Identification of Nutrient Deficiency and Disease Detection in Medicinal Plants

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ABSTRACT

Medicinal plants are an essential source of medicinal chemicals used in both conventional and alternative medicine. The pharmaceutical and healthcare sectors must guarantee their optimum development and well-being. In this study, we explore the potentially useful application of one-shot learning approaches for the diagnosis of illnesses and nutrient deficiencies in medicinal plants, offering a practical and economical approach to plant health management.

KEYWORDS: Medicinal plants; nutrient deficiencies; one-shot learning approach; Performance Assessment

1. INTRODUCTION

Since ancient times, medicinal plants have been crucial to healthcare because they are a rich source of bioactive substances that are employed in both conventional and cutting-edge medical procedures. However, these plants' nutritional and overall health have a major impact on their quality and medicinal qualities. Reduced plant growth, changed chemical compositions, and diminished therapeutic potential can result from illnesses or inadequate nutrition levels. A promising solution to these problems is one-shot learning, a branch of machine learning that makes it possible to quickly identify illnesses and dietary deficits.

1.1 Nutrient Deficiency Identification

Plant development, growth, and the synthesis of bioactive chemicals all depend on nutrients. Deficits in some nutrients can have a significant effect on the health of plants, which in turn can hinder the plants' ability to repair.

Understanding the significance of vital nutrients in plant growth is critical to comprehending how plants grow, develop, and generate the necessary compounds including, in the case of medicinal plants, therapeutic components. Essential nutrients serve a number of crucial functions in several facets of plant life and are substances and elements that plants need for growth and development. Depending on how much of these nutrients are required by plants, they are usually classified as macronutrients or micronutrients.

Macronutrients

Nitrogen (N): Amino acids, the building blocks of proteins, require nitrogen to function properly. Proteins are vital for photosynthesis, respiration, and cell division, among other functions, and they are necessary for the structure and function of plants.

Phosphorus (P): Adenosine triphosphate (ATP), the main source of energy for plant cells, depends on phosphorus. It is essential for root development, flowering, and fruiting. It is also a structural component of nucleic acids (DNA and RNA).

Potassium (K): Potassium is a necessary element for several physiological functions, such as stomatal control, enzyme activation, and osmoregulation. It supports plants' ability to survive environmental stress, fight disease, and maintain water balance.

Calcium (Ca): The cell walls of plants are structurally composed of calcium. Additionally, it is necessary for signal transmission, membrane integrity, and cell division. Deficits in calcium can cause problems such as blossom end rot in peppers and tomatoes.

Magnesium (Mg): An essential part of chlorophyll, the pigment that allows plants to perform photosynthesis, is magnesium. It also contributes to the intake of other nutrients and is involved in the activation of enzymes.

Sulphur (S): Amino acid, vitamin, and coenzyme synthesis all require sulphur. It is essential for plant growth and has a role in the creation of disulfide bonds in proteins.

Micronutrients

Iron (Fe): Photosynthesis and the synthesis of chlorophyll depend on iron. Chlorosis, or the yellowing of leaves, is caused by a deficit in iron because the body is unable to create as much chlorophyll.

Manganese (Mn): Manganese is a cofactor for many enzymes that are involved in respiration, nitrogen metabolism, and photosynthesis.

Zinc (Zn): Zinc is necessary for the synthesis of nucleic acids and the production of plant growth hormones. Additionally, it aids in controlling plant maturity and leaf size.

Copper (Cu): Enzymes involved in the lignin production process as well as antioxidant defence require copper to be activated.

Boron (B): Boron is essential for the formation of pollen tubes, cell walls, and the absorption of other nutrients. It is especially crucial for fruit development and flowering.

Molybdenum (Mo): Nitrates are converted to amino acids by molybdenum, which is involved in nitrogen metabolism.

Chlorine (Cl): Although needed in extremely small quantities, chlorine is important for photosynthesis and controlling stomata.

It's crucial to remember that deficiencies or imbalances in any of these vital nutrients can negatively impact the health and growth of plants. Many symptoms, including leaf yellowing, reduced growth, poor fruit or seed development, and increased vulnerability to infections and environmental stress, can result from nutrient shortages. Therefore, in order to successfully cultivate medical plants and guarantee the production of high-quality plant material with the appropriate medicinal characteristics, effective nutrition management is essential.

1.2 Implications of nutrient deficiencies in medicinal plants

The growth, quality, and therapeutic qualities of medicinal plants can all be significantly impacted by nutrient deficits. These ramifications cover a wide range of plant health and productivity issues. It is crucial to comprehend these ramifications in order to guarantee a steady and superior supply of pharmaceutical plant material. The following are some significant effects of dietary deficits in therapeutic plants.

2. Literature Survey

M. Lavanya, et al., (2022) used Convolution Neural Network (CNN) and Artificial Neural Network in the intended technique to classify the diagnosis of plant nutrient deficiencies (ANN) based on image analysis techniques for identifying nutritional deficiencies.

Hamna Waheed, et al., (2022) used deep artificial neural network and deep learning-based methods for the early detection of diseases, pest patterns, and nutritional deficiencies. The experimental results achieved are comparable with other existing techniques in the literature. In addition, the results demonstrated the potential in improving the yield of ginger using the proposed disease detection methods and an essential consideration for the design of real-time disease detection applications.

Hiram Ponce, et al., **(2021)** proposed a CNN+AHN classifier to estimate low nutrients-nitrogen, phosphorus, or potassium—in tomato plants using an image of their leaves. The method consisted of a hybrid model divided into two parts. The first comprises a set of convolutional layers that act as the feature extraction process. Then, a PCA layer was used to reduce the number of features that enters to the final layer comprised of an AHN with a SoftMax function.

Anu Jose, et al., (2021) uses ANN and designed different activation functions and their performance is analysed and evaluated. In this study, the visible nutritional deficiency symptoms in the leaves are considered, even images of fruits can also be included in the dataset which may increase the precision and accuracy of the classification. Design of convolution neural network for the nutrition deficiency detection may give better results.

R. Sathyavani, et al., (2021) uses CNN to detect the nutritional deficiencies from the leaves of coriander, tomato, pepper, chili using input IoT image acquisition device and nutrition analyser device. The capturing of leaf color and nutrients across each zone is captured by these IoT devices effectively in remote environment. The collected input image data is sent to the data analytics unit that initially removes noises and extracts relevant features from the captured leaves. Finally, the nutrients are extracted using CNN, where it detects the possible nutrients from the plants.

The entire analyses are conducted in hybrid cloud environment, where CNN module acts as a centre controller that helps in classification of nutrients. Simulation on 5000 images of different plants show that the proposed modified CNN model obtains improved training and testing classification accuracy than other methods. Here, the results of simulation shows that the modified CNN has reduced percentage error than other deep learning models.

Zhe Xu, et al., (2020) proposed four DCNNs, Inception-v3, ResNet50, NasNet-Large, and DenseNet121, were used to diagnose various nutrient deficiencies in rice plants based on image recognition using a dataset collected from hydroponic experiments. All the DCNNs obtained accuracies of over 90% and outperformed two traditional machine learning methods, color feature with SVM and HOG with SVM.

Amirtha T, et al., (2020) worked on the identification of nutrient deficiencies is done by the convolutional neural network algorithm and is displayed in the system. The amount of fertilizer for the corresponding nutrient deficiency is also displayed (in terms of percentage). The future work includes the mechanism of fertilizer dressing to the field can be done automatically. Several techniques are used for the automatic fertilizer dressing. The input from various sensors like soil moisture, humidity, temperature, pH is considered for determining the amount of fertilizer. The system can automatically fertilize the field by means of sprinkling mechanism. The fertilizer tank an also be used for irrigation purposes. The weed remover can be attached with the system to remove the weeds, if they exist.

This weed remover is an adjustable and can be replaced with driller for drilling and cutter for harvesting. Thus, entire agricultural work can be integrated in a single system.

Fatima A. M., et. al., (2019) worked on Accurate estimation of nitrogen (N) balance (a measure of potential N losses) in producer fields requires information on grain N concentration (GNC) to estimate grain-N removal, which is rarely measured by producers.

The objectives of this study were to (i) examine the degree to which variation in GNC can affect estimation of grain-N removal, (ii) identify major factors influencing GNC, and (iii) develop a predictive model to estimate GNC, analysing the uncertainty in predicted grain-N removal at field and regional levels. We compiled GNC data from published literature and unpublished databases using explicit criteria to only include experiments that portray the environments and dominant management practices where maize is grown in the US North Central region, which accounts for one-third of global maize production.

2.1 Research gaps identification

In the majority of previously published research works, different machine learning and deep learning models are used for nutrient deficiency classification and disease identification. However, in this research work one-shot deep learning models are explored for higher accuracy with hyper-parameters optimization in the identification of nutrient deficiency and disease identification in medicinal plants based on leaf images.

2.2 Evaluation of conventional techniques for identifying nutrient deficiency and disease detection

In recent years, ML and DL based approaches have been increasingly applied to agriculture and botanical studies. These approaches have shown great potential in improving crop yield, identifying plant lesions and optimizing plant growth. In comparison to traditional approaches, ML and DL based methods offer several advantages and have the potential to revolutionize the field of agriculture and botanical studies. Traditional approaches in agriculture and botanical studies mainly rely on manual inspection and expert knowledge. These methods are often time-consuming, physically demanding, and susceptible to human mistakes. Also, ML and DL approaches requires large amounts of appropriate data and high-performance computing units. In contrast, one-shot learning approaches can automate these tasks, reducing the need for human interference and enhancing precision and efficiency of the process with small dataset. The comparison of different technologies involved in image processing are shown in Table 1.

Table 1: Comparison of different technologies for image processing

Technology	Core Technique	Necessary prerequisite	Suitable Contexts
Traditional Image Processing	Manual design of features, classifier and rules	Significant differentiation between affected and healthy regions, Minimal interference or disturbance.	Plant disease and nutrition detection in controlled environments
ML and DL	Automatic feature learning using CNNs	Large amounts of appropriate data, high-performance computing units	Adaptation to changes in complex natural environments
One-Shot learning	Automatic feature learning using Siamese network	Small amount of data, less training example for each class	Adaptation to changes in complex natural environments

3. Proposed System Methodology

The difficult job of one-shot learning is teaching a model to identify new classes using just one or a small number of instances per class. Given the limited availability of labelled data for uncommon or recently emerging diseases and deficiencies, one-shot learning can be a useful method for the analysis and classification of nutrient shortage and disease detection in medicinal plants using leaf photos. As seen in Figure 1, this is the fundamental approach for carrying out one-shot learning for this particular assignment.

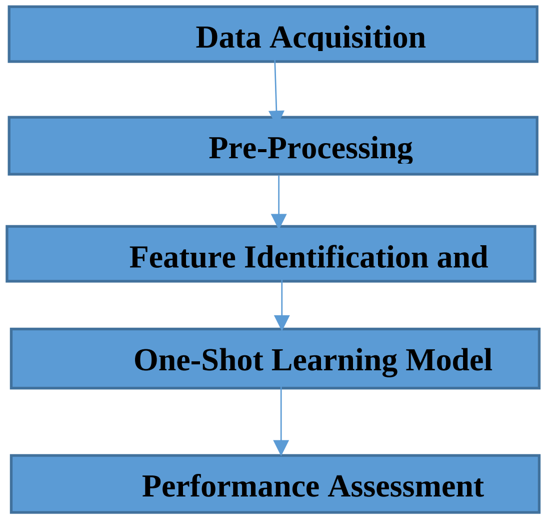

Figure 1: Proposed methodology for Identification of Nutrient Deficiency and Disease Detection.

Data Acquisition: Gather a dataset of photos of the leaves of diverse medicinal plants, both healthy and diseased and nutrient-deficient. To enhance model generalisation, make sure the dataset encompasses a variety of lighting conditions, angles, and backdrops.

Pre-Processing: Prior to processing the leaf photos, resize them to a standard size, normalise the pixel values, convert them to a format that works for the model of choice, and remove any noise.

Feature Identification and Extraction: To identify and extract the most important features from the plant photos, use a convolutional neural network or other trained deep learning model as a feature extractor. For the model to capture general visual features, it needs to be pre-trained on a sizable dataset, such ImageNet.

One-Shot Learning Model: Using the feature representations from the pre-trained model, implement a one-shot learning model that requires little in the way of training data to identify vitamin shortages. Common architectures for one-shot learning problems are Siamese Neural Networks or Prototypical Networks.

The pre-processed dataset, which includes pictures of therapeutic plants with nutritional deficits and the labels that go with them, will be used to train the One-Shot learning model.

Performance Assessment: Divide the dataset into testing and training sets so that the performance of the model can be assessed. Utilise indicators such as recall, accuracy, precision, and F1 score to evaluate how well the model detects nutrient deficits.

If the model's performance isn't up to par, more data may be needed for fine-tuning and hyperparameter optimisation in order to increase generalisation and get the best results.

Conclusion

A steady supply of superior medicinal plants is essential to the pharmaceutical and medical sectors. For the purpose of diagnosing illnesses and nutritional deficits in medicinal plants, one-shot learning provides an effective and economical method. A quick and affordable way to detect illnesses and nutrient shortages in medicinal plants is by one-shot learning.

References

[1] Lavanya, M., Devi, M. K., & Vani, M. S. (2022). Deep Learning for Identification of Plant nutrient Deficiencies. Journal of Pharmaceutical Negative Results, 3284-3291.

[2] Waheed, H., Zafar, N., Akram, W., Manzoor, A., Gani, A., & Islam, S. U. (2022). Deep Learning Based Disease, Pest Pattern and Nutritional Deficiency Detection System for "Zingiberaceae" Crop. Agriculture, 12(6), 742.

[3] Ponce, H., Cevallos, C., Espinosa, R., & Gutiérrez, S. (2021). Estimation of low nutrients in tomato crops through the analysis of leaf images using machine learning. Journal of Artificial Intelligence and Technology, 1(2), 131-137.

[4] Jose, A., Nandagopalan, S., Ubalanka, V., & Viswanath, D. (2021, May). Detection and classification of nutrient deficiencies in plants using machine learning. In Journal of Physics: Conference Series (Vol. 1850, No. 1, p. 012050). IOP Publishing.

[5] Sathyavani, R., JaganMohan, K., & Kalaavathi, B. (2021). Detection of plant leaf nutrients using convolutional neural network-based internet of things data acquisition. International Journal of Nonlinear Analysis and Applications, 12(2), 1175-1186.

[6] Li, Y., & Chao, X. (2021). Semi-supervised few-shot learning approach for plant diseases recognition. Plant Methods, 17, 1-10.

[7] Zhong, F., Chen, Z., Zhang, Y., & Xia, F. (2020). Zero-and few-shot learning for diseases recognition of Citrus aurantium L. using conditional adversarial autoencoders. Computers and Electronics in Agriculture, 179, 105828.

[8] Argüeso, D., Picon, A., Irusta, U., Medela, A., San-Emeterio, M. G., Bereciartua, A., & Alvarez-Gila, A. (2020). Few-Shot Learning approach for plant disease classification using images taken in the field. Computers and Electronics in Agriculture, 175, 105542.

[9] Xu, Z., Guo, X., Zhu, A., He, X., Zhao, X., Han, Y., & Subedi, R. (2020). Using deep convolutional neural networks for image-based diagnosis of nutrient deficiencies in rice. Computational Intelligence and Neuroscience, 2020.

[10] Amirtha, T., Gokulalakshmi, T., Umamaheswari, P., & Tech, T. R. M. (2020). Machine Learning Based Nutrient Deficiency Detection in Crops. Int. J. Recent Technol. Eng, 8(6), 5330-5333.

[11] Tenorio, F. A., Eagle, A. J., McLellan, E. L., Cassman, K. G., Howard, R., Below, F. E. & Grassini, P. (2019). Assessing variation in maize grain nitrogen concentration and its implications for estimating nitrogen balance in the US North Central region. Field Crops Research, 240, 185-193.

[12] Wulandhari, L. A., Gunawan, A. A. S., Qurania, A., Harsani, P., Tarawan, T. F., & Hermawan, R. F. (2019). Plant nutrient deficiency detection using deep convolutional neural network. ICIC Express Lett, 13(10), 971-977.

[13] Aleksandrov, V. (2019). Identification of nutrient deficiency in bean plants by prompt chlorophyll fluorescence measurements and Artificial Neural Networks. arXiv preprint arXiv:1906.03312.

[14] Leena, N., & Saju, K. K. (2018, April). Vision based nutrient deficiency classification in maize plants using multi class support vector machines. In AIP Conference Proceedings (Vol. 1952, No. 1). AIP Publishing.

[15] Vassallo-Barco, M., Vives-Garnique, L., Tuesta-Monteza, V., Mejía-Cabrera, H. I., & Toledo, R. Y. (2017). Automatic Detection of Nutritional Deficiencies in Coffee Tree Leaves through Shape and Texture Descriptors. Journal of Digital Information Management, 15(1).