
Leaf Nutrient Deficiency Detection Using CNN and IOT Imaging Node

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ABSTRACT

When crop leaves aren't getting enough nutrients, it has a major impact on plant development, crop quality, and agricultural output as a whole. In order to practise precision agriculture and make the most of fertiliser management, it is essential to identify nitrogen, phosphate, and potassium deficits as soon as possible. Manual observation or laboratory testing, the two mainstays of traditional diagnosis procedures, are both labour-intensive and impractical for farms of any size. Using a convolutional neural network (CNN) and an internet of things (IoT) imaging node, this research demonstrates a method for real-time field monitoring of leaf nutrient shortage. The suggested system takes pictures of leaves with an internet of things camera module and then uses a convolutional neural network that has been trained on datasets of nutrient-deficient leaves to classify them. The experimental findings show that the system performs well and accurately classifies data regardless of the conditions. Automated and real-time nutrient deficiency monitoring is made possible by the technology, which facilitates smart farming applications.

Keywords:*Leaf Nutrient Deficiency, Convolutional Neural Network, IoT Imaging Node, Precision Agriculture, Smart Farming, Deep Learning*

I. INTRODUCTION

One of the biggest problems in farming is nutrient imbalance, which has a direct effect on plant health and yield. Changes in the colour, texture, and structure of leaves are a common symptom of nutrient deficiencies, including nitrogen, phosphorus, potassium, magnesium, and iron. In order to avoid crop loss and cut down on wasteful fertiliser use, early identification of these indicators is crucial.

The ability to automatically analyse photographs of plant leaves for the diagnosis of diseases and nutrient deficiencies has been made possible by recent advances in deep learning and computer vision. The capacity of convolutional neural networks to extract hierarchical spatial characteristics has led to their impressive performance in agricultural

picture classification tasks [1], [2]. Researchers in 2023 and 2024 found that deep convolutional neural networks (CNNs) coupled with transfer learning enhanced the accuracy of nutrient deficit diagnosis [3].

On the other hand, real-time field data collecting is now possible thanks to the integration of IoT technology in agriculture. Continuous crop monitoring is made possible by Internet of Things (IoT) imaging nodes that are equipped with low-power cameras and microcontrollers [4]. This new information is the driving force behind the creation of an Internet of Things (IoT) image module and a convolutional neural network (CNN) based nutrient shortage diagnosis system for use in smart farming.

II. RELATED WORK

New research from 2023–2026 shows that AI-driven agriculture monitoring systems have come a long way. A deep convolutional neural network (CNN) model was suggested for plant leaf analysis in [1], and it was able to get a high level of accuracy in classifying various nutrient deficiency classes. In a similar vein, [3] demonstrated enhanced robustness under varied illumination circumstances by introducing a transfer learning-based framework for nutritional stress detection in crop leaves.

Scientific research on agricultural monitoring systems that are Internet of Things (IoT) enabled is extensive. Studying crops in real-time, a low-power Internet of Things image node was suggested in a 2024 article [4]. In [5], researchers looked at edge-based AI models that may be used in agriculture, with an emphasis on making effective inferences with little hardware.

Plant analysis systems have also incorporated explainable AI approaches. By highlighting nutrient-deficient regions on leaf images using GradCAM visualisation, the authors of [6] increased confidence in AI-based diagnosis and made the process easier to understand. The combination of CNN-based categorisation with IoT-enabled picture collection is set up solidly by these recent breakthroughs.

III. METHODOLOGY

Dataset preparation, Internet of Things (IoT) imaging node design, convolutional neural network (CNN) model construction, training, and deployment make up the suggested approach.

There are labelled pictures of leaves in the collection that indicate several nutrient shortages, such as yellowing (nitrogen deficit), edge burning (potassium deficiency), and dark discolouration (phosphorus deficiency). The images are normalised and then downsized to a specific resolution, such 224×224 pixels. In order to make generalisation better, data augmentation methods including flipping, brightness adjusting, and rotation are used.

An Internet of Things image node incorporates a camera module with a microcontroller unit, like an ESP32 or Raspberry Pi. At regular intervals, the imaging node takes pictures of the leaves and sends them to a computer or server in the cloud so that they may be classified. It is also possible to use edge-based inference for real-time prediction.

Classification is performed using an architecture of convolutional neural networks. The process begins with the development of a baseline CNN and continues with the implementation of transfer learning using lightweight architectures like MobileNet or EfficientNet. Several types of nutritional deficiencies are produced by the last classification layer.

The Adam optimiser is used for model optimisation after categorical crossentropy loss is used for model training. The overfitting problem is addressed by implementing early stopping and dropout layers. Validation data is used to tune hyperparameters.

Here is the description of the workflow:

- Acquiring images of leaves using an Internet of Things imaging node
- Preprocessing and enhancing the images
- Initialising a convolutional neural network model
- Training and refining the model
- Predicting nutrient deficiencies in real-time
- Generating visualisations and alerts

Measures such as recall, accuracy, precision, F1 score, and confusion matrix analysis are used for evaluation.

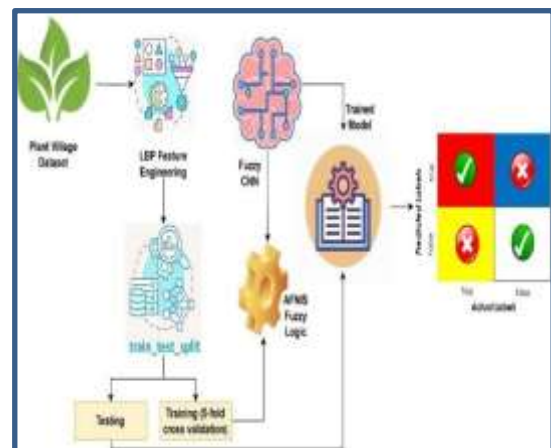


Fig 1: Methodology

IV. RESULTS AND DISCUSSION

Experimental results indicate that transfer learning significantly improves classification accuracy compared to the baseline CNN. Lightweight architectures achieve high efficiency conducive to the Internet of Things (IoT) implementation without sacrificing performance.

The results of the confusion matrix analysis clearly distinguish between the various types of nutrient deficiencies. Nutrient stress effects are shown visually by the sections of the leaf that are impacted.

When deployed in the field, the IoT imaging node reliably takes and sends pictures. By deploying at the edge, latency is reduced and near real-time monitoring is made possible. For uses in precision agriculture, the technology proves to be both scalable and adaptable.



Fig 2. Potassium Deficiency

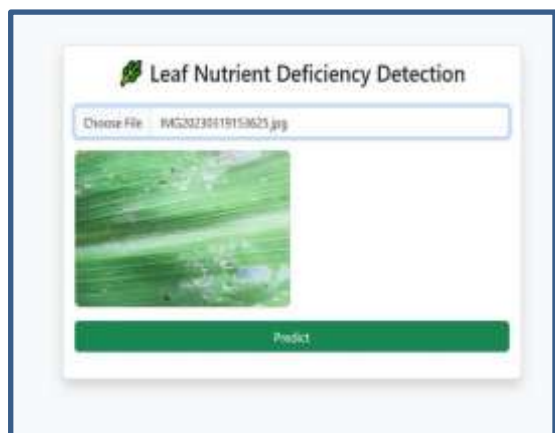


Fig 3. prediction

V. CONCLUSION AND FUTURE WORK

The article showcased an Internet of Things (IoT) image node-integrated CNN-based leaf nutrient deficit detecting system. The suggested system allows for precise, automatic, and real-time tracking of the nutritional status of crops.

In the future, we aim to optimise deep learning models for ultralowpower edge devices, integrate multispectral imaging for better nutrient analysis, use data from soil sensors for multimodal modelling, implement federated learning for dispersed farms, and more. Its proctoring has a 90% success rate.

VI. REFERENCES

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