Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 162-173, 9, 2025

Araştırma Makalesi

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 162-173, 9, 2025

Research Article

https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

A Simple Deep Learning Application for Leaf Deficiency Classification

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(Received: 13 September 2025, Accepted: 21 September2025)

(2nd International Conference on Pioneer and Academic Research ICPAR 2025, September 15-16, 2025)

ATIF/REFERENCE: Ilten, E. (2025). A Simple Deep Learning Application for Leaf Deficiency Classification, *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(9), 162-173.

Abstract – Leaf deficiencies caused by nutrient imbalances or environmental stresses significantly affect plant growth, crop yield, and agricultural productivity. Traditional methods for identifying leaf deficiencies rely on visual inspection or laboratory analysis, which are time-consuming, subjective, and unsuitable for large-scale monitoring. In this study, a simple deep learning application is proposed for the automated classification of leaf deficiencies using image data. The approach employs a convolutional neural network (CNN) model designed to extract and learn discriminative features from leaf images corresponding to common deficiencies such as nitrogen, potassium, magnesium, calcium, and dehydration stress. The dataset consists of 10 images for each leaf deficiency class. The accuracy of the developed model is 72.22% and an acceptable success rate is achieved with a limited dataset. The model is implemented in a simplified framework to ensure ease of use and adaptability for agricultural practitioners with limited computational expertise.

Keywords – Leaf Deficiency, Plant Deficiency, Deep Learning, Classification, Matlab.

I. INTRODUCTION

Leaf deficiency refers to the physiological and visual symptoms that arise when plants do not receive adequate nutrients or water to sustain normal growth and metabolic functions. Because leaves are the main sites of photosynthesis, respiration, and transpiration, any deficiency quickly manifests in their structure, color, or vitality. Common signs include chlorosis (yellowing), necrosis (death of tissue), curling, wilting, or reduced leaf size. Identifying the type of deficiency is essential for diagnosing plant health problems and implementing corrective measures [1–3].

Several specific deficiencies are particularly important in both agricultural and ecological contexts:

- **Calcium Deficiency:** Calcium plays a key role in maintaining cell wall stability and membrane integrity. Deficiency typically results in distorted or necrotic young leaves, tip burn, and impaired growth of meristematic tissues. Since calcium is immobile in plants, symptoms appear first on new leaves [4].

- **Dehydration (Water Deficiency):** Water stress leads to wilting, leaf rolling, and in severe cases, scorching or complete desiccation. Reduced turgor pressure disrupts photosynthesis and nutrient transport, severely affecting crop yield and survival [5].

- **Magnesium Deficiency:** As the central atom of the chlorophyll molecule, magnesium is vital for photosynthesis. Deficiency is often expressed as interveinal chlorosis in older leaves, where veins remain green but surrounding tissues turn yellow. Prolonged deficiency can reduce photosynthetic efficiency and plant vigor [6].

- **Nitrogen Deficiency:** Nitrogen is essential for amino acids, proteins, and chlorophyll synthesis. Deficiency symptoms include uniform yellowing (chlorosis) of older leaves, reduced leaf size, and stunted growth. Since nitrogen is mobile, plants reallocate it to new tissues, leaving older leaves visibly affected [7].

- **Potassium Deficiency:** Potassium regulates stomatal activity, enzyme activation, and osmotic balance. Deficiency symptoms appear as marginal chlorosis, scorching, or necrosis at leaf edges, often accompanied by curling. This deficiency also reduces stress tolerance and overall plant resilience [8].

Understanding these deficiencies is critical for effective crop management and sustainable agriculture. By monitoring leaf health, growers can identify early warning signs, correct imbalances through proper fertilization, irrigation, or soil amendments, and ultimately ensure optimal productivity and plant quality.

Deep learning is a specialized branch of machine learning and artificial intelligence (AI) that employs artificial neural networks with multiple layers to learn from data. Inspired by the structure and function of the human brain, deep learning systems automatically extract and refine features from raw data, enabling them to recognize patterns and make predictions with high accuracy. Unlike traditional machine learning, which often depends on handcrafted features and domain-specific expertise, deep learning can directly process raw inputs such as images, speech, or text, making it particularly powerful for complex and unstructured datasets [9,10].

The origins of deep learning trace back to the 1940s and 1950s, when early computational models of neurons were first introduced. The perceptron, developed by Frank Rosenblatt in 1958, was one of the first neural network models capable of binary classification. However, its limitations in solving non-linear problems (such as XOR) led to a decline in interest, a period sometimes referred to as the "AI winter." [11,12].

Renewed progress came in the 1980s with the development of the backpropagation algorithm, which allowed neural networks to adjust internal weights more effectively. During this period, multilayer perceptrons (MLPs) demonstrated that deeper architectures could solve more complex problems. However, the lack of sufficient computational power and limited availability of large datasets constrained practical applications [13].

The modern rise of deep learning began in the 2000s, driven by advances in computational hardware (especially GPUs), large-scale datasets, and algorithmic improvements. Breakthroughs such as AlexNet (2012) in the ImageNet competition showcased the power of convolutional neural networks (CNNs) in computer vision, sparking a wave of research and applications [14]. Subsequent models such as VGGNet [15], ResNet [16], and Inception networks further demonstrated the scalability of deep architectures. In natural language processing, recurrent neural networks (RNNs) [17] and long short-term memory (LSTM) [18] models proved effective for sequence modeling, while the introduction of transformers revolutionized the field by enabling parallel processing of text data, leading to state-of-the-art models like BERT [19] and GPT [20].

Today, deep learning is integral to many technologies and industries:

- **Computer Vision:** Image recognition, object detection, facial recognition, and medical imaging [21].
- **Natural Language Processing:** Machine translation, sentiment analysis, question answering, and generative AI [22].
- **Speech and Audio Processing:** Voice recognition, speech synthesis, and audio classification [23].
- **Autonomous Systems:** Robotics, self-driving cars, and intelligent control systems [24].
- **Healthcare:** Disease prediction, drug discovery, and personalized medicine [25].

Despite its remarkable success, deep learning still faces significant challenges. One key issue is interpretability, as deep models are often regarded as “black boxes,” making it difficult to understand their decision-making processes. Data dependency is another limitation, since large, labeled datasets are typically required for training, which may not always be feasible. Additionally, computational cost and energy consumption remain pressing concerns, especially as models grow larger. Researchers are also working on improving robustness, reducing bias, and developing more efficient architectures that can operate on limited resources [26].

Deep learning represents a major paradigm shift in AI, enabling machines to achieve human-level or even superhuman performance in certain tasks. Its success is the result of decades of theoretical progress, computational advances, and the availability of vast amounts of data. As research continues, deep learning is expected to expand further into new fields, offering transformative solutions while also raising important questions about efficiency, ethics, and responsible deployment.

MATLAB provides a powerful and user-friendly environment for developing and deploying deep learning applications. With its *Deep Learning Toolbox*, MATLAB offers a rich set of functions and prebuilt models that enable users to design, train, and evaluate neural networks without requiring extensive programming expertise. Popular architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformers are supported, making it possible to address a wide range of real-world applications [27].

One of the key advantages of MATLAB for deep learning is its integration with data preprocessing, visualization, and simulation tools. Researchers and engineers can import and process datasets, visualize network behavior, and fine-tune hyperparameters in a single environment. Additionally, MATLAB facilitates the use of transfer learning by providing access to pretrained models, which can be adapted to new tasks with limited labeled data. Its compatibility with GPU acceleration ensures faster training, while deployment options allow integration into embedded systems, cloud platforms, and production environments [28].

Plant health monitoring is a critical aspect of modern agriculture, as nutrient deficiencies and environmental stresses directly impact crop yield and quality. Among the various indicators of plant health, leaf condition serves as one of the most reliable sources of information. Leaves exhibit visible symptoms such as chlorosis, necrosis, curling, and discoloration when essential nutrients like nitrogen, potassium, magnesium, or calcium are deficient, or when plants experience dehydration. Traditionally, the diagnosis of leaf deficiencies has relied on manual inspection by experts or laboratory-based chemical analysis of soil and plant tissue. While effective, these methods are time-consuming, labor-intensive, and prone to human subjectivity, making them unsuitable for large-scale or real-time agricultural applications [29,30].

In recent years, deep learning has emerged as a powerful tool for automated leaf deficiency classification. Leveraging artificial neural networks, particularly convolutional neural networks (CNNs), deep learning models can automatically extract hierarchical features from leaf images, eliminating the need for handcrafted features [1,2]. This capability allows the models to identify subtle patterns and symptoms of deficiencies that may not be easily distinguishable to the human eye. Unlike conventional image processing techniques, which depend heavily on manual feature design, deep learning systems learn directly from raw image data, achieving higher accuracy and generalization in classification tasks.

The integration of deep learning into precision agriculture offers several advantages. First, it enables rapid and non-destructive diagnosis, allowing farmers to detect nutrient imbalances at early stages before significant crop loss occurs. Second, deep learning-based systems can be deployed through mobile applications, drones, and IoT-enabled devices, facilitating large-scale and real-time monitoring of agricultural fields. Finally, the scalability of such models supports diverse crop types and deficiency categories, making them adaptable to different farming environments [31–33].

Despite its success, challenges remain in applying deep learning for leaf deficiency classification. Issues such as limited availability of labeled datasets, variability in lighting and imaging conditions, and the need for computationally efficient models suitable for field deployment continue to be active research areas. Nevertheless, the integration of deep learning into plant health assessment represents a significant step toward sustainable agriculture, reducing reliance on chemical inputs, optimizing resource management, and ensuring food security [29,34].

This paper is organized as follows: The deep learning GoogLeNet structure and leaf deficiencies are explained in Section 2. The modeling process and the obtained results are analyzed in Section 3. The conclusion is given in Section 4.

II. MATERIALS AND METHOD

In this study, a deep learning model is developed to identify five different leaf deficiencies (calcium, water, magnesium, nitrogen, and potassium) and healthy conditions. Example images for the healthy conditions and five different leaf deficiencies are presented in Fig. 1.

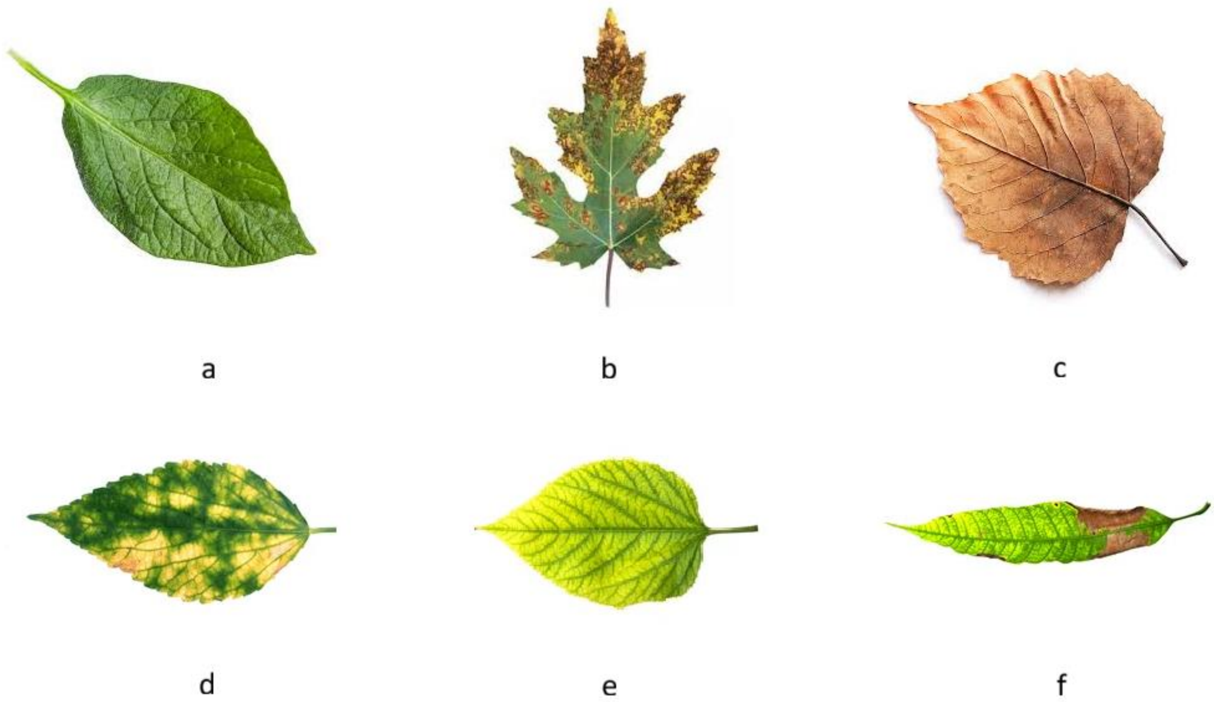

Fig. 1 Leaf deficiencies: a) Healthy leaf, b) Calcium deficiency, c) Dehydration (water deficiency), d) Magnesium deficiency, e) Nitrogen deficiency, f) Potassium deficiency.

A dataset consisting of 10 images for each condition is prepared. The prepared dataset is given in Figs 2, 3, 4, 5, 6 and 7. However, this dataset consists of leaves from a variety of plants, not just one variety. Although the limited dataset and the presence of different leaves will negatively impact model accuracy, it is believed to be sufficient for a simple modeling study.

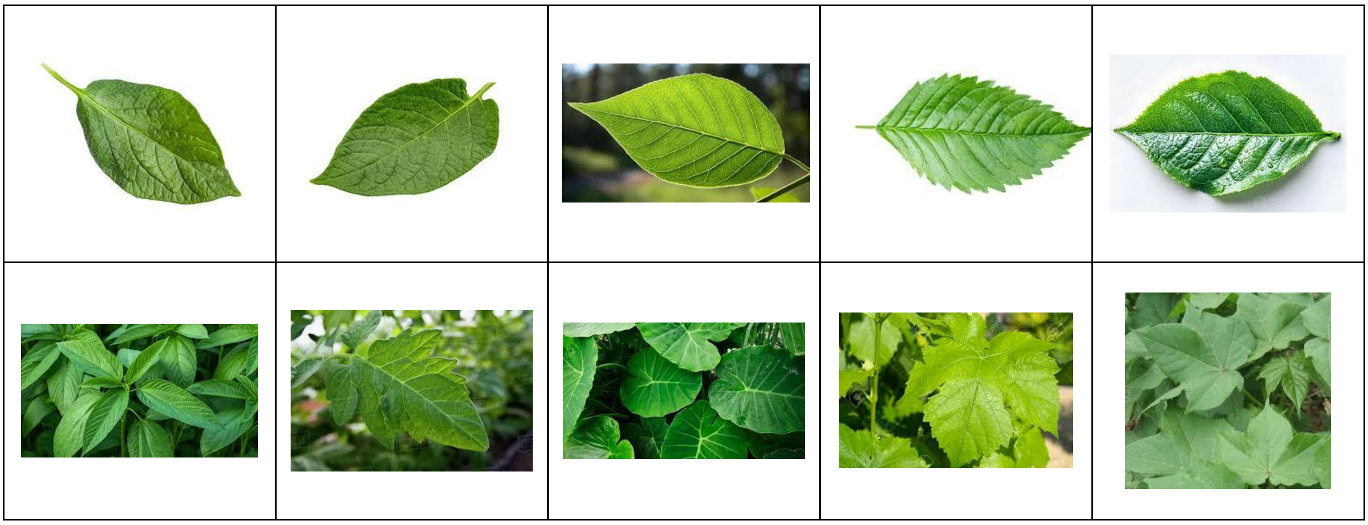

Fig. 2 Dataset for healthy condition.

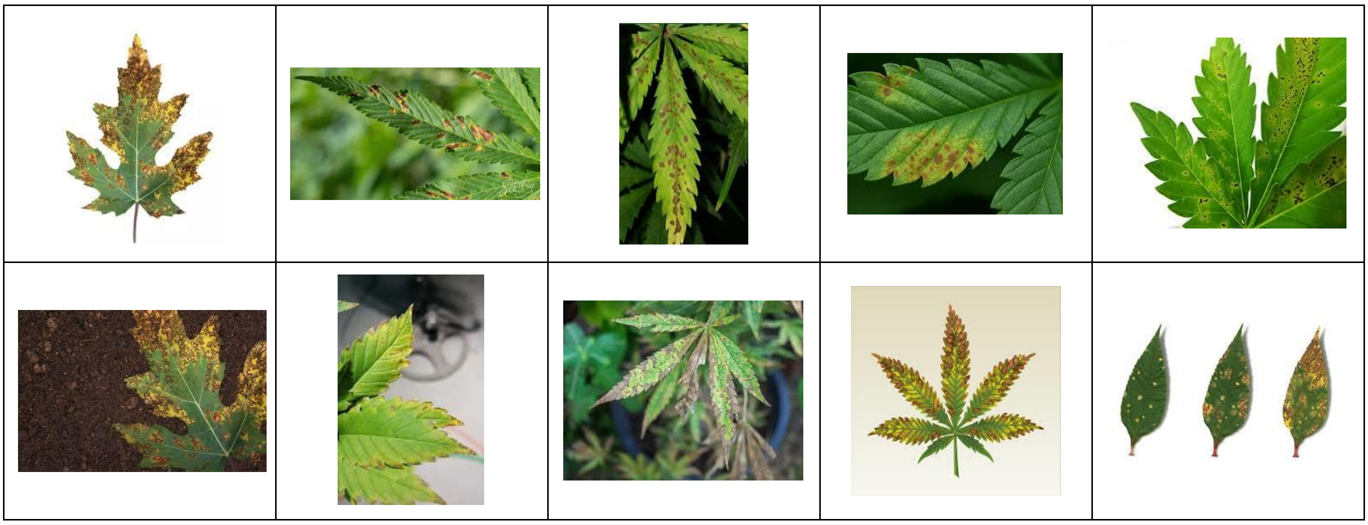

Fig. 3 Dataset for calcium deficiency.

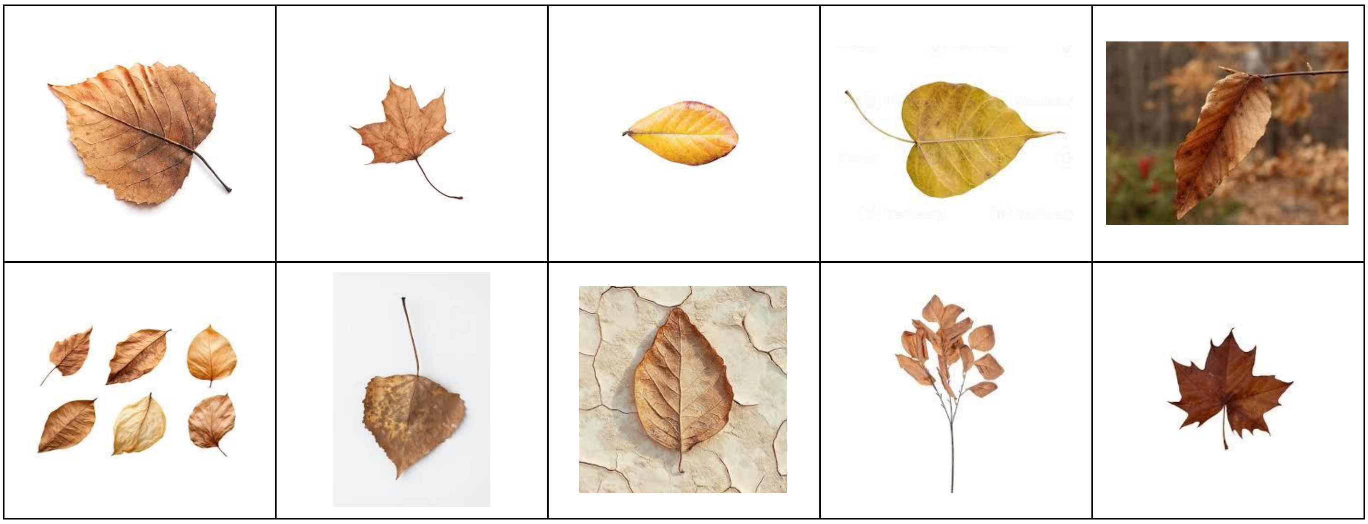

Fig. 4 Dataset for dehydration (water deficiency).

Fig. 5 Dataset for magnesium deficiency.

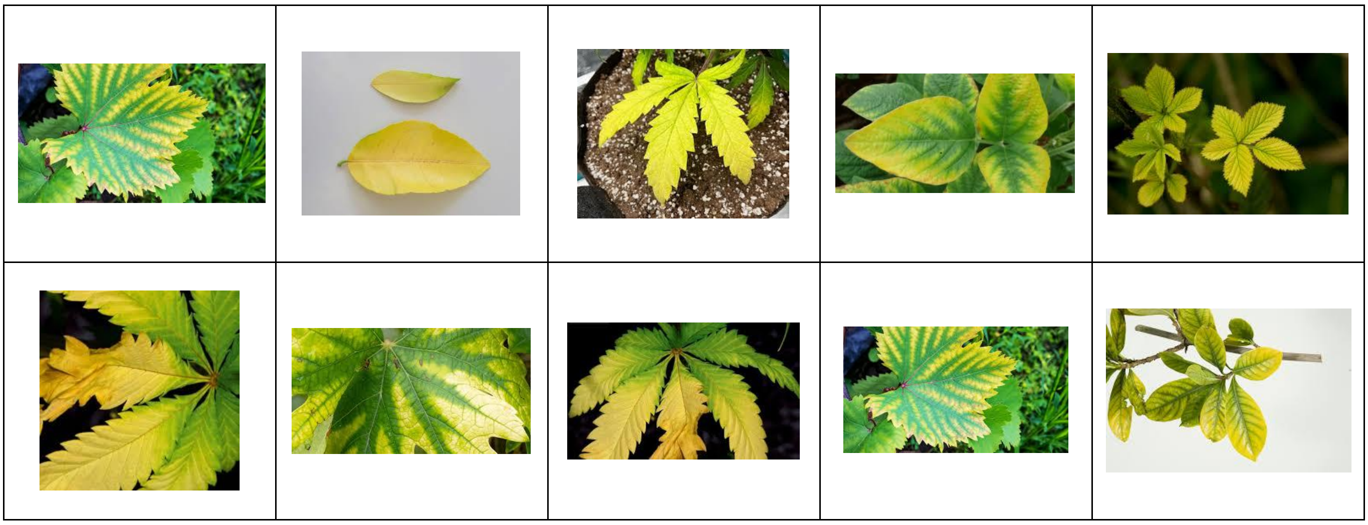

Fig. 6 Dataset for nitrogen deficiency.

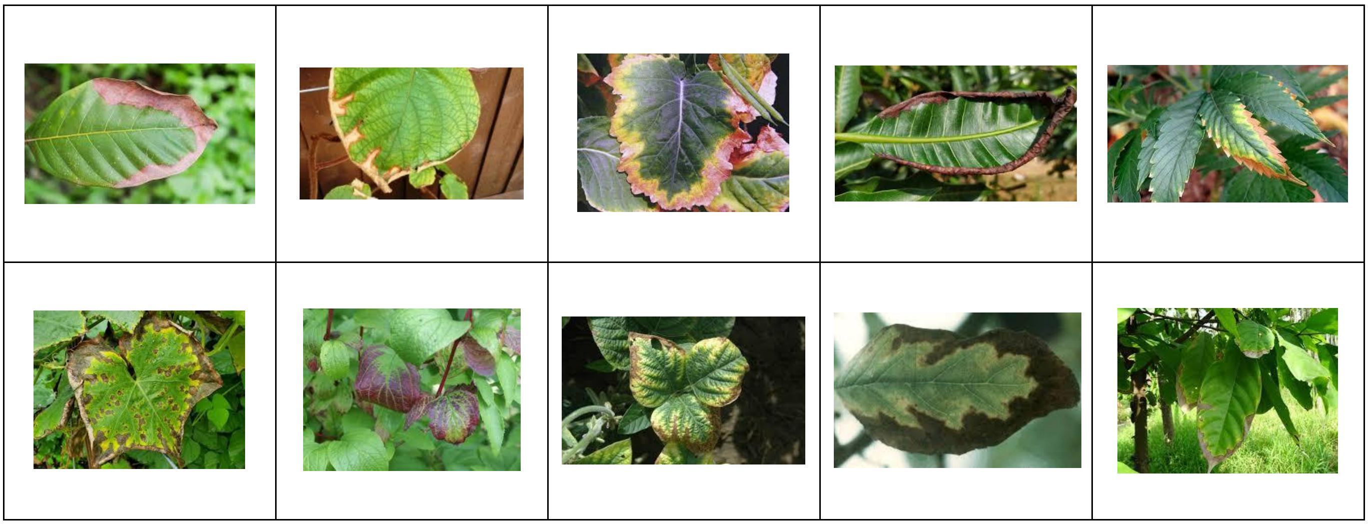

Fig. 7 Dataset for potassium deficiency.

In this study, GoogLeNet architecture is preferred in the deep learning process. GoogLeNet is a deep CNN architecture developed by researchers at Google and introduced in the ILSVRC 2014 (ImageNet Large Scale Visual Recognition Challenge). It is part of the Inception family of models, and its full name is Inception-v1. GoogLeNet achieved state-of-the-art performance in image classification at the time, winning the 2014 ImageNet competition with a top-5 error rate of 6.67%, outperforming previous architectures like AlexNet and VGGNet [35,36].

Key Characteristics of GoogLeNet:

1. **Inception Module:**
    - The core innovation of GoogLeNet is the Inception module.
    - Instead of choosing a fixed kernel size (e.g., only 3×3 filters), the module applies multiple filters in parallel (1×1, 3×3, 5×5 convolutions, and max pooling).
    - Outputs are concatenated, allowing the network to capture both fine and coarse features at the same time.

2. **Depth and Efficiency:**
   - GoogLeNet is a 22-layer deep network, much deeper than AlexNet (8 layers) but designed to be computationally efficient.
   - It uses 1×1 convolutions for dimensionality reduction, which reduces the number of parameters and computational cost.

3. **Global Average Pooling:**
   - Instead of fully connected layers at the end (which add many parameters), GoogLeNet uses global average pooling, reducing overfitting and improving generalization.

4. **Performance:**
   - GoogLeNet significantly reduced the number of parameters (~5 million) compared to VGGNet (~138 million), while still achieving higher accuracy.

Block diagram of the GoogLeNet architecture is demonstrated in Fig. 8.

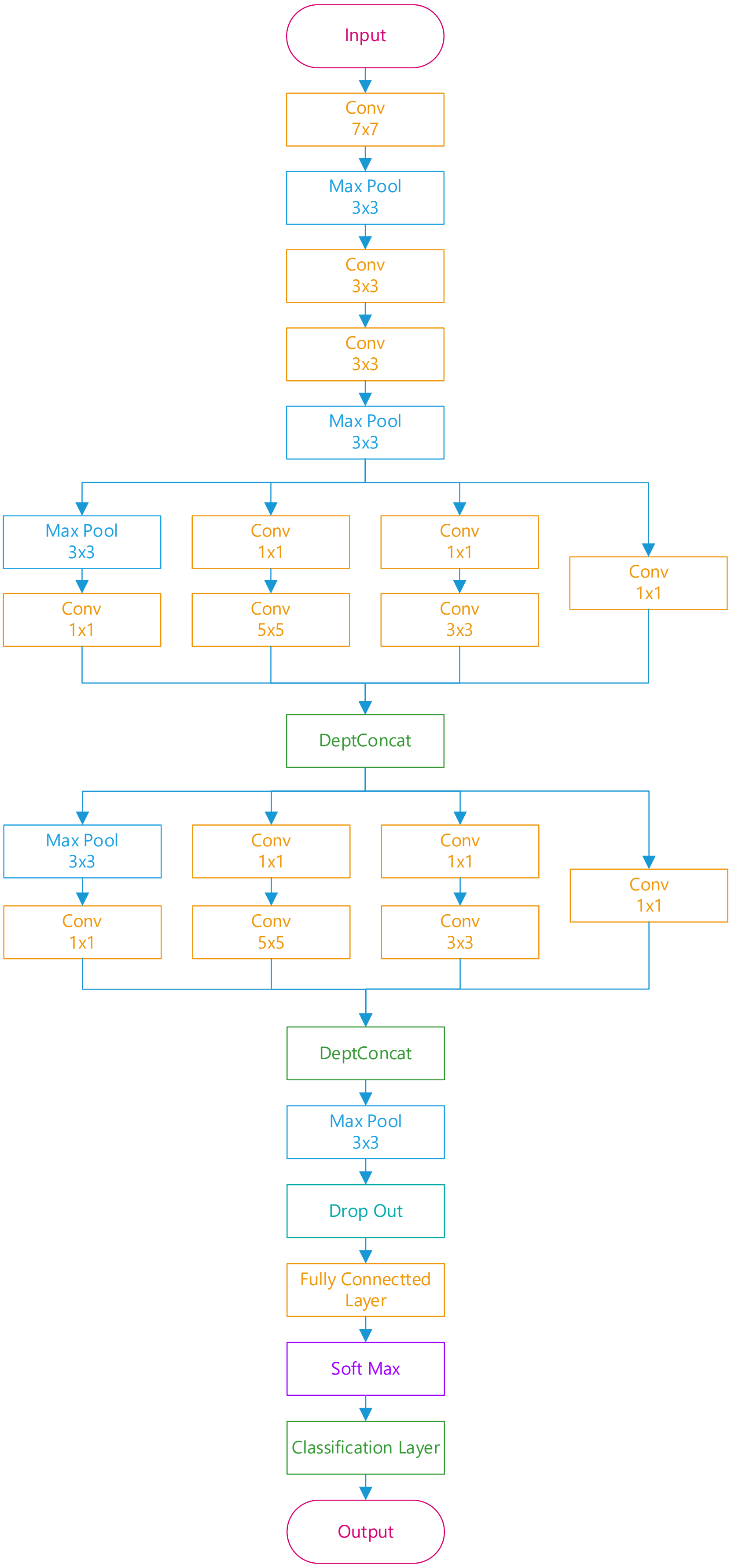

Fig. 8 Block diagram of the GoogLeNet.

Deep Learning Toolbox of MATLAB is used to classify leaf deficiencies with GoogLeNet. The options specified for model training are listed in Table 1.

Table 1. Training options.

Method	Stochastic Gradient Descent with Momentum (SGDM)
Momentum	0.9000
Initial Learn Rate	3.0000e-04
Max Epochs	100
Learn Rate Schedule	'none'
Learn Rate Drop Factor	0.1000
Learn Rate Drop Period	10
Mini Batch Size	5
Shuffle	'every-epoch'
Checkpoint Frequency	1
Checkpoint Frequency Unit	'epoch'
Sequence Length	'longest'
Preprocessing Environment	'serial'
L2 Regularization	1.0000e-04
Gradient Threshold Method	'l2norm'
Gradient Threshold	Inf
Verbose	0
Verbose Frequency	50
Validation Data	[1×1 augmentedImageDatastore]
Validation Frequency	8
Validation Patience	Inf
Objective Metric Name	'loss'
Checkpoint Path	' '
Execution Environment	'auto'
Output Fcn	[ ]
Metrics	[ ]
Plots	'training-progress'
Sequence Padding Value	0
Sequence Padding Direction	'right'
Input Data Formats	"auto"
Target Data Formats	"auto"
Reset Input Normalization	1
Batch Normalization Statistics	'auto'
Output Network	'auto'
Acceleration	"auto"

III. RESULTS

For the deep learning training process, the dataset was split into two parts: 70% training and 30% validation. Training in MATLAB with the *Deep Learning Toolbox* took 5 min 50 sec. The training resulted in 72.22% validation accuracy. The training process is presented in Fig. 9.

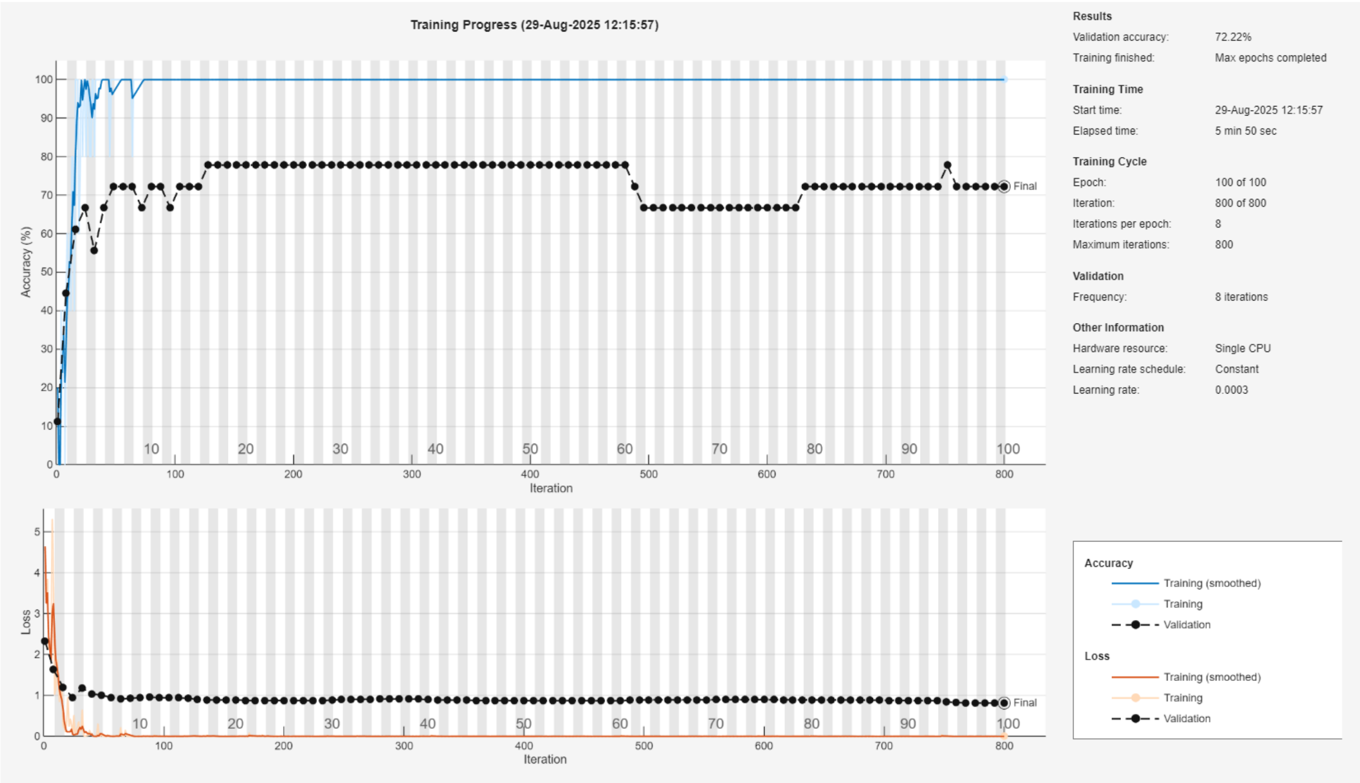

Fig. 9 Training progress.

IV. CONCLUSION

In this study, a simple deep learning application is proposed for the automated classification of leaf deficiencies using image data. The approach employs a convolutional neural network (CNN) model designed to extract and learn discriminative features from leaf images corresponding to common deficiencies such as nitrogen, potassium, magnesium, calcium, and dehydration stress.

GoogLeNet architecture is preferred in the deep learning process. The accuracy of the developed model is 72.22% and an acceptable success rate is achieved with a limited dataset. The model is implemented in a simplified framework to ensure ease of use and adaptability for agricultural practitioners with limited computational expertise.

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