Plant Identification Based on AI and ML System

Nidhi Garg
Poornima Institute of Engineering and Technology
Dept. of Computer Engineering
Jaipur, India

Jahanvi Sharma
Poornima Institute of Engineering and Technology
Dept. of Computer Engineering
Jaipur, India

Himanshu Sharma
Poornima Institute of Engineering and Technology
Dept. of Computer Engineering
Jaipur, India

Abstract:

This mobile plant-identification app employs Artificial Intelligence (AI) and Machine Learning (ML) towards effectively recognizing plant species in real-time from images captured on smartphones. Deep learning algorithms using CNNs recognize features such as the shape of the leaf, texture, or color for further study. Employing a vast and varied dataset of plant images, the ML classification accuracy is model is constructed. The application interface enables simple use by botanists, students, gardeners, and nature lovers to take and identify species of plant species in their surroundings. The app thus makes it swift and feasible to identify plants in more varied environments under applications in education, agriculture, and biodiversity conservation.

Keywords: *Image Recognition, Machine Learning, Deep Learning, Convolutional Neural Networks (CNNs), Mobile Application Development, Plant Database*

1. Introduction:

Plant identification is of utmost importance in botany, agriculture, and environmental science. Traditionally, botanical keys and expert experience are employed, which require a lot of training and are time-consuming. The last few years have seen a revolution in plant identification with Artificial Intelligence (AI) and Machine Learning (ML) (Labrighli et al., 2022).

Plant identification systems based on Artificial Intelligence (AI) scan plant images to look for leaf shape, texture, color, and other features. Machine Learning (ML) models classify the plant species based on the patterns. More advanced Deep Learning models,such as Convolutional Neural Networks (CNNs), learn features automatically and improve accuracy (Picek et al., 2022). Other methods, such as Vision Transformers (ViTs) and k-Nearest Neighbors (kNN) in deep embeddings, advance classification further by recognizing detailed image characteristics (Goëau et al., 2016).

Such AI-based identification systems have extensive uses in precision agriculture, protection of biodiversity, and disease detection in plants. However, research currently under way is meant to address limitations such as restricted datasets, differentiation of species with similar appearances, and improving accuracy within real environments. Future advances would aim at producing more powerful models that employ fewer datasets and are robust within diverse environments.

Comparison of Plant Identification Techniques

Method	How It Works	Accuracy (%)	Reference
Traditional Taxonomy	Uses botanical keys and expert knowledge to identify plants.	Varies by expertise.	Labrighli et al. (2022)
Machine Learning (ML)	Extracts features (shape, texture) and classifies using algorithms like SVM, kNN.	70-97 %	Labrighli et al. (2022)
Deep Learning (CNNs)	Learns plant features automatically from images.	72-99 %	Picek et al. (2022)
Vision Transformers (ViTs)	Uses attention mechanisms to analyze plant images.	92-99 %	Picek et al. (2022)
kNN in Deep Embeddings	Matches new plant images to known species using deep learning features.	88-96 %	Goëau et al. (2016)

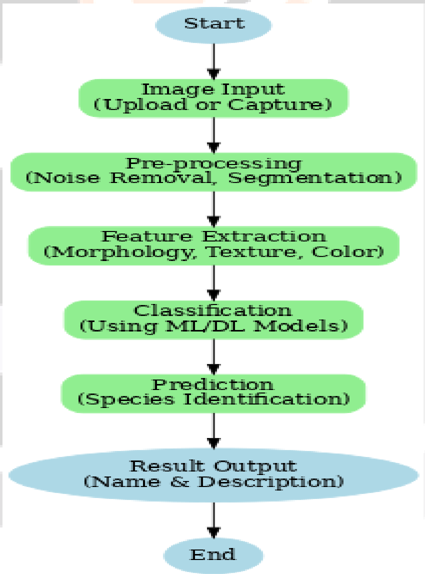

Figure 1: Functionality of Supply Chain Management

2. Literature Review

The use of artificial intelligence (AI) and machine learning (ML) in plant identification has been a topic of much interest over the past few years. Researchers have tried different methodologies, such as machine learning algorithms, deep learning models, and computer vision methods, to improve species recognition accuracy. This section highlights the key contributions and developments in the area of AI-based plant identification.

2.1 Classical Methods of Plant Identification

In the past, identification of plants has relied on morphological, anatomical, and molecular characteristics investigated by taxonomists. Botanical studies have had samples of herbaria at the center, providing the foundation for the classification of species. Manual identification is slow, requires expert knowledge, and creates challenges in handling species with subtle morphological differentiation (Labrighli et al., 2022).

To tackle such problems, researchers designed computer systems employing image processing and computer vision. Early attempts attempted to draw the shape, texture, and color features of the leaves so as to categorize the species in terms of traditional ML approaches such as SVM, kNN, and Decision Trees (Herdiyeni & Wahyuni, 2012). But these approaches failed to deliver when it came to handling enormous plant datasets along with varying environmental conditions (Du et al., 2013).

2.2 Machine Learning-Based Techniques

Machine learning (ML) methods have significantly contributed to automating plant classification. Several researchers have investigated the application of feature extraction techniques and traditional ML classifiers:

- **Feature Extraction Techniques:**
  Principal Component Analysis (PCA) and Local Binary Pattern (LBP) are commonly applied to leaf texture and shape feature extraction. For example, Herdiyeni & Wahyuni (2012) used fuzzy color histograms and local binary patterns to classify Indonesian medicinal plants with 74.5% accuracy.

- **ML Classifiers**:
  Support Vector Machine(SVM) and kNN classifiers have been used for the classification of species. Begue et al. (2017) used Random Forest and SVM classifiers for the classification of medicinal plants with 90.1% accuracy.
  Likewise, Aakif & Khan (2015) obtained 96% accuracy with Artificial Neural Networks (ANNs) using Fourier descriptors.

- **PlantCLEF Challenges:**
  The PlantCLEF challenge has significantly impacted plant identification research by providing big datasets. In 2011 and 2012, editions confirmed that the type of image affects classification precision, with better performance from leaf images scanned as opposed to field photos (Goeau et al., 2011; 2012).
  Despite such progress, ML-based systems were accompanied by hand feature selection and therefore were less versatile for applications in real-life plant identification. This lack resulted in the implementation of deep learning methods for auto feature extraction and classification.

2.3 Deep Learning Methodologies in Plant Identification

Deep learning (DL) has revolutionized plant recognition using automation of feature extraction and extensive species classification. Convolutional Neural Networks (CNNs) have been the dominant approach due to their ability to process high-dimensional image data.

- **Convolutional Neural Networks (CNNs):**
  CNNs have surpassed conventional ML methods in plant recognition. Goeau et al. (2016) proposed CNNs at the 2016 PlantCLEF challenge and attained a 72.4% accuracy in a 113,205 image dataset. Grinblat et al. (2016) applied CNNs to identify leaf venation patterns and attained a 96.9% accuracy.

- **Hybrid Deep Learning Models:**
  Hybrid architectures combining CNNs and attention mechanisms as well as transformer networks have been investigated in scientific studies. Deep neural networks based on kNN for plant classification in deep embeddings with enhanced generalization ability have been researched by Picek et al. (2022). Comparison of DL Architectures: Various studies have compared deep learning architectures to identify plants:
  ResNet-50 and InceptionNet: Performed well with high accuracy in large datasets like PlantCLEF 2017 (Goeau et al., 2017).
  VGGNet and DenseNet: Offered strong feature extraction, improving species recognition despite the presence of noise (Kaya et al., 2019).

- **Transfer Learning Strategies:**
  Interpreted that end-to-end learning is not as good as transfer learning when implemented on plant classification as they achieved a 90.56% accuracy on UCI Leaf.
  These advances indicate that CNNs and transformer-based architectures have predominantly improved plant identification rates over the traditional ML method. However, challenges arise in addressing dataset imbalance, between-species resemblance, and practical environmental

differences.

2.4 Challenges and Future Directions

Challenges:

- **Intra-Class Variability**
  Plants belonging to a single species can appear differently based on age, light, or season, presenting uniform identification as a challenge.
  (Wäldchen & Mäder, 2018)

- **Inter-Class Similarity**
  Most plant species have analogous visual characteristics, particularly leaves and flowers, leading to confusion in classification.
  (Lee et al., 2015)

- **Limited High-Quality Datasets**
  Large, diverse, and well-labeled datasets are lacking, especially for regional and lesser-known plant species.
  (Joly et al., 2016)

- **Real-Time Processing on Mobile Devices**
  Deep learning models face real-time performance on smartphones with high computational demands.
  (Reyes et al., 2015)

Future Directions:

- **Construction of Large, Diverse Datasets**
  Upcoming research will aim to harvest global, labeled plant datasets spanning all seasons and regions.
  (Joly et al., 2016)

- **Lightweight AI Models**
  Lightweight, optimized models such as MobileNet or EfficientNet can make real-time plant identification on smartphones possible.
  (Howard et al., 2017)

- **Explainable AI (XAI)**
  The inclusion of explainability in plant recognition systems will raise user trust and enable improved decision support.
  (Samek et al., 2017)

- **Multilingual Support and Accessibility**
  Offering region language support and audio output can make plant identification tools more accessible.
  (Wäldchen & Mäder, 2018)

3. References:

• Labrighli, K., Moujahdi, C., El Oualidi, J., & Rhazi, L. (2022). Artificial Intelligence for Automated Plant Species Identification: A Review. International Journal of Advanced Computer Science and Applications, 13(10), 814-825.

• Aakif, A., & Khan, M. F. (2015). Automatic classification of plants based on their leaves. Biosystems Engineering, 139, 66-75.

• Begue, A., Kowlessur, V., Singh, U., Mahomoodally, F., & Pudaruth, S. (2017). Automatic recognition of medicinal plants using machine learning techniques. IJACSA, 8(4).

• Goeau, H., Bonnet, P., & Joly, A. (2011). The CLEF 2011 plant images classification task. CLEF Conference Proceedings, 1177.

• Goeau, H., Bonnet, P., & Joly, A. (2012). The ImageCLEF 2012 plant identification task. CLEF Conference Proceedings, 1178, 23-28.

•Goeau, H., Bonnet, P., & Joly, A. (2016). Plant identification in an open-world (LifeCLEF 2016). CLEF Workshop Proceedings, 1609, 428-439.

•Grinblat, G. L., Uzal, L. C., Larese, M. G., & Granitto, P. M. (2016). Deep learning for plant identification using vein morphological patterns. Computers and Electronics in Agriculture, 127, 418-424.

•Joly, A., Goeau, H., Kahl, S., et al. (2020). Overview of LifeCLEF 2020: A system-oriented evaluation of automated species identification. Lecture Notes in Computer Science, 342-363.

•Kaya, A., Keceli, A. S., Catal, C., et al. (2019). Analysis of transfer learning for deep neural network-based plant classification. Computers and Electronics in Agriculture, 158, 20-29.

• Labrighli, K., Moujahdi, C., & El Oualidi, J. (2022). Artificial Intelligence for Automated Plant Species Identification: A Review. IJACSA, 13(10).

• Picek, L., Šulc, M., Patel, Y., & Matas, J. (2022). Plant recognition by AI: Deep neural nets, transformers, and kNN in deep embeddings. Frontiers in Plant Science, 13, 787527.

• Goëau, H., Bonnet, P., & Joly, A. (2016). Plant Identification in an Open-world (LifeCLEF 2016). CLEF: Conference and Labs of the Evaluation Forum.

• Howard, A. G., et al. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv:1704.04861.

• Joly, A., et al. (2016). A look inside the Pl@ntNet experience. Multimedia Systems, 22(6), 751–766.

• Lee, S. H., Chan, C. S., Wilkin, P., & Remagnino, P. (2015). Deep-plant: Plant identification with convolutional neural networks. IEEE ICIP.

• Reyes, A., Caicedo, J. C., & Camargo, J. E. (2015). Fine-tuning Deep Convolutional Networks for Plant Recognition. CLEF.

• Samek, W., Wiegand, T., & Müller, K. R. (2017). Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. arXiv:1708.08296.

• Wäldchen, J., & Mäder, P. (2018). Plant species identification using computer vision techniques: A systematic literature review. Archives of Computational Methods in Engineering, 25(2), 507–543.