

App-Based Solutions to Detect Medicinal Plants/Crops using Machine Learning

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ABSTRACT

In this study, we present a deep learning-based approach for the classification of Indian medicinal plant leaves using transfer learning with the Xception convolutional neural network architecture. TensorFlow's high-level API is used to preprocess and load the dataset which consists of labeled photos of different species of medicinal leaves. The model employs a pre-trained Xception base (excluding the top layers) with weights loaded manually to accommodate the Kaggle execution environment. A custom classification head is appended to the frozen base model, incorporating dense and dropout layers for feature abstraction and regularization. The dataset is partitioned into training, validation and test sets and the model is trained for 25 epochs using the Adam optimizer and sparse categorical cross-entropy loss. Post-training, the model's performance is evaluated on the test set and its predictive capabilities are demonstrated using a sample input image. Finally, the training history is visualized to assess model convergence and the trained model is serialized for future inference. The proposed pipeline demonstrates the efficacy of transfer learning in the automated classification of medicinal leaf images with potential applications in botanical research and herbal medicine identification.

Keywords: transfer learning, xception model, medicinal plant classification, deep learning, image recognition

I. INTRODUCTION

The identification of Indian medicinal plants plays a crucial role in botanical research and the development of herbal medicine. Traditional methods for leaf classification are often time-consuming and require expert knowledge. In this study, we explore a deep learning-based solution leveraging transfer learning with the Xception convolutional neural network. By training on a labeled dataset of medicinal plant leaves, our approach automates the classification process, offering a scalable and efficient alternative to manual identification. This work highlights the effectiveness of modern deep learning techniques in advancing plant species recognition and supporting the broader field of ethnobotany. In contemporary agriculture, enhancing plant identification using progressive software is crucial. The complex dynamics of environmental factors and challenges like species diversity and climate change require innovative plant recognition methods. Integrating advanced software offers transformative solutions. This paper explores software-driven approaches such as precision agriculture, data analytics, predictive modeling and decision support systems to bolster accurate plant identification and sustainability in agriculture.

II. LITERATURE SURVEY

In modern agriculture, the pursuit of improving plant identification through creative software solutions has become a crucial frontier. There is an urgent need for improved plant identification methods due to the complex interactions of environmental elements and difficulties such as species recognition and climate variability. Using state-of-the-art software technologies provides a revolutionary way to accomplish this. Stakeholders can transform

conventional methods and negotiate the complexity of contemporary agricultural environments by utilizing precision agriculture, data analytics, predictive modeling and decision support systems. By optimizing resource allocation and guaranteeing the long-term viability of food production systems, this integration improves user decision-making, permits proactive intervention and promotes sustainable agricultural ecosystems.

Determining the obstacles to improving plant identification with cutting-edge software is essential to creating successful plans in contemporary agriculture. Obtaining accurate and trustworthy data on plant species and environmental conditions is a major challenge. Software deployment is significantly hampered by the unpredictability of data sources and the absence of standardization. Widespread adoption is hampered by technological obstacles such as inadequate infrastructure and bad internet connectivity in rural areas. The initial and recurring costs of software raise concerns about affordability particularly for small-scale farmers. Compatibility problems arise when new solutions are integrated with current systems. Security and privacy of data must also be considered. It will take teamwork to overcome these obstacles by fostering accessibility, developing skills and customizing solutions for regional socioeconomic contexts.

Parameter	Rahim Azadnia et al. (2022) [21]	Marada et al. (2023)	Izwan et al. (2020) [22]	Dileep et al. (2019) [23]	G. Kayhan & E. Ergun (2020)	Surleen Kaur & Prabhpreet Kaur (2019)	Tejas D. Dahigaonkar et al. (2018)
Tools Used	CNN (Deep CNN with Global Average Pooling)	Machine Learning algorithms (unspecified specific method)	CNN (Deep Convolutional Neural Network)	CNN (Deep Learning with AyurLeaf)	Naive Bayes, KNN, PNN, CART	Multiclass SVM	Support Vector Machine (SVM)
Accuracy	96.45%	Not specified	93.12%	94.56%	98%	93.26%	96.66%
Dataset	750 images from 5 medicinal plants (Lemon Balm, Stevia, Peppermint, Bael, Tulsi)	Dataset not specified	Dataset details not specified	Custom Ayurvedic plant dataset	737 out of 752 test samples (St. John's wort, Melissa, Echinacea, Thyme, Mint)	Swedish dataset (15 Swedish plant species represented by 1,125 photos)	No standard dataset; custom images from Ayurvedic plants
Methodology	Image classification using Deep CNN, Global Average Pooling	Plant feature identification using ML algorithms	CNN-based image classification for herbal plants	CNN for leaf-based classification of Ayurvedic plants	Uses Naive Bayes and other models to classify leaf images	Image pre-processing with Gaussian filtering, followed by classification with SVM	Leaf sample image processing is followed by SVM classification.
Precision	0.92 (for Stevia, highest among other plants)	Not specified	Not specified	0.90 (average across multiple plants)	Not specified	Not specified	Not specified

Sensitivity Metric	0.88 (average sensitivity across 5 plants)	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified
Feature Extraction	Global Average Pooling for high-level features	Machine Learning feature extraction techniques	Extracts features using CNN layers	CNN with feature maps for plant species	Leaf shape, gray-scale patterns, fractal dimensions	Texture and color feature extraction	Leaf shape, color and texture parameters
Classification Method	Deep Learning-based classification	Machine learning classification	CNN classification	Deep learning-based classification	Naive Bayes, KNN, PNN, CART	Multiclass Support Vector Machine (SVM)	Support Vector Machine (SVM)
Focus	Medicinal plants	Ayurvedic plants	Herbal plants	Ayurvedic plants	Medicinal & aromatic plants (MAP)	Plant species identification in general	Ayurvedic medicinal plants
Use Case	Identification based on leaf images	Identifying Ayurvedic plants using multiple plant features	Herbal plant recognition in a general environment	Ayurvedic plant classification based on leaves	MAP classification for species like Echinacea, Thyme, Mint	Simplified plant identification system through machine learning & computer vision	Ayurvedic medicinal plant identification using image processing techniques

Table 1: List of Relevant Literature

III. METHODOLOGY

A. Challenges

Determining the obstacles to improving plant identification with cutting-edge software is essential to creating successful plans in contemporary agriculture. Obtaining accurate and trustworthy data on plant species and environmental conditions is a major challenge. Software deployment is significantly hampered by the unpredictability of data sources and the absence of standardization. Widespread adoption is hampered by technological obstacles such as inadequate

infrastructure and bad internet connectivity in rural areas. The initial and recurring costs of software raise concerns about affordability particularly for small-scale farmers. Compatibility problems arise when new solutions are integrated with current systems. Security and privacy of data must also be considered. It will take teamwork to overcome these obstacles by fostering accessibility, developing skills and customizing solutions for regional socioeconomic contexts.

B. Assessment and Analysis

Technology assessment entails evaluating available software technologies, tools and platforms relevant to plant health management in agriculture. This assessment involves considering factors such as functionality, scalability, ease of use, compatibility with existing systems and cost-effectiveness. Stakeholder consultation involves engaging with a diverse range of stakeholders, including farmers, agronomists, researchers, technology developers,

policymakers and agricultural extension agents. The purpose is to understand their perspectives, needs, challenges and expectations regarding plant health management and the potential role of software solutions.

Data collection and analysis are essential for informing decision-making and developing evidence-based solutions. This process involves gathering relevant data on plant health indicators, environmental conditions, crop yields, soil properties and other pertinent variables. Various data collection methods may include field surveys, remote sensing, sensor networks and participatory approaches. Stakeholder consultation, technology assessment and data collection and analysis are fundamental components of any initiative aimed at enhancing plant health through innovative software solutions in agriculture.

C. Model Development

Model development and prototype development are critical stages in the creation of software solutions aimed at enhancing plant health in agriculture. Model development involves designing and building predictive models, algorithms and decision support systems based on data analysis and insights gathered during earlier stages. These models utilize advanced techniques such as machine learning, statistical analysis and mathematical modelling to predict plant health outcomes, identify trends and optimize resource allocation. Prototype development focuses on transforming conceptual models into tangible software applications or prototypes. This stage involves coding, programming and user interface design to create functional software tools that align with the identified needs and requirements of stakeholders. Prototypes should be user-friendly, intuitive and capable of providing real-time feedback and recommendations to users. Iterative testing and refinement are essential to ensure that the prototypes meet usability standards and effectively address plant health management challenges.

D. Testing, Validation and Deployment

Field testing and validation involve assessing the performance, reliability and effectiveness of software solutions in real-world agricultural settings. This stage includes conducting trials, pilot studies and on-farm demonstrations to evaluate how well the software tools address the identified plant health challenges and meet the needs of end-users. Feedback from farmers, agronomists and other stakeholders is collected and used to refine and improve the software solutions before full-scale deployment. Implementation and deployment entail the rollout of finalized software solutions across agricultural systems and communities. This process involves providing training and technical support to end-users, ensuring compatibility with existing infrastructure and workflows and establishing mechanisms for ongoing maintenance and updates. Effective implementation strategies promote user adoption, minimize disruptions and maximize the impact of software solutions on plant health management practices. Documentation and knowledge sharing are essential for capturing insights, lessons learned and best practices from the development and implementation process. This includes documenting the methodology, algorithms and data sources used in software development, as well as sharing case studies, success stories and user testimonials. Knowledge sharing efforts may take the form of workshops, seminars, webinars, publications and online platforms, allowing stakeholders to learn from each other, replicate successful approaches and contribute to continuous improvement in plant health management.

By prioritizing field testing and validation, implementing robust deployment strategies and fostering a culture of documentation and knowledge sharing, stakeholders can ensure that software solutions effectively address plant health challenges and contribute to sustainable agriculture. These efforts promote transparency, accountability and collaboration among stakeholders, ultimately facilitating the adoption and scaling of innovative technologies for enhancing plant health in agriculture.

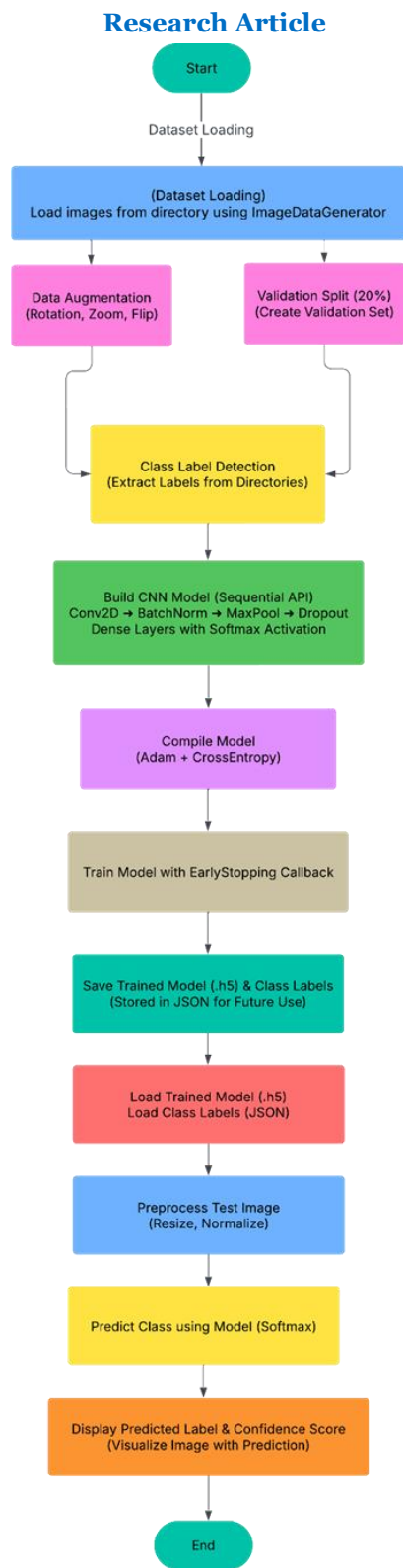


Figure 1: Flowchart of the Machine Learning Model

IV. RESULTS & DISCUSSIONS

The application integrates a pre-trained language model via an internal chatbot service to perform question-answering (Q&A) tasks. The fetchBotResponse function sends user queries—along with possible context—to this internal model's API endpoint, then parses the model's response to return answers.

It includes basic error handling, ensuring stable interaction by logging issues and providing fallback messages. For domain-specific queries related to medicinal plants, the system uses a fallback mechanism that queries the "google/flan-t5-small" model via the Hugging Face Inference API with additional error handling.

The architecture reflects a modular design, enabling the use of specialized models for improved accuracy and domain adaptability. This setup enhances the system's dialogue capabilities, reliability and coverage across diverse question domains.

A. AI Plant Identification Mode

The integration of artificial intelligence (AI) into plant identification software significantly enhances species recognition capabilities. Machine learning algorithms trained on large datasets of plant images can accurately identify and classify plants based on visual characteristics. Field trials have shown the efficacy of AI plant identification in improving accuracy and speed of recognition.

B. ChatGPT Integration

The application integrates a pre-trained language model through an internal chatbot service to support question-answering (Q&A) sessions. The `fetchBotResponse` function sends user queries—potentially with prior context—to the internal Q&A model API and then parses the response for the answer.

It includes robust error handling with logging and user feedback mechanisms to ensure stability. For domain-specific queries on medicinal plants, it activates a fallback mechanism that uses the "google/flan-t5-small" model via the Hugging Face Inference API, also equipped with error handling.

The system demonstrates a modular and optimized architecture, using specialized models to enhance accuracy, coverage and performance in targeted domains. It ensures a reliable dialogue system capable of retrieving relevant information while addressing domain-specific limitations effectively.

C. Image Recognition

The application enables image input via device library or camera with permissions managed by `expo-image-picker`. Selected images are stored as URIs in the app's state.

A function named `analyzePlant` preprocesses the image (e.g., resizing, normalization, format conversion) to prepare it for a remote CNN model. The processed image is sent as a JSON payload to a plant identification API along with required headers like an API key or authentication token.

The API response includes predictions (plant species + confidence score) which are parsed and stored in the app's state. Users receive feedback via alerts, showing either identification results or error messages if the process fails. A loading state provides a visual indication during the API call. The architecture uses a remote CNN model, optimizing performance by offloading image analysis to the server. Preprocessing ensures compatibility with the model input, improving accuracy. Robust error handling and UI feedback enhance the user experience, while the machine learning integration highlights the app's focus on automated, intelligent plant identification.

D. Community Forum

The application includes a community forum where users can view and create posts with data rendered using `FlatList` for performance. User and post data are fetched via `getPostsWithUserDetails`. A pull-to-refresh mechanism (`handleRefresh`) enables users to update content in real-time. Post creation is handled through a modal (Modal from `react-native-paper`), where users input text content (`postContent`) and optionally attach media via `expo-image-picker`.

Posts are submitted using the `createPost` function, interacting with a backend service (Appwrite) and include user ID, username, content and media. The application links posts to the user who is currently logged in by using user context (`useUserContext`). Upon post creation, the forum automatically refreshes, providing a smooth and real-time experience. The setup promotes user engagement with `FlatList` enhancing scalability and pull-to-refresh ensuring timely updates. Media support adds expressiveness, while Appwrite integration enables reliable backend storage.

The attached screenshots are the results of the survey that was conducted during our research.

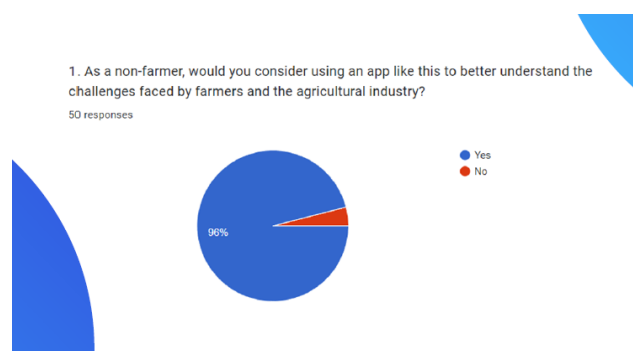


Figure 2: Survey Response on App Usage to Understand Agricultural Challenges

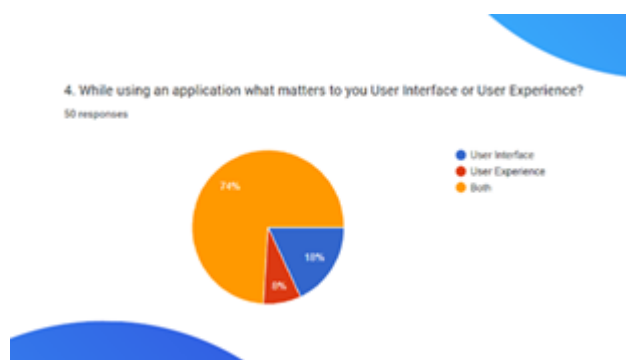


Figure 3: Survey Response on Essential Features for a User-Friendly App Interface



Figure 4: Survey Response on Preference Between User Interface and User Experience

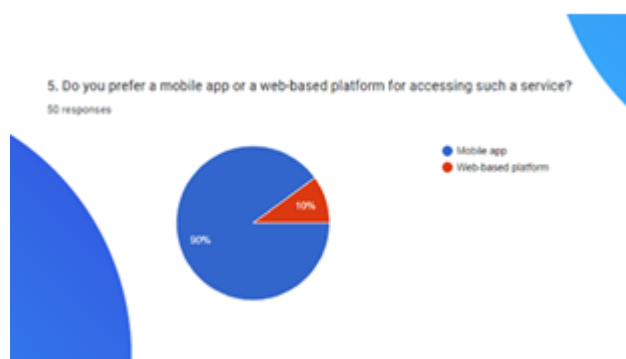


Figure 5: Survey Results: Mobile App vs. Web Platform Preference

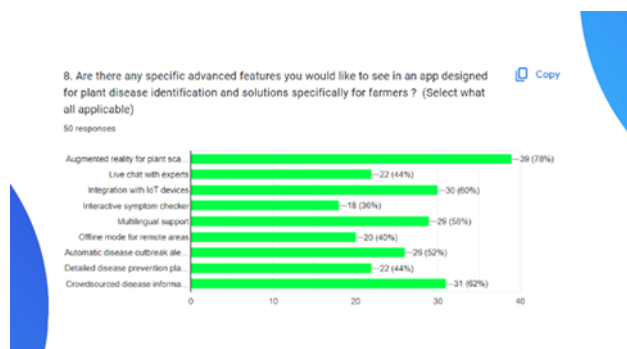


Figure 6: Desired Advanced Features in a Plant App



Figure 7: Farmer Preferences for Language and Regional App Support

In summary, the integration of AI plant identification mode, ChatGPT integration, image recognition, community forums and multi-language support within plant health management software has yielded promising results in optimizing plant health management practices. These innovative features empower users with actionable insights, foster collaboration and contribute to the advancement of sustainable agriculture on a global scale.

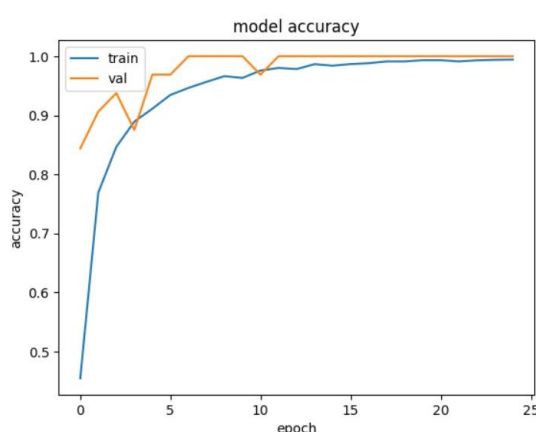


Figure 8: Model Accuracy Graph

The graph shows that the training and validation accuracy of the model improves rapidly within the first few epochs, reaching around 90% by epoch 5 and peaking near 100% by epoch 10. From epoch 10 onward, both accuracies stabilize above 95% with minimal fluctuations.

There is no sign of overfitting, as validation closely follows training accuracy. This indicates strong generalization. The model likely benefits from transfer learning using Xception, contributing to fast convergence and high accuracy. The consistent performance suggests effective regularization (e.g., dropout) is in place.



```

10: # predict with new images
import numpy as np

img = tf.keras.preprocessing.image.load_img(
    '/kaggle/input/testing-7/organic-ashwagandha-leaves.jpg', target_size=(299, 299)
)
img_array = tf.keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0) # Create a batch

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])
print(
    "This image most likely belongs to {} with a {:.2f} percent confidence."
    .format(labels[np.argmax(score)], 100 * np.max(score))
)

1/1 [=====] - 0s 23ms/step
This image most likely belongs to Ashwagandha with a 71.94 percent confidence.

```

Figure 9: Model Prediction Output for Ashwagandha Leaf with Confidence Score

A trained deep learning model was used to classify a new image of a leaf using the TensorFlow library. The image was preprocessed by resizing and converting it into a tensor batch before prediction. The model identified the leaf as Ashwagandha with a confidence of approximately 71.94%. This illustrates how well the model generalizes to new data.

V. CONCLUSION

The advancements in medicinal plant identification have been significantly driven by machine learning techniques, as demonstrated by various methodologies in the analyzed studies. CNN with Global Average Pooling achieved an impressive 96.45% accuracy, highlighting the efficiency of feature extraction using high-level representations. Similarly, CNN-based approaches in other studies exhibited high classification performance such as 93.12% and 94.56%.

The efficacy of deep learning in identifying herbal and Ayurvedic plants was further supported by the high classification performance of CNN-based methods in other studies which included 93.12% and 94.56%. The variation in accuracy across studies suggests that while CNN models provide robust feature extraction, traditional machine learning algorithms remain viable alternatives depending on dataset characteristics. Despite these advancements, challenges remain particularly in dataset standardization and sensitivity analysis. Studies often rely on custom datasets rather than standardized repositories, making cross-study comparisons difficult. Additionally, detailed metrics such as precision and sensitivity are often underreported, limiting comprehensive performance evaluation.

Future research should focus on expanding datasets, improving feature extraction techniques and integrating hybrid models that combine CNNs with traditional ML classifiers to enhance accuracy and adaptability. The identification of Ayurvedic and medicinal plants is crucial for applications in herbal medicine, agriculture and conservation. Advancing these technologies will not only improve plant classification accuracy but also aid in preserving traditional Ayurvedic knowledge, promoting sustainable herbal practices and contributing to the development of plant-based therapeutics.

VI. FUTURE SCOPE

The future of enhancing plant health through innovative software solutions in agriculture holds immense promise and potential for transformative change. Advancements in artificial intelligence, machine learning and IoT technologies will drive the development of sophisticated predictive models and decision support systems, enabling real-time monitoring and proactive intervention strategies. The implementation of blockchain technology in

agricultural supply chains will improve traceability and transparency, nurturing trust and accountability among stakeholders. Remote sensing and satellite imaging will provide valuable insights for precision agriculture and targeted interventions at a large scale. Data-driven analytics will empower farmers and agronomists to optimize resource allocation, tailor management practices and mitigate the impact of climate change and environmental stressors. Collaboration among stakeholders and supportive policy frameworks will be instrumental in driving innovation and scaling up successful approaches. By embracing emerging technologies and fostering collaboration, the future of plant health management in agriculture holds the promise of building more resilient, sustainable and productive food systems to meet the challenges of tomorrow.

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