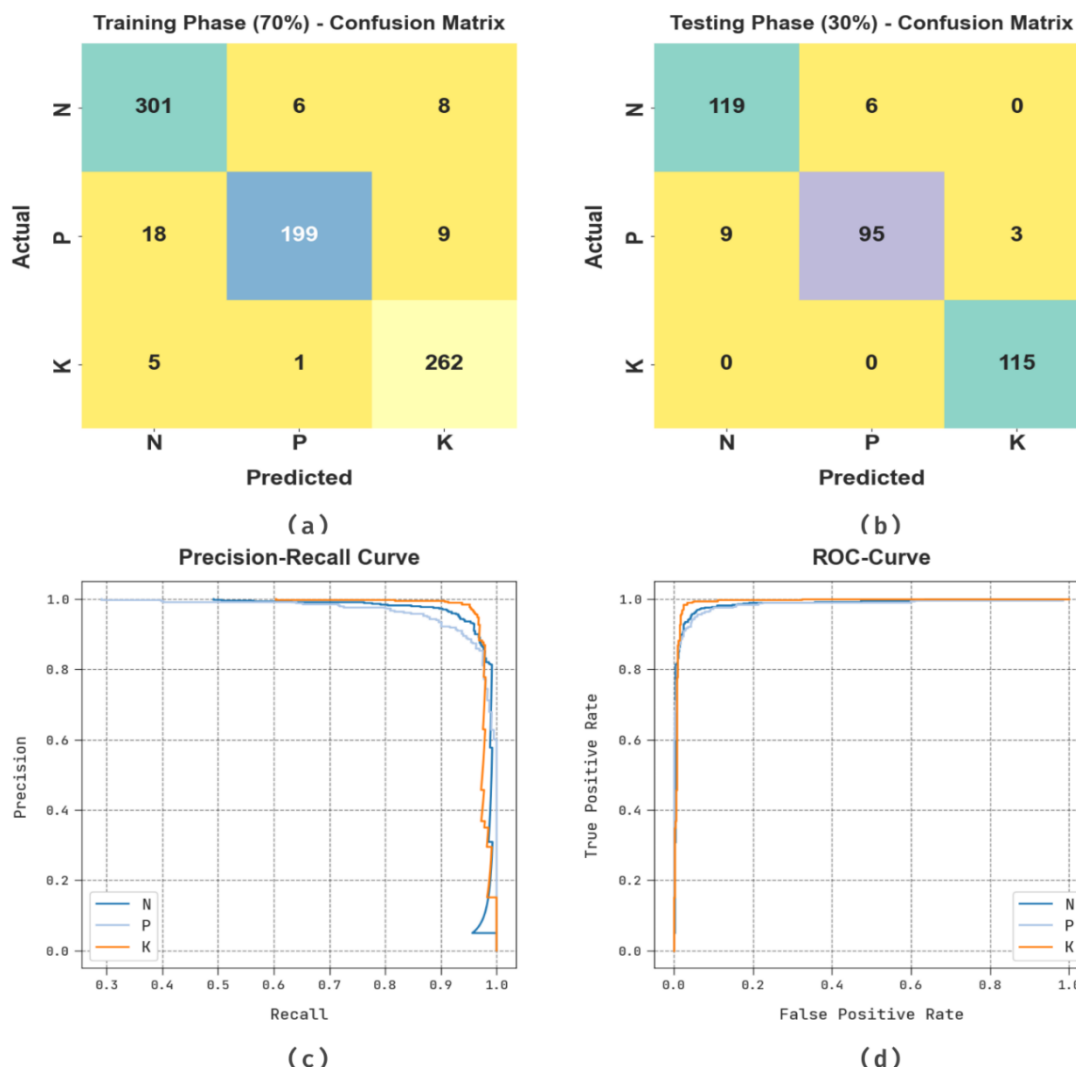


Table 2 exhibits the overall nutrient deficiency classification results of the SFODL-NDD method on 70:30 of TR/TS data. Fig. 5 examines the performance of the SFODL-NDD model on nutrient deficiency recognition on 70% of TR data. The SFODL-NDD model has effectually recognized the N, P, and K samples proficiently. For instance, with N class, the SFODL-NDD model has obtained  $accu_y$  of 95.43%,  $prec_n$  of 92.90%,  $reca_l$  of 95.56%,  $F_{score}$  of 94.21%, and MCC of 90.46%. Likewise, with P class, the SFODL-NDD technique has gained  $accu_y$  of 95.80%,  $prec_n$  of 96.60%,  $reca_l$  of 88.05%,  $F_{score}$  of 92.13%, and MCC of 89.45%. Similarly, with N class, the SFODL-NDD approach has attained  $accu_y$  of 97.16%,  $prec_n$  of 93.91%,  $reca_l$  of 97.76%,  $F_{score}$  of 95.80%, and MCC of 93.69%.

Table 2 Nutrient deficiency outcome of SFODL-NDD approach on 70:30 of TR/TS databases

Class	Accuracy	Precision	Recall	F-Score	MCC
<b>Training Phase (70%)</b>					
N	95.43	92.90	95.56	94.21	90.46
P	95.80	96.60	88.05	92.13	89.45
K	97.16	93.91	97.76	95.80	93.69
<b>Average</b>	<b>96.13</b>	<b>94.47</b>	<b>93.79</b>	<b>94.04</b>	<b>91.20</b>
<b>Testing Phase (30%)</b>					
N	95.43	92.90	95.56	94.21	90.46
P	95.80	96.60	88.05	92.13	89.45
K	97.16	93.91	97.76	95.80	93.69
<b>Average</b>	<b>96.13</b>	<b>94.47</b>	<b>93.79</b>	<b>94.04</b>	<b>91.20</b>

Fig. 5. Nutrient deficiency outcome of SFODL-NDD approach on 70% of TR database

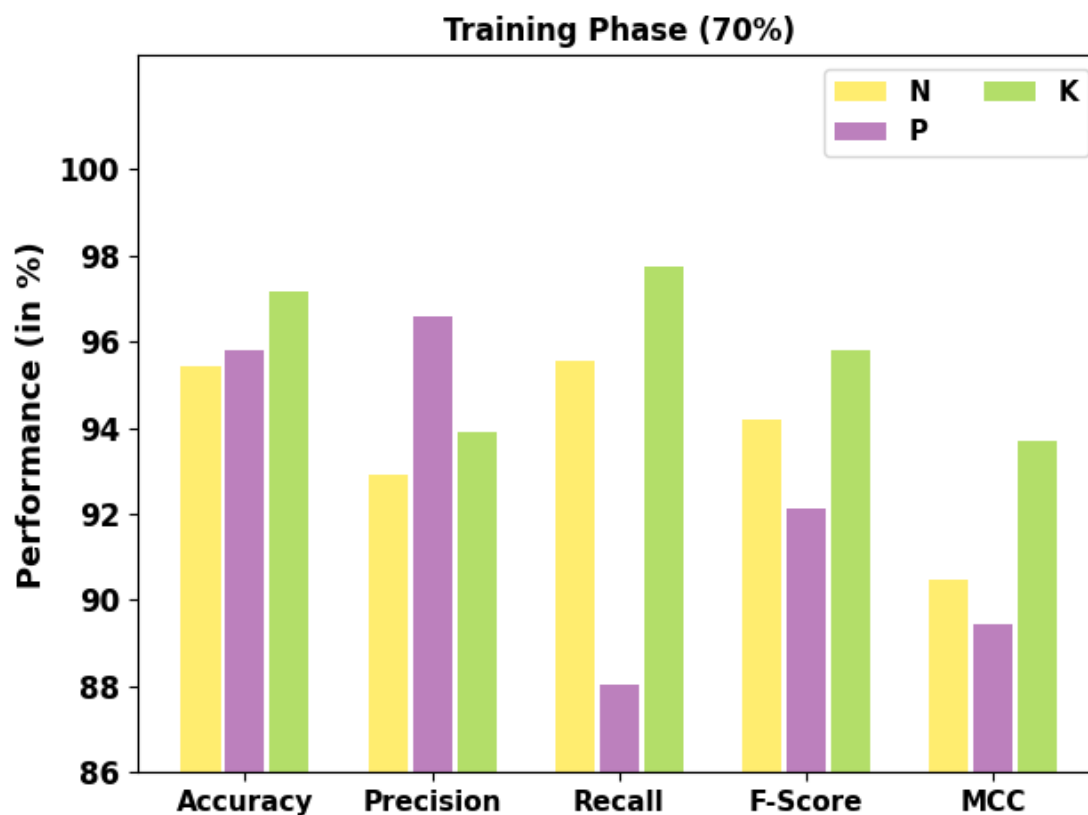
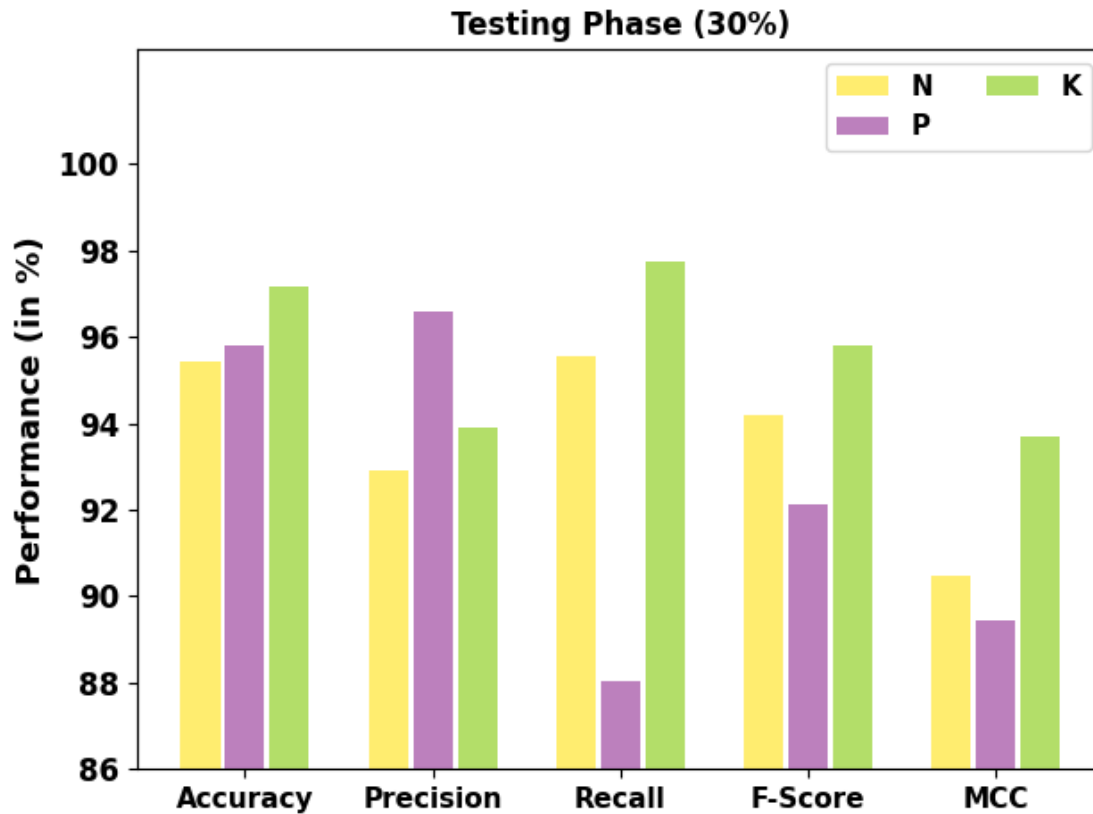


Fig. 6 examines the performance of the SFODL-NDD algorithm on nutrient deficiency recognition in 30% of TS data. The SFODL-NDD technique has effectually recognized the N, P, and K samples proficiently. For example, with N class, the SFODL-NDD approach has obtained  $accu_y$  of 95.43%,  $prec_n$  of 92.90%,  $reca_l$  of 95.56%,

$F_{score}$  of 94.21%, and MCC of 90.46%. Likewise, with P class, the SFODL-NDD approach has attained  $accu_y$  of 95.80%,  $prec_n$  of 96.60%,  $reca_l$  of 88.05%,  $F_{score}$  of 92.13%, and MCC of 89.45%. Similarly, with N class, the SFODL-NDD technique has gained  $accu_y$  of 97.16%,  $prec_n$  of 93.91%,  $reca_l$  of 97.76%,  $F_{score}$  of 95.80%, and MCC of 93.69%.

Fig. 6. Nutrient deficiency outcome of SFODL-NDD approach on 30% of TS database



The TACC and VACC of the SFODL-NDD method are investigated on nutrient deficiency performance in Fig. 7. The figure implied that the SFODL-NDD method has shown improved performance with increased values of TACC and VACC. Notably, the SFODL-NDD method has reached maximum TACC outcomes.

The TLS and VLS of the SFODL-NDD technique are tested on nutrient deficiency performance in Fig. 8. The figure inferred that the SFODL-NDD method has revealed better performance with least values of TLS and VLS. Seemingly, the SFODL-NDD approach has resulted in reduced VLS outcomes.

Fig. 7. TACC and VACC analysis of SFODL-NDD approach

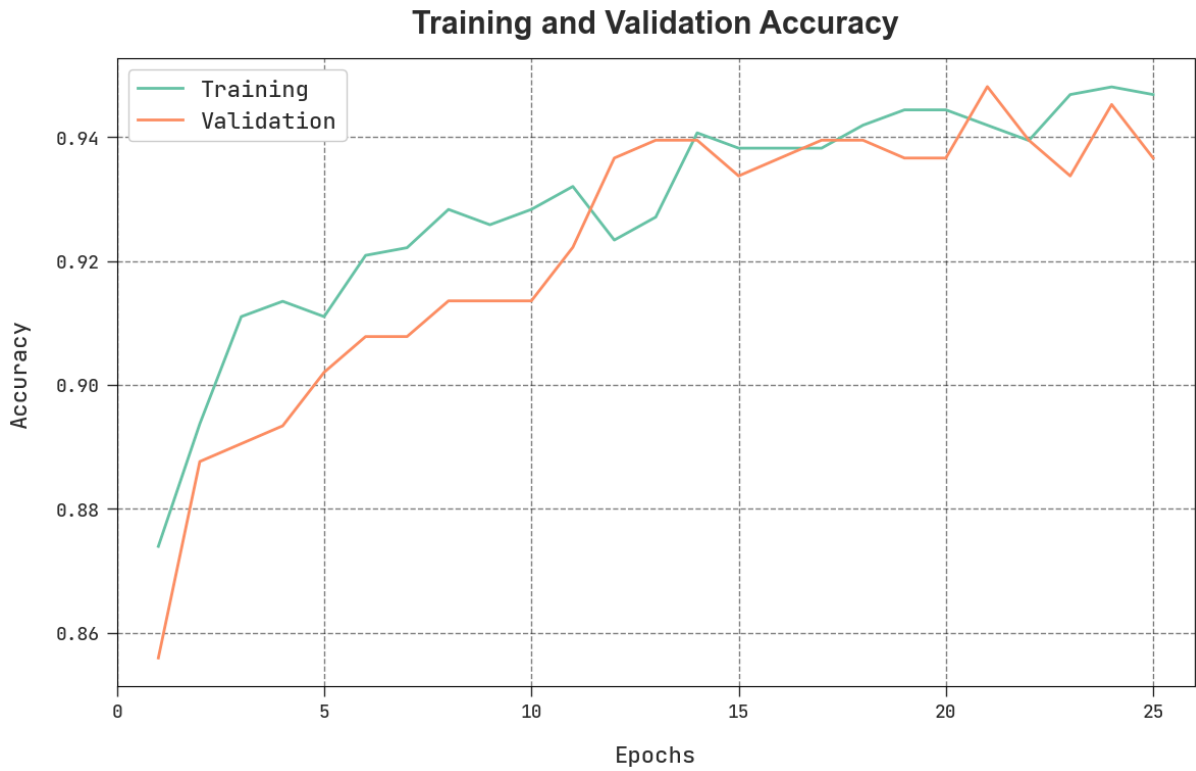
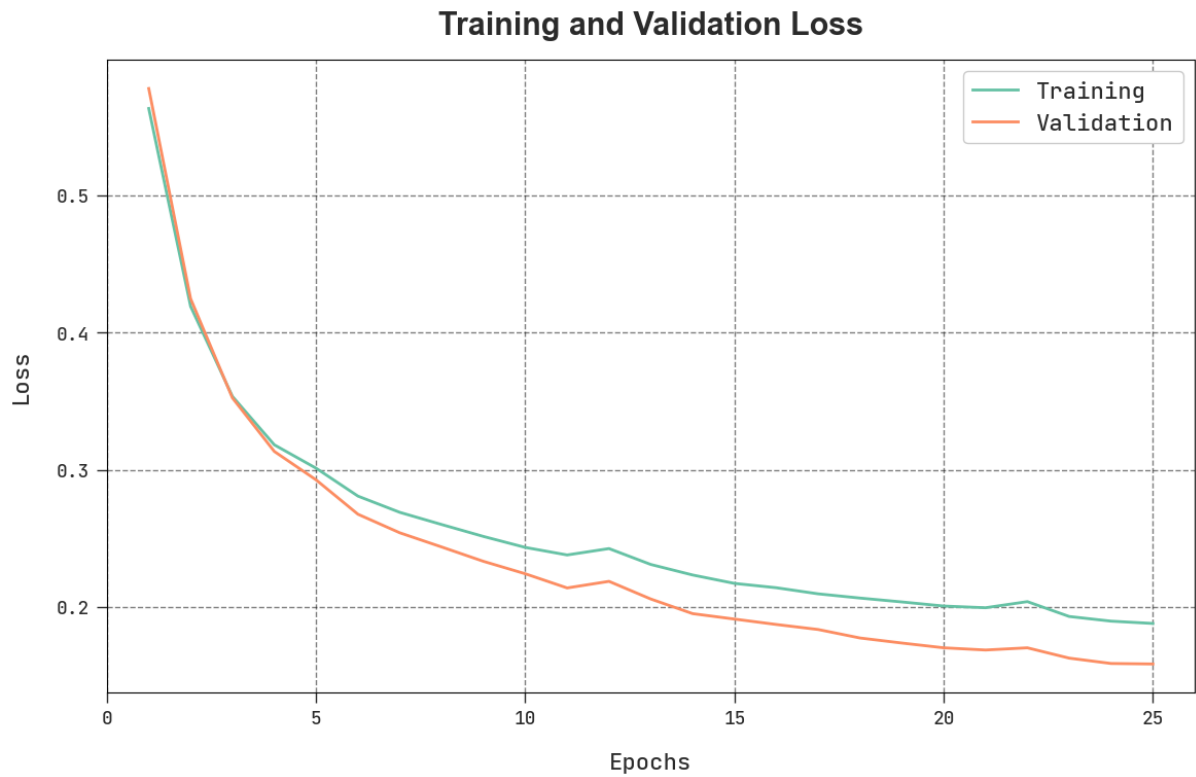


Fig. 8. TLS and VLS analysis of SFODL-NDD approach



To demonstrate improved performance of the SFODL-NDD model on plant nutrient detection, a detailed comparative analysis is made in Table 3 [11]. Fig. 9 inspects the results of the SFODL-NDD model with other DL models in terms of  $accu_y$ . The results indicated that the SFODL-NDD model has reached enhanced results over

existing DL models. Based on  $accu_y$ , the SFODL-NDD model has reached higher  $accu_y$  of 96.13% while the Inception v3 model has obtained least  $accu_y$  of 50.78%.

Table 3 Comparative analysis of SFODL-NDD approach with other DL techniques

Methods	Accuracy	Precision	Recall	F1-Score
SFODL-NDD	96.13	94.47	93.79	94.04
InceptionResNet-V2	89.89	89.51	89.25	89.92
Xception	78.60	79.14	79.02	80.76
DenseNet201	83.38	75.89	83.19	87.45
VGG19	79.29	79.99	79.39	81.25
InceptionV3	50.78	50.26	42.16	56.00
ResNet152-V2	83.56	83.24	83.69	83.33

Fig. 9.  $Accu_y$  analysis of SFODL-NDD approach with other DL techniques

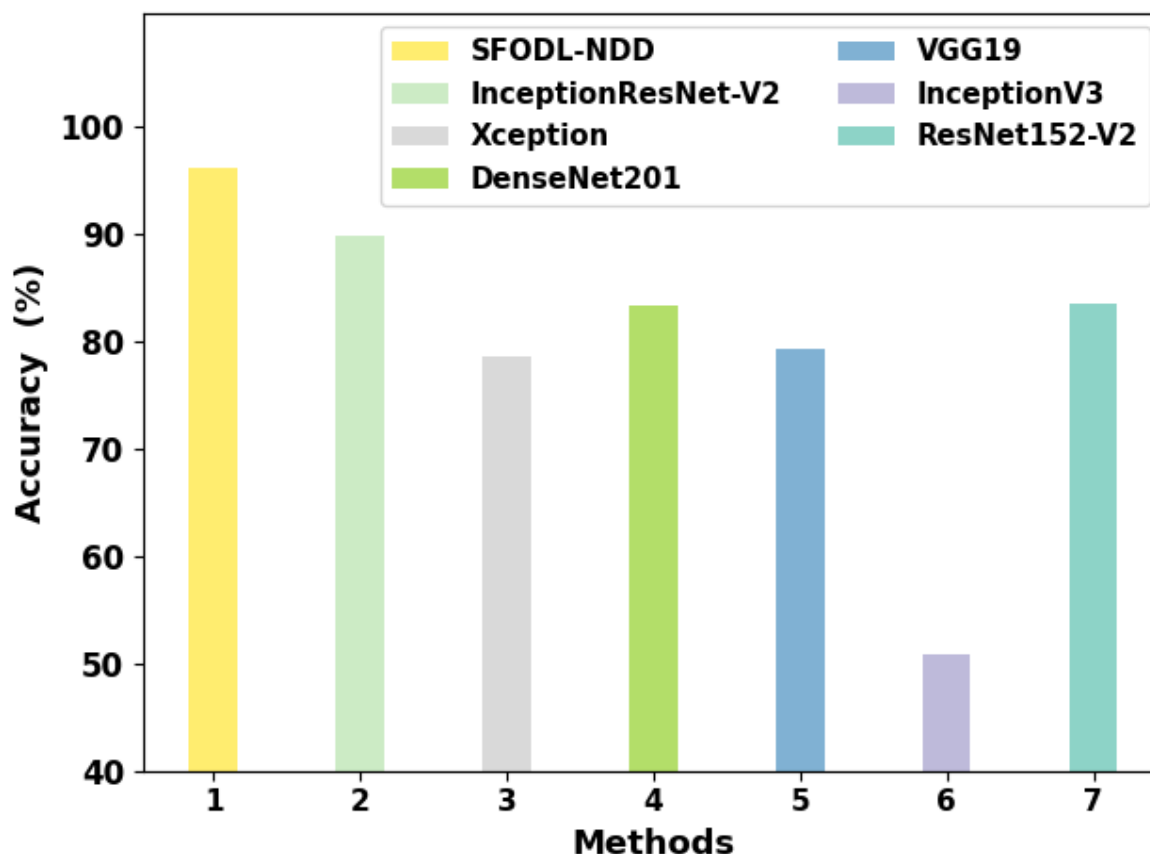
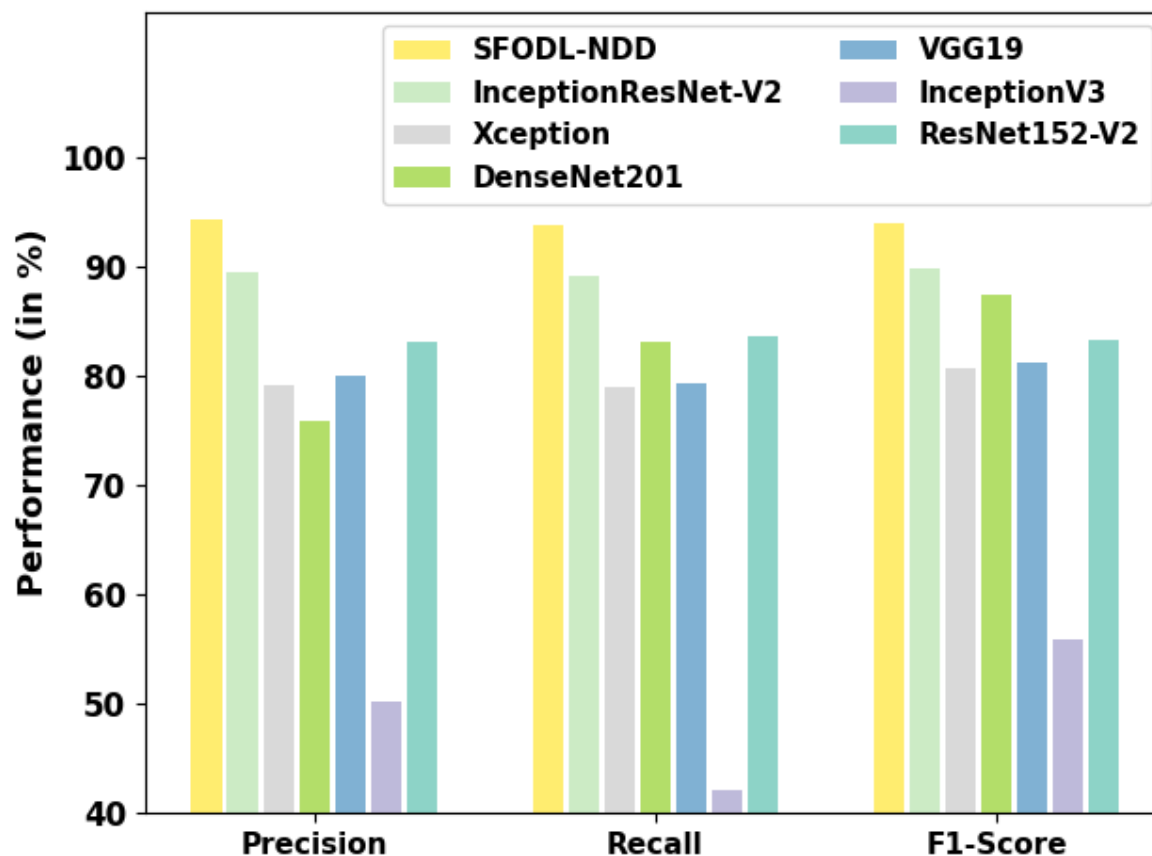


Fig. 10 reviews the results of the SFODL-NDD technique with other DL models in terms of  $prec_n$ ,  $reca_l$ , and  $F1_{score}$ . The results specified that the SFODL-NDD method has reached enhanced results over existing DL approaches. Based on  $prec_n$ , the SFODL-NDD algorithm has reached higher  $prec_n$  of 94.47% while the

Inception v3 method has reached least  $prec_n$  of 50.26%. Likewise, based on  $reca_l$ , the SFODL-NDD technique has reached higher  $reca_l$  of 93.79% while the Inception v3 approach has gained least  $reca_l$  of 42.16%. Last, based on  $F1_{score}$ , the SFODL-NDD method has reached higher  $F1_{score}$  of 94.04% while the Inception v3 approach has gained least  $F1_{score}$  of 56%.

Fig. 10.  $Prec_n$ ,  $Reca_l$ , and  $F1_{score}$  analysis of SFODL-NDD technique with other DL approaches



These results demonstrated that the SFODL-NDD model gained maximum nutrient classification performance.

## 5. Conclusion

In this study, we have presented a new SFODL-NDD method for the identification of nutrient deficiencies in rice plants. The presented SFODL-NDD technique focuses on the identification of nutrients using DL and computer vision approaches. Initially, the SFODL-NDD technique employed the MF approach for noise elimination process. Next, the SFODL-NDD technique uses Xception model for feature extraction with SFO algorithm as hyperparameter optimizer. At last, the nutrient deficiencies can be recognized by XGBoost classifier. The experimental evaluation of the SFODL-NDD technique is tested using rice plant dataset from Kaggle repository. The experimental outcomes stated the better performance of the SFODL-NDD approach over other methods in terms of different measures. In future, the efficiency of the SFODL-NDD technique can be improvised by advanced DL classifiers.

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