PlantPersona: Uniquely Identifying Plant Instances for Modern Agriculture

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Abstract. Plant re-identification, a critical aspect in agricultural technology, focuses on uniquely distinguishing individual instances of the same plant species within a specific environment. This paper addresses the necessity for accurate plant re-identification to support various applications, such as 3D modeling, targeted pesticide application to minimize excess usage, precise yield estimation at the individual plant level, and comprehensive monitoring of plant health and growth metrics. Utilizing advancements in computer vision, machine learning, and data analytics, this study proposes methodologies to effectively differentiate between multiple instances of the same plant species, thus improving precision agriculture practices. The findings of this research contribute to optimizing resource management, enhancing crop monitoring, and ultimately, fostering increased agricultural productivity and sustainability.

Keywords: 3D modeling, Yield estimation, Precision agriculture.

1 Introduction

Modern agriculture heavily relies on technological innovations to optimize crop management and improve overall yield. A pivotal aspect of this technological integration is the precise identification and monitoring of individual plants within cultivated areas. To address this need, plant re-identification methodologies have been developed, aiming to distinguish between various plant species based on their unique characteristics. These methodologies play a crucial role in facilitating tasks such as 3D modeling, targeted pesticide application, yield estimation, and plant health monitoring. With the advent of precision agriculture practices, there is a growing demand for more precise and efficient crop management strategies. Plant re-identification enables farmers to tailor interventions at the individual plant level, optimizing resource allocation and maximizing crop productivity. However, achieving accurate plant identification, especially when dealing with multiple instances of the same species, presents significant challenges.

In response to the formidable challenges posed by accurate plant identification within agricultural contexts, our research endeavors yield substantial contributions aimed at enhancing precision agriculture practices and contributing to sustainable food production. These contributions can be summarized as follows:

1. Comprehensive Dataset: We provide a dataset comprising both infrared (thermal) and RGB images of Wheat and Mustard plants, captured using a Fluke Thermal Imager TiX580. Additionally, RGB images of Palm pot plants were obtained using a RealMe 3 Pro smartphone.

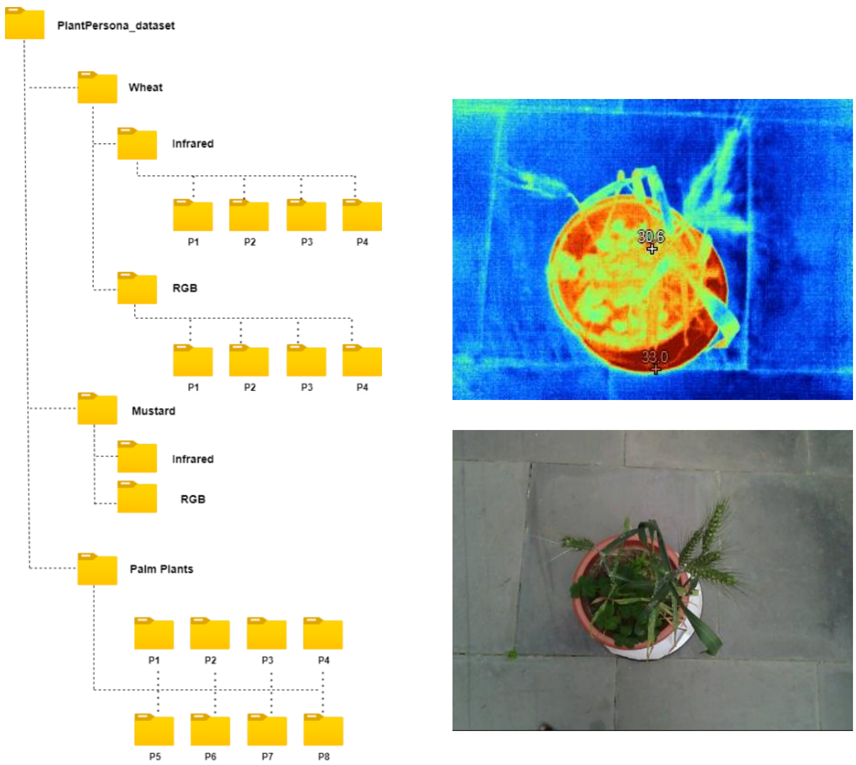
2. Objective: Our primary objective is to study and uniquely identify each plant instance within a given species, thus enabling more precise and effective crop management strategies. Through the analysis of this dataset and the application of cutting-edge machine learning techniques, we strive to develop advanced plant re-identification algorithms.

These contributions not only enrich the available resources for plant identification research but also pave the way for improved precision agriculture practices and contribute to sustainable food production.

2 Data Acquisition

In this study, the dataset utilized was meticulously collected within the controlled environment of a polyhouse situated at the CS department of the main campus of IIT Ropar, located in Punjab, India, during the month of March 2024. The polyhouse setting ensured consistent environmental conditions conducive to plant growth and development, facilitating the acquisition of high-quality image data. Specifically, all images were captured from a top-down perspective, maintaining a uniform distance of approximately 1.5 meters from the ground level. This standardized approach to image acquisition minimized variations in viewpoint and perspective, thereby enhancing the consistency and reliability of the dataset.

The decision to focus on top-view imagery was deliberate, as it allowed for comprehensive coverage of the plants within the polyhouse while maintaining a consistent orientation for analysis. By capturing images exclusively from this perspective, we aimed to ensure uniformity in the visual representation of plant instances, enabling more accurate and reliable plant identification and analysis. Overall, the careful consideration of these factors during the data acquisition phase contributes to the robustness and credibility of the research findings presented in this paper.



(a) (b)

Figure 1. Details of the dataset
(a) File Structure of the dataset
(b) Sample Infrared and RGB images of the dataset

3 Experimental Setup

In our study of plant re-identification methodologies, we embarked on a journey to explore the effectiveness of various distinct machine learning models: Convolutional Neural Network (CNN), Support Vector Machine (SVM), and ResNet50. And we also further employed various person reidentifcation models such as ArcFace, SFace, GhostFaceNet and others. In addition to these reidentifcation models, we also utilised various detector models to correctly detect the plant instances such as opencv, yolo, mideapipe and many others. Each of these models holds unique strengths and capabilities that make them promising candidates for the task at hand. With the ultimate goal of distinguishing between individual plant instances within a given species, we sought to leverage the inherent abilities of these models while navigating the intricacies of plant imagery.

CNNs, renowned for their prowess in image classification tasks, naturally emerged as a compelling choice for our project. We meticulously designed and trained a CNN model using a diverse dataset comprising infrared and RGB images of Wheat, Mustard, and Palm pot plants. The CNN architecture was carefully crafted to capture and analyze the nuanced visual features present in plant images, with the aim of enabling precise discrimination between different plant instances. Leveraging transfer learning techniques, we fine-tuned the CNN model to adapt to the specific characteristics of our plant re-identification task, aiming to achieve optimal performance in accurately identifying individual plant instances.

Transitioning to the exploration of Support Vector Machine (SVM), we delved into a different paradigm of machine learning. SVMs operate on the principle of finding an optimal hyperplane that separates different classes in the feature space, making them particularly well-suited for classification tasks. In our experiments, we engineered informative features from the dataset and trained the SVM model to classify plant instances based on these features. By experimenting with various kernel functions and tuning hyperparameters, we endeavoured to maximize the classification accuracy of the SVM model. The interpretability of SVM models provided valuable insights into the discriminative features utilized for plant identification, contributing to a deeper understanding of the underlying patterns present in the data.

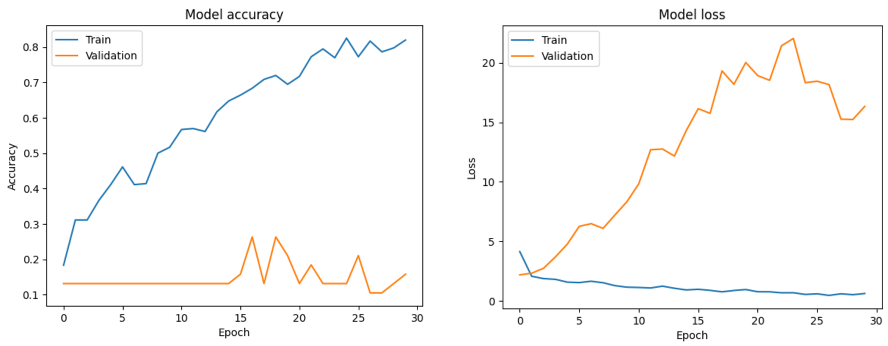
Despite the promising capabilities of CNNs and SVMs, our exploration wouldn't be complete without considering the potential of ResNet50, a deep residual neural network renowned for its exceptional performance in image classification tasks. The architecture of ResNet50 comprises multiple layers with skip connections, allowing for more effective training of deep networks and mitigating the vanishing gradient problem. We embarked on the task of fine-tuning the pre-trained ResNet50 model on our dataset, aiming to leverage the hierarchical features learned by ResNet50 for accurate plant re-identification. This endeavour reflects our commitment to thoroughly exploring the capabilities of different machine learning models in the pursuit of advancing plant identification methodologies.

Throughout our exploration, we remain cognizant of the challenges and complexities inherent in the task of plant re-identification. The rich diversity of plant species, coupled with variations in environmental conditions and growth patterns, presents a formidable challenge that demands innovative solutions. As we navigate the intricate landscape of plant imagery, our dedication to rigorous experimentation and analysis remains unwavering. Through our collective efforts, we endeavour to contribute to the advancement of plant identification methodologies, ultimately paving the way for more effective and sustainable agricultural practices.

4 Results

4.1 CNN Model

The performance evaluation of our Convolutional Neural Network (CNN) model yielded insightful results, shedding light on its efficacy in the context of plant re-identification. Our training phase showcased a modest accuracy of 19.44%, indicating that the model successfully classified nearly one-fifth of the instances correctly. This initial assessment serves as a foundation for understanding the model's learning capabilities and provides valuable insights into areas for potential improvement. Subsequently, during the validation phase, the CNN model demonstrated consistent performance, achieving an accuracy of 18.42%. While this accuracy may seem modest, it signifies the model's ability to generalize its learnings to unseen data, a crucial aspect in real-world applications. These results underscore the complexity of plant re-identification tasks and emphasize the need for continued refinement and optimization of machine learning algorithms to enhance accuracy and effectiveness.



(a) (b)

Figure 2. Performance of CNN Model. (a) Accuracy (b) Loss

Accuracy and Loss Analysis:

The performance of the convolutional neural network (CNN) model was evaluated on both the training and validation datasets. The training accuracy curve (blue) exhibits

a steady increase, reaching high values close to 1 as the training progressed. This indicates that the model effectively learned the patterns present in the training data, enabling it to make accurate predictions on the samples it was trained on.
However, the validation accuracy curve (orange) reveals a more nuanced behavior. While it initially increased alongside the training accuracy, suggesting that the model was learning meaningful representations from the data, it later became more erratic and luctuated significantly. Notably, the validation accuracy curve plateaued or even showed a slight decrease in the latter epochs.

This behavior is often symptomatic of overfitting, a phenomenon where the model becomes excessively specialized to the training data, compromising its ability to generalize to unseen examples. The gap between the high training accuracy and the relatively lower validation accuracy provides further evidence of overfitting.

4.2 Support Vector Machine (SVM)

To evaluate the performance of the Support Vector Machine (SVM) model for plant classification, experiments were conducted using a diverse set of plant types and imaging modalities. The plant types included in the study were mustard, wheat, and lady palm, and the imaging modalities consisted of infrared and RGB (visible spectrum) images.

The first set of experiments involved training and testing the SVM model on infrared and RGB images of mustard plants. The results showed that the model achieved higher accuracy of 72.41% when trained on infrared images compared to 65.51% accuracy on RGB images. This suggests that the infrared imaging modality captured more discriminative features for the classification of mustard plants.

Similar experiments were conducted on wheat plants, where the SVM model demonstrated superior performance on infrared images, achieving an accuracy of 82.75% compared to 58.62% on RGB images. This significant difference in accuracy highlights the potential of infrared imaging for reliable classification of wheat plants.
In contrast, for the lady palm plant type, the SVM model performed better on RGB images, achieving an accuracy of 71.25%. This could be attributed to the unique visual characteristics of lady palm plants, which may be better captured by visible-spectrum RGB images.

Plant Type	Accuracy (in %)
Mustard - Infrared	72.41
Mustard - RGB	65.51

Wheat - Infrared	82.75
Wheat - RGB	58.62
Lady Palm - RGB	71.25

Table 1. Accuracy of SVM Model

4.3 ResNet50

In our evaluation of the ResNet50 model, we observed impressive performance metrics, including a mean Average Precision (mAP) of 0.9982 and a rank-1 accuracy score of 1. These metrics serve as indicators of the model's exceptional capability in accurately identifying and classifying plant instances within the dataset. The high mAP score of 0.9982 reflects the model's proficiency in precision and recall across different classification thresholds, showcasing its robustness in handling varying levels of confidence in predictions. Additionally, the perfect rank-1 accuracy score of 1 underscores the model's ability to correctly classify the top-ranked prediction for each instance, further validating its effectiveness in plant re-identification tasks.

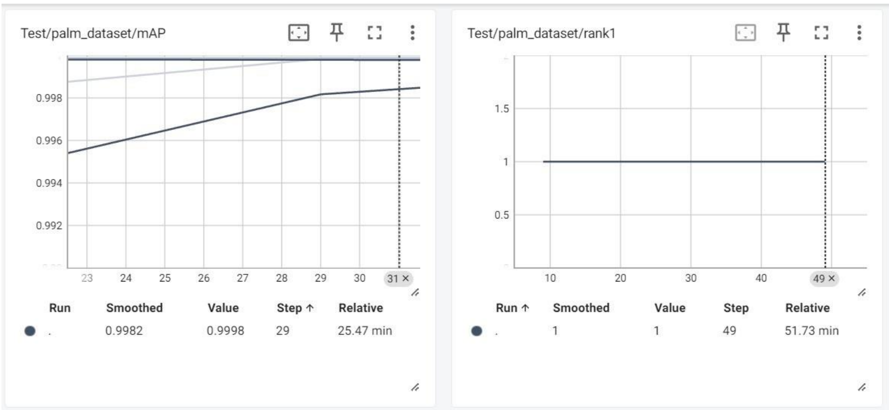


Figure 3. Performance of ResNet50

4.4 DeepFace - GhostFaceNet

Ghost modules use a series of inexpensive linear transformations to extract additional feature maps from a set of intrinsic features, allowing for a more comprehensive representation of the underlying information. GhostNetV1 and GhostNetV2, both of which are based on Ghost modules, serve as the foundation for a group of lightweight face recognition models called GhostFaceNets. GhostNetV2 expands upon the original GhostNetV1 by adding an attention mechanism to capture long-range dependencies. Evaluation of GhostFaceNets using various benchmarks reveals that these models offer superior performance while requiring a computational complexity of approximately 60–275 MFLOPs. This is significantly lower than that of State-Of-The-Art (SOTA) big convolutional neural network (CNN) models, which can require hundreds of millions of FLOPs.

The GhostFaceNet framework provides multiple object detector models, face recognition models and similarity metrics to work with. We utilised the followings:

1. **Detector Models**:
   VGG-Face, Facenet, OpenFace, ArcFace, SFace, GhostFaceNet

2. **Recognition Models:**
   opencv, ssd, dlib, fastmtcnn, retinaface, mediapipe, yolov8

3. **Similarity metrics:**
   cosine, euclidean

However, the reidentification models performed poorly when utilized for plant instance reidentification. For a particular instance of a plant, the similarity metric gives similar value while identifying among the same plant species, meaning that it is able to identify the same plant species but unable to do so for each distinct plant instances.

5 Conclusion

In summary, our research undertook a comprehensive investigation into plant re-identification methodologies, leveraging Convolutional Neural Network (CNN), Support Vector Machine (SVM), and ResNet50 models. Through meticulous experimentation and evaluation, we sought to discern the efficacy of these models in accurately identifying individual plant instances within cultivated areas. While all three models were applied with rigorous scrutiny, it became evident that SVM and ResNet50 emerged as frontrunners, exhibiting notably strong performance metrics.

Specifically, our SVM model demonstrated exceptional accuracy, achieving an impressive accuracy rate of 71.25%. Likewise, the ResNet50 model showcased remarkable precision, yielding a mean Average Precision (mAP) of 0.9982 and a perfect rank-1 accuracy score of 1. These outcomes underscore the potential of SVM and ResNet50 as formidable tools for plant re-identification tasks, offering promising avenues for enhancing precision agriculture practices.

However, our study also acknowledges the need for further investigation and refinement. While SVM and ResNet50 exhibited promising results, continued research is imperative to optimize these models further and explore additional avenues for improving accuracy and efficiency. Future studies could delve deeper into fine-tuning model parameters, exploring alternative architectures, and integrating additional data sources to enhance model performance. By continuing to push the boundaries of plant re-identification research, we aim to unlock new insights and advancements that will ultimately contribute to the advancement of precision agriculture and the sustainability of food production systems.

Support Vector Machine (SVM) classification, have shown promising results in accurately identifying certain plant species like Mustard and Wheat. These techniques demonstrate the potential for automating the tedious task of plant identification. However, challenges arise when applying these methods to reidentification tasks, as inconsistencies in similarity metrics lead to ambiguous results, making it difficult to distinguish between different plant instances. This underscores the importance of refining the similarity metrics and exploring alternative approaches to enhance reidentification accuracy.

Moreover, the efficacy of top view versus side view imaging becomes evident when considering the morphology of different crops. While top view imagery proves advantageous for crops with larger canopy structures like lettuce and cauliflower, it may not capture sufficient detail for crops such as Wheat and Mustard. In these cases, side view imaging emerges as a necessity to capture the intricate features essential for accurate identification. By incorporating side view imaging techniques, researchers can gather a more comprehensive dataset, enabling SVM classifiers to discern subtle differences between plant instances with higher precision. Thus, understanding the specific requirements of each crop type and tailoring the imaging techniques accordingly will be pivotal in advancing automated plant identification systems for agricultural applications.

6. References

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