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A LIGHTWEIGHT DEEP LEARNING FRAMEWORK INTEGRATING CBAM AND LION OPTIMIZER FOR SUGARCANE NUTRIENT DEFICIENCY DETECTION

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ABSTRACT

Sugarcane is a widely cultivated crop and is grown worldwide. Sugarcane yield is severely affected by the nutrient deficiency problem. Some elements like Nitrogen, Potassium, Phosphorus (macro nutrients), and Boron (micro nutrients) are essential for the growth of the crop. Early detection of deficiency of these nutrients is essential. In the age of Artificial Intelligence, deep learning techniques are widely used for nutrient deficiency detection. |In this paper a popular deep learning model, MobileNetV3-L, is used to detect the nutrient deficiency in the sugarcane crop. The model is modified by introducing an Attention Module, Convolution Block Attention Module(CBAM) , after the base model to refine the extracted feature, then transfer learning techniques are used to train the model according to our own dataset of 1024 images of sugarcane leaves. Also, we use Lion optimizer for model training. The model gives an accuracy of 93.2% and correctly detected all the above deficiencies.

Keywords: Nutrient Deficiency, Sugarcane, Deep Learning, Mobile Net, Attention Mechanism

1. INTRODUCTION

Sugarcane is one of the world's most popular crops. Cultivation of sugarcane is spread from Brazil to China and from India to Australia. They are cultivated in most parts of the world. Brazil is the top producer of sugarcane, followed by India, Thailand, and China.[1]. In India, sugarcane's contribution to the national GDP is about 1.1 % [2]. Nutrient deficiency is one of the major problems in sugarcane cultivation. It reduces the crop quality and yield. Therefore, detecting nutritional deficiency in a timely manner is necessary for the crop's growth. Nutrient deficiency affects a sugarcane plant in many different ways, such as stunting growth, bad juice quality, and even detritus. The farmer uses different ways to observe the nutrient deficiencies in a plant. They include soil testing for the pH values, tissue analysis, and manual observation to detect various deficiencies.[3] . The deficiencies of a sugarcane crop are broadly divided into two categories: the macronutrients and micronutrients. Macronutrients are the main nutritional elements that include Potassium(P), Nitrogen (N), Phosphorus (P) , Calcium (Ca), and Magnesium (Mg). Micro nutrients are needed in small quantities but are very essential for the growth of the crops. It includes Boron(B), Iron(Fe), Copper (Cu), and Zinc(Zn). A sugarcane plant requires 11 different nutritional elements in its different stages, and these deficiencies are identified by specific symptoms, like leafage discoloration, spots, and malformation of plant leaves. Some symptoms look similar to the human eye and make it difficult to trace.

With the growth of precision agriculture, AI tools like machine learning and deep learning are widely used in the agriculture sector. Especially computer vision with deep learning plays a major role in the problem of detecting disease and nutrient deficiency in crops. Progress in image classification offers a chance to enhance the early detection of nutrient deficiencies in the sugarcane crop. Implementing deep learning-driven image analysis provides a fast, non-invasive, and non-destructive method for identifying nutrient issues.

In computer vision technology, leaf images are used to detect nutrient deficiency in sugarcane crops using deep learning techniques. Deep learning is a branch of machine learning that uses multilayer neural networks that can solve complex problems and work like human brains. Various deep learning models are trained to perform classification tasks and detect patterns in text, photos, videos, audio, and other types of data. A deep learning model is trained with a large amount of labelled data , Then, this model is used to predict unseen data. Deep learning techniques are widely used in various fields of agriculture, like crop yield prediction, plant disease detection, and nutrient deficiency detection.

Deep learning techniques have shown promising results in analysing agricultural data, particularly in areas such as image processing, predictive modelling, and decision support systems. For instance, deep learning models have been employed for crop recognition, yield prediction, and disease detection, demonstrating superior performance compared to traditional machine learning approaches. [4][5] . Now, pre-trained deep learning models are used to detect crop nutrient deficiency. These models are already trained on a large public dataset like ImageNet, then the transfer learning process is used for a particular dataset to create a new model that can detect the nutrient deficiency of sugarcane using the leaf images. Most popular models that are used to detect the nutrient deficiency are Densenet121, ResNet, MobileNet, EfficientNet, etc.

The content of this paper is organized as follows. The second section explores the different work done so far, related to this field. The third section explains the methodology proposed and the structure of the modified MobileNetV3-L model. This section also explains the role and working of the CBAM module in the existing MobileNetV3-L model. The fourth section provides details about the dataset used in the research, including its collection process and the total number of different images. In section fifth, the training details of the model are given with the details of different hyperparameters given to tune the model with our own dataset. The final result and the discussion of the results in different conditions are explained in the sixth section its also elaborates different graphs found in the experiment. Finally section seven concludes the paper with future scope.

2. RELATED WORKS

Various studies and research are available to identify nutrient deficiency in sugarcane and other crops using pre-trained deep learning techniques. These techniques are used with images of different nutrient-deficient leaves to train a deep learning model and achieve good accuracy. In a study R. Madhumathi et al. [3] presented research to detect Nitrogen (N) , Phosphorus (P), Potassium (K) deficiency in sugarcane crop. The data is collected from the field, and all augmentation and cleaning techniques are used to prepare the data, then transfer learning techniques are used to train pre-trained models like DenseNet121 and Resnet152v2 with the new dataset of sugarcane leaf images. The tuned model shows an accuracy of 93 %. . In another study M, S. Vallabhaneni et al. [6] conducted research on rice plant to detect N, P, K deficiencies. They used transfer learning on five deep learning models, VGG16, ResNet 50, Inception v3, Xception, and MobileNet, with an ensemble technique to combine the results of each model and select the best one. The dataset has been collected from the public database Kaggle. This model leverages the strengths of all the pre–trained models used and achieves an accuracy of 97%. A research paper presented by Vrunda Kusanur et al. [7] to detect calcium and magnesium deficiency in tomato plant. In this paper, transfer learning techniques are used on InceptionV3, ResNet50, and VGG16 with RF and SVM classifiers to predict the deficiency. They achieve an accuracy of 99.9% To detect the N, P, K deficiency in groundnut crops, Kummari Venkatesh et al. [8] presented a paper in which they used the VGG16 model and modified it using transfer learning according to their own data. They also used machine learning model SVM3 to classify the data accurately They get an accuracy of 98%. Borja Espejo-Garcia et al [9] experimented on two different data sets: the DND-SB sugar beat dataset and the orange leaf image dataset. They are using a transfer learning technique to detect the nutrient deficiency in the above datasets. They detected N,P,K deficiency in the DND-SB dataset and Fe,K , Mn, and Mg deficiency in the orange leaf database. The EfficientNetB4 model is used for this purpose, which is fine-tuned with the above dataset and give an accuracy of 98.0% . Deep learning CNN models, ResNet18 and InceptionV3, are used by Taha, M. F et al. [10] with the image segmentation technique to detect nutrient deficiency in plants grown in aquaponics. This paper achieves an accuracy of more than 98%. There are other research papers available that are not related to nutrient deficiency detection, but are used for image classification using pre-trained deep learning techniques. To detect the disease in sugarcane plant Daphal, S.D., et al. [11] used a modified learning rate policy to train the deep learning model for the new dataset. The MobilenetV2 architecture is used with fine tune according to the dataset. The proposed learning rate is applied to the model, and it has achieved more than 89 % accuracy. In an image classification task to detect maize seed defects.Li C, Chen Z, et al [12] used a lightweight model, MobileNetV3. Combining it with an attention mechanism, CBAM to achieve an accuracy of 93.1 %. Another research on image classification for bamboo stick counting. L. Jia et al [13] used the mobilenetV3-Large model and integrated the CBAM module into it to get an accuracy of 97%. In this research, the original SE module of MobileNetV3 is replaced with the CBAM module. Chang Guo et al.[14] proposed a paper in which the classification of breast cancer pathological images was done using MobileNetV3 and two attention mechanisms. The first SK (Selective Kernel) mechanism is used in the initial stage, and the improved SCA (squeeze-and-excitation coordinate) mechanism is used in the later stage. This model achieved an accuracy of more than 94%.

After the literature survey, it is found that most research of nutrient deficiency detection is focused on N, P, K (Macro nutrients), but there are fewer studies for micro nutrient deficiency like Boron (B), Iron (Fe), Copper (Cu), Magnesium (Mg) these micro nutrient is also very essential for the growth of the crop. Especially, Boron (B) is an essential element for the sugarcane crop. Also, it has been observed that different techniques are used to modify the pre-trained models according to their own datasets. Researchers mainly used Densenet201, InceptionV3, Resnet51, and MobileNet models for this purpose.

Table 1

Table 1 Comparative Analysis of Various Research Done

S.No	Author	Study Field	Crops	Algorithm	Modification Details	Results
1	R. Madhumathi et al	Crops Nutrient deficiency	Sugarcane	ResNet , DenseNet VGG16	Using Transfer Learning	93%
2	M, S., Vallabhaneni et al	Crops Nutrient deficiency	Rice	Five different DL models	Using Transfer Learning and an ensemble technique	97%
3	Vrunda Kusanur et al	Crops Nutrient deficiency	Tomato	VGG16,InceptionV3 ,ResNet	Using Transfer learning with RF and SVM classifier	99.90%
4	Daphal, S.D., et al	Crop Diseases	Sugarcane	MobileNetV2	Using transfer learning and Modified learning rate policy	89%
5	Li C, Chen Z, et al	Seed Defect	Maize	MobileNetV3	Use CBAM attention Module	93.10%
6	L. Jia et al	Bamboo Stick Counting	NA	MobileNetV3-L	SE Module is replaced with CBAM	97%
7	Chang Guo et al.	Breast Cancer	NA	MobileNetV3	Use two attention (SK snd SCA)	94%

3. MATERIALS AND METHODS

3.1. PROPOSED FRAMEWORK

Figure 1

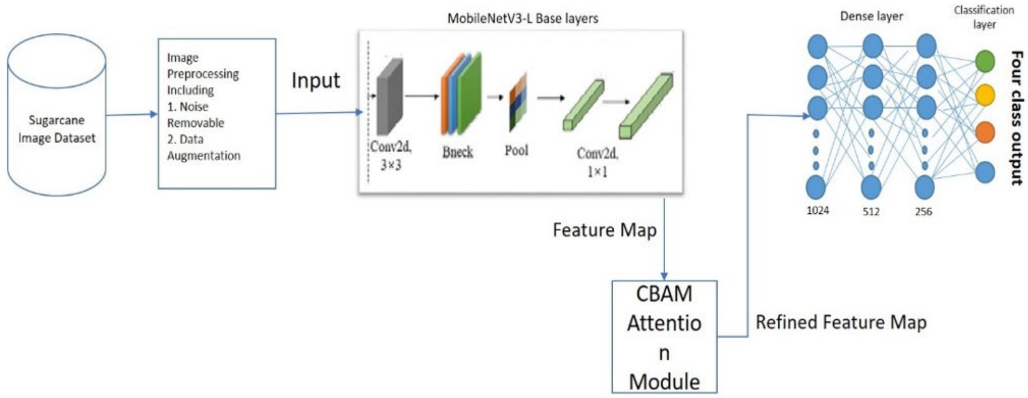


Figure 1 Flow Diagram of the Proposed Model

This study proposes a lightweight deep learning framework for nutrient deficiency detection in sugarcane leaves using an enhanced MobileNetV3-Large architecture. The overall pipeline consists of image acquisition, preprocessing, feature extraction using a pre-trained convolutional neural network, attention-based feature refinement, and final classification.

The MobileNetV3-Large model is selected as the base architecture due to its efficiency and suitability for mobile and edge devices. To further improve feature representation, a Convolutional Block Attention Module (CBAM) is integrated into the network. The CBAM module enhances the discriminative capability of the model by sequentially applying channel attention and spatial attention mechanisms.[16] The model performs better since it makes use of the NetAdapt algorithm to figure out how many convolutional kernels and channels are best. There are two versions available in MobileNetV3, the Large and Small. in this paper, we select MobileNetV3-Large because it can learn complex patterns easily. It also has a built-in attention mechanism that focuses only on the required part of the image, which is helpful in detecting minor deficiencies in new leaves of the sugarcane crop, especially in the case of Boron (B). The Convolution Block Attention Module (CBAM) is a combination of a channel attention module (CA) and spatial attention module (SA) that works is a particular order. The CBAM is like the squeeze excitation layer, but slightly different. It breaks down the input tensor into two successive vectors of dimensionality (c × 1 × 1) rather than using global average pooling (GAP) to reduce the feature mappings to a single pixel. Global max pooling (GMP) generates one of these vectors, while GAP generates the other. [17][18].

Figure 2

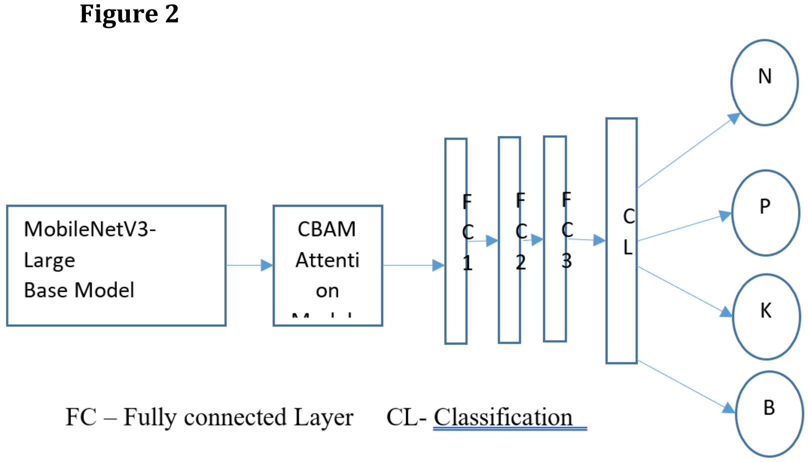


Figure 2 Block Diagram of the Proposed Model

3.2. MODIFIED MOBILENETV3-L MODEL

The proposed model is developed using transfer learning. The original classification head of MobileNetV3-Large (pre-trained on ImageNet) is replaced with a custom classification block. The architecture consists of:

Base Model: MobileNetV3-Large (pre-trained on ImageNet)

Attention Module: CBAM added after the final convolutional block

Fully Connected Layers:

Dense (1024 neurons, ReLU activation)

Dense (512 neurons, ReLU activation)

Dense (256 neurons, ReLU activation with L2 regularization)

Output Layer:

Dense (4 neurons, Softmax activation)

The MobileNetV3 model is trained with the ImageNet dataset with 1000 classes. We modify the model using transfer learning techniques by replacing the outermost classification layer with three fully connected layers and a classification layer of four classes. The CBAM module refines feature maps by focusing on informative regions and suppressing irrelevant background information, which is particularly useful for detecting subtle visual symptoms of nutrient deficiencies.

3.3. ATTENTION MECHANISM (CBAM)

Figure 4

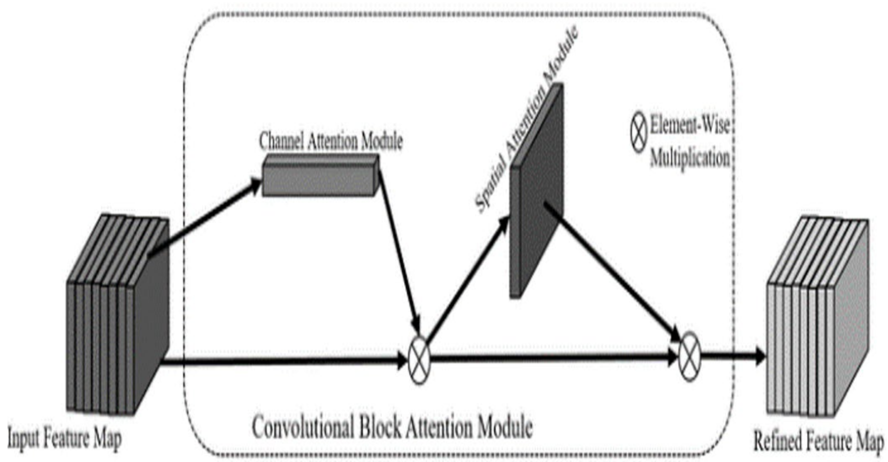


Figure 3 The Convolution Block Attention Module [24]

The above figure explains the working of the CBAM module in the paper. The CBAM module has both spatial attention and channel attention modules. The CBAM module applies attention in two sequential dimensions: channel and spatial. Given an input feature map F, the refined feature map is computed as:

$$F' = Mc(F) \otimes F$$
$$F'' = Ms(F') \otimes F'$$

where Mc and Ms denote channel and spatial attention maps, respectively, and $\otimes$ represents element-wise multiplication.

This mechanism enables the network to emphasize relevant features such as discoloration patterns and leaf texture variations.

The CBAM module is added at the end of the last convolution block, which enhances the overall performance of the model. Three fully connected layers are added with 1024, 512, and 256 neurons. The L2 regularizer is used with the third layer to avoid overfitting. We also use the early stopping technique to reduce overfitting. The model is compiled with a new optimizer, Lion, which is developed by Google. This optimizer efficiently updates model parameters during training. The Lion focuses on tracking only the momentum of the gradient, which makes it more memory efficient. Softmax is used for an output function to get the classification of four classes.

4. DATA SET USED

In this paper, we used our own collected datasets of the sugarcane crop. All data are collected from the Sugarcane Research Institute, Lucknow, and from some online sources.[20][21] We collected 1024 different images of sugarcane leaves, with different deficiencies of Nitrogen (N), Phosphorus (P), Potassium (K), and Boron (B). The details are shown in the following table.

Table 2

Table 2 Data Summary

Catogory	No. of Images
Nitrogen	295
Phosphorus	289
Potassium	216
Boron	224
Total	1024

All these deficiencies can be recognized visually. Because they all exhibit different symptoms in terms of colour, shape, and texture.

The data is collected using a high-definition camera. After collection, it is pre-processed and modified according to the model. Data pre-processing is applied for background removal and noise reduction to improve image quality and reduce complexity. The dataset is divided into an 80:20 ratio for training and testing. All data augmentation techniques, like flip, rotation, and zoom, are used before the training process.

5. TRAINING STRATEGY

Transfer learning is employed by freezing the majority of the base model layers while fine-tuning the top layers. Only the last few layers are unfrozen to adapt the model to the specific dataset.

The Lion optimizer is used instead of traditional optimizers such as Adam. Lion utilizes a sign-based update rule and momentum tracking, leading to improved memory efficiency and stable convergence.

To prevent overfitting, the following techniques are applied:

- Data augmentation (rotation, flipping, zooming)
- L2 regularization
- Early stopping based on validation loss

Table 3

Table 3 Implementation Details

Parameters	Value
Maximum epochs	50
Batch Size	32
Early stopping after	20
Learning rate	.0001
Optimizer	Lion

The training process starts with a batch size of 32 and an epoch of 50, but it shows overfitting, which is managed by the early stopping technique. The accuracy constantly improves up to 8 epochs, but after 10 epochs, it improves very slowly. The training is stopped automatically after 20 epochs because the accuracy has not improved from the last 5 epochs. After stopping, the best accuracy is saved. Dubey and Dubey (2026)

6. RESULTS AND DISCUSSION

We compile the model with MobileNetV3-Large and a simple transfer learning technique, MobileNetV3-Large and the CBAM module, and MobileNetV3-Large, CBAM, and the Lion optimizer. In the first part of the experiment, we get an accuracy of 88.1 %, which is further improved to 88.2 % with the use of L2 regularization. After adding the CBAM module, the accuracy is increased to 89.9 %. In both tests, the fluctuations are shown in the accuracy graph. But with the use of LION optimizer in training and a lower learning rate, we will get the accuracy of 93.4 %, and get a smooth accuracy and loss graph. We will test all these experiments with 50 epochs and a batch size of 32, but the training stops at 15 epochs with the highest accuracy. before 15 epochs, the training shows overfitting. The model is tested with a test dataset with new images of various deficiencies of sugarcane crop, i.e, potassium, nitrogen, phosphorus, and boron. The model detects all the deficiencies accurately. But the Boron deficiency can only be detected when we use the Lion optimizer. The results at different conditions are shown I the table below.

Table 4

Table 4 Different Results

Test	Accuracy
MobileNetV3 + TL	88.1%
MobileNetV3 +CBAM + TL	89.9%
MobileNetV3 +CBAM +LION + TL	93.4%

6.1. PERFORMANCE METRICS

To evaluate the model comprehensively, multiple performance metrics are used, including Accuracy, Precision, Recall, and F1-score.

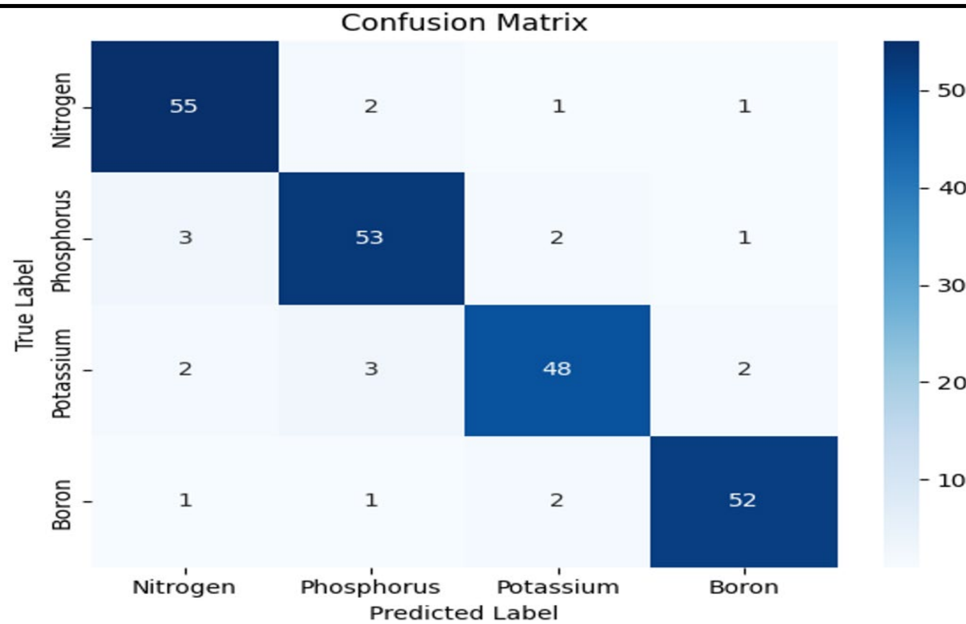
Table 5

Table 5 Performance Metrics

Metric	Value
Accuracy	93.4%
Precision	93.2%
Recall	93.8%
F1-score	93.8.%

6.2. CONFUSION MATRIX ANALYSIS

The confusion matrix demonstrates that the model effectively distinguishes between all four nutrient deficiencies. The highest accuracy is observed for Nitrogen and Phosphorus classes, while slight misclassification occurs between Potassium and Boron due to visual similarity.



The matrix indicates that the model performs well across all classes, with minor misclassifications observed between Potassium and Boron due to similarity in visual symptoms

6.3. COMPARATIVE ANALYSIS

To validate the effectiveness of the proposed approach, it is compared with standard deep learning models.

Model	Accuracy
ResNet50	89.5%
EfficientNetB0	90.2%
MobileNetV3 (Baseline)	88.1%
MobileNetV3 + CBAM	89.9%
Proposed (CBAM + Lion)	93.7%

The results show that the integration of CBAM and Lion optimizer significantly improves performance over the baseline model.

These results indicate that the proposed model achieves balanced performance across all classes. The test set and training loss value were noted for every training cycle the model finished during the training procedure. First Figure displays how each network's accuracy rate varies with the number of epochs, whereas second Figure displays how the loss function varies with the number of epochs.

In previous papers, it has been seen that for nutrient deficiency detection mainly DenseNet, ResNet InceptionV3 models are used , even this models give good results , its execution is slow in comparison to our model, which is based on MobileNetV3. This model is fast and lightweight can be easily implemented in mobile device . Most of the previous papers mostly focused on N,P,K detection , but this paper also focused on Boron detection, which is an important nutritional part of plants. In other studies where CBAM module is used, it replaces the original SE attention module of MobileNetV3, but in our paper CBAM model is added with the SE module to give better performance. Also the use of Lion optimizer in the place of Adam optimizer give accurate results particularly in the case of Boron deficiency.

Figure 4

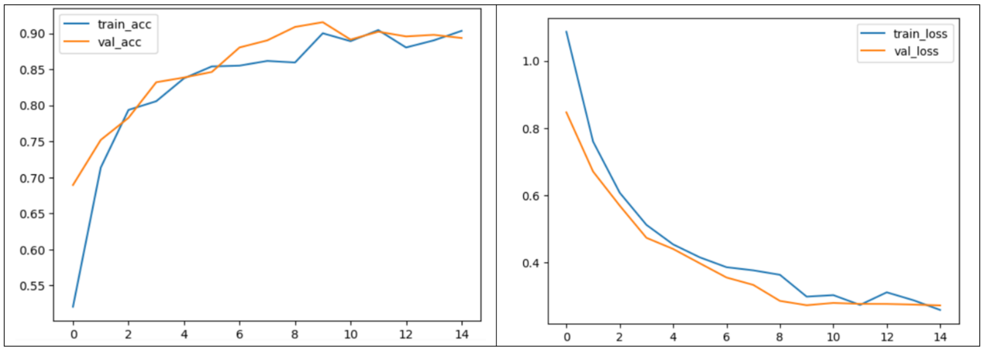


Figure 4 Validation and Loss Graph for Mobilenetv3 and Transfer Learning

Figure 5

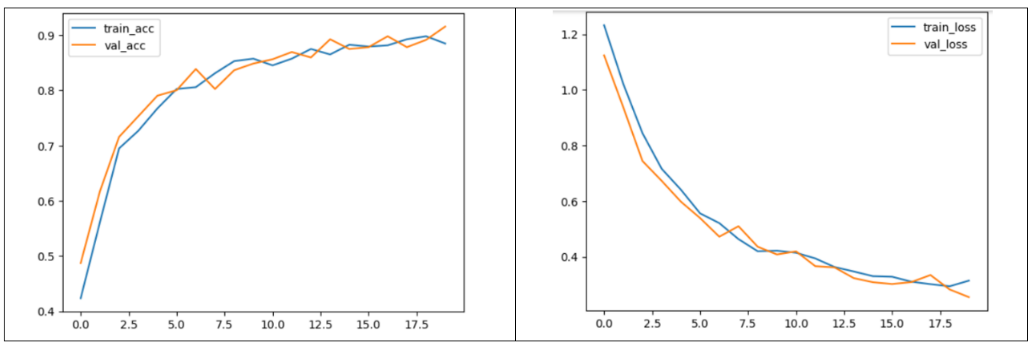


Figure 5 Validation and Loss Graph for Mobilenetv3, CBAM and Transfer Learning

Figure 6

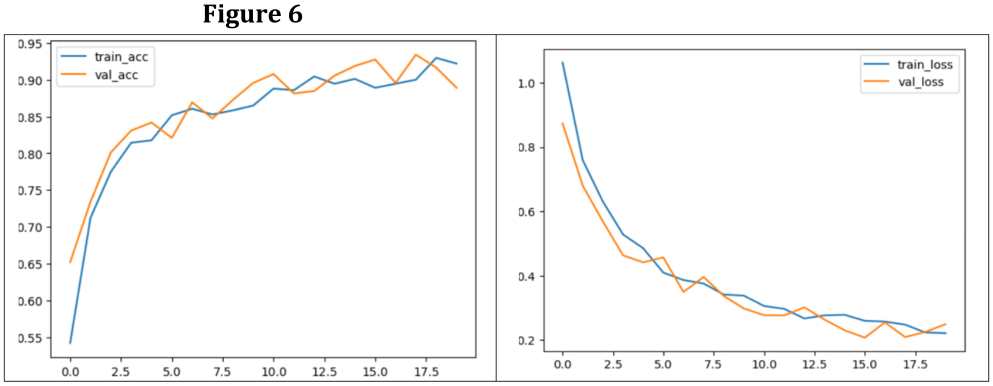


Figure 6 Validation and Loss Graph for Mobilenetv3, CBAM ,Lion Optimizer and Transfer Learning.

In the above graphs it is clear that we can get best accuracy and loss graph when we use LION optimizer with MobileNetV3-L and CBAM attention module . Here we get 93.4 % accuracy and it will detect all the deficiency correctly Compared to heavier models such as ResNet and EfficientNet, the proposed approach offers a better trade-off between accuracy and computational cost, making it suitable for real-time agricultural applications.

7. LIMITATIONS AND FUTURE WORK

Despite promising results, this study has certain limitations. The dataset size is relatively small, which may affect the generalization capability of the model. Additionally, the images are collected under controlled conditions, which may not fully represent real-world variability such as lighting changes and occlusions.

Future work will focus on expanding the dataset, incorporating additional micronutrient deficiencies, and deploying the model in real-time mobile applications for field use. Furthermore, integration with IoT-based agricultural monitoring systems can enhance practical usability.

8. CONCLUSION

This paper presents a lightweight and efficient deep learning framework for detecting nutrient deficiencies in sugarcane crops using leaf images. By integrating the CBAM attention module with MobileNetV3-Large and employing the Lion optimizer, the proposed model achieves an accuracy of 93.7%, outperforming the baseline model.

The model successfully detects both macronutrient (N, P, K) and micronutrient (Boron) deficiencies, addressing a key gap in existing research. The lightweight architecture makes it suitable for deployment in mobile and edge-based agricultural systems. The results demonstrate that attention mechanisms and optimized training strategies can significantly enhance the performance of deep learning models in precision agriculture.

CONFLICT OF INTERESTS

None.

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None.

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