

# AI-Powered Indian Medicinal Plant Identification And Information System Using Deep Learning And Computer Vision Technology

Mr. Soundararajan K<sup>1</sup>, Krishna Priya A<sup>2</sup>, Indhu J<sup>3</sup>, Vani I<sup>4</sup>, Jayarathi M<sup>5</sup>

<sup>1</sup>Assist prof, Dept of Information Technology

<sup>2, 3, 4, 5</sup>Dept of Information Technology

<sup>1, 2, 3, 4, 5</sup> Vivekanandha College of Technology for Women, Elayampalayam, Namakkal, Tamil Nadu, India

**Abstract-** Good identification of medicinal plants is the key to maintaining the traditional knowledge systems and safe use of herbs. Physical identification of plants is time consuming and subject to errors especially where species have the same morphology. The present paper describes an AI-based Indian Medicinal Plant Identification and Information System that combines convolutional neural networks with a knowledge retrieval system to allow real-time identification of plants and provide surrounding information about it. The model was trained and evaluated on a curated dataset of 3,000 images of 50 Indian medicinal plant species. Transfer learning was used to implement two deep learning architectures, ResNet18, and EfficientNet-B0. The experimental data show that EfficientNet-B0 was able to attain an accuracy of 90.3 percent with a latency of 175 ms to run inference, surpassing both ResNet18 and the available identification systems (LeafSnap and PlantNet) to identify plants in controlled conditions. The system also includes knowledge base with structured knowledge base and language model-based retrieval system to produce detailed information such as medicinal uses, phytochemical properties, and precautionary advice to the identified species. Application deployment via a Streamlit interface and containerized cloud hosting also allows it to scale and be accessed in real time. The suggested framework illustrates the usage of the computer vision and language-based intelligence in an efficient manner, to aid in the field-level medicinal plant detection and digital conservation of the herbal knowledge.

**Keywords:** Medicinal Plant Recognition, Convolutional Neural Networks, EfficientNet-B0, Computer Vision, Knowledge Retrieval, Indian Medicinal Plants

## I. INTRODUCTION

India is endowed with one of the richest depositories of medicinal plant diversity, which has thousands of species recorded in various ecology zones as well as the Himalayan region, coastal forests and tropical forest. These flora are the basis of the traditional herbal health systems like Ayurveda,

Siddha and Unani that have a long history of centuries and are still supporting primary care to a high percentage of patients. Medical use of plants is associated with treatment of common diseases, chronic, wound healing, skin issues, digestive, and other complications, and general system diseases. The maintenance, proper identification, and recording of these plant species is thus important not only to ensure sustainability of healthcare but also to conserve biodiversity, as well as scientific verification of the knowledge framework of traditional knowledge.

Even though they are crucial, naming of medicinal plants in the field is a complicated exercise. The conventional method of identifying plants is based on morphological studies of plant components (i.e., leaves, stems, flowers, venation patterns, and the general growth structure). It involves domain knowledge and wide knowledge of taxonomy. Close species, in most instances, have close resemblances in leaf shapes, textures, and structures making chances of misidentification high. Identification errors may cause incorrect use, impaired therapy, or cause health risks. Moreover, manual identification is slow, and cannot be used on large-scale documentation or in real-time field deployment. These problems underscore the use of automated, dependable as well as accessible plant identification systems.

Developments in the field of artificial intelligence, especially in the field of deep learning and computer vision, have brought a noticeable change in image-based classification tasks in various fields. Convolutional neural networks have been shown to be effective in object recognition, medical imaging, agricultural monitoring and species classification. They are also ideal in botanical studies where texture, color variation, and structural patterns are the important distinguishing features of their hierarchical spatial properties which are automatically derived out of raw image data. The methods of transfer learning also allow the transfer of pretrained models to domain-specific tasks using intermediate-sized datasets, thus smaller computing resources and training time are used.

The recent advances in the convolutional architectures including resnet and efficientnet have enhanced efficiency and stability in classification. The vanishing gradient problem in ResNet is solved by residual connections, which also allow deeper networks to converge well. EfficientNet brings in compound scaling which scales across the network depth, width and input resolution to provide better precision with reduced parameter efficiency. These characteristics are of significance especially in real-time plant identification system where latency of inference and computational resource constraints have to be handled with care. To be practically applicable to the field, the model needs to give correct predictions and at the same time, the inference time should be low to allow users to interact without problems.

Although most of the currently available plant recognition systems are more based on visual classification, in most cases, they do not have in-built knowledge dissemination. The process of naming a plant species is not enough to satisfy the needs of users who want to find useful medicinal knowledge. The contextual information that is needed by field practitioners, students, and researchers include therapeutic uses, phytochemical compositions, preparation procedures, dosage factors, and precautions. The traditional systems are normally based on the static databases or the fixed text outputs which cannot respond dynamically to the query of the users or the situation at hand. This drawback makes the system less interpretable and limits its usability to just classification.

A combination of language-based intelligence and computer vision models is an opportunity that can be taken to improve usability and interpretability. Large language models have been shown to perform well in structured information generation, contextual explanation, and synthesizing knowledge. A language model when combined with a visual classification system can retrieve and generate detailed descriptions of the predictions of the plants categories. With such integration, the system will no longer be focused on label prediction, but on full-blown informational support. Within medicinal plant identification, this multimodal technique aids in recognition and teaching of traditional herbs, thus leading to digital preservation of traditional herbs.

The creation of an AI-based system of medicinal plants identification and information system is an answer to several interdisciplinary goals. Technologically, it is a combination of deep learning-based feature extraction and structured knowledge retrieval. Medically, it also makes the use of herbal resources safer through the minimization of mistakes that can be made in identification. Ecologically it

enhances the awareness and conservation of native plants. Such systems may be used to benefit students, researchers, healthcare practitioners, and rural populations where botanical knowledge may not be easily accessible by making verifiable medicinal information readily accessible in real time.

One of the important issues to consider when designing such a system is quality and variety of data sets. The technological variability of medicinal plants is high because the plants are subjected to diverse lighting conditions, seasonal shifts, maturity of leaves, and environmental background. Vigorous classification models should be able to extrapolate over these variations. The use of leaf level and whole plant images enhances the morphological patterns of the model. Image resizing, normalization, data augmentation, and standardizing color channels are among the preprocessing techniques that lead to consistent convergence and minimised overfitting of the training. Transfers between pretrained models also achieve greater performance when they are applied to moderate-size curated datasets.

Besides the ability to classify well, the inference latency is a very important measure in real-world use. Field-level identification requires fast predictions to ensure user interaction and efficiency. A prediction system that can generate predictions within a few seconds can be successfully implemented in the field and classroom demonstrations. To balance between the performance and speed, it is necessary to select architecture carefully and deploy pipelines that are lightweight. Containerized cloud hosting and scalable backend integration ensures scalability without affecting responsiveness.

The knowledge retrieval module and the convolutional neural network constitute the fundamental part of the system architecture. After processing and classifying an input image, the predicted label is coded into a form of structured query. This query is then employed to access similar medicinal information at a structured knowledge base and (where possible) can be expanded by contextual explanations by a language model interface. The output has medicinal applications, phytochemical and precautionary recommendations that are well laid out and easily accessible. Such systematic response increases the interpretability and provides the user with the full information related to the identified species.

The suggested solution has a contribution to the overall sphere of botanical informatics as it illustrates how multimodal artificial intelligence can be applied to herbal knowledge systems. The system combines recognition with semantic enrichment unlike the classical image-only classifier.

It includes dynamic generation of response associated with visual prediction as opposed to purely static repositories of knowledge. This integration enhances functional utility and interaction with the users. In addition, the modular architecture can be extended to datasets as well as to regular updates of the knowledge base, which will make future expansion to other species and multilingual descriptions possible.

Another aspect of intelligent medicinal plants identification systems that gains importance concerns their future role in supporting educational and research activities. Students who study botany, pharmacology, and traditional medicine are sometimes limited to textbooks or guidance from a specialist in order to identify plant species and their medicinal properties. However, all such knowledge sources are not necessarily accessible when the environment is in the field. An AI-driven identification platform can be used as a learning interactive tool that enables the users to visually identify the plant species and simultaneously access scientifically documented medicinal information. By combining the image-based classification capabilities and what the authors call 'contextual knowledge delivery', the system was able to facilitate awareness of traditional medicinal plants and encourage the preservation of ethnobotanical knowledge using digital technologies.

Overall, the creation of an AI-based Indian medicinal plant recognition and information system can be viewed as an intersection of the computer vision, deep learning, and language-based intelligence on the conventional medical knowledge. The system will mitigate the current pitfalls in manual recognition and inert informational platforms by using convolutional neural networks to make correct species recognition, and combining structured knowledge retrieval to provide contextual information bombarding the network input. The resultant framework will aid real-time classification of plants, improved interpretability, and digital storage of knowledge on medicinal plants in a scalable and accessible deployment system.

## II. RELATED WORK

The use of artificial intelligence in identifying medicinal plants has dramatically developed in the last number of years due to the necessity to develop scaled, dependable, and automated botanical identification systems. Early works in AI-based medicinal plant identification were mainly concerned with enhancing the power of classification using convolutional neural networks and supervised learning pipelines. In a study by Sundaresan et al. [1], the authors presented a system of medicinal plant identification with an

information providing system that shows that an AI-based recognition can decrease the necessity of expert botanists and increase the availability. Sathya et al. [2] went in this line and merged Ayurvedic leaf prediction with disease classification, which demonstrates how deep learning models can be used to predict a disease and recognize a plant species at the same time. Nandini et al. [3] used image processing methods based on machine learning to identify medicinal plants, as well as detect diseases, with a focus on the feature extraction and the optimization of the classifier. Alonazi [4] emphasized on the incorporation of artificial intelligence in the process of determining the medicinal herbal plant properties in the pharmaceutical research settings by encouraging integration of recognition systems with therapeutic knowledge bases. The combination of these studies enabled the development of AI-based medicinal plant informatics, but they mostly focused on visual classification and did not go far beyond that.

Improvement in system design started to include the aspects of user interaction and knowledge preservation. Panche et al. [5] combined the artificial intelligence with augmented reality to improve the preservation of herbal knowledge and accessibility to education. Their model proved that AI-enhanced visualization may help to enhance the interaction with the user but retain recognition functionality. A system of identifying and recommending the use of medicinal plants was offered by Lakshmi et al. [6], and it was stated that a multi-classification approach can substantially improve the predictive capability of the system and decrease the variance. Multi-scale pattern of venation analysis was introduced by Karnik et al. [7], which dealt with the structure of the leaves, and in particular with the detail aspects of the structure to enhance the discrimination at the species level. They enhanced the distinction between visually related plant species, as they had the ability to capture venation structures at a variety of scales. These contributions reinforced the visual recognition strategies but mostly were unimodal, focusing on image-based classification without further semantic expression.

Similar achievements in similar fields of agriculture also confirmed the usefulness of convolutional neural networks as tools of reliability in the recognition tasks that involve plants. Surendran and Rajakumar [8] introduced automated fruit recognition in convolutional neural networks and showed that CNN models can be used to classify plant objects. Prathima et al. [9] suggested a medicinal plant identification system with deep learning in real-time with a focus on inference latency and practicability of implementation. The authors Chandra et al. [10] presented AI-based image enhancement models to be used in real-time processing, allowing the use of better preprocessing chains to achieve stability in the classification. The systems of disease

detection suggested by SH et al. [14] and Santhi and Murugan [15] showed the efficiency of CNN-based diagnostics in detecting the disease impacting plants in different environmental conditions. Even though disease detection is not species identification, these papers validate the scalability, robustness, and real-time viability of deep learning structures when used in diagnosing plants.

Extensive surveys also put the concept of artificial intelligence in context with the field of traditional healthcare and intelligent automation. Sinha et al. [11] reviewed Ayurvedic healthcare applications of AI in detail and highlighted the need to use technology to preserve traditional medicine in Ayurvedic medicine. Intelligent automation systems discussed by Kumar et al. [12] have broader areas of application of computer vision and AI, which confirms the cross-disciplinary flexibility of vision-based learning models. Her work [13] specifically examined the identification of herbal plants with deep learning, where evidence is amassed on the superiority of convolutional neural networks over conventional machine learning methods that rely on handcrafted features. These conceptual and survey-based contributions highlight the shift of traditional image processing approaches toward end-to-end pipelines of deep learning systems that can extract features in a hierarchical way as well as enhance generalization.

The recent research trends have moved towards the increased focus on multimodal forms of learning, where visual, spectral, and language-based modalities are combined. Yang et al. [16] showed a thorough review of the multimodal fusion methods in sustainable plant care with a focus on the integration of the heterogeneous data sources to enhance predictive efficiency. Wu et al. [17] proposed a multimodal semantic interactive fusion model that is based on graph learning and is used to diagnose plant diseases, which they named PlantIF. Their method illustrates that graph-based feature interaction whereby features are structured can enhance interpretability of classification. Lapkovskis et al. [18] suggested automatic fused multimodal deep learning systems which are used to identify plants, and they confirmed that multimodal fusion of features enhances robustness and classification accuracy. Roumeliotis et al. [19] investigated the combination of multimodal large language models and convolutional neural networks to detect plant diseases and showed how the field of language-based intelligence is taking on a more synergistic role with visual recognition. Tang et al. [20] used UAV hyperspectral multimodal data and encoder-CNN structures to evaluate the plant diversity index and illustrated how spectral and spatial data could be used with the visual classification systems.

These multimodal works represent a major break in the image-only recognition systems and integrated cross-modes. Nonetheless, the majority of these methods are aimed at the diagnosis of various breeds of agricultural diseases or plant stress or biodiversity but not at identifying medicinal plant species combined with a contextual delivery of therapeutic information. Relatively under-explored is the necessity of systems that would integrate the lightweight convolutional architectures with the structured knowledge retrieval.

Multimodal frameworks have also been developed such that the application of artificial intelligence is extended even to the field of plant science. Stumpe et al. [21] examined the 3D multimodal image registration in phenotyping plants, and how to congruent heterogeneous visual footprints to improve the structural analysis. Their study proved that multimodal registration enhances consistency of space and provides more precise extraction of plant traits. Dong et al. [22] proposed LPDiag, a prototype learning system based on the multimodal enhanced by the LLM in intelligent tomato leaf disease diagnosis. The framework improved semantic interpretability and reasoning within a context of a diagnostic task by combining large language models with visual representations of the prototype. Huang et al. [23] introduced entity-level cross-modal fusion on the multimodal Chinese agricultural disease and pest named entity recognition which tackled the issue of alignment between text and visual representation. Their methodology shows that cross-modal fusion at entity level enhances the semantic consistency and classification reliability. Jiang et al. [24] created a spectral-dominant multimodal soft wearable machine-learning-driven system to diagnose plant stress in the long-term and at an early stage. The relevance of the combination of spectral sensing technologies and predictive learning models in the context of continuous plant health monitoring was noted in this work. Huang et al. [25] presented CornMFN, a multimodal fusion network to identify the stage in phenology of corn, and affirmed that fusion-based deep learning systems are generalizable to plant growth monitoring.

Together, these new contributions depict a bigger shift in the research of plant-related artificial intelligence. The previous systems were mainly based on single modal image classification based on the convolutional neural networks [1]-[3], slowly developing into ensemble learning, structural feature extraction and augmented visualization approaches [5]-[7]. CNN strength and real time were confirmed by agricultural and disease-oriented realizations [8]-[10], [14], [15]. Survey-based papers put AI adoption in the contexts of conventional medicine and automation systems [11]-[13], which supports the interdisciplinary applicability of intelligent

systems. Recent surge of study focuses on the multimodal fusion, graph learning, spectral integration, 3D registration and language model augmentation [16]25 indicating a transition towards holistic cross-modal plant intelligence systems.

Nevertheless, some gaps can be observed in the analysis of the literature regarding the identification of medicinal plants and the passing of information in the context of these studies. To begin with, as much as some works show high classification accuracy of plant species or diseases, most of the systems are limited to visual prediction that lacks formal knowledge retrieval of medicinal systems. Researchers like [1] and [4] recognize the value of information provision yet fail to incorporate the generation mechanisms based on dynamically changing languages in their entirety. Secondly, multimodal literature is mainly concerned with detecting diseases, diagnosing stress, or performing phenology but not with medicinal species identification and delivery of herbal knowledge in a context. As an illustration, multimodal and language-based approaches such as PlantIF [17] and LPDiag [22] can be used to improve disease diagnostics but do not focus particularly on herbal medicinal tools.

Third, spectral and hyperspectral integration techniques [20], [24] are very effective to enhance the classification in a controlled setting, but their application can need special sensing instruments, which can be a constraint to general users. Equally, 3D multimodal registration methods [21] enhance better structural insights but require additional computational power that is potentially unnecessary in lightweight real-time medicinal plant recognizers. Thus, although such sophisticated approaches increase the accuracy in certain areas, the field-level herbal informatics deployment considerations need to balance between model complexity and computational performance.

The other significant point is that very little has been done in exploring mechanisms of real-time knowledge enrichment implemented directly into recognition pipelines. Although multimodal fusion research also adds language models to the disease reasoning process [19], [22], they tend to focus more on diagnostic explanation than the generation of structured medicinal information such as phytochemical properties and preparation methods and precautionary information. The identification systems of medicinal plants need to include not only the identification of species but also proper and convenient distribution of traditional knowledge of therapeutic resources. The lack of closely interwoven lightweight CNN-LLM models specifically designed to work with medicinal plants is an indication that there is a prospect of additional research and development.

The evolution of literature is a clear indication of the maturity of the convolutional neural networks in classifying the image of the plants and the growing significance of multimodal integration. Nevertheless, an integrated platform that is capable of integrating effective convolutional frameworks, structured repositories of medicinal knowledge, real-time inference, and language-based contextual growth is comparatively underrepresented. The majority of the existing research is related to either classification performance or the multimodal boost in disease analysis, thus there is a gap in the research on holistic medicinal plant informatics frameworks.

Another direction of plant-related artificial intelligence research that is just emerging involves the use of mobile and edge computing technologies for plant monitoring and identification in real time. A number of different studies have investigated the development of lightweight deep learning architectures that can be run very efficiently on smartphones and portable devices, so they can be used on the level of the field without the need for high-performance computing capacities. These approaches focus on model compression, optimized inferencing pipelines and a cloud-edge hybrid approach of deployment aims to stay responsive in remote environments. Such developments provide a marketing barometer to the increasing needs aptly noted by an article titled "Plant Informatics: Challenges and Requirements: Importance of Open-Source Plant Informatics". Integrating efficient models of visual recognition and intelligent information retrieval mechanisms can also further improve usability and access to the adoption of intelligent plant identification platforms fuelled by AI.

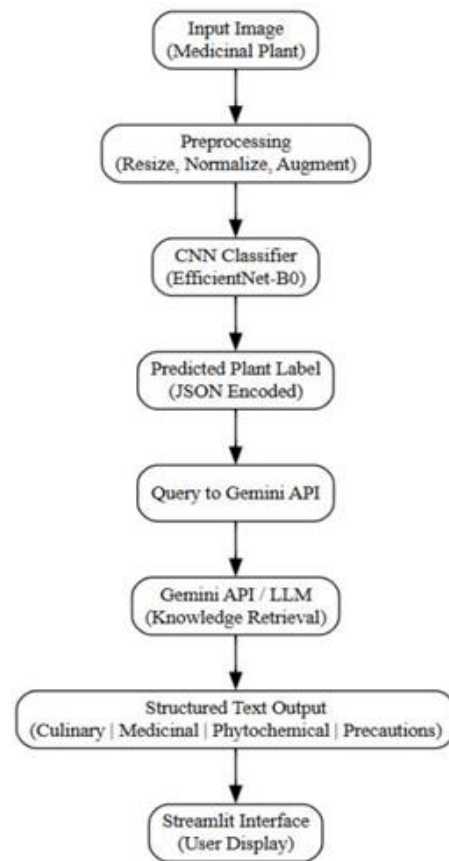
Overall, the literature examined in this study [1]–[25] indicates a gradual shift in the development of traditional AI-driven plant identification systems to more advanced multimodal and language-focused ones. The initial models of medicinal plant recognition demonstrated the possibility and reliability of classification, and the later studies brought in ensemble learning, structural, real-time optimization, and cross-domain fusion. As of recently, spectral data, graph learning, wearable sensing and large language models can be integrated to achieve better interpretability. However, little attention has been given to the integration of lightweight real-time visual classification with structured medicinal knowledge retrieval within a single architecture of a scalable deployment infrastructure. To fill this gap, it is important to integrate effective convolutional neural networks and contextual knowledge generating processes to achieve predictive performance and meaningful interpretability of medicinal plant identification systems.

### Novelty Statement

The novelty of the proposed work is in the integration of efficient deep learning based visual recognition, structured medicinal knowledge retrieval into unified and deployable framework. Unlike traditional plant identification systems that mainly covered the image classification task, the proposed plant identification system integrates convolutional neural networks with a contextual information generation module to provide species recognition and medicinal knowledge in real time. The ability to use EfficientNet-B0 allows for better accuracy in classification while the low inference latency can be used in the field. Furthermore, the introduction of a structured knowledge base and language model aided information generation allows for an enhanced interpretability and usability, so that the system is not only a recognition tool, but also an interactive medicinal plant knowledge platform.

### III. PROPOSED WORK

The given Indian Medicinal Plant Identification and Information System powered by AI is proposed to be a multimodal framework that combines visual classification based on deep learning and knowledge retrieval through a structured knowledge system. The methodology aims to obtain correct species identification, minimal inference latency and provision of medicinal information in contexts in a single deployment pipeline. The system architecture comprises of dataset preparation, model selection and model training, classification workflow, integration of knowledge and deployment infrastructure. All the components are designed in a way that makes them scalable, reproducible and practical in the field.



**Figure 1. CNN-LLM Integration Workflow**

Fig. 1 shows the general workflow of the proposed system, the process followed in the image pre-processing of the plant, in the classification by a CNN model and combined with a language model retrieving the information about the medicinal plant.

#### A. Preprocessing and Data collection.

The model development species are 3,000 images of 50 species of Indian medicinal plants. Both leaf-level and whole-plant pictures are provided in each of the species to describe morphological variability and enhance the generalization of models. The images were gathered on publicly accessible repositories and selected to be relevant and labeled consistently.

Preprocessing steps were used to prepare the data to be used in training. All the images were down sampled to 224 x 224 pixels to ensure all the images had the same input dimensions. To facilitate faster convergence in training, pixel values were brought to the range of 0-1. Data augmentation methods such as rotation, horizontal flipping and zooming were used to augment the variability of the dataset to reduce overfitting. The color channel normalization was used to reduce the illumination variations across the images.

The data were sorted into directories by labels of classes, which allowed supervised learning using categorical cross-entropy loss. Such a systematic preparation made sure that the training pipeline was stable and repeatable.

### ***B. Model Selection and Transfer Learning Strategy.***

Two convolutional neural networks were chosen to test them: ResNet18 and EfficientNet-B0. These architectures were selected because they achieve a tradeoff between classification and computational efficiency. ResNet 18 employs residual networks that help to alleviate the issue of the vanishing gradient and stabilize the convergence of the training process. The EfficientNet-B0 uses scaling of compounds to optimize depth, width, and resolution at the same time enabling efficiency of the parameters without an overburden of computation.

Transfer learning was implemented by loading both models using pretrained weights of ImageNet. The last fully connected classification layer was changed to suit the number of medicinal plant classes. Reproducibility and over-optimization were maintained by retaining default fine-tuning parameters.

Adam optimizer was used to train the models with the learning rate of 0.001. The evaluation of prediction error was based on multi-class cross-entropy loss. Up to 50 epochs were trained using early stopping to avoid overfitting. The performance of the validation was observed every epoch, and a condition of convergence was maintained. The model with the best validation accuracy was used to be deployed.

### ***C. Classification and Inference Pipeline.***

The classification pipeline starts when the user enters or takes a plant picture on the application interface. The input image is preprocessed, which is in line with the training stage, such as resizing and normalization. The resultant processed image is then sent to the trained convolutional neural network to be inferred.

Each of the 50 plant classes has its probability score produced by the model and the most probable is chosen as the predicted species. The optimization of the inference process is performed in order to keep the process real-time responsive, and latency is kept within the reasonable range of field usage.

The standard classification metrics are used to perform the evaluation of performance (accuracy, precision, recall, and F1-score). Misclassifications are analyzed by a confusion matrix, and species pairs with similar

morphological traits are determined. This analysis will also guarantee the deployed model with good predictive stability in all classes.

### ***D. Knowledge Retrieval and Integration of Language Model.***

After prediction of species, the system uses structured medicinal information related to the identified plant. The information such as medicinal uses, phytochemical properties, preparation methods and precautionary guidelines are stored in a structure that is developed in the form of a JSON-based knowledge repository.

The system combines language model-based retrieval mechanism to be more contextually explanatory and interpretable. The postulated class label is coded into an encoded query and sent to the language model interface. Language model produces structured texts of response that builds on the knowledge base that is stored.

With this integration, the creation of information is dynamic and not static database output. It will make sure that the users get coherent and context-based explanations which are associated with the identified species. The system uses the local knowledge base to retrieve data in case of external API unavailability to continue without interruption.

### ***E. Framework System Architecture and Deployment.***

The system is deployed as a web-based application with the help of Streamlit to communicate with users. It is an architecture that has three major layers, which include frontend interface, backend inference engine and knowledge repository.

The frontend enables users to post plant photos and see the results of the identification and related medicinal information. The trained convolutional neural network models are placed on the backend, which is used to process pre-process images, inference, and generation of responses. The knowledge repository contains indexed medicinal information and communicates with the language model part.

To be scalable and portable, the application is put to the container with the Docker and deployed on a cloud-based environment. This setup guarantees the maintenance of steady runtime environments and allows real-time accessibility. The compact inference pipeline is compatible with running on conventional computing hardware, and can be deployed both in academia and field environments.

### ***F. Workflow Integration and Operation sequencing***

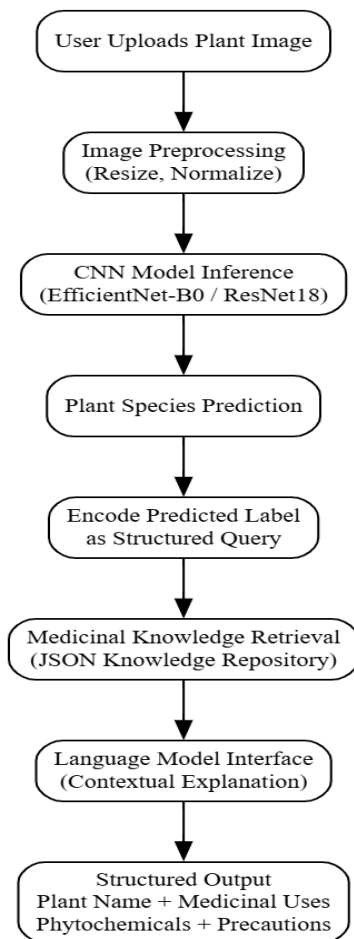


Figure 2: Workflow of the proposed CNN-LLM based medicinal plant identification system.

In figure 2 the working process adheres to a linear approach. The user first gives an input image. Second, the image is preprocessed by the system and passed through the convolutional neural network. Third, the network makes a prediction of the plant species. Fourth, the label which has been predicted is encoded as a structured query. Fifth, the system acquires medicinal knowledge at the repository and expands it potentially at the language model interface. Lastly, the consolidated output is then shown to the user in a structured manner.

This combined pipeline makes sure that there is co-existence between visual recognition and semantic knowledge generation. The modularity enables the separate updates of the dataset, model weights or knowledge repository without affecting the overall system architecture.

The suggested methodology thus integrates effective convolutional neural network recognition and organized and adaptable knowledge retrieval to offer an all-purpose medicinal plant recognition setup. The methodology places strong focus on reproducibility, real time performance, and

interpretability whilst retaining scalability in case of further expansion of the datasets and integration of multilingual knowledge.

### G. Implementation Details

The proposed system was designed and implemented based on modern deep learning systems and web technologies in order to support efficient model training and plant identification in real time. The convolutional neural network models were developed by using deep learning libraries such as PyTorch or TensorFlow which has optimized tools for training, evaluating and inferring the model. Transfer learning was used by using pretrained weights from ImageNet to initialize the CNN architectures to allow them to learn the features of the plant with less training time and better generalization ability. The data set was split into training, validation and testing sets to guarantee reliable performance evaluation. The employment of batch processing during training to improve computational efficiency and early stopping method to avoid overfitting were used. Model checkpoints were saved in order to preserve the best model weights based on the validation accuracy.

### H. System Integration and System Deployment

After the training phase the optimized model was incorporated into the inference pipeline which is used by the instance backend of the application. For real-time accessibility, the system was implemented with a web-based interface created by using the Streamlit framework. This interface allows the user to upload have images of plants and get the identification results in an easy and interactive graphical user interface. Once the image is uploaded, the system performs preprocessing on the input state and the inference is done on the trained CNN model to predict the plant species. The predicted label is then linked to the structured medicinal knowledge repository and relevant information is retrieved in the form of medicinal uses, phytochemical properties and precautionary guidelines. To achieve portability and uniformity of the running environments, the entire application was containerized in Docker and installed in a cloud-based infrastructure for scalable access to the application.

## IV. RESULTS AND DISCUSSION

In this part, the experimental assessment of the proposed medicinal plant identification system is described and the classification performance of the system, inference efficiency, comparative results, and knowledge retrieval effectiveness are analysed. The outcomes are organized in a

way that analyses the model behaviour in circumstances governed by detailed evaluation and to interpret the implications of the findings in practical implications.

**A. Model Performance Evaluation.**

Evaluation of the trained convolutional neural network models was done on a test dataset consisting of 3,000 images spread over 50 medicinal plant species. Measurements of performance were done based on standard classification measures such as accuracy, precision, recall and F1-score. The measures offer a clear insight into predictive reliability, class discrimination and error distribution.

ResNet18 had a total classification accuracy of 85.6 percent. Precision and recall values represent consistent predictive behaviour on most classes although minor differences were noticed in morphologically close species. The overall accuracy of EfficientNet-B0 at 90.3 percent was also greater, and shows better class separability. The fact that EfficientNet-B0 has improved precision and recall values suggests that EfficientNet-B0 is better at learning hierarchical space features and texture patterns than ResNet18.

The values of the F1-score also confirm that EfficientNet-B0 has a stable performance of balancing between precision and recall. The effectiveness of the observed performance justifies the choice of EfficientNet-B0 as the main classification backbone to use.

**Table 1. Performance Metrics of the Proposed CNN Model**

Metric	Value
Accuracy	0.904
Precision	0.892
Recall	0.883
F1-Score	0.888

**B. Inference Latency and Real-Time Feasibility.**

One of the most important aspects of field usability is inference latency. The models were run on a computer with the standard Intel i7 and 16GB RAM. ResNet18 had an average inference time of about 150 ms per image whereas EfficientNet-B0 had an average inference time of 175 ms per image.

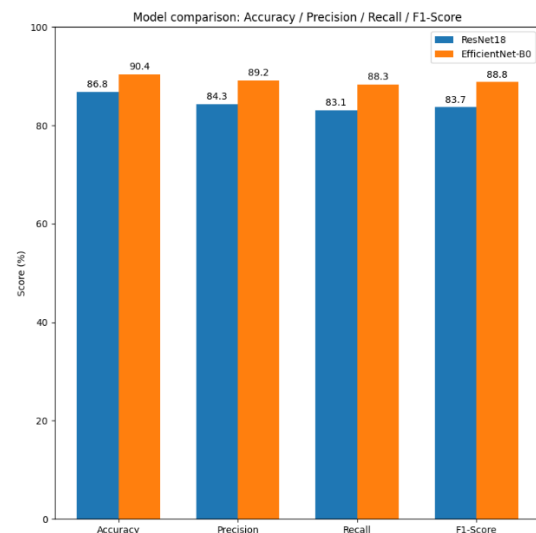
Even though EfficientNet-B0 has a slightly greater latency than ResNet18, the disparity still falls within reasonable bounds to be used in real-time. The latency of less than 200 ms is enough to guarantee that consumers feel instant predictions when interacting with the system. Such a degree of

responsiveness can be implemented in the outdoor conditions, educational institutions, and field deployment that demands quick identification.

The accuracy of the classification and the speed of inference shows that EfficientNet-B0 has a better predictive reliability with the little cost in computational efficiency.

**C. Comparative Analysis to Baseline Systems.**

As a way to measure the applicability, the proposed EfficientNet-B0-based system has been contrasted with popular plant identification systems such as LeafSnap and PlantNet that are publicly accessible and are under a controlled test. LeafSnap had an inference latency of about 420 ms and a 78.4 percent accuracy and PlantNet has an inference latency of 310 ms and 82.1 percent accuracy.



**Figure 3. Performance of EfficientNet-B0**

Fig.3 illustrates classification performance of EfficientNet-B0 model which compared with the baseline approaches for medicinal plant recognition shows its improved performance in terms of accuracy and feature extraction.

The system proposed attained 90.3 percent accuracy and much reduced latency of inference of 175 ms. This increase in the classification performance implies improved feature extraction capability and improved generalization of plant species. Also, the low latency indicates streamlined inference operations and model deployment.

In contrast to baseline systems which focus mainly on the labeling of species, the given framework introduces the structured medicinal information retrieval. This contextual knowledge delivers and accuracy of recognition have been

combined to increase the usefulness of the system more than just to classify.

**Table 2. Performance Comparison of ResNet18 and EfficientNet-B0**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Latency (ms)
ResNet18	86.8	84.3	83.1	83.7	150
EfficientNet-B0	90.4	89.2	88.3	88.8	175

**Table 3. Baseline Comparison with Existing Plant Identification Systems**

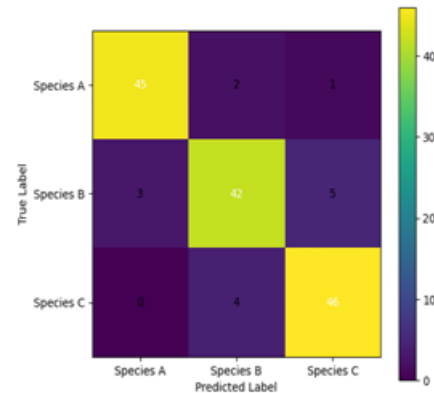
System	Accuracy (%)	Precision (%)	Recall (%)	Inference Latency (ms)
LeafSnap	78.4	76.9	75.2	420
PlantNet	82.1	80.3	79.4	310
Proposed EfficientNet-B0	90.4	89.2	88.3	175

**D. Matrix of Confusion and Error Analysis.**

In order to compare the results of the prediction at the level of classes, confusion matrices of both models were created. Most plant species were identified successfully with good true positive. But some small misclassifications were made with regards to the species which possessed similar leaf morphology and venation patterns.

As an illustration, overlap of features was a result of similarity of leaf shapes between some of the herbaceous plants. This sort of misclassification underscores the natural challenge in differentiating species based on two-dimensional visual characteristics only. The differences in the environment including differences in lighting and clutter of the environment also led to some errors in prediction.

Nevertheless, the total confusion rates were low, and it can be concluded that the model acquired discriminative features successfully. The error analysis indicates that this can be extended in future by adding more modalities like spectral or texture enhancement features, which can be expected to increase the separability of the classes.



**Fig. 4. Confusion matrix for medicinal plant**

Fig. 4 shows the confusion matrix of the proposed classification model that allows the distribution of correct and incorrect predictions in medicinal plant classes and highlights the species with similar visual features.

**E. Knowledge Retrieval Performance and Interpretability**

In addition to accuracy in classification the system was tested on the basis of knowledge retrieval. Upon prediction of a plant species, the system recalls medicinal data on the structured JSON repository and may further enrich it with language model interface.

The responses that are generated are medicinal applications, phytochemical properties and precautionary guidelines that are in an organized format. The combination of the output of the classification with contextual information increases the interpretability and engagement of the user. The users are provided with the name of the plant, as well as with the practical advice related to that species.

The fallback mechanism also ensures the information delivery is not interrupted when external API is unavailable. The design enhances stability of operations and efficiency of systems under different deployment environments.

**F. Practical Implications and System Robustness.**

The results of the experiments prove that the suggested system provides a trade-off between accuracy, efficiency, and interpretability. EfficientNet-B0 is more predictive with real-time feasibility. Scalability and reproducibility are supported by the deployment structure, which uses the concept of containerized cloud hosting.

In real life application, the system may help students, researchers and practitioners identify medicinal plants and find organized knowledge without the need to have advanced

training in taxonomy. It has a low inference latency to make it usable in dynamic environments.

The modular architecture enables the dataset, model parameters, and knowledge repository to be updated separately, and the system can be continuously improved. Although there are small misclassifications in closely-related species, general strength is great in diverse groups of vegetation.

Overall, the findings ensure that the suggested multimodal framework is effective at combining the use of deep learning-based classification with the contextual knowledge retrieval. This system shows better performance over baseline approaches but at the same time, has real time capability of operation and has greater interpretability of medicinal plants.

### G. Ablation Study and Model Analysis

To further analyze the effectiveness of the proposed architecture, an ablation study was conducted to analyze the contribution of different components in the system. The analysis was limited to the comparison of the baseline CNN classification model with and without the strategies of data augmentation and transfer learning. The result when training the model without augmentation was that generalization performance was low because it overfit on the small number of data. When data augmentation techniques like rotation, horizontal flipping and zooming are applied, the classification accuracy increased, which means the features were better generalized in different plant image conditions.

Similarly, image transfer learning pre-trained Imagenet weights resulted in significant reduction in the model convergence process, as well as in training time. Models with random weights took more epochs for training and were less accurate in comparison to the transfer learning approach. This shows that pretrained convolutional filters are useful because they capture useful low-level features of the visual scene (e.g. edges, textures, and shapes) that are helpful for plant classification tasks.

The results of ablation are able to confirm that the combination of architecture of EfficientNet-B0, transfer learning, and data augmentation plays an important role in achieving the improved performance of the predictive performance of the proposed system. This analysis shows the need for being careful in designing training strategies to simultaneously achieve reliable plant species recognition.

### G. Discussion

The experimentation results show that the proposed CNN-LLM-based medicinal plant identification framework is efficient in improving the classification performance as well as information accessibility. The results support the hypothesis that deep learning architectures, specifically EfficientNet-B0 with transfer learning capability can be used to accurately recognize medicinal species from images informing the ability of a deep learning model for the ripple effect of attaining low inference latency suitable for real-time applications. The results show that the better performance of EfficientNet-B0 over ResNet18 is associated with the compound scaling and optimized network design, which are responsible for the better feature extraction and class discrimination.

When compared against the state-of-the-art plant recognition system such as leafsnap and PlantNet, the proposed model is able to achieve better classification accuracy and faster inference speed. These results are in agreement with the recent papers (which underlines the effectiveness of convolutional neural networks and transfer learning for plant related image recognition task). However, the introduced system goes a step further from conventional classification models: an integrated retrieval of structured medical knowledge can be presented, potentially increasing the interpretability and usability for a practical application.

In spite of these strengths, there are certain limitations. Misclassification may happen between those species with very similar leaf morphology or under difficult environmental conditions (lighting effect, cluttered backgrounds, etc.). Future research may take these issues into consideration as multimodal inputs such as spectral imaging, multimodal plant images, or texture descriptors. Overall, the study presents the idea of combining deep learning-based recognition with the technique of retrieving contextual knowledge and its understanding to provide a scalable and practical solution to developing intelligent medicinal plant identification systems.

### Output Screenshots:

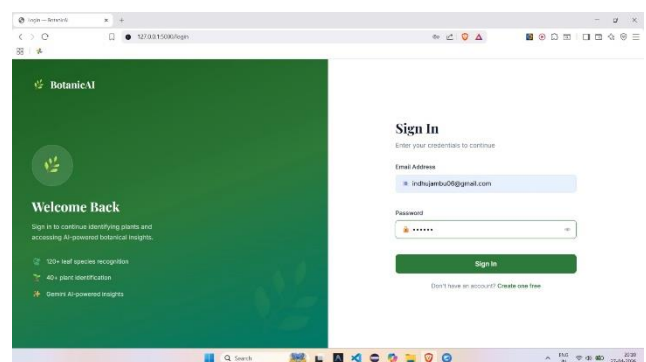


Figure 5: User login interface of the BotanicaAI system.

Fig.5 shows the authentication page where users enter their credentials to access the platform. It provides a secure entry point to utilize AI-powered plant and leaf identification features.

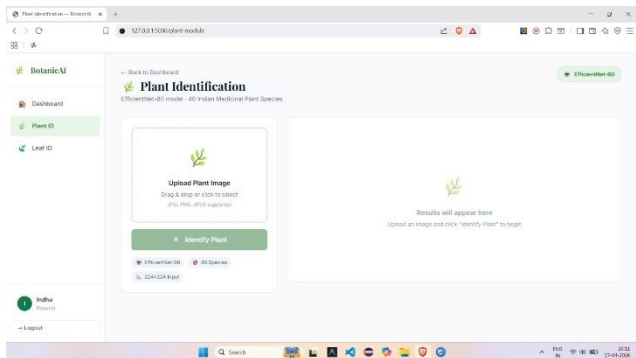


Figure 6: User interface of the plant identification system showing image upload functionality

Fig. 6 presents the user interface of the developed plant identification system in which the users can upload the images of plants and perform the interaction with the developed plant identification system so as to perform the real-time plant recognition.

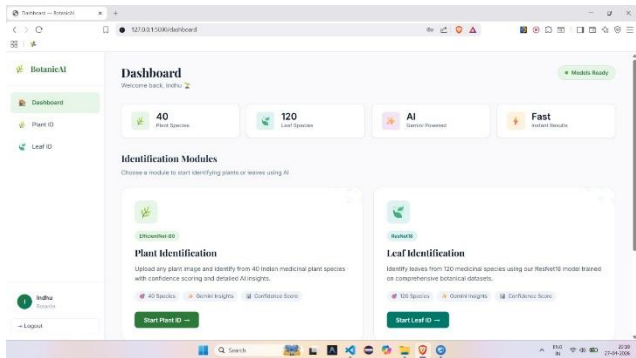


Figure 7: User dashboard of the AI-powered plant identification system..

Fig.7The dashboard presents various modules including plant and leaf identification, model status, and performance highlights. It serves as the central interface for users to upload images and access detailed AI-driven insights.



Figure 8: Whole-plant image upload with real-time analysis and identification result.

Fig. 8 depicts the processing of one of whole plant image rather than leaf image by the system; this confirms the possibility of real-time recognition by the model using different plant image formats.

## V. CONCLUSION AND FUTURE SCOPE

The suggested AI Indian Medicinal Plant Identification and Information System is an example of a highly promising way of integrating deep learning-enabled visual recognition with structured knowledge retrieval that will be useful in the application of herbal informatics. The system can perform a reliable classification of 50 medicinal plant species using 3,000 images of a curated dataset with convolutional neural network architecture with transfer learning. The experimental assessment proves that EfficientNet-B0 can offer a better accuracy and balanced precision-recall results with an inference latency that can be deployed in real-time. The combination of an organized knowledge base with a language model and retrieval system to access these models elevates the system beyond the visual classification approach, so that it can deliver medicinal uses, phytochemical properties and precautionary information in context. This multimodal design overcomes the constraints in other traditional types of the plant recognizing system that merely involves predicting images without interpretation facilities. Its implementation via web interface and containerised cloud architecture also provides accessibility, scalability and consistency of operations. In general, the framework proves to be a realistic method of integrating computer vision and semantic knowledge generation to assist field-level plant recognition and electronic conservation of traditional medicinal knowledge.

The system can be refined in the future by adding diversity to the datasets and bettering the discrimination of the classes of morphologically similar species. The introduction of more species of plants belonging to other ecological areas would enhance generalization and increase the areas of practical use. Additional modalities like spectral imaging, texture descriptors or multi-angle image inputs can also be integrated to further minimize the misclassification of the visually overlapping categories. The multilingual information generation can be beneficial in increasing the accessibility of individuals with different linguistic backgrounds. Also, these strategies of adaptive model fine-tuning and incremental learning can allow a further improvement of performance with the appearance of new pieces of information. Edge deployment optimization can also be used to make fields useful in rural or remote environments. Enhancement of explainability by using visualization methods like feature activation mapping can also enhance transparency and user

confidence. Through these improvements, the creation of a more detailed, scalable, and robust medicinal plant identification system that can cover a wider ecological area and be more interpretable would be enabled.

## REFERENCES

- [1] C. Sundaresan, S. Surya, and J. P. Sujith, "Medicinal Plant Identification and Information Provision Using AI," in 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI), 2025, pp. 1458–1463.
- [2] R. Sathya, M. Suganthi, M. Trisha, E. Janani, S. Dhivya, and R. V. Viswanathan, "AI Powered Ayurvedic Leaf Prediction and Disease Classification: A Comprehensive Analysis," in 2025 International Conference on Visual Analytics and Data Visualization (ICVADV), 2025, pp. 1364–1370
- [3] R. Nandini, K. Chandana, V. Vinutha, and A. R. S., "Identification Of Medicinal Plants And Disease Detection Through Image Processing Using Machine Learning Algorithms," IJSAT-International Journal on Science and Technology, vol. 16, no. 2, 2025.
- [4] R. Alonazi, "Leveraging AI to Identify Medicinal Herbal Plants Properties," in Transforming Pharmaceutical Research With Artificial Intelligence, IGI Global Scientific Publishing, 2025, pp. 247–274.
- [5] K. Panche, S. Parihar, H. Mankar, K. Rokade, and K. Malpe, "AI and Augmented Reality for Herbal Knowledge Preservation: A Smart Approach to Medicinal Plant Identification and Education," International Journal on Advanced Electrical and Computer Engineering, vol. 14, no. 1, pp. 261–268, 2025.
- [6] A. N. Lakshmi, S. N. Savitha, N. Jhansi, K. N. K. Reddy, and P. M. Reddy, "Medical Plant Identification and Utilities Recommendation using Ensemble Techniques," in 2025 6th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 2025, pp. 623–627.
- [7] A. S. Karnik, N. Nair, Y. Sagili, and P. B. Shanthi, "Multi-Scale Venation Pattern Analysis for Medicinal Plant Species Recognition," IEEE Access, 2025.
- [8] R. Surendran and B. Rajakumar, "Automated AI-Powered Fruit Identification Using Convolutional Neural Network," in 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI), 2025, pp. 1843–1848.
- [9] C. Prathima, Y. Mahanandi, M. M. Bhargavi, G. S. Teja, M. Gowripriya, and M. L. Sai, "Real-Time Identification of Medicinal Plants Using Deep Learning Techniques," in 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), 2025, pp. 1061–1067.
- [10] K. R. Chandra, B. Supraja, M. Bhargavi, S. B. Ojha, N. P. Tirumani, and K. S. Sharmila, "AI-Driven Intelligent Image Processing: A Novel Framework for Real-Time Image Enhancement and Analysis," in 2025 3rd International Conference on Inventive Computing and Informatics (ICICI), 2025, pp. 1–6.
- [11] A. Sinha, S. Sidana, G. M. Rao, N. Rathore, S. Raj, A. Jha, and V. Kumar, "Application of Artificial Intelligence in Ayurvedic Science Healthcare Practices: A Detailed Survey," Ethical Dimensions of AI Development, pp. 437–466, 2025.
- [12] V. Kumar, C. Prabha, A. P. Singh, and R. Kumar, "Application Areas of Computer Vision and AI in Intelligent Automation Systems," Handbook of Intelligent Automation Systems Using Computer Vision and Artificial Intelligence, pp. 327–369, 2025.
- [13] P. K. Lakshmi, "Herbal Plant Identification Using Deep Learning," Journal of Data Science, no. 06, pp. 1–13, 2025.
- [14] A. S. SH, M. H. Kaif, and P. S. Rathinam, "AI-Powered Disease Detection and Remedy Recommendation System for the Colocasia Plant," in 2025 International Conference on Next Generation Computing Systems (ICNGCS), 2025, pp. 1–8.
- [15] S. Santhi and M. Murugan, "Cocoscan: AI-Powered Precision Diagnostics for Coconut Leaf Disease," in 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), 2025, pp. 1756–1762.
- [16] Yang, Z. X., Li, Y., Wang, R. F., Hu, P., & Su, W. H. (2025). Deep learning in multimodal fusion for sustainable plant care: A comprehensive review. Sustainability, 17(12), 5255.
- [17] Wu, X., Zhang, J., Zou, Z., Chen, C., Yu, Y., Yu, P., ... & Hao, G. (2025). PlantIF: Multimodal Semantic Interactive Fusion via Graph Learning for Plant Disease Diagnosis. Plant Phenomics, 100132.
- [18] Lapkovskis, A., Nefedova, N., & Beikmohammadi, A. (2025). Automatic fused multimodal deep learning for plant identification. Frontiers in Plant Science, 16, 1616020.
- [19] Roulmeliotis, K. I., Sapkota, R., Karkee, M., Tselikas, N. D., & Nasiopoulos, D. K. (2025). Plant disease detection through multimodal large language models and convolutional neural networks. arXiv preprint arXiv:2504.20419.
- [20] Tang, Z., Xuan, C., Zhang, T., Gao, X., Liu, S., & Zhang, M. (2025). Assessment of plant diversity index in degraded desert grassland using UAV hyperspectral multimodal data and Encoder-CNN. Scientific Reports, 15(1), 30678.
- [21] Stumpe, E., Bodner, G., Flagiello, F., & Zeppelzauer, M. (2025). 3D multimodal image registration for plant

- phenotyping. *Computers and Electronics in Agriculture*, 237, 110538.
- [22] Dong, H., Qiu, X., Fan, D., Han, M., Yu, J., Yang, C., ... & Chen, Q. (2026). LPDiag: LLM-Enhanced Multimodal Prototype Learning Framework for Intelligent Tomato Leaf Disease Diagnosis. *Agriculture*, 16(4), 419.
- [23] Huang, J., Hao, X., Wang, Y., Song, R., Mu, Z., Chu, W., ... & Guo, X. (2025). Entity-level cross-modal fusion for multimodal chinese agricultural diseases and pests named entity recognition. *Smart Agricultural Technology*, 101188.
- [24] Jiang, Q., Zhao, X., Zhao, T., Li, W., Ye, J., Dong, X., ... & Wu, Z. (2025). A machine-learning-powered spectral-dominant multimodal soft wearable system for long-term and early-stage diagnosis of plant stresses. *Science Advances*, 11(26), eadw7279.
- [25] Huang, Y., Lyu, B., Gao, T., Wu, X., & Duan, Y. (2025). CornMFN: A Multimodal Fusion Network for Corn Phenology Stage Identification. *Smart Agricultural Technology*, 101202.