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Research Article

Nutrient Deficiency Prediction in Banana Leaves Using Advanced UNET Architecture

V. Rekha[1*], Uma Shankari Srinivasan[2]

[1*]Research Scholar, Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, Tamilnadu, India
* **Corresponding Author Email:** rekhaonmail@gmail.com - **ORCID:** 0009-0001-8380-2740

[2]Associate Professor, Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, Tamilnadu, India
Email: umabalajees@gmail.com - **ORCID:** 0000-0001-6102-0476

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Abstract:

India is an agriculture-based country whose maximum population depends on agricultural productivity for their wealth. India is the second leading country in farming and agriculture is the backbone of economic development. The need for agricultural products is increasing daily, and at the same time, the changing environment produces many changes in biodiversity, which influences the farming and productivity of plants. The growth and health of plants mainly depend on soil nutrients, and most of the time, they are not easily identified by farmers and experts. It is necessary to take suitable remedial actions, such as adjusting fertilizer usability and improving the soil quality to optimize plant growth and avoid nutrient deficiency in plant leaves. So, it needs support from computer-aided techniques that easily predict the nutrient deficiency plants of plant leaves. This study adapts Deep Convolutional Generative Adversarial Networks (DCGAN) for data augmentation, Denosing AutoEncoder (DAE) for noise removal, and used UNET, Advanced UNET for nutrient deficiency prediction. This proposed model experimented with the Mendeley Banana Nutrient deficiency dataset and achieved an accuracy of 99.18% for Advanced UNET and 97.09% for UNET. This experiment recommends Advanced UNET for banana leaf nutrient deficiency detection.

1. Introduction

Bananas are Rich nutrient food known for their high levels of iron, manganese, potassium, magnesium, and calcium. India is the largest banana producer globally as of 2022, and Tamil Nadu ranks fourth among the states in banana production in India. Farmers must offer disease-free and healthy banana cultivation to attain high productivity and higher-quality bananas. Proper maintenance is required at every stage of banana farming, including pest monitoring, disease control, proper irrigation, and soil maintenance practices, which are essential to increase the yield of bananas and crop health. In particular, analyzing nutrient deficiencies in banana cultivation is crucial as it gives precise insights into how to prevent them and optimize nutrient management practices. Early identification of nutrient deficiency aids farmers in taking action, which results in good, free yields. The proportion levels of nutrients in banana leaves varies from 0.1% - 0.3% Iron (Fe), 0.05 - 0.2% Manganese (Mn), 1.2% - 2.5% Potassium (K), 0.2% - 0.8% Magnesium (Mg) and 0.5% - 1.5% Calcium (Ca) approximately. Henceforth, the lack of these nutrients affects the leaves, and the majority of plant disease occurs in the spot of the leaf.
Manual identification of this nutrient deficiency is difficult and needs external tests. This research analyses the nutrient deficiency in banana leaves to provide a proper solution to prevent this deficiency. Table 1 shows the nutrient deficiency symptoms.

2. Related Work

Dabalos et al. (2017) developed a Leaf CheckIT mobile application to capture the Potassium (k), Phosphorus (p) and Nitrogen (N) deficiency symptoms on banana leaves.

Table 1. *Nutrient deficiency symptoms.*

Nutrient Deficiency	Symptoms
Boron	Abnormal formation of leaves, fruit cracking
Calcium	Curling and Burning of leaf edges
Potassium	Scorching of leaf margins, bad shape of fruits
Magnesium	Interveinal chlorosis of leaves
Sulphur	Yellow colour in younger leaves
Zinc	Stripes and irregular formation of leaves
Iron	Pale white colour leaves
Manganese	Yellow colour leaves and brown colour leaves

The author experimented with the WEKA tool for this analysis and attained 100% and 91.64 % accuracy [1]. Sunitha et al. (2023) created a real-time banana leaf dataset for nutrient deficiency, and this dataset contains 3000 nutrient deficiency images with 7000+ augmented images. Agriculture scientists manually labelled the dataset [2]. Memon et al. (2005) proposed a tool for analysing the nutrient diagnostic tool named Diagnosis and Recommendation Integrated System (DRIS). It considers the cropping history, nutrient concentration and environmental influences for interpreting the system. This system also used Plant Analysis with Standardized Scores (PASS) [3]. Keerthana et al. (2024) experimented with work on disease management for banana plants and their soil nutrient deficiency. The author also recommended a solution to control nutrient deficiency through pest control [4]. Guerrero et al. (2021) proposed CNN to identify a nutrient deficiency in banana leaves, and the presented model achieved high precision. Finally, a web platform was developed to guide farmers [5]. Almeyda et al. (2020) developed pest incidence identifiers using machine learning algorithms such as logistic regression and support vector machine. This model was designed to capture climate data using IoT sensors as input, which offers 79% pest incidence [6]. Gaitan et al. (2020) elaborated on the usability of machine learning algorithms for classification, detection and forecasting [7]. Jean et al.; (2022) proposed a model by providing several representations of pest incidence. It is tested at both linear and non-linear relationships, which attains higher accuracy for handling pest management [8]. Kirtan et al. (2019) discussed various automation practices, including IoT, Wireless Communications, Machine Learning, Deep Learning and Artificial Intelligence. These practices aid in identifying crop diseases, pesticide control, weed management and storage management. Author also surveyed different research works in agriculture related to these practices [9]. Jose et al.,(2021), experimented red spot thrips and black sigatoka pest in banana production. The author used the machine learning algorithm SVM with IoT to check pest accuracy and recommend pest control management to save production costs [10]. Arif et al. (2012) created two ANN models for estimating soil moisture in paddy fields. Model1 estimates ET, including minimum, average and minimum air temperature. Model 2 was developed to gather solar radiation, precipitation, and soil temperature. Both models offer high accuracy, which leads to less labour with minimum time [11-13].

2.1 Research gap

A review reveals that little research has been done on predicting banana leaf nutrient deficiency using the Deep learning model Advanced UNET. Hence, effective identification models using deep learning schemes are needed.

2.2 Research Objectives

1. To augment input banana plant leaf images to enhance the data diversity and robustness of the model.
2. To Experiment with UNET and refine the structure of existing UNET to produce Advanced UNET for the prediction of nutrient deficiency.
3. To carry out a comparative analysis between existing and proposed models by estimating related evaluation metrics
4. To validate the model performance by recommending a suitable model for predicting banana plant nutrient deficiency.

3. Methodology

Automatic detection and diagnosis are essential for improving the agricultural sector. Deep learning's superior performance ensures early detection of plant deficiencies. This study employs DCGAN to augment to-encoder-based denoising to remove noise. Advanced UNET is carried out to predict nutrient deficiency. The figure 1 depicts the performance of the proposed model.

3.1 Dataset Description

This work considers the Mendeley dataset to analyse nutrient deficiency. This dataset comprises eight classes of nutrient deficiency, including Boron, Calcium, Iron, Potassium, Manganese,

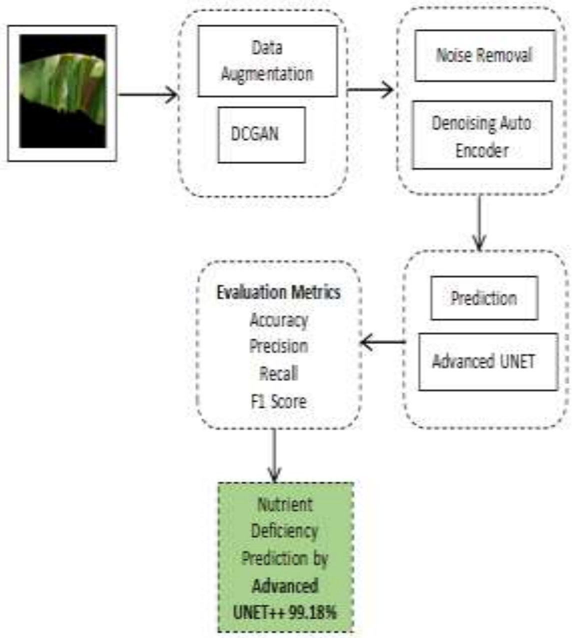


Figure 1. *Work Flow of the proposed model*

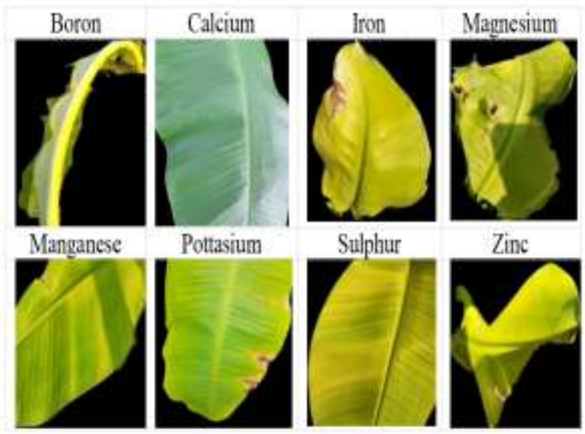


Figure 2. *Nutrient Deficiency Images*

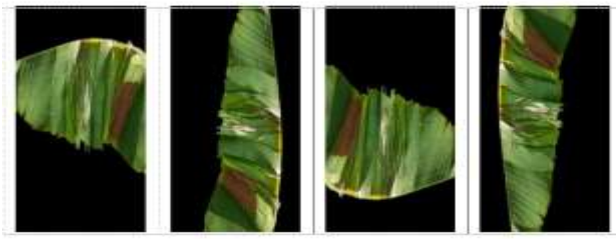


***Figure** 3. DCGAN generated Images*

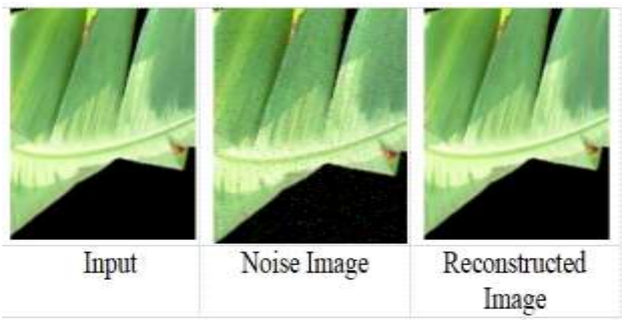


Figure 4. *Reconstructed Image*

Magnesium, Manganese, Sulphur, and Zinc. It contains 3000 nutrient-deficient banana leaf images with 7000+ augmented images. The figure 2 shows eight classes of nutrient-deficient images of the considered dataset.

3.2 Data Preprocessing:

Data pre-processing is considered a crucial step to remove noise and unwanted distortions from an image. Augmentation and Denoising are the two steps involved in the pre-processing stage. It is carried out using an Auto-encoder model.

3.3 Data Augmentation

The data augmentation uses the Deep Convolution Generative Adversarial Network (DCGAN) model. This technique was developed by Ranford et al. in 2015, and it produces realistic images on learning from sample images. It is the combination of generator and a discriminator neural network. Generator networks take a latent vector as input, thus creating images which resemble training data. It consists of multiple up-sampling layers that aid in generating high-resolution images. A discriminator network is a binary classifier that takes images as input and produces outputs that show the probability of fake or real images. Both the generator and discriminator act like min-max theory. It comprises convolutional, transposed convolutional layers, batch normalization and Leaky ReLu activation functions. The figure 3 shows the augmented banana leaf images.

3.4 Denosing Auto Encoder

Auto-encoder is employed for denoising purposes to eradicate noise present in augmented image samples. This combination of decoder and encoder is capable of handling lower dimensional data. An encoder consists of one or more hidden layers in a neural network, and it receives noisy input data, creating an encoding process. The decoder function plays an extension function and reconstructs the original data. It also has one or more hidden layer. The primary goal is to produce noise-free images using DAE, which could be attained using the reconstruction loss function, which is employed to evaluate the disparity between reconstructed and clean output. This loss function will be minimized using the backpropagation model. Therefore, weight is updated in the encoder and decoder model. Image quality is checked by reconstructing error estimates by measuring Mean Squared Error (MSE) and Peak Signal Noise Ratio (PSNR) metrics.

Mean Squared Error (MSE)

It calculates the average squared difference between original and reconstructed data. It is represented as shown:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (x_i - x_i)^2$$

In this, n - Total number of Data Points, x_i - Original data, x_i - Reconstructed data

Peak Signal to Noise Ratio (PSNR)

It calculates the quality of the reconstructed signal and original signal; due to this property, it is employed in image processing. It is measured as follows:

$$PSNR = 10.log_{10}\left(\frac{max^2}{MSE}\right)$$

Where, max - maximum possible pixel value, MSE - Mean Square Error

The table 2 and figure 4 show the values of MSE & PSNR. The represented table values show that the reconstructed image produces a minimum loss.

Table 2. *Evaluation of MSE & PSNR*

Image	MSE	PSNR
Original	0.00067	38.2341
Reconstructed Image	0.00065	40.4532

3.5 Model Analysis

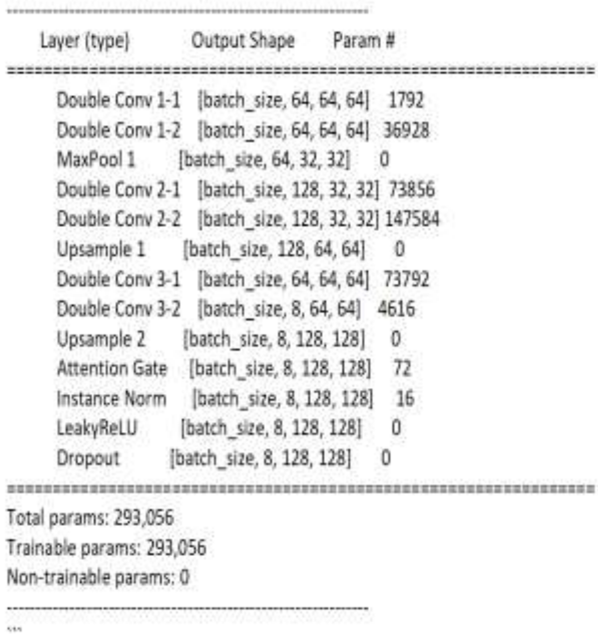
Classification is a supervised learning task that aims to separate input data into classes based on its characteristics. This study uses UNET and Advanced UNET algorithms.

UNET

Olaf Ronneberger developed a model of UNET that is implemented similarly to the autoencoder. It comprises the contracting path, an expanding path and a bottleneck. The encoder gets input; thus, the decoder offers an output from the given input. It combines a 3x3 convolutional layer, ReLU activation function, same padding and max pooling layers. Its expanding path contains the same layers in Adam optimization and sigmoid activation function for the final fully connected layer. The batch size and epoch are also fixed to train the model. By adjusting several convolution layers and parameters, this study proposes Advanced UNET.

3.6 Advanced UNET

Advanced UNET replaces the single convolution layer and adds a double convolution layer to increase the capacity of the network. The local and global features were captured by group convolution. The gradient flow facilitates residual skip connections and improves information propagation. This study also adds an attention gate to skip connections to enable the model to suppress irrelevant features. Stride convolution is employed to downsample the feature maps and fractionally stride convolution for upsampling instead of max pooling and transpose layers. The normalization layer is used for stabilizing training and to enhance convergence. LeakyReLU activation function improves network performance. Dropout helps in preventing the issue of overfitting. Weight initialization is carried out by He initialization, which enhances the training process, thereby handling convergence. Hyperparameters such as batch size, epoch, and optimizers are employed to analyse the model. figure 5 shows the Proposed layers of Advanced UNET. Figure 6 shows the architecture of proposed model.



Layer (type)	Output Shape	Param #
Double Conv 1-1	[batch_size, 64, 64, 64]	1792
Double Conv 1-2	[batch_size, 64, 64, 64]	36928
MaxPool 1	[batch_size, 64, 32, 32]	0
Double Conv 2-1	[batch_size, 128, 32, 32]	73856
Double Conv 2-2	[batch_size, 128, 32, 32]	147584
Upsample 1	[batch_size, 128, 64, 64]	0
Double Conv 3-1	[batch_size, 64, 64, 64]	73792
Double Conv 3-2	[batch_size, 8, 64, 64]	4616
Upsample 2	[batch_size, 8, 128, 128]	0
Attention Gate	[batch_size, 8, 128, 128]	72
Instance Norm	[batch_size, 8, 128, 128]	16
LeakyReLU	[batch_size, 8, 128, 128]	0
Dropout	[batch_size, 8, 128, 128]	0

Total params: 293,056
Trainable params: 293,056
Non-trainable params: 0

Figure 5. *Advanced UNET Layer Architecture*

4. Result & discussion

In this section, an experiment showcases the outcome of the proposed model and actual UNET with various learning rates, epochs, and optimizers. The table 3 shows the performance of UNET for banana leaf nutrient deficiency prediction with a learning rate of 0.0001, epoch 5 to 25, and optimizer Adam and RMSProp. The figure 7 shows that the lower MSE value attained indicates the good performance of DAE. The figure 8 shows that a high PSNR value indicates the performance of DAE. Figure 9 shows UNET performance with learning rate 0.0001 for RMSProp Optimizer (upper) and for Adam Optimizer (lower).

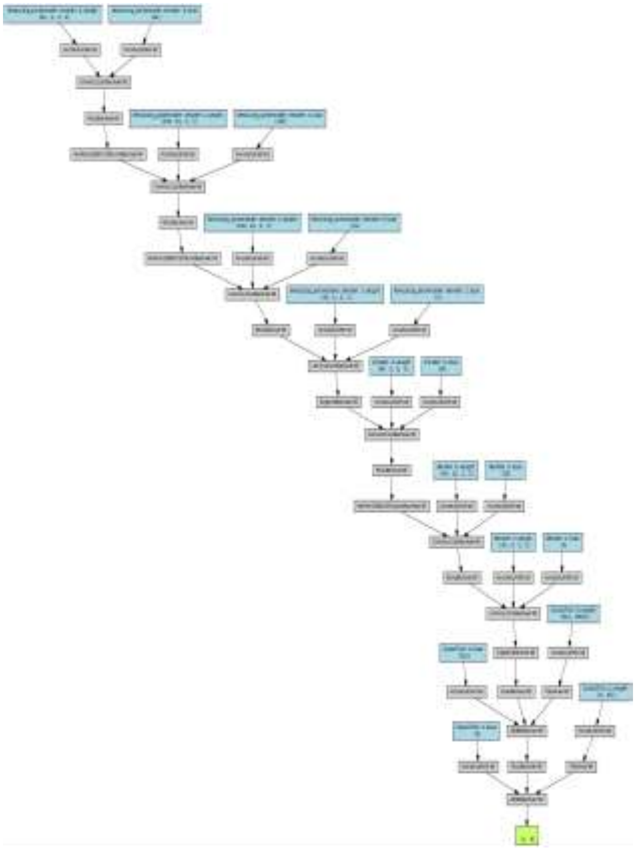


Figure 6. *Proposed model architecture*

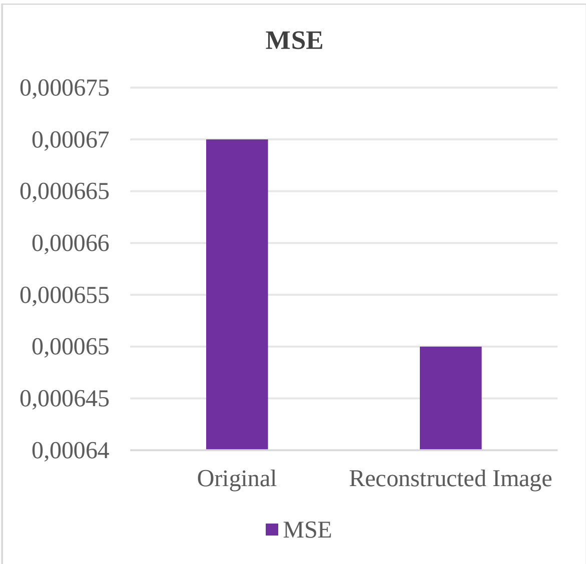


Figure 7. *DAE Performance evaluated by MSE*

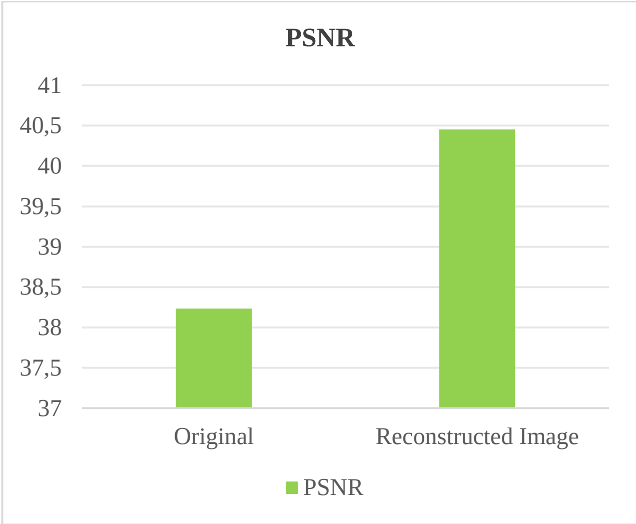


Figure 8*. DAE Performance evaluated by PSNR*

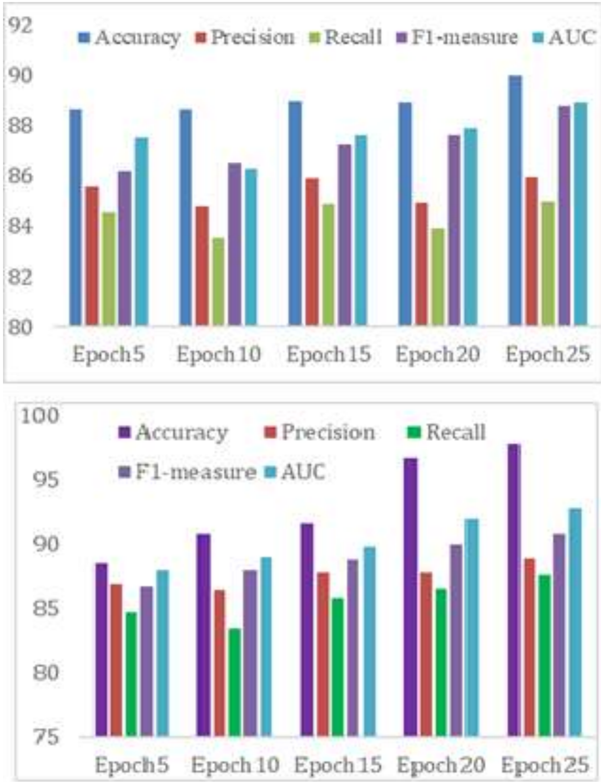


Figure 9. *UNET performance with learning rate 0.0001 for RMSProp Optimizer (upper) and for Adam Optimizer (lower).*

Table 3.(a). *UNET performance with learning rate 0.0001 & RMSProp Optimizer*

Epoch	Values in %				
	Accuracy	**Precision**	**Recall**	**F1-measure**	**AUC**
5	88.652	85.581	84.565	86.175	87.521
10	88.656	84.810	83.535	86.499	86.289
15	88.964	85.889	84.872	87.232	87.629
20	88.937	84.941	83.920	87.638	87.892
25	89.995	85.957	84.965	88.775	88.929

Table 3. (b). *UNET performance with learning rate0.0001 & Adam Optimizer*

Epoch	Values in %				
	Accuracy	Precision	Recall	F1-measure	AUC
5	88.591	86.896	84.765	86.769	87.991
10	90.792	86.469	83.432	87.987	88.989
15	91.658	87.828	85.867	88.798	89.869
20	96.691	87.836	86.524	89.987	91.989
25	97.852	88.928	87.647	90.798	92.869

Table 4. *Advanced UNET performance with learning rate 0.0001 & Adam Optimizer*

Epoch	Values in %				
	Accuracy	Precision	Recall	F1-measure	AUC
5	95.112	85.439	84.895	93.813	88.821
10	95.612	85.883	84.792	92.756	89.823
15	95.910	86.744	85.995	93.875	90.451
20	98.671	87.689	86.421	94.564	92.785
25	99.181	88.556	87.996	95.753	93.991

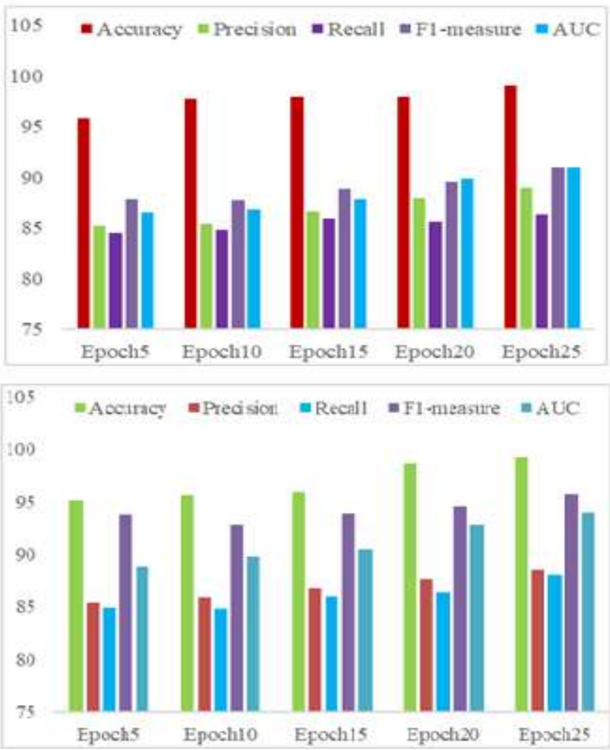


Figure 10. *Advanced UNET performance with a learning rate of 0.0001 for RMSProp Optimizer (upper) for Adam Optimizer (lower).*

Table 4 is advanced UNET performance with a learning rate of 0.0001 & RMSProp Optimizer Figure 10 shows advanced UNET performance with a learning rate of 0.0001 for RMSProp Optimizer (upper) for Adam Optimizer (lower). The figure 11 shows accuracy and loss visualization for UNET and Advanced UNET models with 25 epochs, a learning rate 0.0001, using the Adam optimizer.

4.1 Findings

Preprocessing with Denoising Auto Encoder performs well in noise removal
The proposed model Advanced UNET offers high accuracy for Adam optimizer with a Learning Rate of 0.0001 for epoch 25.

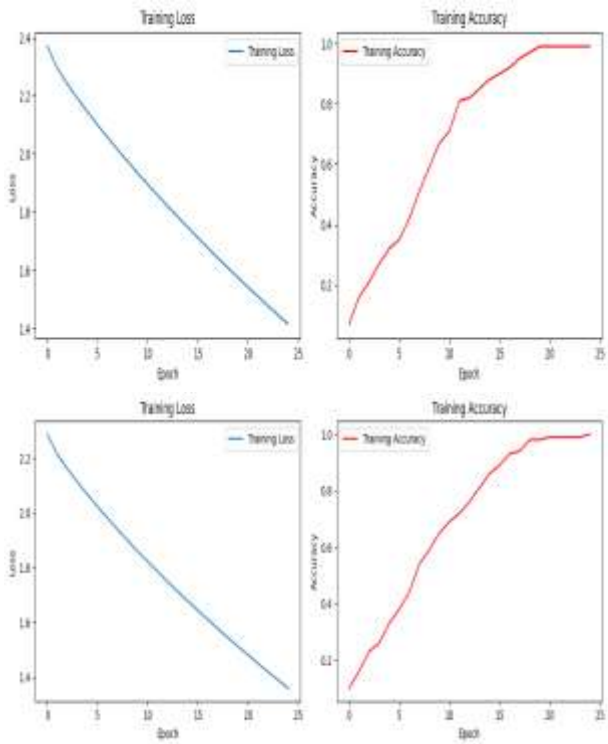


Figure 11 (a). *Accuracy and loss Visualization for UNET* ***(b).*** *Accuracy and Loss Visualization for Advanced UNET*

5. Conclusion

The deep learning model plays an essential role in developing agricultural practices. AI technique offers an advanced solution that ranges from weed detection to pest management. Early detection of nutrient deficiencies allows farmers to take timely actions, enhancing overall quality management. In banana farming, UNET and proposed Advanced UNET models were experimented with to identify nutrient-deficient banana plants. UNET architecture was refined to develop the proposed Advanced UNET, and various hyperparameters were experimented with. Both models were trained and tested for 5 to 25 epochs, with a learning rate of 0.0001 using Adam and RMSProp optimizers. Evaluation metrics revealed that the proposed UNET model offers a precision of 88.92%, a Recall rate of 87.64%, an F1 Score of 90.79 %, an Accuracy rate of 97.85%, and an AUC of 92.86%. In contrast, the proposed Advanced UNET model offers a higher precision rate of 88.55%, a Recall rate of 87.99%, an F1 Score of 95.75%, an Accuracy of 99.18%, and an AUC of 93.99%. Comparative analysis indicates that the proposed Advanced UNET model effectively identifies nutrient deficiencies in banana plants.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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