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TOWARDS SMART AGRICULTURE: AN OPTIMAL ENSEMBLE DEEP LEARNING SCHEME FOR BANANA LEAF NUTRIENT DEFICIENCY IDENTIFICATION

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ABSTRACT

Crop's Nutrition is highly essential for health conditions at the time of its growth phase and yield. The lack or shortage of needed nutrients is regraded one such crucial factor that impacts overall yield of crop. A novel approach for automated recognition and classification of banana leaf nutrition deficiency is presented using Ensemble Deep Learning approach. Initially, the input images are pre-processed, filtered and augmented. It is then segmented using Improved TGV-FCM (Total generalized variation-Fuzzy C-Means) scheme. From the segmented image, the features are extracted using Residual GCN (graph convolution network) followed by selection of suitable optimal features through Enriched Glow swarm (EGSO) optimization approach. Ranking based Ensemble MobileNet v2 and LeNet classifier model is used for classification for diagnosing nutrition deficiency in banana leaf. The validation of proposed model is estimated and are compared with traditional models in terms of various metrics to exemplify the efficacy of presented model.

Keywords: *Banana crop, Nutrition Deficiency Detection, Deep Learning, Residual Graph Convolution Network, Enriched Glow Swarm Optimization, Ranking based Ensemble MobileNet v2 and LeNet classifier*

1. INTRODUCTION

In recent days, agriculture undergoes several changes for creating huge sustainable environment and for supplying population demand [1]. A crop under several environmental conditions will be subjected to varied kinds of biotic and abiotic stress that affects the output of overall production and losses at the time of its life cycle [2-4]. The automation techniques like precision agriculture aids farmers and experts in strengthening and monitoring production of agriculture. Among these stresses, the deficiency of nutrient plays a dynamic factor that the critical growth constraining factors affects some visible qualities of plant that might decrease the yield of agriculture significantly. Typically, crops might suffer from deficits on or in nutrient overabundance [4-7], that could hinder the crop growth and reduces output of yield [8]. The food output quality depends on nutrients available in crop at the time of its growth [9-12]. In this research work, banana crop is chosen for detecting its nutrient deficiency over leaf images with the use of computer vision methodology along with Deep Learning models [13-15]. Artificial Intelligence (AI) aids in the recognition of plant illness depending on presence of plant and visual symptoms which imitate the behaviour of human's were considered. Till now, the models to find crop images have been focused typically on leaf symptoms, which will be easier for identification.

1.1 Research Problem/Motivation

The motivation behind this model lies in the objective of contributing the earlier detection of banana leaf diseases with the use of Machine learning & Deep learning models. This work aims at addressing the crucial enquiries like the existence of suggested model for the earlier detection, selection of AI and DL models for the prediction and classification process by enhancing the accuracy rate, practical application for farmers benefit, and need for preprocessing, feature extraction, optimal selection for the classification process. Thus, to overcome the existing issues, the proposed model is presented.

1.2 Objective

The primary objective of this work is to present Ensemble Deep Learning model for the detection and recognition of nutrient deficiency in Banana leaf. This model enhances classification performance and detection accuracy while addressing challenges like reduced accuracy and false predictions. On comparing the suggested scheme with existing literature, the model aims at demonstrating enhancement in scalability, accuracy, and applicability in real-world industry scenarios.

1.3 Paper Structure

A brief description regarding the remaining part of research paper is given as provided: The study was carried on related works in section II based on disease detection and recognition of banana crop and various plants. The proposed methodology study was explained in detail in section III. The proposed model validation and its comparison with existing model is given in section IV. The research study was concluded in section V.

2. RELATED WORKS

A concise review on various existing methodologies related to the detection and recognition of nutrition deficiency in Banana leaf plant is provided here.

The author presented a new model in the work [16] using InceptionV3Dense model based average learning scheme to identify micro-nutrient deficiency in the crops of banana. The suggested ensemble model termed InceptionV3+Dense169 offers better accuracy and F1-score on comparing other models used. In the work, [17] a study was presented which intends at assessing the explainability and performance of those models for facilitating good decision making in the field of agriculture. The three DL schemes were CNN, and 2 pre-trained models like InceptionV3, VGG-16. The author in the work [18] focused on in what way the ML model performs well on smaller datasets of Kaggle having 1156 images. About 3 pre-trained models of CNN like MobileNet, DenseNet169, DenseNet121 along with additional pooling layer dropout layer in bottom were carried on augmented dataset. An ensemble of them in an average outperforms and augments the testing accuracy. This in turn yields ROC_AUC of about 99.62%. A study has been carried in [19] for performing the systematic review on research works which deploys machine learning (ML) approaches in agriculture, that are applicable for banana plant and production of fruit. A robust deep ensemble CNN scheme (DECNN) was suggested in the work [20] which could diagnose the nutrient deficiency of rice crop with better accuracy. A new DL based strategy was suggested in the work [21] to identify the plant nutrient deficiency and classification of disease with the use of graph convolutional network (GCN) along with base CNN. Moreover, GCN was employed for capacitating the learning of fine details so as to classify plant diseases and nutrients insufficiency. In the work [22], review on various ML and DL schemes were employed for classifying varied kinds of leaf diseases like SVM, RF, and multiple twin SVM (MTSVM) which were some known ML schemes to predict leaf diseases, whereas CNN, ResNet, VGG, DenseNet (DNet), Back propagation Neural Network (BPNN), LeNet, and Deep CNN were the common models employed for the leaf disease detection. This work [23] intends at determining the manner for developing mobile apps for the lower end Android phones which employs ML for detecting insufficiency of nitrogen. This model was constructed by utilizing the Tensorflow and Keras library for training Single Shot Detector (SSD) MobileNet scheme. A smart nutrient deficiency prediction system (SNDP) was suggested in the work [24] for detecting and categorizing the range of chlorophyll concentration (CCR) through which the concentration of nitrogen could be known. A study was investigated in the work [25] which investigated interpretability and performance of CNN for this model. By suing banana and rice datasets, three CNN architectures were compared like CNN, VGG-16, and Inception V3. This inception v3 attains enhanced accuracy. A hybrid DL model was suggested in the work [26] that combines SVM and DWT which makes performance accuracy lower. Although SVM was strong this was unusual still for attaining satisfactory level of accuracy. A method of traditional DNN employed for banana leaf disease detection needs more parameters thus utilizing complex architectures. Thus, a new model was developed in the work [27] to address existing issues, by employing GAN modified faster region-based CNN with fuzzy (MGAN-MFRCNN) with fuzzy) to identify banana leaf disease. From this, most accurate scores of classifications were attained on integrating fuzzy model with ensemble scheme.

3. PROPOSED WORK

The detailed narration of suggested scheme's working model is given in this section. The input image dataset is considered and the images are pre-processed with the use of image filtration technique,

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augmentation of filtered image followed by enhancement technique using rescaling, brightness range, zoom range, rotation range, and horizontal flipping.

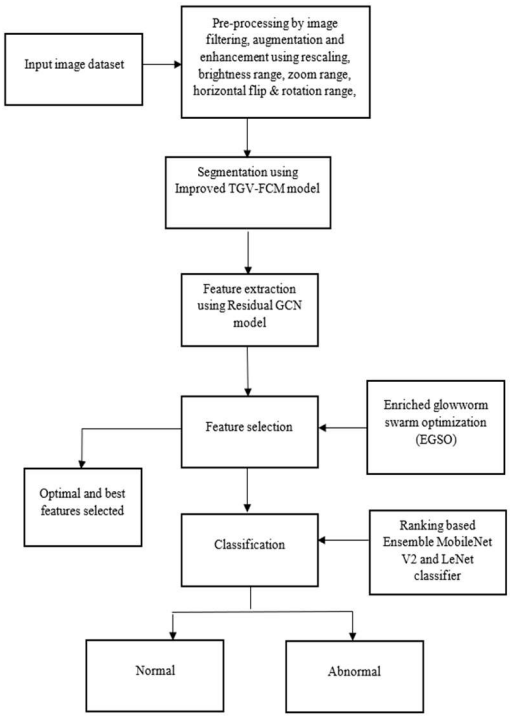

Figure 1: Illustration of Overall Proposed Flow

The pre-processed image is segmented by employing Improved TGV-FCM scheme. The extraction of feature is carried using Residual GCN and optimization is employed for selecting the best optimal range of features. For the optimization process, Enriched Glowworm swarm optimization model is employed. From the best fitness function attained and selected features, the classification process is carried by means of Ranking based Ensemble MobileNet V2 and LeNet classifier model to detect and classify the banana leaf image as normal or abnormal. From the abnormal images, the type of nutrient deficiency is found finally. Figure 1 is the flow of proposed model.

3.1 Image Preprocessing and Augmentation

Primary stage of predicting banana leaf disease is image preprocessing and augmentation at which the considered data are preprocessed, augmented, enhanced by removing noise, artefacts, rescaling, resizing, flipping, rotation, and filtering. The input banana leaf images are acquired usually in RGB color space. The color regarded as a significant feature since color value indicates variations depending on the infection of disease caused in plant. Both HSV & HIS color space models are usually used for the identification of leaf disease since it was equal to the perception of human. At HIS model color, value of color & hue is taken into consideration for manipulation.

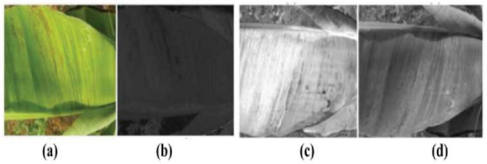

Figure 2: Input and preprocessed image (a) Input image (b) component of Hue (c) Saturation Component (d) HSI model's Intensity Component

Figure 2 is a representation of input image and pre-processed image (hue component, saturation component, HIS model's intensity components). At the time of pre-processing image, it is being altered to offer excess information regarding affected leaf regions. By the better interpretations visually, the information of leaf image is presented efficiently. This model will not alter information of leaf image inherently; however, it changes the desired aspects for localization dynamically, thereby permitting exact localization. Also, the process of filtering & rescaling/resizing is regarded as a typical approach used in the diagnosis of banana leaf disease. The segmentation process is carried next to processing stage and is detailed in next section.

3.2 Improved TGV-FCM segmentation

Once the process of pre-processing is completed, the segmentation process is carried using improved TGV-FCMS. The technique of improved TGV-FCM is more robust to edge preserving and noise. The regularization process of TGV images still desired separation order is beneficial specifically to measure the attributes of images such as edge sharpening and removal of noise. This model is developed for including regularization of TGV at the term of smoothening so as to minimize the undesirable noise & artifacts from the approach based on FCM. Fig. 3 shows the segmented image sample.

Figure 3: segmented image sample

The following expression shows the formulation of TGV framework.

$$TGV_a^k(u) = sup\left\{\int_\Omega udiv^k vdx | v\varepsilon\mathbb{C}_c^k\left(\Omega, sym^k\left(\mathbb{R}^d\right)\right), \|div^l v\|_\infty \leq a_l\right\} \quad (1)$$

In this, l=0,1,…,k-1, and $k \in \mathbb{N}$ specifies the positive weight of TGV. $sym^k\left(\mathbb{R}^d\right)$ denotes the symmetric k-tensors space. Intended for every component, $\eta\varepsilon M_{k-1}$, l-divergence of k-tensor field symmetric will be assumed by:

$$(div^l v)_\eta = \sum_{r\varepsilon M_1} \frac{l!}{\gamma!} \frac{\partial^l v_{\eta+\gamma}}{\partial x^\gamma} \quad (2)$$

Mk denotes the multi-index of k order provided by:

$$M_k = \left\{\eta\varepsilon\mathbb{N}^d | \sum_{i=1}^d \eta_i = k\right\} \quad (3)$$

A $\infty - norm$ for the k-vector symmetric field is provided as:

$$\|v\|_\infty = \sup_{x\varepsilon\Omega}\left\{\left(\sum_{\eta\varepsilon M_k} \frac{k!}{\eta!} v_\eta(x)^2\right)\right\} \quad (4)$$

It is for the reason that first gradient and the gradients of higher order in above equation both are restricted as sparse.

In this, TGV of second order is provided by:

$$TGV_a^2(u) = sup\{\int_\Omega udiv^2 vdx | v\varepsilon\mathbb{C}_c^2(\Omega, S^{d\times d}), \|v\|_\infty \leq a_0, \|div^l v\|_\infty \leq a_1)\} \quad (5)$$

In this, $\mathbb{C}_c^2(\Omega, S^{d\times d})$ denotes the compact vector space that are maintained over symmetric matrices set $S^{d\times d}$. The computation of divergence & norms could be signified as:

$$(divv)_i = \sum_{j=1}^d \frac{\partial v_{ij}}{\partial x_j}, (div^2 v)_i = \sum_{j=1}^d \frac{\partial^2 v_{ii}}{\partial x_i^2} + 2\sum_{i<j} \frac{\partial v_{ij}}{\partial x_j \partial x_j} \quad (6)$$

and

$$\|v\|_\infty = \sup_{x\varepsilon\Omega}\left(\sum_{i=1}^d |v_{ii}(x)|^2 + 2\sum_{i<j} |v_{ii}(x)|^2\right)^{1/2} \quad (7)$$

$$\|divv\|_\infty = \sup_{x\varepsilon} \left(\sum_{i=1}^d |\sum_j^d \frac{\partial^2 v_{ii}}{\partial x_j^2}(x)|^2\right)^{1/2} \quad (8)$$

A least solution will be reserved over entire fields of vector on Ω and $\varepsilon(v) = (\nabla v + \nabla u^T)/2$ will be derivative symmetrically., The above equation denotes that the smoother regions are likely more to be created with 2 than by 1, once 2 is added to smoother regions. In case, v=0, then the minimization could be attained at neighbor edges at which 2u is higher than u. Hence, the positive weight ratio $\alpha_0 and\ \alpha_1$ might be employed for attaining balance over first and second order derivatives. Those weights are set as 0.10 and 0.15 correspondingly for the practical cause. A suggested segmentation model is capable of offering outcomes that are robust to noise highly and preserving details over the second-order TGV definition. The feature extraction process is carried after segmentation model.

3.3 Residual GCN for Feature extraction

Once the banana leaf images are segmented, the features from the segmented region are extracted so as to make prediction process successful. For this reason, Residual GCN based feature extraction model is employed. Typically, GCN approach is employed most widely in various fields and applications like edge attribute modelling, node classification, knowledge graph, citation network and so on. In this, it is employed for feature extraction of banana leaf images. This residual GCN is formulated using stacked multiple graph convolutional layers having non-linearity over existing convolutional layers that is CNN. Specifically, this type of GCN stacks in the deeper layer of image thus improves the capacity of model learning. This linear formulation of GCN makes process simpler which is competent of optimizing the parameters of each layer through convolution with parameter θ and filter g_θ, that could optimize single parameter further. In this, simplified residual GCN model will be defined as shown:

$$g_\theta * X \approx \theta(I_P + D^{-0.5}AD^{-0.5})X \quad (9)$$

A graph Laplacian (Ψ) might further be normalized for mitigating vanishing gradients of image.

$$\Psi = I_P + D^{-0.5}AD^{-0.5} \rightarrow \tilde{D}^{-0.5}\tilde{A}\tilde{D}^{-0.5} \quad (10)$$

In this, the binary adjacency matrix $\tilde{A} = A + I_P$ signifies A having self-connections, whereas I_P having the identity matrix with degree matrix $\tilde{D}_{ii} =$

$\sum_j \tilde{A}_{ij}$ & X denotes input image of graph. A simpler convoluted matrix of signal Ω is provided by:

$$\Omega = \tilde{D}^{-0.5}\tilde{A}\tilde{D}^{-0.5}X\Theta \quad (11)$$

At which, input features $X\epsilon\mathbb{R}^{C\times F}$, the parameters of filter $\Theta \in \mathbb{R}^{P\times F}$ denotes signal matrix that are convoluted. In this, number of nodes P, input channel is C, and feature map or filter signified by F. At this stage of graph convolution, the above equation is employed for addressing the present issue of extracting feature. Thus, the feature extraction process is carried efficiently by means of this residual GCN model. The best features among these extracted ones are selected by means of employing optimization-based selection module which is given in detail in subsequent section.

3.4 Enriched Glowworm swarm optimization to Select Optimal Features

For selecting best optimal features, Enriched Glowworm swarm optimization model is employed. So as to optimize the GSO hyperparameters, the glowworms collection stage is initialized and distributed arbitrarily from solution space in such a way which is effectual. The mitted light intensity will be linked to luciferin amount which is integrated closely over it, at which the glowworms will be located from their motion and thus having range of dynamic decision $r_d^i(t)$ which is limited by range of spherical sensor $rs(0 < r_d^i \leq= r_s^i)$. At first, glowworm consists of similar luciferin count l_0. Depending on the luciferin values resemblance, glowworm i thus chooses its adjacent one's j having probability p_{ij} and thus shifts from decision range direction $rs(0 < r_d^i \leq= r_s^i)$, however, the glowworm position i is signified as $xi(xi \in Rm, i = 1,2,\dots,n)$.

The stage of luciferin is updated which is affected by values of function in the place of glowworm. At the stage of luciferin upgrade, principle is expressed as:

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma J(x_i(x+1)) \quad (12)$$

In this, $l_i(t)$ signifies the values of luciferin that are connected to glowworm i in time t, the luciferin decay is represented by ρ constant $0 < \rho < 1, \gamma$ signifies constant of luciferin improvement, and $J(x_i(t)$ denotes the main function values at i agent place in time t.

Together with the involved process in the technique of GSO, glowworm will be fascinated with their neighbors which glow brightly. Therefore, at the time of movement stage of glowworm, the glowworms thereby make utilize the probabilistic process to move over neighbor which has higher intensity of luciferin. In such a case of each glowworm i, possibility of neighbor glowworm moving is signified by:

$$p_{ij}(t) = \frac{l_j(t)-l_j(t)}{\sum_{k\epsilon N_i(t) l_k(t)-l_i(t)}} \quad (13)$$

In this, $j \in N_i(t)$, $N_i(t) = \{j: d_{ij}(t) < r_d^i(t), l_i(t), l_i(t) < l_j(t)\}$ signifies the collection of closer glowworms i in time t, $d_{ij}(t)$ signifies the Euclidean distance between the glowworm i and j at time t, $r_d^i(t)$ signifies the range of neighbor variable that are related to i glowworm at t time. The restricted variable with range of radial sensor $(0 < r_d^i < rs)$.

$$x_i(t+1) = x_i(t) + s\left[\frac{x_j(t)-x_i(t)}{||x_j(t)-x_i(t)||}\right] \quad (14)$$

In this, $s(> 0)$ signifies step sizes, and $\| \|$ denotes the operator of Euclidian norm. However, $x_i(t) \in R^m$ signifies the glowworm place i in time t from m dimensional real space R^m. Then, consider r_0 as initialized ranges of neighborhood of entire glowworms that is $r_d^i(0) = r_0, \forall i$.

$$r_d^i(t+1) = \min\left\{r_s, max\{0, r_d^i(t) + \beta(n_r - |N_i(t)|\}\right\} \quad (15)$$

In this, β denotes constant, and parameter used for degree control is signified by n_r. By this, an optimal range of features are selected and the classification process is carried further which is explained in detail subsequently.

3.5 Ranking based Ensemble MobileNet V2 & LeNet classifier

The classification technique is carried by means of employing MobileNet v2 structure which consists of convolutional layers at which every one of them are followed by the batch normalization layer and ReLU6 non-activation layer function without including output layer. Typically, MobileNet V2 blocks are built usually with residual connection that helps in converging network weight. This depth wise utilization detachable convolutions 3x3 with

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modification of resolutions over layers that implies on decreasing the computation complexity that corresponds to the standardized form of convolutions instead of small decrease in accuracy.

An input chosen will thus be exploited for the diseased leaf image classification and is employed for estimating the LeNet model. Typically, probability equation is employed to plot abnormality function. The abnormal data values are computed once the prior likelihood function is identified. By following this, abnormal signal values are estimated.

$$Abn\ valueof\ image\ =\ min_{j=1}^{N} OS_{*}^{j} \quad (16)$$

As soon as abnormal image is estimated, image affected by disease are classified. The classifier model employed covers the coevolutionary layers to train input image. This layer is accountable to eradicate the low-level features that is kernels. The convolutional operator is invariant, moreover this is invariant to rotation. Another layer of raising is termed likewise as pooling layers that decreases the image size. Essentially, suggested classifier consists of fully connected neural network model. The subsequent steps are the part of training classifier which is reverse and feed propagation. The network error is therefore estimated at step of feed forward by associating variance among network output based on image given and real output of image is thus labeled. An intensity of classifier is thus having substantial effect on suitable prediction, as the depth of classifier rises, classification error is thus reduced. The classification of target is categorized conferring to likelihoods. The residual connection-based scheme of LeNet helps inconsistency over single variable and more than one dissimilar value are restrained. By this, initially recommended ones are read and reallocate the image on employing its class likelihood to measure classifier process.

$$G = \det[N] - k\left(abnormal\ signal\ classify\ (N)\right)^2 \quad (17)$$

In this G denotes feature, N signifies pointed feature,$\lambda_1\lambda_2$ implies classified features. It is then expressed by:

$$\det[N] = \lambda_1\lambda_2\ \ classify(N) = \lambda_1 + \lambda_2 \quad (18)$$

The classification of LeNet scheme is concluded by:

$$G=\lambda_1\lambda_2 - K(\lambda_1 + \lambda_2)^2 \quad (19)$$

In this, K signifies empirical constant. The model of proposed classifier utilizes score dependent functions at which the estimation of score values and predictions are more effectual. The computation of score value is estimated using below equation. The proposed classifier model employs a score-based function.

$$score = \sum_{i=1}^{M}\sum_{j=1}^{N}(A_1(i,j) + A_2(i,j))/2) \quad (20)$$

In this, A denotes score generated by classifier presented. n signifies the class number and M denotes test sets. On employing above equation, new score having size M×N is attained. After that, using newer score values, label of class is thus calculated as per maximum value of each line (M). From this, presented classifier model the classification of normal and abnormal banana leaf is predicted and classified effectively. The performance analysis is done in subsequent section.

4. PERFORMANCE ANALYSIS

The validations of proposed model are carried for testing effectiveness of each specific objective described in this research work. It is presented in the subsequent sections. The details of input dataset are given and the performance of proposed model and its comparison over other existing models [29], [30] are given here.

4.1 Details of Input Dataset

The input dataset (Mendeley dataset) comprises of several categories of banana leaf deficient images which includes Rasthali, Poovan, and Monthan. These are the images of dataset that are captured in various environmental conditions like low illumination, sunlight from different places of India and Karnataka states. The images are stored in .png and .jpg format [28].

Figure 4: samples of nutrient deficient banana leaf image input data

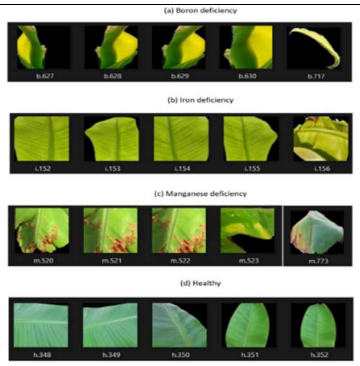

Figure 5: Nutrient deficient images from Mendeley dataset

A total of about 3450 images is chosen from the dataset, among them 800 are Boron deficient ones, 860 are Iron deficient, 840 are Manganese deficient and 950 of them are healthy. Fig. 4 is the samples of nutrient deficient banana leaf images input image and Fig. 5 is the nutrient deficient images from the Mendeley dataset.

Table 1: Training, validation, and testing data

Data	Number of images	Batch size
Training data	3200	16
Testing data	305	1
Validation data	800	16

In the input dataset, the images are having a resolution of size 256×256. The disk size is 52.9 MB. In this work, the dataset selected is splitted as training 80% and validation 20%. Around 305 model images unseen real time images and about 5% from validation images were employed for testing the performance of model as represented in table 1.

4.2 Performance Comparison of Proposed Scheme

The performance estimation of proposed ensemble classifier model with the use of segmentation model is analyzed and the outcomes are projected below. From fig. 6, it is apparent that the proposed model with ITGV-FCM segmentation attains specificity rate of 98.97%, sensitivity rate of 97.84%, and accuracy of 99.76%. The attained level is higher than the existing models like FCM segmentation with preprocessing and CNN with TGVFCM model. The sensitivity, specificity, and accuracy rate increase gradually (nearly 15%-19%) once the proposed classifier is trained with the technique of Improved TGV-FCM with ranking based ensemble classifier. This shows that the ensemble model of classifier with improved segmentation approach attains better performance than existing models [29].

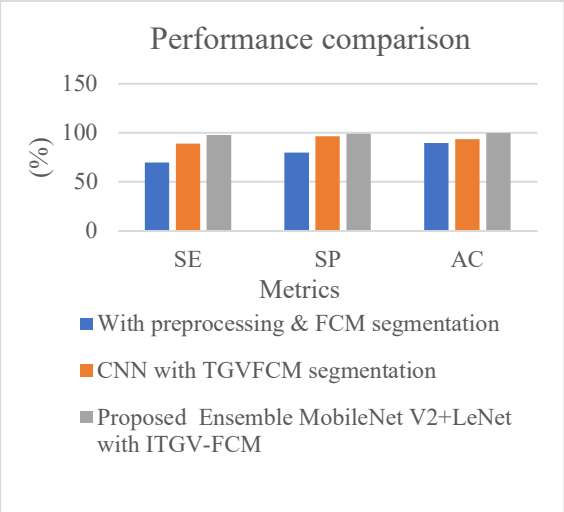

Figure 6: Proposed model's performance with Ensemble classifier and segmentation

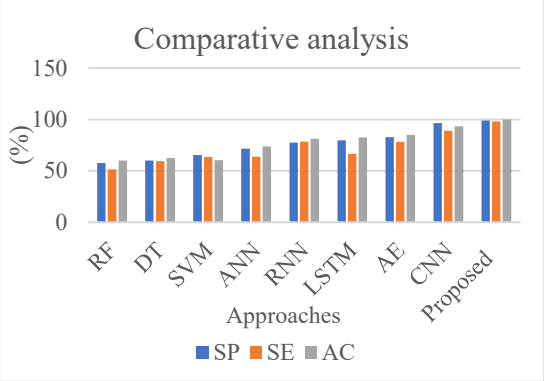

Figure 7: Evaluation of performance for proposed Ranking based Ensemble classifier

Figure 7 is the graphical illustration of proposed model in terms of accuracy. In this, the traditional models like RF, DT, LSTM, ANN, AE, SVM, and CNN are compared with proposed ranking based ensemble MobileNet V2+LeNet classifier model. The techniques KNN, ANN, and SVM attains 63% of SE, 65-70% of SP, and 71% of accuracy nearly. The CNN attains somewhat increased performance than other models like AE. However, the performance of proposed model ensemble MobileNet V2+LeNet classifier offers specificity rate of 98.97%, sensitivity rate of 97.84%, and accuracy of 99.76% which is higher than all other existing models compared. It is because the proposed model is trained with improved

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segmentation, residual GCN based feature extraction, and optimal selection of features which enhances the overall performance on comparing other techniques compared.

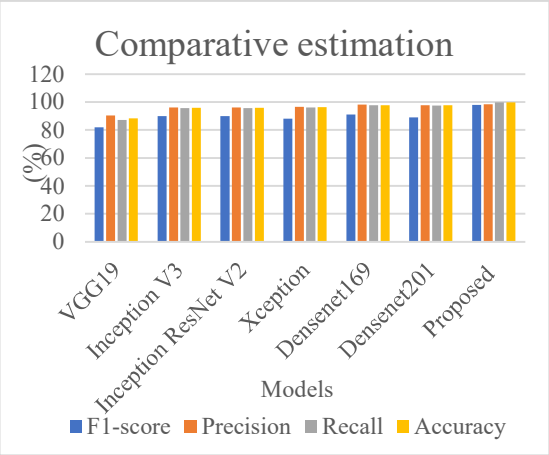

Figure 8: Overall Performance Comparison

Figure 8 is the representation of overall performance of proposed ranking based classifier model with various existing models. The performance is given in terms of average training time, number of epochs, precision, recall, and accuracy. It is clear from the table that the proposed model attains enhanced performance for entire metrics on comparing other traditional schemes [30]. Table 2 denotes the prediction performance made with test images in terms of true and false predictions. the true prediction for proposed model is 97.87% and it is 2.13% for false predictions.

Table 2: performance of prediction with test images

Methods	True predictions (%)	False Predictions (%)
VGG19	82.30	17.70
Inception V3	90.16	9.84
Inception ResNet V2	90.16	9.84
Xception	87.54	12.46
Densenet169	91.15	8.85
Densenet201	89.84	10.16
Proposed Ensemble MobileNet V2+LeNet	97.87	2.13

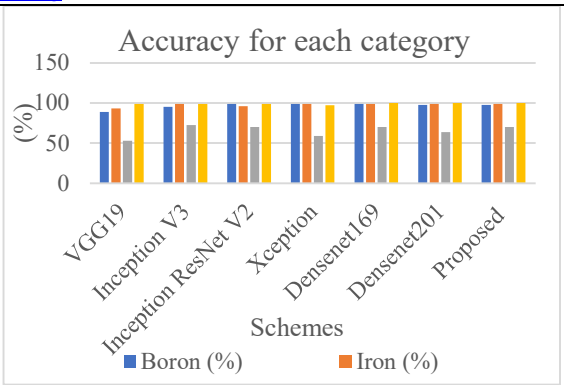

Figure 9: Performance of accuracy for each category

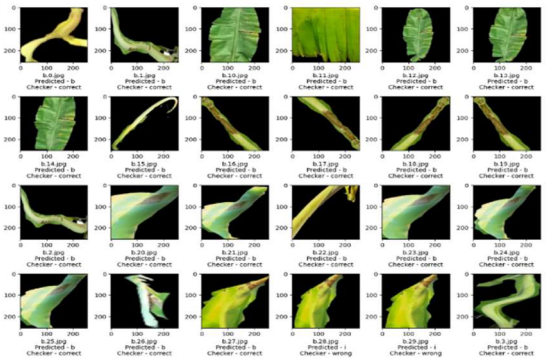

Figure 10: Predicted outcome sample

Figure 9 is the graphical representation of accuracy performance for each category of nutrient deficiency of banana leaf like Boron, iron, manganese, and healthy. The prediction is made for proposed model with various existing models [30] like VGG19, Inception V3, Inception ResNet V2, Xception, DenseNet169, and DenseNet201. The prediction accuracy for each category class is enhanced for proposed scheme on comparing other existing approaches.

Figure 10 shows the predicted outcome samples. the classified outcome from the proposed model representing the category of nutrient deficiency in banana leaf is shown. On reviewing the above outcomes attained, it is obvious that the proposed model provides enhanced and augmented results on comparing other traditional approaches taken for comparison. Thus, the proposed model is effective and is validated over other methodologies.

4.3 Practical Implications

The suggested scheme offers significant benefits for the real-world applications. Their scalability and efficiency make them suitable for real-time industry scenario like smart manufacturing, healthcare imaging, and AI-driven automation. On enhancing

the robustness and reducing computational overhead on comparing traditional methods, the model supports cost-effective and sustainable deployment in present industrial systems.

5. CONCLUSION

In this paper, an automated optimal DL based framework was employed for predicting nutrient deficiency in banana leaf images. An input images are pre-processed and were segmented using Improved TGV-FCM scheme. The extraction of feature was made by Residual GCN. An Enriched Glowworm swarm optimization model was employed for optimization purpose. The classification process was carried using Ranking based Ensemble MobileNet V2 and LeNet classifier model for detecting and classifying the banana leaf image as normal or abnormal. From the abnormal images, the type of nutrient deficiency like Boron, Manganese, and Iron deficient categories are predicted finally. The validation of performance was carried on Mendaley dataset. The performance was estimated for various metrics like sensitivity, specificity, F1-score, accuracy, precision, recall, true prediction, and false prediction rate. From attained outcomes, it was clear that the proposed model gives enhanced rate of performance than existing models compared. This study successfully attained its objective by demonstrating that the suggested scheme enhances accuracy, efficiency, and robustness on comparing traditional models. The outcome validates its practical applicability in real-time industry contexts like smart manufacturing. While minor limitation like high computational resource, and overfitting were observed, the overall findings confirm the contribution of model in advancing effective and reliable solutions, consistent with objectives outlined in introduction. In future, this work will be extended by employing enhanced approaches for classifying both micro and macro nutrient deficiencies of banana crop on varied datasets.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Both authors contributed to the manuscript. First author developed theoretical formalism, performed experimental simulation and wrote manuscript. Second author supervised the research work by providing feedback and helped shaping the research, analysis and manuscript.

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