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Utilizing Random Forests for the Classification of Pudina Leaves through Feature Extraction with InceptionV3 and VGG19

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ABSTRACT: An analysis of the "Pudina Leaf Dataset: Freshness Analysis" reveals distinct classes of dried, fresh, and spoiled mint leaves. Convolutional neural networks, InceptionV3 and VGG19, were used to extract features from the dataset using advanced image processing techniques. The classification task was then performed using a Random Forest machine learning algorithm. In this study, notable results were obtained, proving the effectiveness of the selected methodologies. Mint (Pudina) leaves were classified accurately using InceptionV3-extracted features at 94.8%, demonstrating robust performance in distinguishing freshness states. This deep learning architecture was further shown to be able to capture meaningful patterns within the dataset by utilizing VGG19-extracted features, resulting in an improved accuracy of 96.8%.

Plant leaf classification and freshness analysis can be improved by integrating deep learning architectures with ensemble learning methods, as demonstrated in this study. In addition to demonstrating the suitability of the selected methodologies, these accuracies also provide avenues for further research and refinement with regard to plant leaf quality assessment and analysis.

Keywords: Deep Learning, Image Classification, InceptionV3, Pudina Leaf Dataset, Random Forest, VGG19.

INTRODUCTION

In botany and agriculture, machine learning has become a powerful tool for classifying plant leaves. Mint leaves can be classified with the help of machine learning algorithms, which play a crucial role in the process. Because mint leaves come in a variety of shapes, sizes, and textures, manual classification is time-consuming (Ayumi et al., 2022; Kursun et al., 2023b). Mint leaf images can be used to train advanced machine learning algorithms, such as image recognition and classification algorithms (Cinar et al., 2022; Koklu et al., 2012, 2014), to learn distinctive patterns and features (Babatunde et al., 2015; Chaki & Parekh, 2011). Based on these characteristics, it is possible to develop classifiers that can categorize mint leaves quickly and efficiently. Farmers, researchers, and enthusiasts can use this technology to identify plants, monitor plant health, and even automate precision agriculture processes. Machine learning is being integrated into plant leaf classification to improve the identification process while also contributing to improvements in agriculture (Valliammal & Geethalakshmi, 2011; Zulkifli et al., 2011).

The freshness of mint leaves affects their quality in a significant way because of their aromatic properties and culinary applications (Angayarkanni & Jayasimman, 2023; Gavhale & Thakare, 2020). A detailed analysis of the Pudina Leaf Dataset: Freshness Analysis (Bedmutha et al., 2023; Jadhav et al., 2023) has been conducted to explore and classify mint leaf conditions, including dried, fresh, and spoiled specimens. This study uses advanced image processing techniques to extract features from datasets, including convolutional neural networks (CNNs) such as InceptionV3 and VGG19. Following that, the Random Forest machine learning algorithm is applied to these features to perform classification.

The significance of this research lies in its ability to provide insight into mint leaf quality assessment and analysis, in addition to contributing to our understanding of mint leaf conditions. To maximize their use, mint leaves need to be fresh due to their wide range of culinary and medicinal applications (Ayumi et al., 2022; Yasin et al., 2023). There are a number of studies examining plant leaves (Arman et al., 2023; Meshram & Patil, 2022; Suryawanshi et al., 2022) in this section, with a particular focus on mint (pudina) leaf classification, utilizing machine learning and deep learning capabilities; a selection is presented in this article. The article presents a Convolutional Neural

Network (CNN) method for identifying diseases in mint and basil plants by using the Inception V3 model. The findings indicate that the validation accuracy for mint is 70.89% and for basil, 77.55% (Sathiya et al., 2023).

A machine learning technique based on multispectral and textural data to categorize leaves of medicinal plants was used. Six plant kinds are included in the dataset. The researchers collected and preprocessed leaf images using a computer vision system, producing a dataset containing 65 fused features. Fourteen features were obtained by feature optimization with a chi-square selection method. The multi-layer perceptron outperformed other classifiers with an accuracy of 99.01% after applying five machine-learning classifiers (Naeem et al., 2021).

Nilesh S. Bhelkar and Dr. Avinash Sharma focused on using deep convolutional neural networks to automatically identify and classify medicinal plants based on leaf images. Using a dataset of 45 medicinal plant leaves and the Xception model, the research attains an impressive accuracy of 97.65%. Emphasizing the importance of automated identification, particularly in Ayurveda and the pharmaceutical industry, the study highlights the efficiency of deep learning models like Xception in this context. It also addresses challenges in manual identification and underscores the significance of computer vision methods (Bhelkar & Sharma, 2022).

These research papers cover a bunch of different things about figuring out what plant leaves are (Kursun et al., 2023a). They explore all sorts of ways to do this, from identifying leaf shapes for people with low vision using smartphones (Prasad et al., 2017) to making web apps (Duong et al., 2015) that can tell you what plant it is based on pictures of different parts of the plant. They also investigate recognizing specific plant species by their leaf shapes and using smart machines to automatically recognize different leaves. The papers don't stop there; they also talk about spotting and classifying plant diseases, using special images to identify plants, and how deep learning, a kind of smart technology, can help with things like figuring out what's wrong with paddy leaves or identifying medicinal plants. Altogether, these studies show how using advanced tech, like deep learning, can really boost our understanding of plants in different areas (Du et al., 2007; Muneer & Fati, 2020; Patil & Pawar, 2017; Satti et al., 2013).

This study presents an effective system designed to automatically identify Malaysian herbs, with the aim of simplifying the identification process for pharmacists and botanists. The system integrates two classifiers, a Support Vector Machine (SVM) and a Deep Learning Neural Network (DLNN), into a mobile app for on-the-spot identification. Evaluation using a dataset of 1000 leaves yielded recognition accuracies of 74.63% for SVM and 93% for DLNN. Processing times were 4 seconds for SVM, 5 seconds for DLNN, and a faster 2 seconds using the mobile app. Notably, this research addresses a gap in existing studies on medical herbs in Malaysia, showcasing the efficacy of advanced classification techniques for swift and precise herb identification (Muneer & Fati, 2020).

This study aims to provide a robust mechanism for automatically classifying mint leaves based on their freshness states using machine learning techniques.

MATERIALS AND METHODS

The purpose of this section is to provide an overview of the dataset. Following an overview of the feature extraction process, the authors elaborate on the application of InceptionV3 and VGG19. After this, the Random Forest machine learning algorithm for classification was presented. In this study, a 10-fold cross-validation was employed for training and testing the images (Kursun et al., 2022). The flow diagram for the study is shown in Figure 1.

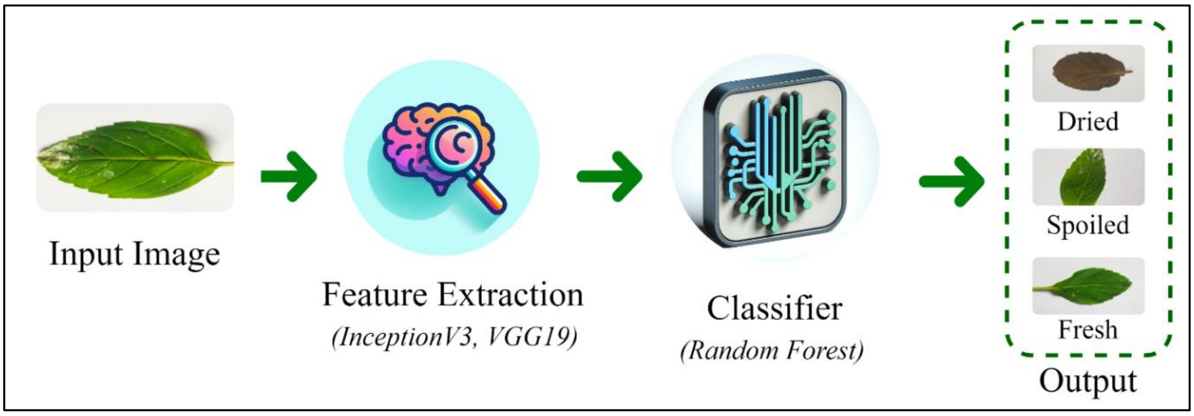

Figure 1. Flow diagram for Pudina leaves classification process

Pudina Leaf Dataset: Freshness Analysis

The Pudina Leaf Dataset is a comprehensive collection designed to analyze mint leaves (pudina) in-depth. Various conditions of pudina leaves are represented in this dataset, including dried, fresh, and spoiled specimens. For researchers and enthusiasts in plant biology, agriculture, and machine learning, the dataset serves as a valuable resource for elucidating the freshness dynamics in pudina leaves. The dataset acquired from the Mendeley Data website comprises 1773 images of fresh mint leaves, 1749 images depicting dried leaves, and 1669 images featuring spoiled leaves. The study was applied to a total of 5191 images. The dataset depicted in Figure 2, includes sample images for each class, accompanied by their respective labels.

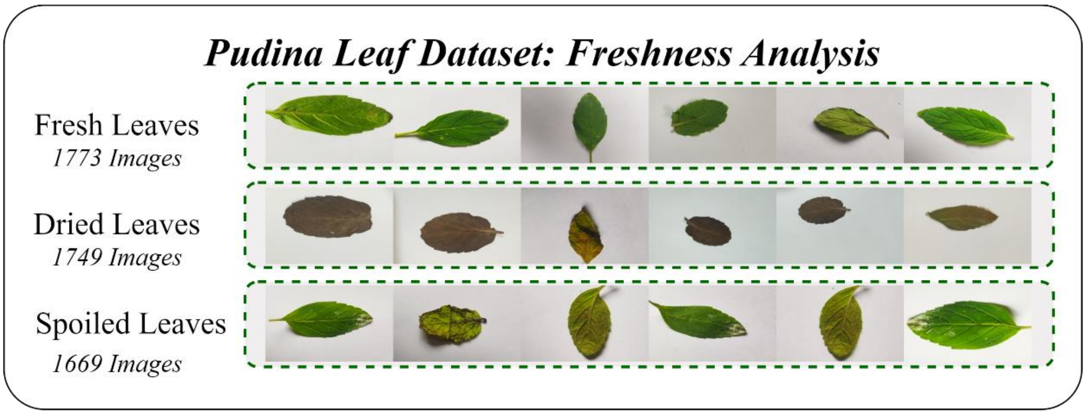

Figure 2. Pudina (Mint) leaves dataset sample images

Feature Extraction

The feature extraction process (Kayhan, 2022) is a critical step in this study, where the distinctive capabilities of InceptionV3 (Yasin & Koklu) and VGG19 (Taspinar et al., 2022)are harnessed. InceptionV3, known for its intricate architecture and ability to capture complex patterns, is applied to extract high-level features from the mint leaf images. InceptionV3 was employed to extract 2048 features from each image in the dataset (Cinar & Koklu, 2021). Simultaneously, VGG19, recognized for its simplicity and effectiveness, is employed for feature extraction to compare its performance with InceptionV3. Using VGG19, we executed an extensive feature extraction procedure, yielding 4096 distinctive features from each image in the dataset.

Random Forest Classification

Following feature extraction, the Random Forest machine learning algorithm is employed for classification. Random Forests are an ensemble learning technique that combines multiple decision trees to enhance accuracy and robustness. In this study, the feature vectors obtained from InceptionV3 and VGG19 are fed into the Random Forest classifier to discern between the freshness states of mint leaves.

Random Forest, Figure 3. initially proposed by Tin Kam Ho and later refined by Leo Breiman (Breiman, 2001) and Adele Cutler, is an ensemble learning method applicable to classification, regression, and various tasks. This technique constructs a collection of decision trees, with each tree originating from a bootstrap sample of the training data. During the creation of individual trees, a random subset of attributes is drawn, and the optimal attribute for a split is determined from this subset, hence the term "Random." The final model is established based on a majority vote from the independently developed trees in the forest, making Random Forest effective for both classification and regression tasks (Butuner et al., 2023). The fundamental properties include specifying the number of trees in the forest and determining the number of attributes considered at each split. If the latter is not explicitly stated, it defaults to the square root of the total number of attributes in the dataset. The choice of Random Forests aligns with the complexity of the task, aiming to capture the intricate patterns associated with mint leaf conditions.

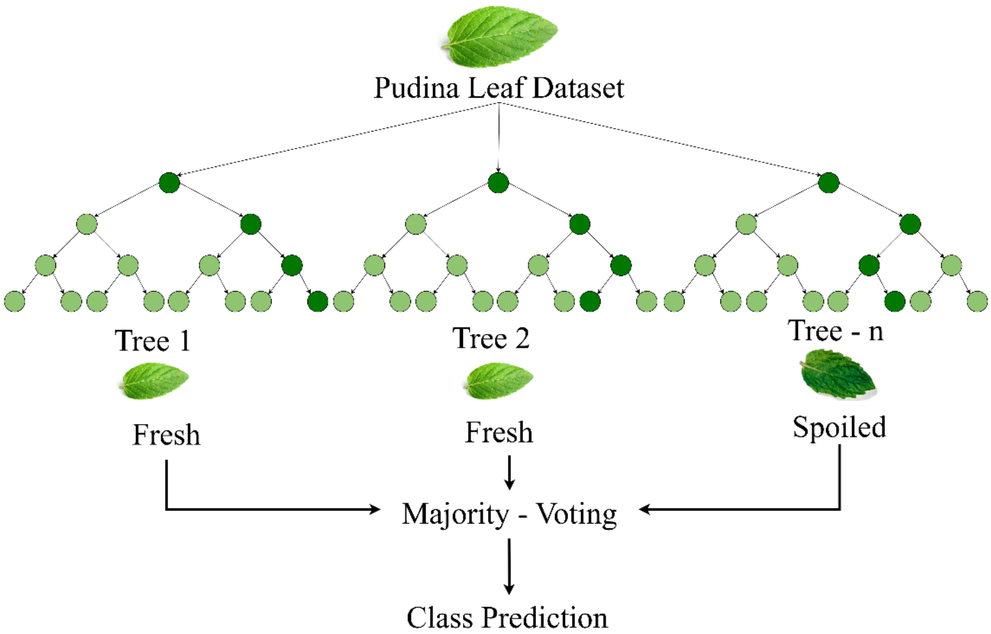

Figure 3. Random Forest classifier diagram

The Random Forest model is configured with 100 trees, an unrestricted consideration of features, and unlimited tree depth. Training is non-replicable, introducing an element of randomness. Nodes stop splitting when instances fall below 5, controlling the granularity of the trees and potentially mitigating overfitting to noisy data.

Confusion Matrix and Performance Metrics

The study categorized classes into three groups, and an informative confusion matrix (Gencturk et al., 2023; Tutuncu et al., 2022) was formulated to visually assess the classification model's performance across these classes. This matrix offers a detailed perspective on the model's accuracy and misclassification for each individual class. Refer to Figure 4 for a graphical representation of the confusion matrix (Ozkan et al., 2021).

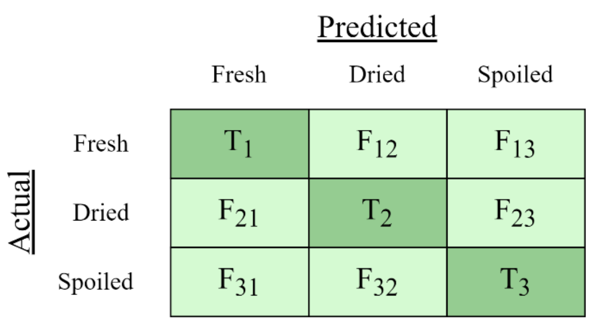

Figure 4. Confusion matrix of the Mint leaves classification

In the context of the confusion matrix, T1 denotes instances where the model correctly identified and predicted fresh leaves. Conversely, F12 represents cases where the images were genuinely fresh leaves, but the model inaccurately classified them as dried leaves. Additionally, F21 corresponds to instances where the model misclassified dried leaves as fresh ones. The matrix's diagonal captures accurately predicted classes, while the upper and lower triangles highlight misclassifications by the model. Refer to Figure 5 a) and b) for the confusion matrices of both Random Forest models (Ozkan et al., 2021; Taspinar et al., 2022).

Actual \ Predicted	Fresh	Dried	Spoiled
Fresh	1687	34	52
Dried	37	1674	38
Spoiled	83	27	1559

a) Features extracted using InceptionV3

Actual \ Predicted	Fresh	Dried	Spoiled
Fresh	1700	35	38
Dried	17	1702	30
Spoiled	98	53	1518

b) Features extracted using VGG19

Figure 5. Confusion matrix of the Mint leaves classification with Random Forest for both InceptionV3 and VGG19 feature extractors

The research assessment involved the computation of training accuracy, alongside the determination of precision, recall, and F1 score (Isik et al., 2023). The formulas for these evaluation metrics are provided in Figure 6.

Metrics	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN} \times 100$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1 Score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$

Figure 6. Performance metrics formulas

RESULTS AND FINDINGS

This study aimed to analyze the "Pudina Leaf Dataset: Freshness Analysis" using convolutional neural networks (CNNs) InceptionV3 and VGG19 for feature extraction, followed by a Random Forest machine learning algorithm for classification. The dataset comprised 1773 images of fresh mint leaves, 1749 images of dried leaves, and 1669 images of spoiled leaves, totaling 5191 images. The results showcase the effectiveness of feature extraction using InceptionV3 and VGG19 for freshness analysis of mint leaves. InceptionV3-extracted features achieved an accuracy of 94.8%, with precision, recall, and F1-score all at 0.948. On the other hand, VGG19-extracted features demonstrated even higher accuracy at 96.8%, accompanied by precision, recall, and F1-score values of 0.968. The results are shown in Table 1.

Table 1. Performance metrics results for the Pudina leaves classification study

Feature extract model	Accuracy	Precision	Recall	F1-Score
InceptionV3	94.8%	0.948	0.948	0.948
VGG19	96.8%	0.968	0.968	0.968

The performance evaluation of InceptionV3 (Koklu et al., 2022) and VGG19 in the precise classification of the freshness states of mint leaves reveals commendable outcomes. Significantly, VGG19 outperformed InceptionV3, achieving an accuracy rate of 96.8% in contrast to InceptionV3's 94.8%. This discrepancy underscores the superior capability of VGG19 in discerning meaningful patterns within the dataset, thereby contributing substantially to heightened classification accuracy. The investigation highlights the efficacy of the Random Forest ensemble learning method in navigating the complexities inherent in the task, yielding robust outcomes for both Convolutional Neural Network (CNN) architectures. Crucially, the findings advocate for the integration of deep learning architectures with ensemble learning methods, positing that this collaborative approach holds promise for substantial advancements in plant leaf classification and freshness analysis.

An analysis of the obtained results was conducted using a preexisting dataset that had previously been used to train different deep learning models. Table 2 presents a summary of the results of this comparative analysis, illustrating the differences between the novel findings and previous model training endeavors.

Table 2. Accuracies obtained from comparative studies

Models	Accuracy	References
Random Forest (InceptionV3)	94.8%	This study
Random Forest (VGG19)	96.8%	
VGG16	88%	(Jadhav et al., 2023)
ResNet50	94%	
MobileNetV2	92%	

CONCLUSION

The "Pudina Leaf Dataset: Freshness Analysis" presents a robust framework for the automated classification of mint leaves into distinct freshness states—dried, fresh, and spoiled. Leveraging advanced image processing techniques and Convolutional Neural Networks (CNNs), namely InceptionV3 and VGG19, we achieved significant success in extracting discriminative features from mint leaf images. The Random Forest machine learning algorithm served as an effective classifier, showcasing its versatility and prowess in handling the intricacies of mint leaf conditions. Notably, results demonstrated an accuracy of 94.8% with InceptionV3-extracted features and an even more impressive accuracy of 96.8% with VGG19-extracted features. These high accuracies underscore the efficacy of our chosen methodologies in capturing and utilizing relevant information for accurate mint leaf classification. The outcomes of this study hold promise for various applications, particularly in the realms of agriculture, food processing, and quality control. The ability to automate the assessment of mint leaf freshness has implications for optimizing production processes, ensuring product quality, and minimizing waste. The integration of deep learning architectures, such as InceptionV3 and VGG19, with the ensemble learning approach of Random Forests, exemplifies a potent strategy for enhancing the accuracy and robustness of plant leaf analysis.

However, as with any study, there are avenues for future exploration and refinement. Fine-tuning hyperparameters, exploring additional deep learning architectures, and expanding the dataset to include variations in lighting and environmental conditions are potential areas for improvement. Furthermore, deploying the developed model on real-world scenarios and validating its performance in diverse environments will be crucial for assessing its practical utility. Findings underscore the potential of combining advanced image processing and machine learning techniques for accurate and automated mint leaf classification. This study contributes not only to the domain of plant leaf analysis but also lays the foundation for further advancements in the broader field of computer vision and agricultural technology. As we navigate towards a future of smart agriculture and automated quality assessment, the methodologies presented in this study offer valuable insights and a steppingstone for future research endeavors.

Data Availability

The dataset pertinent to this study is accessible through the following hyperlink: https://data.mendeley.com/datasets/nvbpydc3fs/1.

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