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RESEARCH ARTICLE

IncepV3Dense: Deep Ensemble Based Average Learning Strategy for Identification of Micro-Nutrient Deficiency in Banana Crop

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ABSTRACT The Nutrition of a crop is very essential for the health conditions during its growth stages and yield. A plant development is dependent on various nutrients absorbed from the natural environment or fertilizer supplements. The shortage or lack of essential nutrients is one of the crucial factors which impacts the overall crop yield. Computer vision based phenomics have become an emerging area in agricultural research. In this part of research work, we propose a significant image classifier model which contributes as an Ensemble based Convolutional Neural Network(E-CNN) that can diagnose banana crop's micro-nutrient deficiency with improved accuracy using the leaf images. We selected Six popular deep learning pre-trained models namely VGG-19, InceptionResNetV2, InceptionV3, Xception, DenseNet169 and DenseNet201 and performed the modification of parameters in the top dense layers to experiment with the public available mendeley dataset containing banana crop leaf images with nutrient deficiencies. The diagnostic accuracy along with precision, recall, F1 score and support score was observed. On comparing the classifying accuracy parameters of the six mutated pretrained models, the modified DenseNet169 model attains the highest testing accuracy. The performance analysis was also done using confusion matrices. Finally, we created three binary ensembled models such as Xception+InceptionV3, Dense169+Xception and InceptionV3+Dense169 based on their top performance accuracy scores for the detection of micro nutrient deficiency in banana crop using the concept of averaging strategy. The proposed mutated ensemble based model InceptionV3+Dense169 **(IncepV3Dense)** attains a validation accuracy of 98.62% and f1 score of 93% for detecting banana crop micro nutrient deficiency.

INDEX TERMS Image classification, transfer learning, deep ensemble learning, micro-nutrient deficiency.

I. INTRODUCTION

Agriculture is undergoing various changes to create a more sustainable environment and to supply the demanding population. A crop under many environment conditions, is subjected to different kinds of biotic as well as abiotic stress which affects overall production output and loss during its life cycle. Automation techniques such as precision agriculture assist farmers as well as experts in monitoring and strengthening the agricultural production [1]. Among the stress, the nutrient deficiency is a major dynamic factor that a crucial growth-limiting factor that affects certain visible plant qualities which could reduce the overall agricultural yield significantly. As the crop growth progresses, the requirement of nutrients also increases as it is in the case of any living being. Conventionally, the farmers were not in a state to recognize the crop nutrient systematically and hence proper diagnosis was not possible. The farmers might lack adequate knowledge about plant nutrition, due to which an improper treatment of crops is possible while using fertilizers. Through

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research related to soil nutrient analysis, experts around the world found that around 30–40% of phosphorus, 30% Iron, 59% Nitrogen and 30% Zinc is deficient in the soil globally which affects the total yield severely [2]. There are seventeen key elements for plant nutrition, each with unique properties which contributes to necessity and roles within the plant. The elements are broadly classified as Macronutrients (primary and secondary) and Micronutrients. Crops may suffer from deficits in or an overabundance of nutrients, which can hinder growth and lower yield output. During the pre-production stages like soil preparation and pH maintenance, the farmer ensures that nutrients are readily available through good rooting [3]. The quality of food output is dependent on the available nutrients in the crop during its growth. In this work, we have chosen banana crop to detect its nutrient deficiency through the leaf images using the methodology of computer vision associated with deep learning. Banana is considered as one of the most popular fruits, which is consumed worldwide because of its rich nutrients essential for human health. Another name for banana is "Apple of Paradise.´ With an annual production of 168,13,500 mt and a growing area of approximately 4,90,700 ha, India is the world's largest producer of bananas, accounting for approximately 17% of global production. TamilNadu, Karnataka, and Maharashtra are recognised as having the largest shares of the nation's overall production among all the states in India [4].

A. ABBREVIATIONS AND ACRONYMS

Convolutional Neural Network (CNN) Nutrient deficiency (ND) Unmanned Aerial Vehicle (UAV) Internet of Things (IoT) Machine learning (ML) Deep learning (DL) Transfer Learning(TL) Random Forest (RF) Artificial Neural Networks (ANN) Soil Plant and Development (SPAD) Agglomerative Hierarchical Clustering Analysis (AHCA) Support Vector Machines (SVM) Visual Geometry Group-16/19 (VGG 16/VGG 19)

B. NUTRIENT DEFICIENCY (ND)

In general, crops absorb elements or nutrients from the soil, water, air and sunlight. The excess of an element is known as toxicity [5]. When a crop contains an element at a concentration below the critical value, it is considered as deficient of that element. The process of determining nutrients which are lacking in the soil is known as plant nutrient deficiency identification. These deficiency changes in nutrition for a particular crop is so dynamic in nature, similar to as for a human being such that one nutrient is dependent upon other and hence it is very difficult manually to identify the health condition in terms of nutrient content and to keep a balanced state. Many such deficiencies can be recognized by observing plant leaves. But often, these deficiencies are only noticeable to the human observer after the crop has already undergone damages. If this scarcity continues, it may sooner or later lead to crop death. Hence, the crops need to be ensured of the nutrient content and fed appropriately with the deficient nutrient for its optimum survival. The deficiency symptoms in different parts of plant also depends on the mobility of the element. The morphological changes or characteristics in a crop that differ between elements eventually disappears when the specific adequate nutrients are fed. The primary nutrients improve biochemical processes that aid in plant cell growth and enhance the function of plant enzymes. The symptoms of deficiencies are exposed in older tissues first. For instance, the older leaves show signs of nitrogen, potassium, and magnesium deficiencies at initial deficiency stage and later due to chemical reactions, making these elements mobilize in younger leaves. Similarly, secondary elements are required for crops in intermediate levels for carrying out essential functions. The other category namely the micronutrients, are as essential as macronutrients to have better development, yield output and quality in crops. Therefore, the human as well as animal health is well secured with feed of a complete and balanced crop enrichment [6]. Micronutrient element acquisition in crops is often immobile. These deficiencies appear first in the younger leaves and hence they are not transported. For instance, elements like calcium and sulphur are difficult to get released since they are a part of the structural system of a plant cell. This level of understanding about plant nutrition in terms of minerals is of critical importance for horticulture and agriculture. Chlorosis, necrosis, reduced plant growth, early leaf and bud fall, and some blockage in cell division are common deficiencies seen in plants. The lack of chlorophyll content that causes leaves to turn yellow is known as chlorosis. Elements such as nitrogen (N), potassium (K), magnesium (Mg), sulphur(S), iron(Fe), manganese(Mn), zinc(Zn), and molybdenum (Mo) deficiencies are the root cause of this symptom [5]. Similar to this, a lack of calcium(Ca), Mg, copper(Cu), or K causes necrosis, or tissue death. Also, it becomes difficult to identify actual deficiencies between Nitrogen, magnesium and Sulphur. Micronutrient chlorosis is a state of a crop affected with the lack of micronutrients such as iron, manganese or zinc or Loss of chlorophyll [7]. But the farmers are often confused whether the deficiency is occurred due to Macro or Micro nutrients. But when observed very carefully, the symptoms could be differentiated and find solutions for exact deficiency and help to regain the specific nutrient for the crop.

C. IDENTIFICATION OF ND

It's vital to identify nutrient shortages in crops so that appropriate measures could be taken to regain the loss and increase crop yield while preserving proper growth stages, particularly at an early stage. Traditional method of diagnosis includes use of chemicals and other invasive testing methods in soil and plant tissue or laboratory based. But these techniques often were invasive and time-consuming processes. Due to the advancements in science and technology, various researchers around the world contributed

TABLE 1. Crop nutrients and its deficiency symptoms.

Nutrient	Generalized Crop Deficiency Signs
Nitrogen	Leaves appear light green to yellow, especially as they get older; growth is stunted and fruit development is poor.
Phosphorous	Plant growth may be stunted, and leaves may turn purple with a bronze underside.
Potassium	Marginal burning of leaves, irregular fruit development and folds at tip of leaves
Calcium	Drying or death of tips in younger leaves, poor fruit development and appearance of dark green leaves
Magnesium	Early vein yellowing of older leaves that spreads to also the younger leaves, poor fruit development and low yield
Sulphur	Young leaves first turn yellow before spreading to the entire plant (similar to N deficiency)
Iron	Young leaves have first noticeable yellow or white patches between veins that eventually become patches of dead leaf tissue, with the main veins being green
Manganese	Interveinal yellowing or mottling of young leaves
Zinc	Brown leaf spot on paddy, small leaf size, short internodes, and vein yellowing on young leaves
Copper	shortened leaf growth, twisted, narrowed leaves, whitened leaf tips and dying of terminal leaf buds.
Boron	Dysfunction of tissues in root, internal cork of apple fruits, death of terminal buds, and disruption of flowering and fruit development
Molybdenum	Resemble the signs of a N shortage, cauliflower whiptail diseases, withering and scorching of the leaves
Chlorine	Chlorotic sign in leaves and leaf necrosis

to establish significant innovative resources for computing the nutrient content of a crop. Computer vision algorithms distinguishes the nutrient deficiency of the crop by using the leaf pattern that is mapped with appropriate deficiency. Leaf image has color, texture, venation, and shape features. The methodology might involve sensors, digital cameras, satellites, unmanned aerial vehicle (UAV), Internet of Things (IoT) systems. However, the spectral Imaging or optical sensors are very expensive. Hence, these issues are addressed efficiently using machine learning (ML) or deep learning (DL) assisted computer vision models. The area of visual phenotyping of plants is experiencing an unexpected growth due to improvements in the field of deep learning, a subfield of machine learning that enables the automatic extraction of features and predictions on huge amounts of data. Table 1 shows the generalized crop deficiency symptoms. The efficiency of deep learning in managing the vision-based tasks like recognition of objects, semantic categorization, image classification, and scene comprehension is especially well-known. Implementing classification algorithms to create fully autonomous agricultural field systems to monitor pests, nutrient shortages, or crop diseases and instantly report the identified classification to the user on a mobile device or web portal will be made feasible by using IoT-enabled hardware. Therefore, the non-destructive strategy of image processing technology helps to overcome the above stated drawbacks. This work proposes an Deep Ensemble learning approach to rapidly detect Micro-nutrient deficiency using the banana leaf image. The selected deficiency images belong to Boron(B), Iron (Fe), Manganese(Mn). In general, the ensembling technique enhances the classification performance criteria that helps to identify the strategical tuned hyperparameters for appropriate tasks and applications. The proposed model classifies the images based on the symptoms that are related to particular deficiencies. This enables the farmers to identify the exact nutrient that the crop is lacking and further recommendation could be given for supplying the required concentration of nutrients. Figure 1 shows sample leaf pictures of selected micro deficiencies in banana crop.

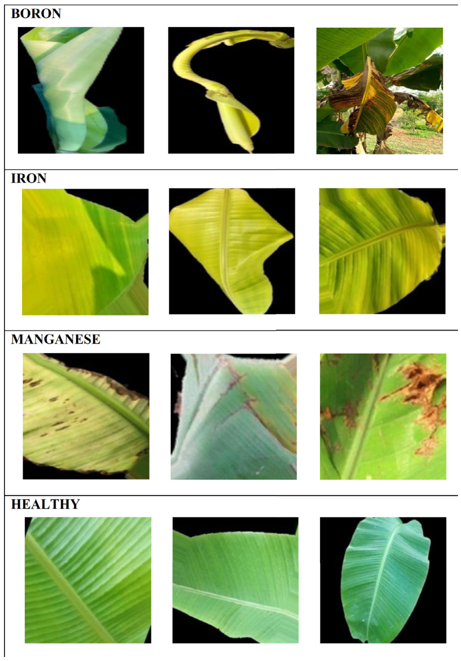

FIGURE 1. Examples of banana deficiencies.

D. CONTRIBUTION OF THIS PAPER

1) This work contributes as an Ensemble of different TL models after the mutation of its layers and to the best of our understanding of literature survey, this is the first work performed for micro nutrient deficiency diagnosis for banana crop.
2) It is carried out on the basis of publicly available mendeley banana dataset that specifically contains secondary nutrient and micro nutrient deficiencies.
3) The performance metrics was evaluated for six modified pre-trained deep learning models.
4) The ensembling of best mutated classifiers is carried out based on the performance results obtained, leading to the improvement in image classification accuracy with lesser training time and complexity.
5) This improvement also contributes as a preliminary work to more generalization of input data and act as a robust model to different operating conditions such as the illumination, rotation angle of images, etc.

E. PAPER STRUCTURE

The remaining content of the document is organised as follows. The related works carried out to identify nutrient deficiencies is provided in Section II. Section III comprises of details of computing hardware, dataset used and proposed approach. Section IV provide the results followed by discussion. Section V consist of conclusion and future work.

II. RELATED WORK

This section expresses the related work done with regard to nutrient deficiency identification. Artificial Intelligence (AI) is extensively employed to address diverse problems, including but not limited to crop identification, yield forecasting, disease identification, and deficiency identification. Plant nutrient deficiencies have been identified using methods like computer vision, image processing, machine learning, and deep learning. Traditionally, the image based applications of agriculture is considered a very flexible and more advantageous, since it is non - destructive, adaptive and versatile as more advanced algorithms are been invented to enhance the results. Various researchers around the world contributed to establish significant innovative resources for computing the nutrient content of a crop by means of ML/DL based models. Several studies have combined traditional machine learning methods with feature selection and reduction techniques to lower computational complexity.

A. IDENTIFICATION OF ND USING ML AND DL METHODS

Jonilyn A. Tejada and Glenn Paul P. Gara (2017) created a combined analyzer tool- LeafcheckIT for identifying the macronutrient deficiencies such as N,P,K in banana leaf using random forest (RF) ML algorithm and a data mining tool named WEKA. They obtained a validation accuracy of 91.64%. Avinash Agarwal et al. (2018) used the combination of multiple linear regression and multivariate data analysis for extracting the image features in leaf to evaluate the chlorophyll content and health status of spinach seedlings. The Correlation of SPAD (soil plant and development) values were assessed by implementing PCA and agglomerative hierarchical clustering analysis (AHCA). However, it was a semi-invasive methodology of diagnosis. Leena et.al (2018) implemented an image-processing classification model for differentiating macronutrient deficiencies in maize plants using MATLAB. It was performed using artificial neural networks (ANN) and using multiclass support vector machines (SVM) for optimization, thereby obtaining accuracy of 90%. Ukrit Watchareeruetai et.al (2018) used convolutional neural networks (CNN) for identifying nutrient deficiency in images of Black gram crop. In their work, the response blocks of CNN are integrated using a multi-layer perceptron and five types of deficiencies such as K, Ca, Mg, Fe and N were identified. Sambuddha Ghosal et.al (2018) contributed for plant stress phenotyping by establishing an explainable deep machine vision framework in classifying diseases and deficiencies. They captured Color based features for measuring severity level based on metrics given by a ranking criteria and obtained the overall classification accuracy as 94.13%. Though it had accepatable accuracy, it had certain limitations on discriminating the disease classification and was less robust to illumination changes. Trung-Tin Tran et.al (2019) conducted a comparison analysis of Deep CNN's ability to predict and categorise macronutrient deficiencies in tomato plant development. With ensemble averaging, the accuracy rates improved from 87.27% to 91%. The dataset was limited to three deficiencies. Sushila Shidnal et.al (2019) predicted the crop yield in Paddy fields by using a two-tiered ML model approach like k-means clustering and together with the support of tensorflow library. The quantitative levels of nutrient deficiencies in crop was determined. They devised a table based on rules, to predict the yield, for which they obtained the accuracy levels ranging between 76-77%. Sethy. P.K et al (2020) proposed a classification model for predicting nitrogen deficiency of rice crop using CNN and SVM. They evaluated six neural network deep learning architectures namely ResNet-18, VGG-16, ResNet-50, GoogleNet, VGG-19 + SVM and AlexNet. Among the six, Res-Net 50 + SVM was superior. Jinhui Yi et al (2020) contributed in developing a DL model for RGB image-based non-invasive nutritional deficiency diagnosis in sugar beet and created a unique benchmark dataset consisting of RGB images with seven types of nutrient treatments. Basavaraj S. Anami et.al (2020) proposed a DL approach for classification of paddy stresses that affects the overall yield by recognising the field of crop images. They used the DL model VGG-16 for the implementation and average accuracy of 92.89% was obtained by using 30,000 field images of five varieties of paddy crop with twelve categories of stress. Vrunda Kusanur and Dr. Veena S Chakravarthi (2021) proposed a classification model for predicting tomato crop nutrient deficiency using transfer learning. The authors compared architectures such as ResNet50, Inception-V3 and VGG-16 in combination with two ML classifiers: RF and SVM. The model VGG-16 along with SVM outperformed the other two with high accuracy. R. Sathyavani et al (2021) detected plant leaf nutrients using CNN based IoT devices and nutrition analyzer device. Muhab Hariri and Ercan Avsar (2022) used CNN and particle swarm optimization for tipburn disorder detection in strawberry leaves. The Performance metrics comparison was performed on proposed Model with six benchmark CNN models namely VGG-16, VGG-19, EfficientNet, Inception-V3, ResNet-V2 and Inception-ResNet-V2. The performance results for accuracy, sensitivity and specificity achieved were 0.9895, 0.9863 and 0.9936 respectively. Janani Malaisamy and Jebakumar Rethnaraj(2022) proposed a smart nutrient deficiency prediction system for groundnut leaf. In their work, they compared the performance characteristics of proposed model with the existing transfer learning models and attained classification accuracy of 95% consuming lesser training time of 5s 163 ms.

B. ENSEMBLING LEARNING METHODS

Sharma. M et al (2022) implemented ensemble averaging methodology of using transfer learning models for detecting nutrient deficiency in the images of rice crop. They considered six architectures such as InceptionResNetV2,

TABLE 2. Summary of related works using machine learning and deep learning.

Ref	Methodology	Crop Dataset used	Ensemble Learning	Detected Deficiency	Results
[8]	Random Forest	Banana / field data	No	N,P,K	Training – 100%, validation – 91.64%
[9]	K-means, FCM feature extraction + SVM	Rice / IRRI datset	No	N,Mg,P,K,Zn	85.06% – 93 %
[10]	Chlorophyll meter, PCA and agglomerative hierarchical clustering analysis (AHCA)	Spinach/ field data	No	N,P,K	highest determination coefficient and lowest mean square error
[11]	Multiclass Support Vector Machines (SVM) and Artificial Neural Networks (ANN)	Maize / field data	No	N, P, K	90%
[12]	Convolution Neural Networks (CNN)	Blackgram / field data	No	Ca, Fe, K, Mg and N	Precision-43.02 %, Recall- 52.13%,F-measure 47.14 %
[13]	Deep CNN with supervised Classifiers	Soyabean / field data	No	Biotic stresses, Fe, K	94.13%
[14]	Deep CNN	Tomato / field data	Yes	N, P, K	87.27% for Inception-ResNet v2 79.09 % for Autoencoder, 91% for ensemble averaging.
[15]	K-means clustering	paddy /field images	No	N, P, K	Prediction accuracy of 76-77% obtained
[16]	CNN, SVM	Rice / field data	No	N- four levels	99.84 %
[17]	Deep Learning (CNN Models) using RGB Images	Sugar Beet/ site data	No	N,P,K,Ca	87% - 98.4 %
[18]	VGG -16 CNN	Paddy/ field data	No	drought stress, N,P,K,B,Zn,Fe	Average accuracy of 92.89%
[19]	CNN	Tomato (field data)	No	N, P, K	(80.45–86.59)%
[20]	RNN-CNN and autoencoder	Soybean (field-data)	No	Fe	CNN based autoencoder -best performance
[21]	InceptionV3, ResNet50, NasNet-large and DenseNet121	Rice (field-work)	No	S, Ca, Mg, N, P, K Mn, Fe, Zn, Si	(91.6 to 97.4)%
[22]	Transfer learning	Tomato / green house data	No	Ca,Mg	99.14 % for VGG-16 + SVM, 98.71 % for Inception V3 + RF
[23]	IoT and DenseNet-BC (CNN)	Rice /kaggle data	No	Mg, Ca, P,K,N,S	96%
[24]	InceptionV3	Maize / field	No	N, P, K	(40–80)%
[25]	CNN – PSO (CNN- particle swarm optimization)	Strawberry / University of Cukurova	No	calcium	Achieved 0.9895 accuracy, 0.9863 sensitivity and 0.9936 specificity
[26]	CNN – Pre trained Models	Groundnut / field data	No	Nitrogen	classification accuracy of 95%, Lesser training time of 5s 163 ms.
[27]	Ensembling of transfer Learning (TL) architectures	Rice / Mendeley,kaggle	Yes	N,P,K	Inception ResNet V2 – 90% and Xception – 95.83%
[28]	Deep Ensemble Learning Methods	Rice / kaggle	Yes	N,P,K	Individual - 96.66% , Ensemble – 98.33 %

InceptionV3, VGG19, DenseNet201, ResNet152V2 and Xception in this work. Mendeley and Kaggle provided two publicly accessible datasets, which were employed in the assessment. With regard to accuracy, the Kaggle and Mendeley datasets yielded the best results while using Inception-ResNetV2 of 90% and for Xception to be 95.83%. The classification accuracy for mendeley dataset was enhanced by the ensemble-based architecture to a maximum of 100% from 99.17%, while the Kaggle dataset saw an improvement to 92% from 90% in classification accuracy. In recent technological advancements, the ensemble of image processing techniques with machine learning or deep learning makes this process more effective. Ensemble pruning or selection methods reduce the complexity, one such method is the ranking method. This method tends to rank the models based on a feature criteria and select the top performing base models for ensembling [29]. In the work, [30] a novel ensemble based network is developed to detect mango leaf disease. First, the images are input to a stack of different deep neural networks after being segmented for the area of interest. To identify leaf disease, the deep neural network's output is combined with a machine learning model. The suggested model performs better scoring of 98.57% accuracy. A classification model for nutrient deficiency is suggested for rice crop using leaf images [31]. The authors evaluated models such as Xception, Vision transformer and MLP mixer model. All three models achieved nutrient deficiency classification accuracy greater than 92%. The Xception model achieved the highest average accuracy of 95.14%. An ensemble transfer learning approach is suggested for nutrient deficiency identification and yield loss prediction in this study [32]. Two experiments are used to assess the suggested approach with rice and groundnut datasets. The first experiment focuses on classifying images based on their nutrient deficiencies, While the second experiment calculates the yield loss based on the severity of the deficient nutrient. The suggested ensemble transfer learning methodology achieves accuracy rates of 94% and 99%, respectively. The Table 2 summarizes the work done related to the identification of nutrient deficiency in crops using machine vision.

III. COMPUTER HARDWARE AND METHODOLOGY

This research work proposes ensembling of Transfer learning models for identifying the major micro nutrient deficiencies such as Boron, Iron and Manganese in banana crop. The data is collected from the publicly available Mendeley dataset of banana crop which comprises of fully labelled nutrient deficient images and healthy leaf images. The individual classifier models were trained using the dataset and evaluated for analysing performance evaluation metrics such as accuracy, recall, precision, F1-score and confusion matrix. Based on the results obtained, we chose the models for integration to further enhance the accuracy and reduction in the complexity of the model. The computing hardware system comprises of Intel i5 11th gen processor, with 2 GB NVIDIA MTX 450 GPU accomodating 8GB RAM. Software tool used is Jupyter notebook in Windows operating system platform.]

A. DATASET DETAILS

The dataset contains various categories of banana leaf deficient images including Rasthali, Poovan, Monthan. Those images are captured at different environment conditions such as sunlight, low illumination. from various places of Karnataka state, India. Images are stored in .jpg and .png format [33]. We chose a total of 3450 images from the dataset, among which 800 are Boron deficient, 860 Iron deficient, 840 Manganese deficient and 950 healthy. The Figure 2 shows the deficiency image classes from the mendeley dataset. The images in the dataset had a resolution of size 256 × 256. The size on disk is 52.9 MB. For our work, the selected dataset is splitted as 80% for training and 20% for validation. About 305 images of model unseen real time images and moreover about 5 % images from validation data was used for testing the model performance, which is shown in the Table 3.

B. DATA PRE-PROCESSING AND AUGMENTATION

We preprocessed the images to scale of 299 × 299, so as to feed into selected pre-trained deep learning models. Also, the dataset was manually rechecked for the appropriate

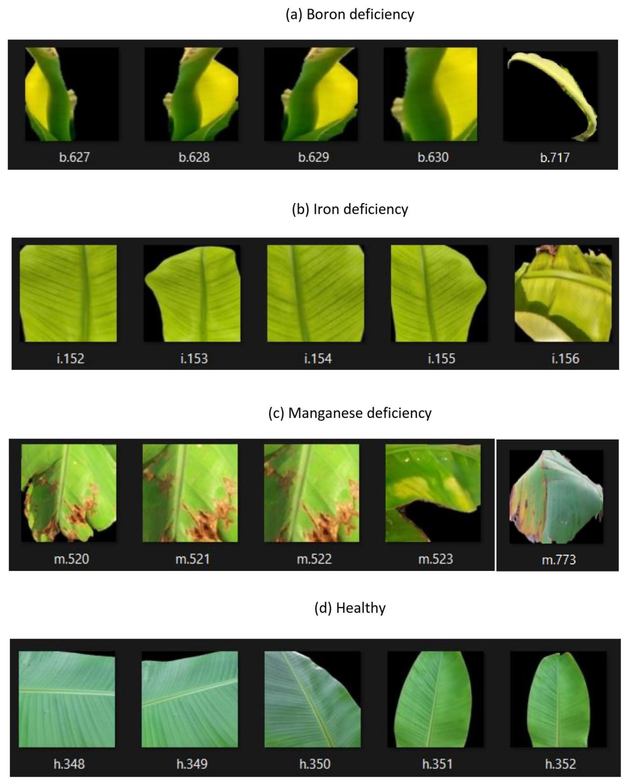

FIGURE 2. Examples of deficiency images from the mendeley dataset [33].

TABLE 3. Training, validation and test data.

Data	No. of Images	Batch Size
Training data	3200	16
Validation data	800	16
Testing data	305	1

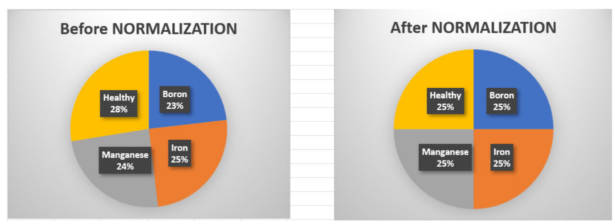

FIGURE 3. Data distribution of classes.

deficiency symptoms before actual training, after which it was fed to augmentation strategies such as rescaling, brightness, rotation, horizontal flip, zooming using Augmentor libraries and ImageDataGenerator to avoid the problem of overfitting. The number of images after augmentation in each class was 1000, resulting total of 4000 images. The Figure 3 shows the selected data distribution from the total dataset. We labelled the images by mapping the filenames with the appropriate class. The prediction of checker is done by comparing the filename split done and the mapped classname. The Augmentation parameters being implemented is shown in the Table 4.

TABLE 4. Augmentation parameters.

Sl.No	Augmentation Strategy	Parameter range
1	Rescaling	1./255
2	brightness	[0.8,0.8]
3	Zoom range	0.2
4	rotation range	90
5	horizontal flip	True

TABLE 5. Evaluation parameters of mutated transfer learning models.

Sl. No	Models	Total Parameters	Trainable Parameters	Non-Trainable Parameters
1	Mutated VGG19	20,222,532	198,148	20,024,384
2	Mutated InceptionV3	22,394,148	591,364	21,802,784
3	Mutated InceptionResNetV2	54,797,028	460,292	54,336,736
4	Mutated Xception	21,452,844	591,364	20,861,480
5	Mutated DenseNet169	13,135,940	493,060	12,642,880
6	Mutated DenseNet201	18,880,580	558,596	18,321,984

TABLE 6. Layers in mutated VGG19.

Layer type	Output shape	Total Parameters
Input layer	(None, 299, 299,3)	0
VGG19	(None, 9, 9, 512)	20,024,384
GlobalAveragepooling2D	(None, 512)	0
dense1	(None, 256)	1,31,328
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

C. SIGNIFICANCE OF TRANSFER LEARNING

Transfer learning is the concept of transferring the knowledge acquired during a task in one field to another and use it for solving problems in different fields. These architectures are also being used in various activities of agricultural research to establish effective solutions. The principle of transfer learning is that the weights in a particular pretrained model are retained and only the classification layer are modified for adapting to our specific research problems. It facilitates less processing time of model weights due to the fact that the model has already been trained on natural image databases, like ImageNet. Therefore, it reduces the time complexity of retraining the model from scratch since the parameters are limited, which is problem specific. Here, we selected six popular TL models namely VGG19, InceptionV3, InceptionResNetV2, Xception, DenseNet169, DenseNet20 for performing the task.

Those TL models are modified by replacing the top layer with two dense layers, globalaveragepooling2D, dropout being 0.5 to avoid overfitting and was evaluated with the selected banana dataset collected from mendeley. The training was done with 35 epochs, keeping the batch size to 16, learning rate was 0.01857 and callbacks such as early stopping technique and appropriately reducing learning rate were implemented to decide the best overall weights. The model training stops if there is no betterment of validation accuracy upto 5 epochs(patience being 5). During training, the Adagrad optimizer and loss function being categorical cross-entropy were used for metrics such as accuracy and precision. The evaluation parameters of the selected TL models is shown in Table 5.

TABLE 7. Layers in mutated InceptionV3.

Layer type	Output shape	Total Parameters
Input layer	(None, 299, 299,3)	0
InceptionV3	(None, 8, 8, 2048)	21,802,784
GlobalAveragepooling2D	(None, 2048)	0
dense1	(None, 256)	524,544
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

TABLE 8. Layers in mutated InceptionResnetv2.

Layer type	Output shape	Total Parameters
Input layer	(None, 299, 299,3)	0
InceptionResnetv2	(None, 8, 8, 1536)	54,336,736
GlobalAveragepooling2D	(None, 1536)	0
dense1	(None, 256)	393,472
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

TABLE 9. Layers in mutated Xception.

Layer type	Output shape	Total Parameters
Input layer	(None, 299, 299,3)	0
Xception	(None, 10, 10, 2048)	20,861,480
GlobalAveragepooling2D	(None, 2048)	0
dense1	(None, 256)	524,544
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

TABLE 10. Layers in mutated DenseNet169.

Layer type	Output shape	Total Parameters
Input layer	(None, 224, 224,3)	0
DenseNet169	(None, 9, 9, 1664)	12,642,880
GlobalAveragepooling2D	(None, 1664)	0
dense1	(None, 256)	426,240
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

TABLE 11. Layers in mutated DenseNet201.

Layer type	Output shape	Total Parameters
Input layer	(224, 224,3)	0
DenseNet201	(None, 9, 9, 1920)	18,321,984
GlobalAveragepooling2D	(None,1920)	0
dense1	(None, 256)	491,776
dense2	(None, 256)	65,792
dropout	(None, 256)	0
Activation	(None, 4)	1028

D. PROPOSED WORK - DEEP ENSEMBLE LEARNING (IncepV3Dense)

In this work, an ensemble system of outperforming Transfer learning (TL) models is proposed for diagnosing micro

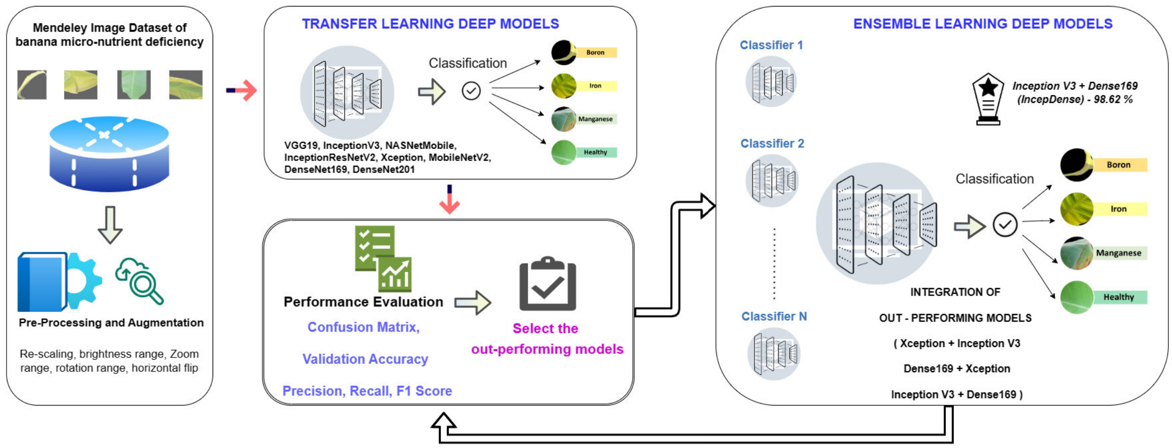

FIGURE 4. Overall proposed work.

TABLE 12. Layers in proposed ensemble classifier- IncepV3Dense.

Layer type	Output shape	Total Parameters
Input layer	(None, 299, 299,3)	0
dense169 (Functional)	(None, 4)	13135940
inceptionv3 (Functional)	(None, 4)	22394148
average (Average)	(None, 4)	0

nutrient deficiency in banana crop. Algorithms for ensemble learning function by combining different base learners and formulating a hypothesis in response to the results. There are various categories and basic approaches of ensembling, namely maximum voting, averaging and weighted averaging. Advanced techniques of ensemble namely bagging, boosting, stacking. The max voting is generally used for various classification problems. Here, various models perform predictions for each data point, called as a 'vote'. The final prediction is based on the majority attained during the model predictions. The final prediction in the averaging technique is derived by taking the average of the probabilities and predictions across all models. The averaging method is expanded upon by the weighted average. Different weights are given to each model, indicating the order of priority or significance for each model in the prediction hierarchy. The estimated probability of multiple base models is determined using the ensemble averaging approach, whereas weighted ensemble learning merge the model outcomes and algorithms by voting procedure in order to select the outperforming model. Figure 4 shows the overall proposed work. The Tables 6,7,8,9,10 and 11 shows the layers in selected Mutated models following which the proposed Averaging ensemble strategy algorithm 1 is depicted and Table 12 shows the layers of proposed ensemble classifier model. The "None" at the beginning of the shape tuple represents the batch size. It suggests that any batch size can be used by the model for inference or training. we used a batch size of 16 during training.

The proposed ensemble learning parameters for training are as follows. Total parameters: 35,530,088, Trainable params: 1,084,424, Non-trainable params: 34,445,664. After obtaining the experimental training and validation results of mutated TL models, we have formed three ensemble classifiers based on the accuracy and loss parameters. The combinations are such as Xception+InceptionV3, Dense169+Xception and InceptionV3+Dense169. Among the three ensemble classifiers, InceptionV3+Dense169 gives the maximum accuracy of 98.62%. The training and evaluation metrics for validation and testing was similar to the usage with the TL models. The learning rate was 0.01857. The proposed ensemble methodology is relies on averaging and introduced stacking while training the pretrained models one by one to determine the prediction capability and rank. Then the dataset is feeded to the created stacked ensembler for final predictions that provides the highest accuracy and low loss or wrong predictions. The ensembled classifier averages the prediction probability produced for our dataset.

E. PERFORMANCE ANALYSIS

In general, a ML/DL model is evaluated for its performance using various parameters and metrics [28]. The metrics is an indicator of the model's efficiency and thereby it helps to select the appropriate model for our task. Hence, the comparison of the models is realized using these mathematical operations. In our work, the evaluation of the proposed model is done using the confusion matrices and by comparing metrics like accuracy, recall, precision and F1 score. Further, the execution time and percentage of correct predictions are also considered.

(i) Accuracy: It is an important parameter in the evaluation of models. It is the number of correct predictions out of the complete dataset and denoted mathematically as follows

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} * 100 \quad (1)$$

Algorithm 1 Averaging Ensemble Strategy

Input: Dataset D

Output: P_z for Ensembling model ENS classifier= [Mo_1 / Mo_2 /Mo_3/.....Mo_i]

Initialisation:

Preprocess D using various augmentation strategies.

set n base Models $Mo_1, Mo_2, Mo_3, \ldots Mo_i$; where i denote the model count

LOOP Process

for n=1 to z **do**

learn Mo_i and predict P_i for generated D, where i varies between 1 to z and for all C, where C -> denotes number of classes, z -> number of epochs

blr= 0.01857; where blr is the base learning rate

fit the models Mo_i using callbacks & patience values.

A= add(P, along Y axis); where A generate classification accuracy data

P_z = max classification accuracy(C, along X axis)

for all classes generate Accuracy, Loss curves and Confusion matrices(P_z,D)

generate accuracy for each class

generate confusion matrices and Classification report(P_z,D)

end for

(ii) Precision: It is the ratio of true positives to total predicted relevant positives.by model and measured by

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} * 100 \tag{2}$$

(iii) Recall: It is the ratio of true positives to total (actual) positives. In other words, It assists in determining how many accurate positive predictions were made out of all the predictions and denoted mathematically as

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \tag{3}$$

where TN stands for true negative, FP for false positive, FN for false negative, and TP for true positive.

(iv) F1 score: It is the harmonic average of the precision and recall indicators, given by

$$F1\ score = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) * 100 \tag{4}$$

(v) Macro Average: It is the arithmetic average of all the categories that are related to F1 score, recall, and precision. The overall performance of a trained multi-class classification model can be given by

$$\begin{aligned}&\text{Macro Average Measure}\\ &= \frac{1}{N}(\text{Measure in class } C_1 + \ldots\ldots + \text{ Measure inclass } C_2\\ &\quad + \text{ Measure in class } C_N)\end{aligned} \tag{5}$$

(vi) Weighted average: It's also employed to assess multiclass classification's overall effectiveness. In this case, each quantity that needs to be averaged is given a weight. It is given by

$$\text{Weighted Avg Measure} = \frac{A + B + \ldots + \ldots N}{\text{Total number of sample}} \tag{6}$$

where A = Measure multiplied by its weight in class 1, B = Measure multiplied by its weight in class 2, N = total number of classes.

Our research objective is related to pattern recognition, matching, identification and image classification of similar symptoms differentiated by the classes, which are closer to the ground truth. We currently focus on image classification using uniform pattern in the banana leaf as a whole and no intra-leaf segmentation needed to classify this specific objective of micro-nutrient deficiency classification in banana crop. As the selected dataset consisting of 4000 images of multiclass images and a balanced dataset, for which we have used model performance evaluation metrics such as Accuracy, precision, recall, F1 score, confusion matrix, Prediction checker, categorical predictions of the TL models.

TABLE 13. Comparison of the results of original CNN models.

Model	Validation Accuracy (%)	Validation Loss (%)
ResNet50	62.50	23.15
RegNetY002	94.50	23.12
VGG16	88.00	32.00
EfficientNetV2B1	88.37	32.63

IV. RESULTS AND DISCUSSION

In this study, we used validation accuracy for comparing the rank in prediction and test results of six different CNN models. The evaluation of selected TL models and the proposed ensemble model was conducted comparing the performance metrics such as precision, accuracy, recall, support and F1 score of labelled classes or categories. During experimental trails and hyperparameter tuning, we selected the best models among those performed better in terms of training as well as validation. We used 305 images for testing the confidence of models. The Tables 13-18 depicts the scored metrics attained during training, validation and testing various models. Table 13 shows the results of original CNN models and the overall performance of various mutated TL models is tabulated in Table 14. Table 15 depicts the additional metrics for evaluating TL models such as [Prediction checker (%) - True predictions vs False predictions] for the test images. The value in rounded brackets represent the number of predicted images out of 305 test images. The categorical scores and accuracy for each category are listed in the Tables 16 and 17, wherein P stands for precision, R stands for recall, F1 stands for F1 score, S stands for support. Table 18 refers the details of the

TABLE 14. Overall performance of TL models.

Model	Number of Epochs	Avg. Training time per epoch	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
Mutated VGG19	34	248 s	90.41	87.25	82	88.37
Mutated InceptionV3	18	55 s	95.98	95.62	90	95.75
Mutated InceptionResNetV2	20	490 s	96.11	95.62	90	95.75
Mutated Xception	12	120 s	96.61	96.13	88	96.25
Mutated DenseNet169	22	75 s	98.12	97.75	91	**97.75**
Mutated DenseNet201	13	100 s	97.74	97.37	89	97.75

FIGURE 5. Sample predicted results.

overall improved performance while using the ensembling methodology.

A. MUTATED TL MODELS

Initially, we started training various original CNN models including ResNet50, VGG16, EfficientNet. However, the above models had poorly performed for our selected dataset with regard to the validation accuracy. The ResNet50 attained 62.50% validation accuracy and loss of 23.15%, RegNetY002 had 94.50% accuracy but the loss was 23.12%, VGG16 being 88.10% accuracy and loss of 32%. We also tried with different versions of EfficientNet. for e.g The EfficientNetV2B1 achieved 88.37% accuracy and loss of 32.63%. Hence we experimented with the other models such as VGG19, Inception V3, InceptionResNetV2, Xception, Dense169 and Dense201.

B. ENSEMBLE MODELS

After evaluating the metric results, confusion matrix and classification report obtained for six TL models, we proposed an ensemble based learning which tends to improve the classification accuracy and minimizing the loss or wrong

TABLE 15. Prediction performances of TL models for 305 test images.

Model	True Predictions (%)	False Predictions (%)
Mutated VGG19	82.30 (251)	17.70 (54)
Mutated InceptionV3	**90.16 (275)**	**9.84 (30)**
Mutated InceptionResNetV2	90.16 (275)	9.84 (30)
Mutated Xception	87.54 (267)	12.46 (38)
Mutated DenseNet169	**91.15 (278)**	**8.85 (27)**
Mutated DenseNet201	89.84 (274)	10.16 (31)

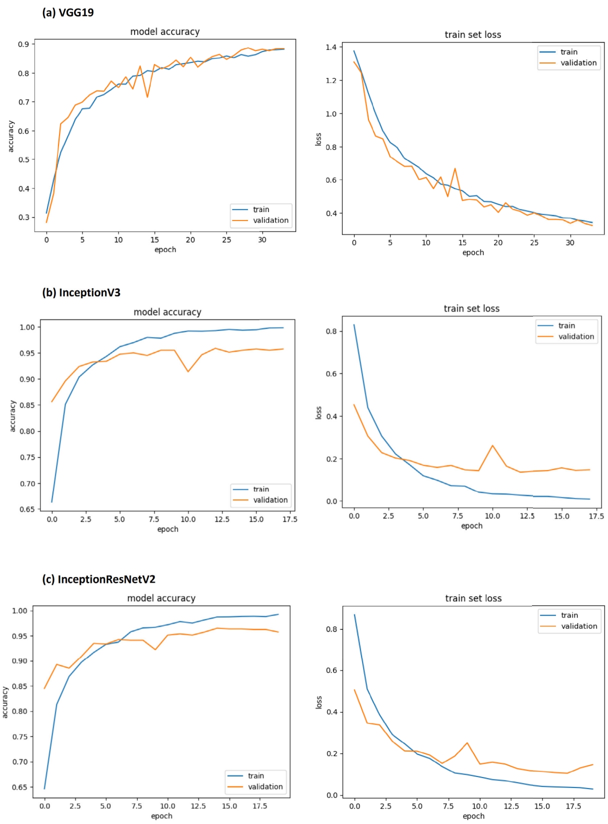

FIGURE 6. Left:Accuracy and Right:Loss plots of mutated pre-trained models.

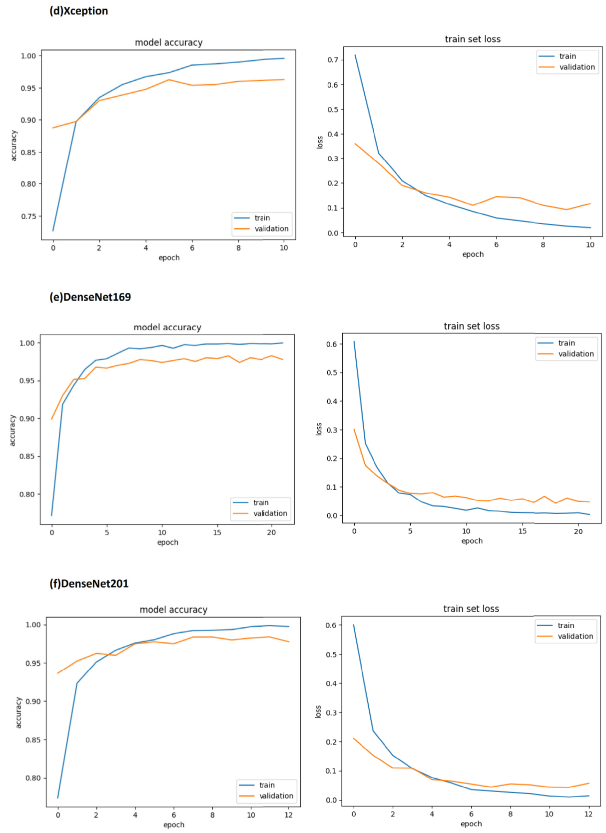

FIGURE 7. Left:Accuracy and Right:Loss plots of mutated pre-trained models.

predictions. Figure 5 shows sample predicted results and Figures 6,7 and 8 shows the Accuracy curves, Loss curves and confusion matrices respectively. Three ensemble classifiers were built using the average ensemble scheme that indicates the best prediction performance of models. The ensemble learners namely InceptionV3+Xception, InceptionV3+Dense169, Dense169+Xception were fed with the dataset and other training hyperparameters for training and finally tested with 305 images for measuring the performance and producing the classification report. All those models performed well by attaining above 97% of validation accuracy, but during testing images, the results differ in terms of the number of wrong predictions(error).

The ensemble classifier InceptionV3 + Dense169 had a good performance on the banana micro nutrient deficiency datatset attaining overall validation accuracy of 98.62% and f1 score of 93%. The suggested model attained True predictions of 285 images and false predictions of 20 out of total 305 test images.

C. DISCUSSION

The main objective of this work is to feed with multi-class images to the mutated deep ensembled models and evaluate various performance metrics for the identification of banana crop micro nutrient deficiency. During the in-depth experimental analysis, We noticed that the healthy and manganese categories retrieved the highest (100) and lowest accuracy(53.01) respectively. The boron and iron categories get the accuracy ranging in between 93 - 98.7. However, the manganese category get highest accuracy by InceptionV3. We selected six TL models namely VGG19, InceptionV3, InceptionResNetV2, Xception, DenseNet169 and DenseNet201 to train and validate. The validation loss and accuracy were initially not improving, after then we tuned the hyperparameters such as number of epochs, batch size and learning rate. The obtained better accuracy scores for the tuned models were ranging in between 88.37% - 97.75%. The number of actual values for Boron, Healthy, Iron and

TABLE 16. Categorical prediction parameters of various TL models.

Models	Deficiency Prediction Parameters															
	Boron				Healthy				Iron				Manganese			
	P	R	F1	S	P	R	F1	S	P	R	F1	S	P	R	F1	S
Mutated VGG19	90	89	89	81	87	99	93	69	69	93	79	72	88	53	66	83
Mutated InceptionV3	99	95	97	81	97	99	98	69	75	99	85	72	97	72	83	83
Mutated InceptionRes-NetV2	96	99	98	81	93	99	96	69	78	96	86	72	97	70	81	83
Mutated Xception	99	99	99	81	99	97	98	69	67	99	80	72	98	59	74	83
Mutated DenseNet169	99	99	99	81	100	100	100	69	74	99	85	72	98	70	82	83
Mutated DenseNet201	99	98	98	81	100	100	100	69	70	99	82	72	96	64	77	83

TABLE 17. Accuracy of each category.

Model	Boron (%)	Healthy (%)	Iron (%)	Manganese (%)
Mutated VGG19	88.88	98.55	93.05	53.01
Mutated InceptionV3	95.06	98.55	98.61	72.28
Mutated InceptionRes-NetV2	98.76	98.55	95.83	69.87
Mutated Xception	98.76	97.10	98.61	59.03
Mutated DenseNet169	98.76	100	98.61	69.87
Mutated DenseNet201	97.53	100	98.61	63.85

TABLE 18. Overall performance of ensemble models.

Model	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
Xception+InceptionV3	97.98	97.25	88	97.37
Dense169+Xception	99.12	98.37	91	98.62
InceptionV3+Dense169	**99.12**	**98.37**	**93**	**98.62**

TABLE 19. Comparison of the results obtained using the mendeley banana leaf dataset.

Author (Year)	Proposed Methodology	Deficiency Classes	Accuracy Results
[34] K. A. M. Han et.al., (**2023**)	ConvNeXtTiny	8 classes and a healthy class	87.89%
[35] J. Mkhatshwa and O. Daramola (**2023**)	pre-trained CNNs (VGG-16 and Inception-V3)	3 classes	VGG16 (82%) Inception -V3 (92%)
[36]Qian Yan et.al., (**2023**)	MobileNetV3-CBAM	Banana dataset classes	96.54%
Our work (**2024**)	Mutated Ensemble based Learning (**IncepV3Dense**)	3 micro-nutrient deficiencies and a healthy class (4 classes)	**98.62%**

Here, the classes used in similar works differ from each author, with the accuracy results being compromised. We selected to experiment on four classes based on manual evaluation of the image patterns in dataset that matches with ground truths to the maximum level. Further, we outperformed the other results in specific terms to Accuracy score.

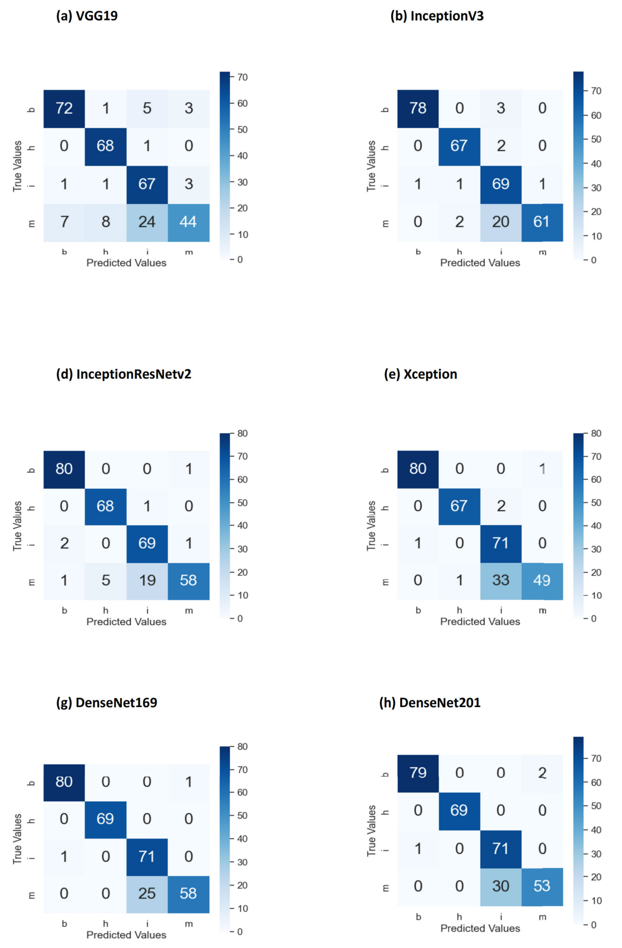

FIGURE 8. Confusion matrices.

manganese are 81, 69, 72 and 83 respectively. The models InceptionResNetV2, Xception and DenseNet169 attained Boron as 80 out of 81. The DenseNet169 and 201 predicts healthy category as 69 out of 69. The models Xception, DenseNet169,201 attain predictions of Iron category as 71 out of 72. The examples of misclassified images for individual classifiers as well as an ensemble is shown in Figure 9. The Inception V3 model attain maximum prediction of manganese category as 61 out of 83. The correct predictions for each category vary between the models. Hence, out of the six classifiers, we tried to create binary ensemble classifiers such as Xception+InceptionV3,

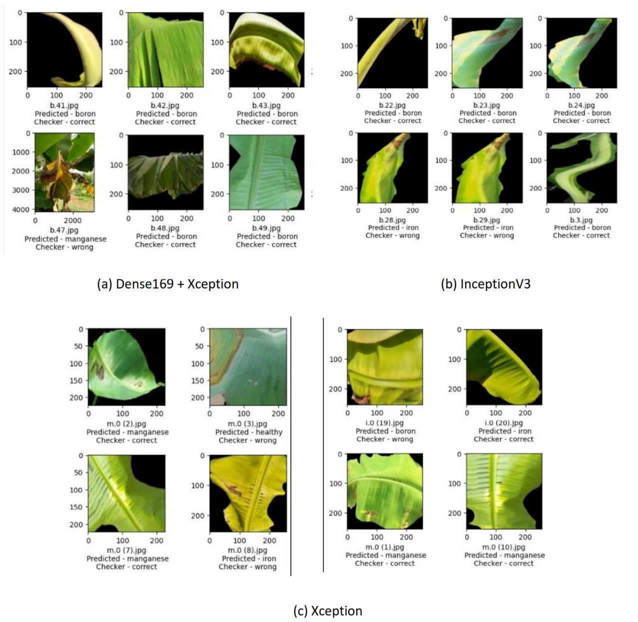

FIGURE 9. Examples of misclassified images.

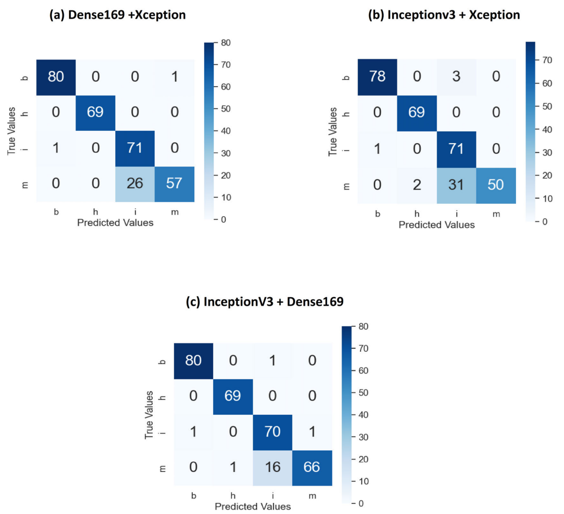

FIGURE 10. Confusion matrices of ensemble classifiers.

InceptionV3+Dense169, Dense169+Xception. After hyper-parameter tuning, we decided to use the parameters for the base learners as discussed in the results section and the dataset has been evaluated for building ensemble classifiers. Among all the three ensemble classifiers, we found that InceptionV3 + Dense169 had a good evaluation score in both validation as well as testing. We also tried combining the Dense169 + Dense 201, the validation accuracy reaches 99.12%, but it does not improve the accuracy of correct predictions during testing. The Table 19 shows the comparison of the results obtained by different authors using the same dataset. The improved number of predictions are revealed by using the confusion matrices in Figure 10.

V. CONCLUSION AND SCOPE FOR FUTURE WORK

In this research work, we have used Ensemble Learning technique for multi class classification of banana crop leaf images specific to micro nutrient deficiencies. Six pre-trained deep learning models namely VGG-19, InceptionV3, InceptionResNetV2, Xception, DenseNet169 and DenseNet201 were reformed with two dense layers and evaluated for their diagnostic accuracy along with precision, recall, F1 score and support score were observed on the mendeley dataset. Based on the results of base learners, a ranking criteria was established to determine the outperforming models to ensemble with averaging method. Therefore, three ensemble classifiers were chosen and again evaluated on the dataset for final improvement of predictions. The proposed model InceptionV3+Dense169 **(IncepV3Dense)** improves validation accuracy by attaining 98.62%. However, our work has a limitation in the usage of dataset, i.e., the labelling of classes used for images and therefore still have to work for more generalized unseen images pertaining to other types of deficiencies like zinc, copper, molybdenum. This work enables the experts and farmers to quickly detect the specific micronutrient deficiency and make future decisions for feeding the crop with appropriate nutrients which enhances the total crop yield.

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