AI Model for Identification of Micro-Nutrient

Deficiency in Banana Crop

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ABSTRACT

This study offers a sophisticated convolutional neural network (CNN) model that uses leaf image analysis to identify micronutrient deficits in banana crops. For the best crop growth and output, proper nutrition is necessary, and deficits in important nutrients can negatively affect the productivity and health of plants. In order to tackle this issue, we have created a customized CNN model that uses detailed leaf photos to identify and categorize different nutrient shortages. A large dataset of banana leaves displaying various deficiency signs was employed in the study to train and assess the model. In order to improve feature extraction and classification skills and enable accurate identification of nutrient-related disorders, the CNN architecture was meticulously adjusted.

Keywords: Banana Crop Micronutrient Deficiency, Convolutional Neural Network (CNN), Leaf Image Analysis, Image-Based Nutrient Diagnosis, Deep Learning in Agriculture, Plant Nutrient Classification, Precision Agriculture, Agricultural Image Processing, CNN-Based Deficiency Detection, AI-Driven Crop Management

I. INTRODUCTION:

By making it possible to automatically analyze and interpret visual input, the Convolutional Neural Network (CNN) model has completely transformed the field of computer vision. By offering precise and effective instruments for identifying problems with plant health, this technology has the potential to revolutionize crop management techniques in the agricultural industry. This study focuses on using CNNs to analyze leaf images and detect micronutrient deficiencies in banana crops. Although adequate nutrition management is necessary to achieve the best possible crop development and production, plant health and productivity can be negatively impacted by deficits in vital nutrients. We hope to develop a model that can accurately identify and categorize nutrient shortages from visual data by using cutting-edge CNN approaches to solve this issue. This would enable more efficient and timely agricultural interventions.

1.2 SCOPE OF THE PROJECT

The scope of this project encompasses the development and evaluation of a CNN model tailored specifically for diagnosing micro-nutrient deficiencies in banana crops. The study entails gathering and preprocessing a large collection of photos of banana leaves that show different signs of nutrient deficiencies. The CNN model is trained to recognize and classify these deficiencies accurately. The project also includes optimizing the CNN architecture to enhance its feature extraction and classification capabilities.

1.3 OBJECTIVE

To find indications of nutritional inadequacies, develop a CNN architecture that can efficiently scan and evaluate leaf pictures. Improve the model's performance in feature extraction and classification. Assess the model's precision and efficacy in differentiating between various nutrient deficits.

II. EXISTING SYSTEM:

An architecture called IncepV3Dense improves picture classification performance by fusing the advantages of InceptionV3 with DenseNet. DenseNet offers value with its dense connection structure that encourages feature reuse and lessens the vanishing gradient issue, while InceptionV3 makes a contribution with its creative usage of Inception modules for multi-scale feature extraction and processing efficiency. By combining these two architectures, IncepV3Dense takes advantage of their complimentary advantages: DenseNet's effective, direct gradient flow and InceptionV3's modular, multi-scale analysis. This hybrid approach aims to improve classification accuracy and robustness, making it particularly effective for complex tasks such as diagnosing nutrient deficiencies in crops

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DISADVANTAGES:

- Increased Complexity.
- Higher Memory Usage.
- Implementation Challenges.

III. PROPOSED SYSTEM

Convolutional neural networks, or CNNs, are deep learning architectures created especially to process and interpret visual data by simulating how images are processed by the human visual system. In order to detect and learn hierarchical features from low-level edges to high-level patterns, CNNs use a sequence of convolutional layers that apply different filters to input images.

Image identification, object detection, and visual pattern analysis tasks benefit greatly from these networks' ability to capture spatial hierarchies through local connectivity, weight sharing, and pooling operations. By down sampling feature maps, CNN pooling layers aid in achieving translation invariance, which improves the model's resilience to changes in input data by enabling the network to identify objects in an image regardless of their location.

ADVANTAGES:

- Feature Learning.
- Parameter Sharing.
- Translation Invariance.

MODULES NAME:

- Dataset
- Analyze the data
- Preprocessing
- Dividing the data

- Train the model
- Model evaluation
- Prediction

IV. EXISTING TECHNIQUE: -

IncepV3Dense combines the characteristics of InceptionV3 and DenseNet to improve photo classification by using the strengths of both models. InceptionV3 is renowned for its use of Inception modules that perform convolutions at different sizes to enhance feature extraction while maintaining computational efficiency. Conversely, DenseNet uses dense connections across layers to promote feature reuse and improve gradient flow throughout the network. By combining the multi-scale feature extraction capabilities of InceptionV3 with the robust gradient propagation and efficient learning of DenseNet, these two architectures produce a model that is well-suited for difficult image classification problems.

V. PROPOSED TECHNIQUE USED OR ALGORITHM USED:

A Convolutional Neural Network (CNN) is a type of artificial neural network that uses convolutional layers to automatically and adaptively learn spatial hierarchies of information, making it excellent at processing grid-like input, like photographs. Convolutional layers, which apply filters to input data, pooling layers, which reduce dimensionality, and fully connected layers, which carry out classification or regression,are commonly seen in CNN architecture.
CNNs can learn complex patterns and features

Implementation

Jupyter notebook software is used to implement the system in a web context. They are perfect for a range of computer vision applications because of their topology, which uses the server as the engineering. By using convolutional filters to automatically learn and extract pertinent features from raw pictures, CNNs eliminate the requirement for human feature extraction and enable the model to adaptively capture significant patterns and structures.

VI. FUNCTIONAL REQUIREMENTS

A software system's or its component's function is defined by a functional requirement. One definition of a function is collection of inputs, the behavior, First off, by utilizing the hybrid cloud architecture, the system is the first to accomplish the common concept of semantic security for data confidentiality in attribute-based deduplication systems.

VII. NON-FUNCTIONAL NEEDS

The system's primary non-functional requirements are as follows:

Usability

There is little to no user intervention because the system is developed with a fully automated procedure.

Supportability

The system is made to work on multiple platforms. Because it is integrated into the system, it can run on any software platform and the platform is Windows 10 Professional and Intelligence Server. The Jupyter selected Python platform make the system more dependable. Python-written code is more dependable.

Performance

This system will respond to the end user on the client system in a very short amount of time because it is being developed in high-level languages and makes use of sophisticated back-end technology.

VIII. Libraries

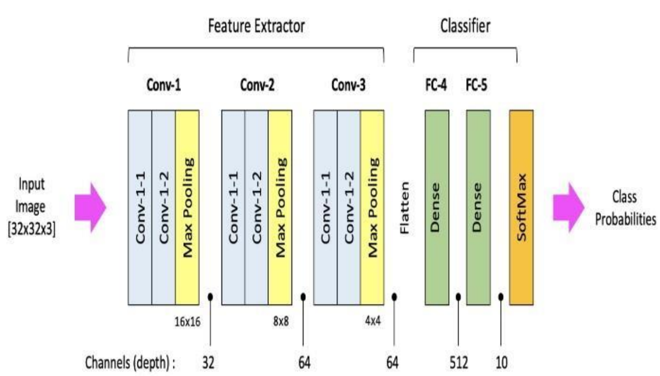
Numpy's-N dimensional array objects are its primary usecase.

Pandas-is a Python data analysis framework that contains dataframes and other objects.

Matplotlib-is a 2D charting package that generates figures of publication quality.

Scikit Learning-The machine learning methods used for data mining and analysis tasks are called scikit- learn.

IX. SYSTEM ARCHITECTURE:



notebook server system serves as the basis for the user interface.

X. Result and Implementation:

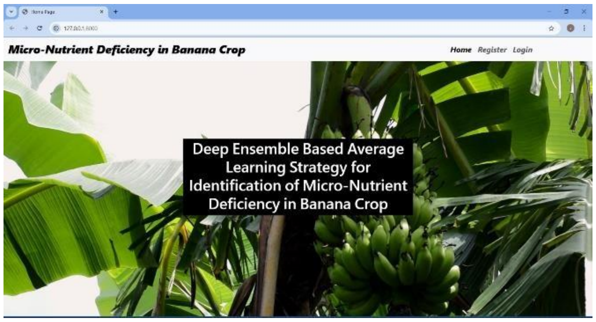


Figure-1: User Interface

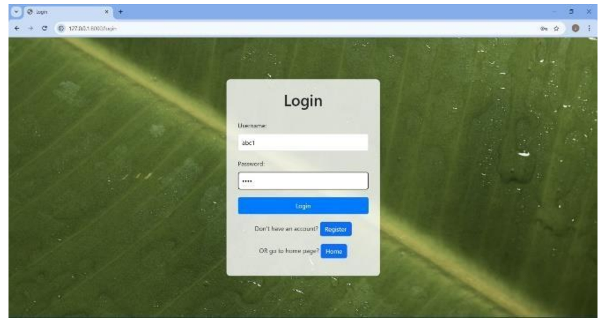


Figure-2: Login page

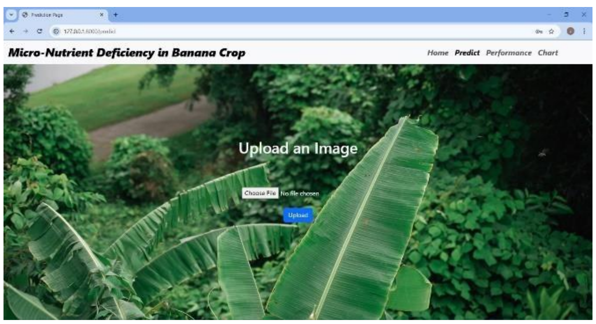


Figure-3: User Interface

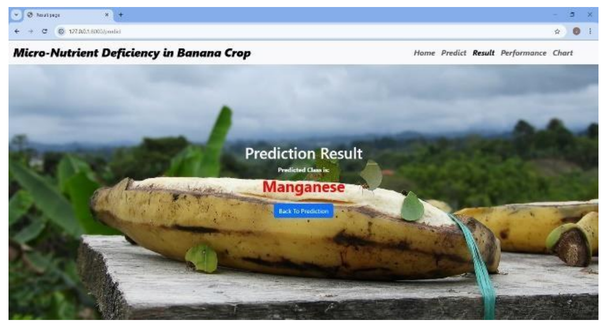


Figure-4: Result

XI. Future Enhancement:

Expanding the dataset to include a wider range of micronutrient deficits than those already included, such as zinc, copper, and molybdenum, should be the main goal of future research. This extension will aid in the creation of a more comprehensive model that can manage a wide range of deficit kinds. Furthermore, adding more complete and varied photos to the dataset will increase the model's resilience and suitability for use in real-world situations. To overcome present constraints and guarantee more precise and trustworthy predictions, future studies could further investigate sophisticated methods for dataset categorization and data augmentation.

XII. Conclusion:

In this study, we are using convolutional neural network (CNN) model to identify micronutrient deficiencies in banana crop leaf photos by multi-class classification. Using a customized CNN architecture, we created a model that can correctly identify different nutrient shortages by examining leaf photos. By efficiently improving the diagnostic procedure, this method provides farmers and agricultural specialists with invaluable assistance in regulating crop nutrition. The enhanced CNN model shows great promise for enhancing crop health monitoring in general and nutrient management strategies in particular.

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