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Boron Deficiency Detection in Banana Leaves using Skip-Connected Convolutional Neural Network (SC-CNN)

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Abstract

Plants rely on a delicate balance of 16 essential nutrients to thrive, with macronutrients being crucial for robust growth, while micronutrients play a vital role despite being needed in smaller quantities. Insufficient nutrient levels can stunt plant growth, hinder flowering, and reduce fruit yield. Accurate diagnosis of these deficiencies is paramount for farmers to address issues effectively, ensuring the cultivation of nutrient-rich crops and maximizing yield. Bananas, a globally significant fruit crop known for its high nutritional value, require meticulous nutrient management to thrive. Micronutrients, such as Boron, are particularly critical for maintaining hormonal equilibrium in banana plants, with deficiencies often manifesting visibly on the leaves. This study proposes a deep-learning approach to detect Boron deficiencies in banana leaves. The developed CNN model with Skip Connections (CNNSC), comprising thirteen layers, outperforms established architectures like VGG16, DenseNet, and Inception V3. Training the model on a specialized dataset of 11,000 nutrient-deficient images, with a split of 70% for training and 30% for testing, yielded impressive results. Evaluation metrics including accuracy, loss, precision, F1 score, recall, and

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the confusion matrix showcase the model's effectiveness, achieving a remarkable accuracy of approximately 95%.

Keywords: Nutrient, Skip Connection, Machine Learning, Boron micronutrient

1. Introduction

Agriculture is indispensable in supplying food, fiber, and vital resources for human survival and economic progress. The integration of deep learning methodologies into agricultural practices has emerged as a promising avenue for enhancing multiple facets of farming. This includes the ability to forecast crop yields, identify diseases, manage pests, optimize irrigation, and more. Enhancing crop yield hinges on cultivating plants rich in essential nutrients, which necessitate a balanced intake of 16 key nutrients. These nutrients span various categories, including:

- Carbon, Hydrogen, Oxygen
- Macronutrients: Nitrogen(N), Phosphorous(P), Potassium(K)
- Secondary nutrients: Calcium (Ca), Magnesium (Mg), Sulphur(S)
- Micronutrients: Boron (B), Chlorine (Cl), Copper (Cu), Iron (Fe), Manganese (Mn), Molybdenum (Mo), and Zinc (Zn)

Soil serves as the primary reservoir for macronutrients, secondary nutrients, and micronutrients crucial for plant growth. However, factors such as soil salinization and imbalanced irrigation practices can deplete the soil's nutrient richness, hindering the absorption of essential nutrients by plants. This deficiency disrupts the vegetative and reproductive stages of a plant's life cycle, leading to stunted growth and reduced crop yields.

Bananas (Musa sp.) have garnered widespread popularity among people of all social strata in India due to their year-round availability, affordability, diverse cultivars, delightful flavor, and myriad nutritional and medicinal benefits. Recognized for its fiber and antioxidant content, bananas promote digestive health and heart well-being. Moreover, the export potential for bananas incentivizes farmers to cultivate nutrient-dense varieties that meet global quality standards.

Micronutrient deficiencies in banana plants, notably Boron often manifest visibly on the leaves. Leveraging deep learning techniques, this study aims to detect and diagnose such deficiencies by analyzing leaf images. The research makes significant strides in:

- Design a deep learning model to detect micronutrient Boron deficiency in banana leaves
- Comparison with existing pre-trained models VGG16, DenseNet, and Inception V3 • Suggest nutritional supplements to improve the plant's entire growth system on detection of nutrient deficiency to enhance the yield

These advancements offer a practical solution for farmers and agricultural experts to effectively monitor and mitigate Boron deficiency in banana plants. Harnessing the capabilities of deep learning and computer vision methodologies, the developed model introduces a streamlined and automated approach for detecting and remedying deficiencies. Such interventions hold the potential to enhance both the productivity and quality of banana crops.

2. Motivation

Micronutrients are integral to a multitude of physiological functions, encompassing growth, cellular activity, metabolic processes, and tissue regeneration. The identification of micronutrient deficiencies is instrumental in tailoring specific nutrient profiles for diverse age demographics, ensuring optimal growth and development.

Bananas, renowned for their nutritional richness, confer numerous health benefits. Packed with vital nutrients, including vitamin C, vitamin B6, folate, potassium, magnesium, and dietary fiber, they contribute significantly to overall well-being. By automating the assessment of plant health, deep learning methodologies offer a range of advantages such as:

- Reduce the time and effort required for manual inspection
- Enabling faster detection of plant diseases, nutrient deficiency, or stress
- Offer more objective and consistent assessments

- Contribute to improving crop management practices and increasing yield
- More sustainable agriculture.

Hence, the motivational reasons, which aim to tackle specific agricultural challenges and leverage cutting-edge technologies to improve crop productivity are:

- Effects of micronutrient deficiency on human health which is depicted in Table 1
- Deficiency of micronutrients is exhibited on the leaves of banana plants which is shown in Table 2

Table 1: Impact of deficiency of micronutrients on human health

Sl. No.	Nutrient Deficiency	Effects [3,11,18]
1.	Boron	Cognitive impairment and Executive dysfunction of the Brain
2.	Iron	Feel tired, Weakness, Dyspnea, and Drowsiness
3.	Zinc	Hair loss, Changes in their nails, Diarrhea, Irritability, Anorexia, Eye problems, Weight loss, Chronic wounds, Anosmia
4.	Manganese	Bone demineralization and poor growth in children, Skin rashes, Hair depigmentation, Decreased serum cholesterol

Table 2 Micronutrients and deficiency Symptoms on leaves of banana plants

Sl. No.	Nutrient Deficiency	Symptoms
1.	Boron	Reduced leaf area, Curly leaves, Lamina deformation, white stripes in young leaves [8,4]
2.	Iron	The younger leaves turn yellow or white
3.	Zinc	Young leaves become smaller in size and more lanceolate in shape
4.	Manganese	The youngest leaf show narrow green edges at the leaf margins, which further spread to the midrib

The phenomenon of micronutrient deficiency, often termed 'Hidden Hunger,' is a pervasive issue impacting billions worldwide.

Hannah [11] reports that approximately two billion individuals, constituting 30% of the global population, grapple with deficiencies in essential micronutrients, highlighting the formidable challenge of combatting malnutrition and nutrient scarcity on a global scale. The ramifications of such deficiencies extend to severe and enduring health complications, profoundly affecting the quality of life for many individuals across the globe.

As the world's population burgeons, the urgency to bolster food production and enhance its nutritional value intensifies. Consequently, prioritizing the cultivation of nutrient-dense crops assumes paramount importance in ensuring a sustained supply of nourishing food for the expanding populace.

Bananas, revered for their exceptional health benefits, accessibility, delectable flavor, and affordability, rank among the most widely consumed fresh fruits worldwide. Abounding in essential micronutrients such as Boron, Iron, Potassium, and Magnesium, bananas hold immense potential to contribute to human health and well-being.

This study endeavors to detect Boron deficiency, a critical micronutrient, in bananas, thereby empowering farmers to cultivate nutrient-enriched banana crops and consequently enhance human health.

While conventional laboratory techniques for soil and plant analysis offer valuable insights into nutrient deficiencies, their reliance on laborious procedures and substantial costs present inherent limitations. Micronutrient deficiencies in banana plants typically manifest through discernible alterations in leaf color, size, and morphology, contingent upon the specific nutrient deficiency. Leveraging deep learning methodologies to detect Boron deficiencies in banana leaves presents a promising avenue. Swift and accurate results derived from deep learning models can equip farmers with timely information to implement remedial measures and foster the cultivation of nutrient-rich banana plants.

3. Literature Survey

The repercussions of nutrient deficiencies extend beyond individual plants to impact overall crop productivity, posing significant challenges to farmers' livelihoods and national economies. Addressing and mitigating nutrient deficiencies in banana plants holds the potential to bolster crop yields, fortify food security, and alleviate hunger in regions heavily reliant on bananas as a staple food source. In recent years, researchers have made notable strides in enhancing agricultural productivity through the integration of AI technologies, yielding innovative solutions and advancements across various facets of farming practices. Continued research efforts in this domain are poised to yield effective strategies for nutrient management, thereby bolstering profitability and sustainability within the banana industry. Researchers have undertaken diverse initiatives to detect nutrient deficiencies in banana crops through image processing and analysis, leveraging both Machine and Deep Learning techniques. Ongoing research endeavors in applying deep learning methodologies to banana plants encompass the following areas:

- Identification and prediction of diseases in banana plants
- Detection of nutrient deficiencies in banana plants

3.1 Identification and Prediction of Diseases in Banana Plants

Prerana et al. [17] devised a unified system that harnesses the power of a Convolutional Neural Network (CNN) to extract pertinent features from images of bananas. These features are subsequently inputted into a K-Nearest Neighbors (KNN) algorithm, facilitating precise disease prognostication in banana plants. The system adeptly identifies diseases such as Mosaic, Black Sigatoka, Yellow Sigatoka, Panama wilt, and Streak, among others. Moreover, it offers proactive measures and precautionary guidance to aid farmers in disease detection and prevention.

Gokula Krishnan et al. [9] explored the efficacy of a hybrid segmentation approach termed Total Generalized Variation Fuzzy C Means (TGVFCMS) on the CIAT image dataset. TGVFCMS exhibited a remarkable 93% accuracy in delineating disease-affected regions and successfully identified five distinct diseases in banana plants, including Fusarium Wilt of Banana (FWB), Black Sigatoka (BS), Xanthomonas wilt of banana or Banana Bacterial Wilt (BBW), Yellow Sigatoka (YS), and Banana Bunchy Top (BBT). The CIAT image dataset comprised 18,000 images, with only 9,000 images allocated to the five disease classes.

On the other hand, Niraj et al. [15] proposed a deep learning methodology aimed at clustering images of banana leaves into two disease types, namely Black Sigatoka and Black Speckle. Their dataset encompassed 653 images distributed across three categories: healthy (360 images), Black Sigatoka (220 images), and Black Speckle (43 images). Their model achieved an impressive accuracy of 90%.

Sophia et al. [21] have pioneered the development of a mobile application geared towards detecting diseases in banana leaves. Leveraging ResNet152 and InceptionV2 deep learning models, trained with 3,000 images each, the application achieved remarkable accuracies of 99% and 95% respectively. Their augmented dataset comprised 18,000 images of banana leaves categorized into three classes: Black Sigatoka, Fusarium Wilt, and healthy leaves. The training involved an 80% training set, a 15% testing set, and a 5% validation set.

Meanwhile, Michael [14] addressed the identification of the major diseases affecting banana plants, including Xanthomonas wilt of banana (BXW), Fusarium Wilt of Banana (FWB), Black Sigatoka (BS), Yellow Sigatoka (YS), Banana Bunchy Top (BBT), and the Banana Corm Weevil (BCW) pest class, utilizing aerial imagery processed with machine learning techniques. Employing three models—Inception, MobileNet, and ResNet50—trained with the CGIAR dataset, they achieved accuracies ranging from 70% to 99%. Their dataset comprised over 18,000 images, with experimental analysis conducted on 12,600 banana leaf images. Nandini et al. [13] introduced a Gated Recurrent CNN architecture tailored for classifying diseased banana plants. The integration of recurrent layers facilitated the recognition of sequential patterns inherent in the data sequence, resulting in an impressive accuracy of 94%.

Cristian et al. [6] monitored the progression of disease infection in banana leaf images utilizing the LesNet deep learning model, while the severity of diseases was quantified using Decision Trees (DT). Anasta [2] pursued disease detection through thermal imaging using a FLIR camera, employing image processing techniques, including multi-threshold methods, to achieve an accuracy of 92%.

Surya et al. [23] conducted an analysis comparing various methods for segmenting diseased banana leaves, concluding that the geodesic method exhibited the least Mean Squared Error (MSE) parameter value among techniques such as Canny, Robert, Prewitt, Color Segmentation, and Sobel. Chaitanya and collaborators [5] devised a 3-layer CNN architecture aimed at detecting four distinct diseases in banana leaves. Trained on a dataset comprising 1,200 images, the model achieved an accuracy of 80%, successfully identifying Freckle and Sigatoka diseases.

Fredy et al. [7] engineered a cost-effective embedded system utilizing a DenseNet CNN model to discern diseases in banana leaves. This system proficiently categorized Bacterial Wilt and Black Sigatoka diseases with an accuracy of 92%. The training utilized a dataset containing 200 images per category, totaling 600 images, meticulously labeled by an expert. The authors allocated 80% of the dataset for training and 20% for testing.

Bolanle et al. [16] developed a pioneering Capsule Network model (CapsNet) dedicated to detecting two major banana diseases, specifically Black Wilt and Sigatoka. Compared to LeNet and ResNet CNN models, the proposed CapsNet achieved a superior classification accuracy of 95%. The training involved a custom dataset comprising 1,000 images collected from cultivated fields across three classes, partitioned into an 80% training set, 10% validation set, and 10% testing set.

SweetWilliam et al. [24] engineered an Artificial Neural Network (ANN) employing Multilayer Perceptron architecture to categorize banana leaves afflicted by Sigatoka disease. Discriminative color features were extracted using a Scalable Color Descriptor, while texture features were derived via a Histogram of Orientation Gradient (HOG). The HOG descriptor notably achieved an outstanding accuracy of 98 Furthermore, an AI-driven banana disease detection system was devised utilizing Deep Learning Convolutional Neural Networks

(CNNs), enabling timely disease detection and the formulation of control measures with an impressive accuracy of 90%. Similarly, Gokulnath et al. [10] undertook the classification of diseased banana leaves employing the Adaptive Neuro Fuzzy Interference System (ANFIS).

3.2 Nutrient Deficiency

Amritha et al. [1] directed their efforts toward crafting an automated robot geared toward detecting Manganese, Potassium, Sulphur, and Zinc deficiencies in various crops. They employed a CNN model to alleviate the burden on farmers.

Renato et al. [19] devised a CNN model trained with fine-tuned transfer learning to identify deficiencies in Nitrogen, Potassium, and Sulphur in images of banana leaves. Utilizing a dataset comprising 995 images, they applied a pre-trained VGG 16 CNN model, leveraging transfer learning and fine-tuning. Their experimentation revealed that Histogram Equalization within the YUV color space yielded an outstanding accuracy of nearly 98.

Meanwhile, Jonilyn et al. [12] developed a web-based mobile application utilizing the Random Forest (RF) machine learning algorithm to detect deficiencies in Nitrogen, Potassium, and Phosphorus on banana leaves. The application underwent training using a 10-fold cross-validation approach, achieving a performance accuracy of 92%. Their dataset comprised 705 images, encompassing 50 healthy leaves, 255 leaf images deficient in Nitrogen, 155 deficient in Phosphorus, and 90 deficient in Potassium.

While the research on applying deep learning techniques to banana plants encompasses various areas, such as disease identification, yield prediction, ripeness assessment, and disease progression monitoring, there has indeed been relatively less focus on specifically detecting micronutrient deficiencies in banana leaves. To ensure the optimal health and productivity of crops, addressing micronutrient deficiencies in banana plants is crucial. Neglecting these issues can result in significant economic losses and challenges in food supply.

3.3 Research Gap

The current machine learning and deep learning techniques employed, primarily concentrate on identifying micronutrient deficiencies such as Nitrogen, Phosphorus, and Potassium, in selected crops such as maize, rice, wheat, and cotton. Only a handful of researchers have ventured into utilizing image analysis methods for diagnosing symptoms of micronutrient deficiencies, despite the significant harm they can inflict on plant/crop growth. Further, bananas being one of the major crops, are the least focused.

This study bridges a research gap by addressing the absence of exhaustive methodologies for detecting Boron micronutrient deficiencies in banana leaves through the utilization of deep learning techniques.

Deep learning techniques have proven successful in detecting micronutrient deficiencies in banana leaves [1,12,19]. As a result, creating a custom image dataset by capturing banana leaf images from various plantations becomes an invaluable approach to achieving the specific research goal of detecting micronutrient deficiencies in banana leaves. By leveraging this dataset, ongoing research has developed a more accurate and reliable model that aids in identifying and addressing boron micronutrient imbalances in banana crops.

4. Methodology

A thirteen-layer Deep Learning model has been crafted and deployed for the precise identification of Boron deficiency in banana leaves. The architecture of this meticulously crafted model is illustrated in Figure 1, showcasing its intricately designed structure.

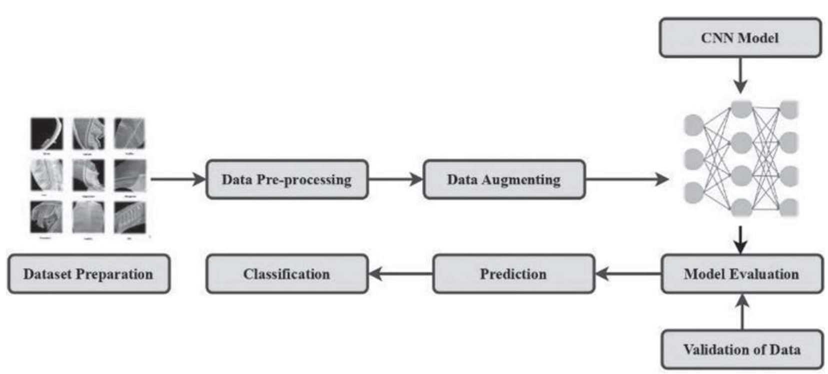


Figure 1: General architecture of the designed model

The subsequent section furnishes an elaborate elucidation of every constituent of the devised model, comprising its architectural framework, accentuating their respective functionalities and contributions to the holistic system.

4.1 Dataset Creation

A meticulously curated dataset forms the cornerstone for training, validating, and evaluating Deep Learning models. An intricately assembled, diverse, and precisely annotated dataset plays a pivotal role in the development of resilient models that demonstrate robust generalization, high performance, and efficacy in addressing real-world challenges.

The construction of a custom image dataset is underway, comprising a comprehensive repository of banana leaf images sourced from a variety of banana plantations. These plantations encompass a range of banana cultivars, including Musa Acuminata (Dwarf Cavendish), Robusta, Rasthali, Poovan, Monthan, and Elakkibale, gathered from disparate locations in and around Hassan, Karnataka, India. Notably, the manifestation of nutrient deficiencies is prominently evident in the leaves of these banana varieties. As such, the images are meticulously categorized by an agriculture expert into nine distinct classes based on observed nutrient deficiencies [22].

Field visits to banana plantations were meticulously conducted to capture images of plants exhibiting discernible signs of nutrient deficiency. Figure 2 showcases a sample selection of leaf images depicting nutrient deficiencies across the nine categorized classes, alongside images of healthy leaves.

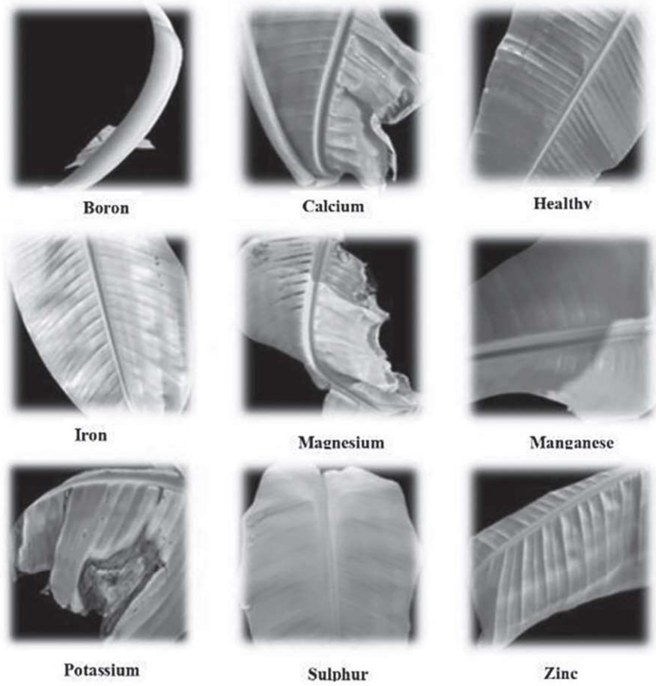


Figure 2: Sample images of nutrient-deficient banana leaves

4.2 Dataset preparation

An extensive range of sources is utilized to gather images, employing digital cameras and state-of-the-art mobile devices to capture leaf samples. These images showcase leaves afflicted by Boron deficiency alongside healthy specimens. The existing dataset comprises diverse images with varying resolutions, lighting conditions, and environmental settings.

4.3 Data Pre-processing

Prior to analysis, images undergo preprocessing, including resizing to a uniform resolution and normalization of pixel values within a desirable range (e.g., 0-1). The online tool Remove Background is employed to render the image background black, enhancing color features and enabling enhanced focus on the subject matter. This process facilitates more precise analysis and processing.

4.4 Data Splitting

The dataset undergoes division into a 70% training set and a 30% testing set. To address data imbalance, each category is meticulously balanced to ensure equitable representation of both Boron deficient leaf images and healthy leaves.

4.5 Data Augmentation

The efficacy of deep learning models heavily hinges on the caliber, volume, and context of the training data, underscoring the pivotal role of data curation and preparation in attaining robust and effective models. Nonetheless, grappling with data scarcity stands out as a prevalent challenge in deep learning model development, often entailing substantial financial and temporal investments. To mitigate this constraint, techniques such as image data generation and autoencoders are leveraged to bolster the training dataset by generating supplementary samples.

4.6 CNN Model

Convolutional Neural Networks (CNNs) streamline the process by autonomously identifying features with exceptional precision, surpassing alternative models. Figure 3 depicts the innovative thirteen-layer CNN model custom-designed for detecting Boron deficiency in banana leaves.

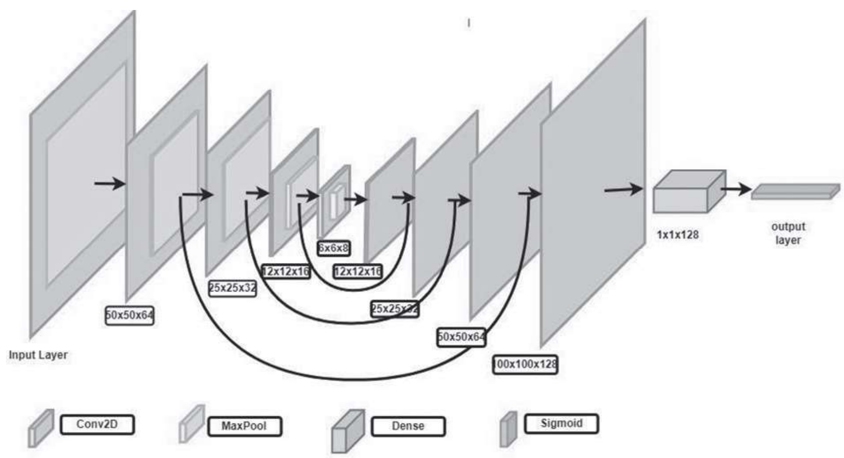


Figure 3: CNNSC model for detecting Boron Deficiency

5. Performance Evaluation

The farmland dataset undergoes a division into 70% for training and 30% for testing. Hyperparameters of the CNN model undergo tuning using the Bayesian Optimization (BO) technique. BO method is utilized to determine an optimized configuration of hyperparameters, encompassing neuron count, activation function, optimizer, learning rate, and batch size for the designed model. By considering past evaluations, BO selects hyperparameters for the next iteration.

Optimization of hyperparameters entails assessing the model's performance across all classes and analyzing metrics derived from the confusion matrix, including Accuracy, Precision, Recall, and F1-score. The hyperparameters tuned are listed below in Table 3:

Table 3: The optimized hyperparameters

Sl. No.	Parameters	Specifications
1.	Activation Function	The Rectified Linear activation (ReLu) and Sigmoid
2.	Regularizer	L2
3.	Cost Function	Categorical Cross entropy
4.	Optimizer	Adam
5.	Epochs	100
6.	Dataset	70% Training, 30% Testing
7.	Learning Rate	0.01 to 0.0001
8.	Batch Size	64
9.	Image Size	150x150

The confusion matrix as depicted in Figure 4, defines the performance of the model followed by the metrics measured.

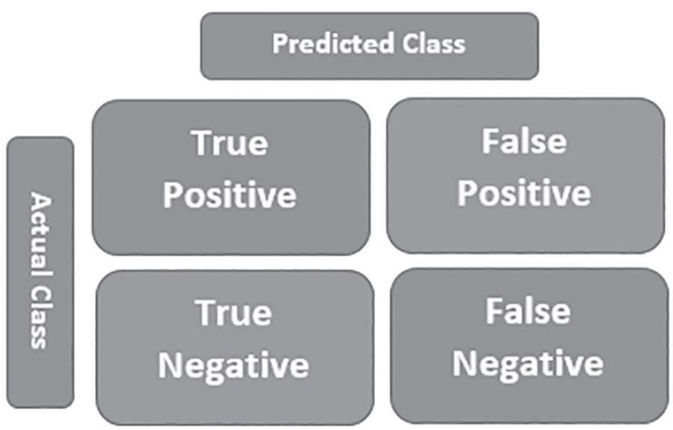


Figure 4: Confusion Matrix

- An accuracy metric serves to gauge the algorithm's effectiveness in a comprehensible manner. In simpler terms, accuracy represents the proportion of correct predictions made by the model.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Number\ of\ Total\ Predictions} = \frac{TP+TN}{TP+TN+FP+FN}$$

- Precision provides insight into the deep learning model's ability to accurately identify positive classifications, giving us a sense of its reliability in this regard.

$$P\ recision = \frac{Number\ of\ correctly\ classified\ positive\ samples}{Total\ number\ of\ classified\ positive\ samples} = \frac{TP}{TP+FP}$$

- The recall measures the models' ability to detect positive samples. The higher the recall, the more positive samples detected.

$$Recall = \frac{Number\ of\ Correct\ Predictions}{Number\ of\ Correct\ Predictions+Number\ of\ Negative\ Predictions} = \frac{T\ P}{T\ P+F\ N}$$

- The F1 score metric amalgamates precision and recall into a unified measure, offering a well-rounded assessment of a classification model's effectiveness. This score reaches its peak when both precision and recall are in equilibrium.

$$F1score = 2 * \text{(precision * recall) (precision + recall)}$$

6. Results

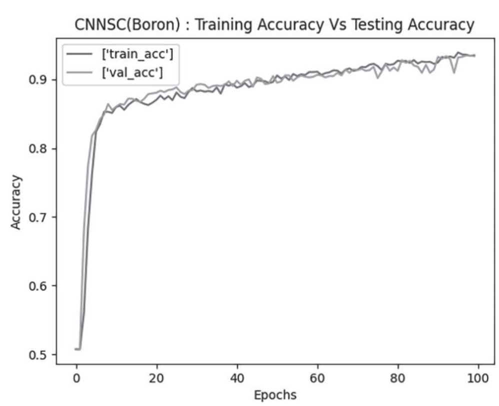
The innovative CNNSC image classification model merges two separate CNNSC models that have been specifically developed for detecting deficiencies in micronutrients, namely Boron. The CNNSC model is composed of Conv2D layers followed by MaxPooling layers. Skip connections are created between layers that share similar filters, allowing for direct connections and information flow between these layers. The model is trained with the dataset consisting of leaf images that encompass both boron-deficient leaves and healthy leaves. The dataset is partitioned into 70% training and 30% testing for evaluating models' performance. Ultimately, the output of the model is integrated to derive the final results. The model undergoes training for 100 epochs, employing various batch sizes including 8, 16, 64, and 128. The Adam optimizer is utilized with an initial learning rate of 0.001, while the momentum and weight decay are set to 0.9 and 0.999, respectively.

During the training process, the model is exposed to input images of different sizes, ranging from 16x16, 32x32, 64x64, 128x128, to 150x150 pixels, enabling it to learn and adapt to various image resolutions. When the image size is reduced, it results in the loss of high-frequency information, potentially impacting the fine details and overall clarity of the visual content. The smaller the image, the less specific the representation becomes. Further, decreasing image size would decrease false negatives and increase false positives. The designed model has achieved the highest accuracy when using an image size of 150x150 pixels, indicating that this resolution yields the most optimal results for the classification task. Table 4 presents the performance accuracy of the designed CNNSC Boron and other different models, providing a comprehensive comparison of their respective performances in accuracy and loss parameters.

Table 4: Comparison of designed CNNSC-Boron and pre-trained models

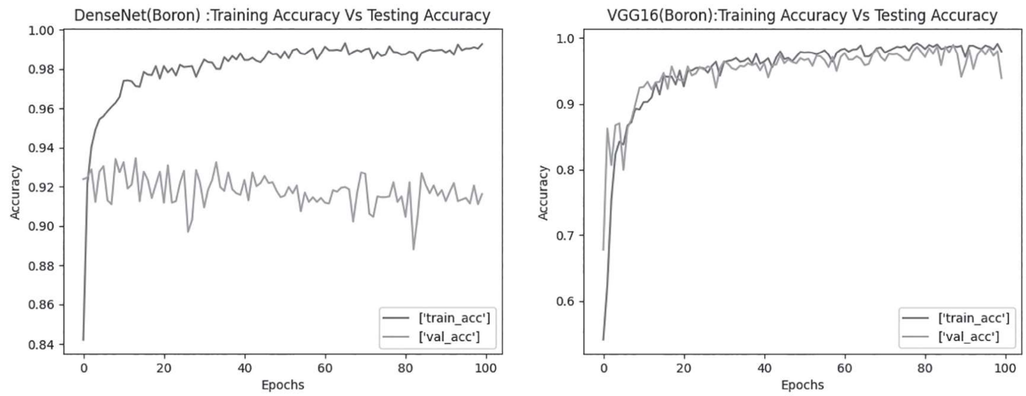
Sl. No.	Parameters	Designed CNNSC	Inception V3	Dense Net	VGG 16
1.	Training Accuracy (%)	94.5	99.02	99.47	98.02
2.	Validation Accuracy (%)	92.16	98.53	92.36	96.16
3.	Training Loss (%)	0.21	0.0023	0.014	0.013
4.	Validation Loss (%)	0.278	0.4532	0.2867	0.254
5.	Execution Time(s)	1467	2430	5620	7376

The accuracy graphs in Figure 5(a-d) and loss graphs obtained in Figure 6(a-d) are analyzed to measure the effectiveness of the models, providing insights into their performance and training dynamics. Upon reviewing Table 4, it becomes evident that Inception V3 attained the highest accuracy of 99% in detecting Boron micronutrient, while the designed CNNSC-Boron model exhibited a slightly lower accuracy of 94%.



(a)

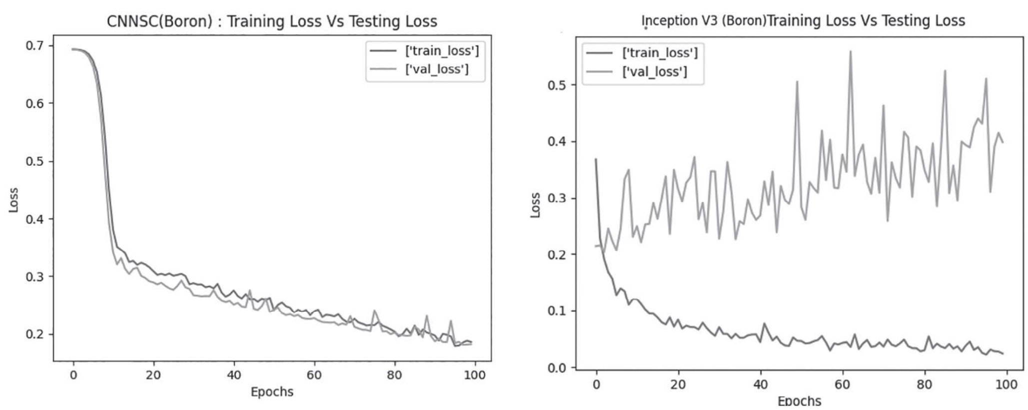
(b)



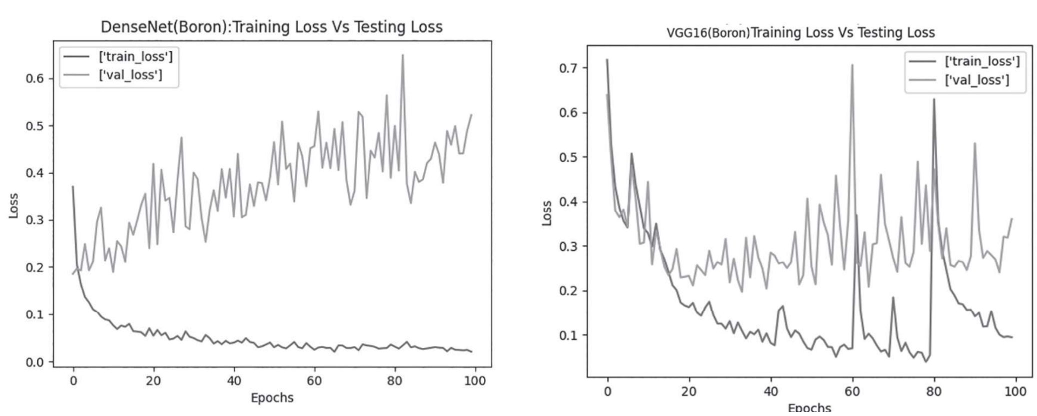
(c) (d)

Figure 5: Accuracy illustration of CNNSC and other pre-trained models

However, a closer examination of the loss graph in Figure 6(a-d) highlights a notable reduction in the loss of the designed CNNSC-Boron model compared to other pre-trained models.



(a) (b)



(c) (d)

Figure 6: Loss illustration of CNNSC and other pre-trained models

Figure 7 presents the confusion matrices of all the models. It demonstrates that the proposed CNNSC-Boron model has given better performance than other models. The matrices indicate that the proposed model has excelled in identifying a higher number of true positives and true negatives compared to other models. Additionally, it has a lower number of false positives and false negatives than the other models.

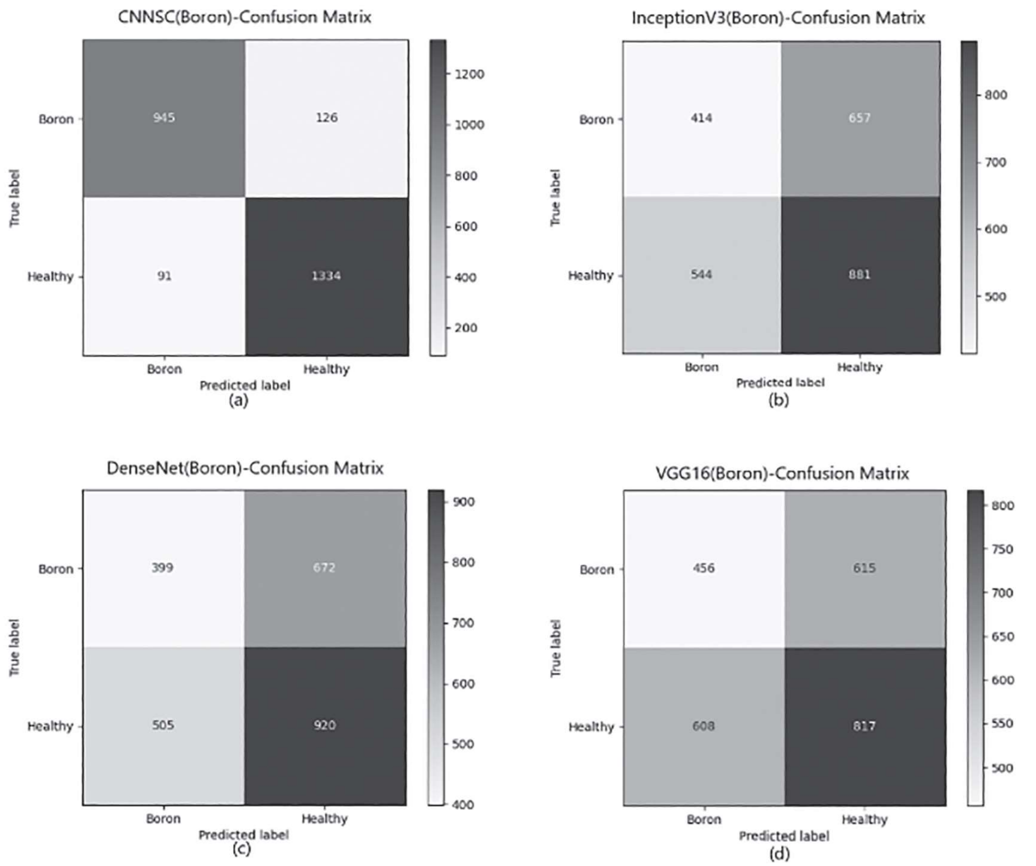
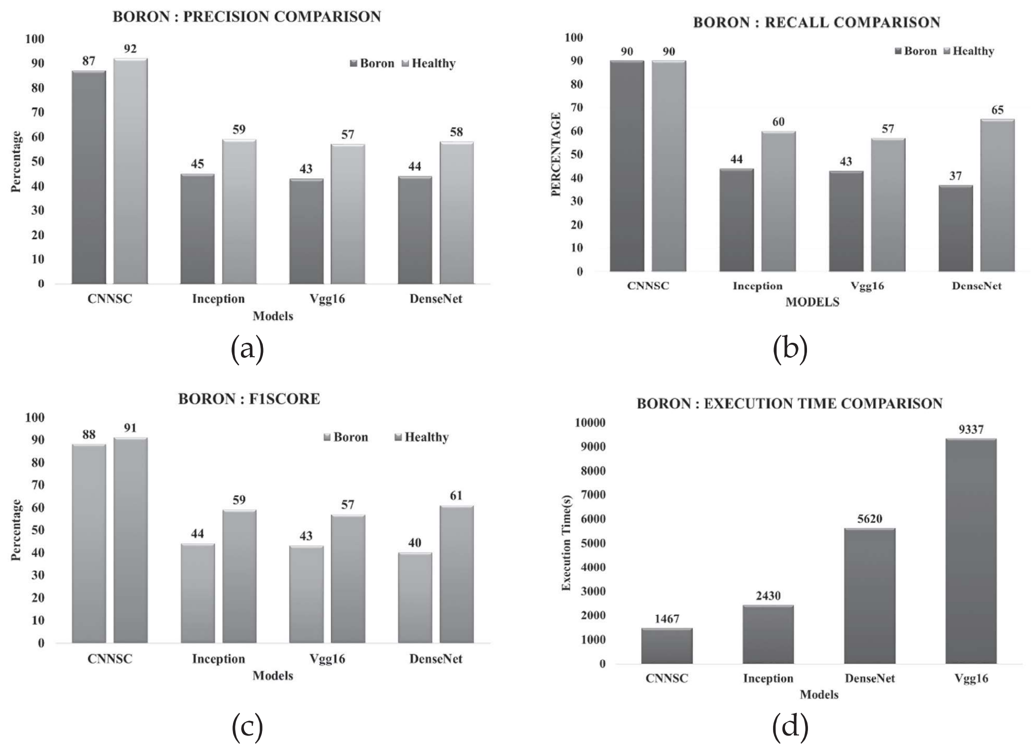


Figure 7: Confusion matrices of the models

Figure 8 illustrates the key metrics derived from the Confusion Matrix namely Precision, Recall, and F1Score. Observing the Precision comparison in Figure 8(a), it is evident that the designed CNNSC-Boron model has exhibited the highest precision value of 90%, outperforming other pre-trained models, which achieved approximately 60% precision. Furthermore, in Figure 8(b) and Figure 8(c), it can be observed that the designed CNNSC-Boron model has achieved the highest Recall and F1Score values of 90%, indicating its superior performance compared to other models.



(a) (b) (c) (d)

Figure 8: Performance metrics derived from the Confusion matrix

The performance of a system can also be determined by its execution time, as performance and execution time have an inverse relationship.

$$\frac{Performance\ of\ A}{Performance\ of\ B} = \frac{Execution\ Time\ of\ B}{Execution\ Time\ of\ A}$$

Applying the aforementioned equation confirms that the execution time of the designed CNNSC model [Figure 8(d)] is 1.6 times faster than InceptionV3, 5 times faster than VGG16, and 3 times faster than DenseNet, indicating superior efficiency and faster processing capabilities. It is evident from the analysis that the designed Skip Connection CNN model performs well when classifying leaf images into two classes of micronutrients namely Boron deficient and Healthy.

The advantages of considering the CNNSC model for detecting micronutrient-deficient banana leaves are as follows:

- The designed model is 40% more precise
- CNNSC is 30% faster in providing timely decision

The aforementioned features serve as evidence that the designed model surpasses the existing pre-trained Deep Learning models in terms of efficiency and performance. Furthermore, Table 5 presents a detailed breakdown of the number of layers in the model.

Table 5: Layers in the models

Sl. No.	Models	No. of Layers
1.	CNNSC	13
2.	InceptionV3	46
3.	VGG16	16
4.	DenseNet	121

The minimized count of Conv2D layers in the designed CNNSC model enables them to arrive at decisions much faster than their counterparts. The proposed model has undergone extensive experimentation with varying hyperparameters, resulting in a 13-layer CNNSC model. Fewer layers in a deep learning model typically lead to faster execution. Therefore, compared to other pre-trained models, the proposed CNNSC model has fewer layers, thus enhancing its performance.

7. Conclusion and Future Work

The meticulously engineered CNNSC model emerges as a robust solution for precisely identifying micronutrient deficiencies in banana plants. Trained on a tailored dataset comprising 11,000 banana leaf images, the model achieves an impressive accuracy rate of 95%. In comparison to leading counterparts, the CNNSC model demonstrates commendable performance. Examination of the confusion matrices reveals superior precision, recall, and F1 scores exhibited by the CNNSC model. Moreover, analysis of the loss graph unmistakably showcases significantly lower losses incurred by the CNNSC model in contrast to its competitors. Designed to provide timely insights to farmers, the model facilitates targeted nutrient supplementation, thereby promoting the growth of nutrient-rich plants and substantially enhancing overall crop yields. This proactive approach not only contributes to sustainable agricultural practices but also reinforces global food security initiatives.

A user-friendly Graphical User Interface (GUI) is crafted using Gradio, enabling the input of real-time images of banana leaves for nutrient deficiency prediction.

Upon detecting Boron deficiency, it is advisable to address the issue through the following steps

- Soil application of Borax @ 25 g per plant or
- Foliar application of 0.1 % Boron (Solubore) or
- Foliar application of Banana special @ 5g per litre

Detecting multi-nutrient deficiencies in crops via visual symptoms presents a formidable challenge, as the possibility of multiple nutrients causing similar symptoms complicates the diagnostic process.

For instance,

- Magnesium deficiency often manifests as yellowing between leaf veins, resembling symptoms seen in Iron and Manganese deficiencies
- Potassium deficiency may cause marginal leaf scorching or browning, which can be confused with symptoms of drought stress or disease
- Calcium deficiency symptoms may include distorted or irregularly shaped leaves, similar to symptoms caused by environmental stress or certain pathogens
- Phosphorus deficiency can lead to slow or stunted growth, as well as purplish discoloration on leaf undersides, which may be mistaken for symptoms of nutrient toxicity or root damage
- Excess Nitrogen can result in lush, green foliage but may lead to reduced fruit quality and increased susceptibility to pests and diseases
- Excessive Potassium levels can cause salt burn on leaf margins and tip dieback, which can be misinterpreted as symptoms of drought or fungal infections.

Detecting deficiencies in multiple nutrients simultaneously poses a formidable challenge, yet there is promising potential to expand this research to encompass the identification of multi-nutrient deficiencies in banana plants.

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