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Flora-Vision: A Quality Assurance System for the Pharmaceutical Industry

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Abstract

In contemporary pharmaceutical production, the persistent challenges of manual labor, human error, and contamination risks pose significant obstacles to efficiency and product quality. Particularly in sectors such as Ayurvedic products, cosmetics, and medicines, the need for innovation is pressing. Revolution in production process can be addressed by introducing innovative solutions and thereby challenges could be overcome. Through the utilization of advanced technology, the proposed system streamlines sample management and quality control procedures, offering a timely response to the industry's most pressing concerns. With a focus on Real-time Recognition & Classification and Quality Checking, the system ensures precise identification and labeling of samples while detecting anomalies to uphold stringent quality standards. By automating critical processes, the system minimizes labor costs, increases accuracy, and ultimately enhances overall efficiency and customer satisfaction. This project represents a crucial step forward in pharmaceutical production, promising increased reliability and regulatory compliance in an ever-evolving industry landscape.

Keywords: Convolutional neural network, deep learning, machine learning, classification, regression, pharmaceutical industry

INTRODUCTION

The need of the hour is to provide essential healthcare products to consumers worldwide by the pharmaceutical industry. Within this industry, the production of Ayurvedic products, cosmetics, and medicines require meticulous attention to detail and stringent quality control measures to ensure product safety and efficacy. However, traditional manual methods of sample collection, segregation, and quality checking pose significant challenges, including labor intensiveness, human error, and the risk of contamination. To address these challenges and enhance efficiency in pharmaceutical production, this project proposes the development of a smart system that integrates advanced technology and automation. The proposed system aims to streamline the sample management and quality control processes by leveraging real-time recognition and classification algorithms, coupled with intuitive user interfaces. Administrators will have access to a range of functionalities through the system, including real-time sample recognition and quality checking. Through the implementation of sophisticated recognition algorithms, the system will be capable of accurately identifying and labeling samples in real time, reducing the reliance on manual labor and minimizing the risk of errors. Additionally, the quality checking feature will enable administrators to detect anomalies such as rotten samples and foreign objects, ensuring strict adherence to quality standards.

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LITERATURE SURVEY

Sameer Chand Pudaruth et al. proposed "MedicPlant: A mobile application for the recognition of medicinal plants from the Republic of Mauritius using deep learning in real- time" [1]. This presents a novel mobile application for identifying medicinal plants in real-time using deep learning techniques. The authors, affiliated with the ICT Department at the University of Mauritius and the Department of Health Sciences at the Faculty of Medicine and Health Sciences, University of Mauritius, introduced an app where users can identify medicinal plants through three methods: taking a new picture, selecting an existing one from the gallery, or using real-time detection. The real-time detection feature allows users to instantly identify plants by pointing their mobile phone camera at them. The paper demonstrates the effectiveness of the application with examples, showing correct identifications along with confidence levels. Additionally, the app provides detailed information about identified plants, including scientific names, English names, Mauritian common names, plant descriptions, medicinal purposes, and information sources.

Jafar Abdollahi proposed "Identification of Medicinal Plants using Deep learning" [2]. In this paper the author uses a deep learning technique to identify different medicinal plants by using transfer learning to train a convolutional neural network and thereby uses MobileNetV2 algorithm. The methodology involves collecting a database of medicinal plant images and preprocessing them to remove noise and enhance relevant sections. Image processing algorithms are then employed to detect leaves and extract significant leaf attributes for classification. Deep learning classifiers are utilized to categorize leaf images based on various plant traits such as shape, vein, and texture. The paper presents a proposed machine block diagram and model architecture to illustrate the process. The proposed approach aims to provide a reliable and efficient method for the real-time recognition of medicinal plants, contributing to the field of plant identification and pharmacology [3].

MATERIALS AND METHODS

Dataset

The dataset for "Flora-Vision" is obtained from the Mendeley dataset repository, encompasses approximately 9 GB of high-quality image data, totaling around 18,000 images. These images are categorized into 24 distinct classes, with each class containing between 600 and 800 images. The dataset is meticulously divided into three subsets to facilitate machine learning tasks: the training set includes about 14,000 images, while both the testing and validation sets consist of roughly 2,000 images each. This division ensures that a substantial portion of the data is available for training, enabling the development of robust models, while also providing sufficient data for testing and validation to evaluate model performance. The high quality of the images across all classes guarantees that the models trained on this dataset can achieve reliable and consistent results. This comprehensive dataset structure supports effective training, thorough testing, and accurate validation, making it an invaluable resource for developing and fine-tuning machines learning algorithms.

Algorithms

1. *YOLOv8:* YOLOv8 utilizes C2f module which is the modification of the CSP layer of YOLOv5. The module contains two convolution cross stage partial bottleneck which enhance the detection of accuracy by combining high level features with contextual information. The decoupled head independently handles object detection, classification and regression tasks. The output layer contains sigmoid function as the activation function for object scores indicating the probability of an object being present within the bounding box. To represent class probabilities, SoftMax function is used which signifies the probability of an object belonging to each class. CIoU and DFL loss functions are used for bounding box loss and binary cross-entropy for classification loss. Object-detection performance can be enhanced by these loss functions when dealing with smaller objects. The three main parts of the model are the neck network, the prediction output head and the backbone network, which were chosen for this article. The core component of the YOLOv8 model is the backbone network, which oversees identifying in the RGB color input images. The prediction output head and the backbone network are separated by the neck network. Its main responsibility is to compile and process the features extracted by the backbone network. In YOLOv8, the neck network plays a crucial role in integrating features of different roles. The neck network employs a structure called Feature Pyramid Network (FPN), which efficiently

combines features from different scales to create a more through representation [4, 5]. The highest component of the YOLOv8 model, the prediction output head, oversees recognizing and locating different object types in the photos. Typically, the output head has several detectors, each of which oversees determining the location and kind of object. To help the model recognize objects of varied sizes, YOLOv8 uses three sets of detectors, each with a distinct scale.

2. *ResNet:* ResNet, short for Residual Network, is a pioneering deep learning architecture introduced by researchers at Microsoft in 2015. The concept of residual learning can be introduced to address the challenges of deep neural networks. The degradation problems in deep networks will lead to higher training errors if we add more layers. Layers can learn residual functions with reference to the layer inputs rather than learning unreferenced functions by the introduction of residual blocks of ResNet. Two or more convolutional layers are included in the residual block where the input to the block is added to the output. The vanishing gradient problem can be effectively reduced by introducing this shortcut connection which enables the training of much deeper networks. The architecture has variants such as ResNet-50, ResNet-101, and ResNet-152, where the numbers indicate the depth of the network. ResNet has significantly influenced computer vision, achieving state-of-the-art results in image classification, object detection, and segmentation tasks. Its ability to train deep networks without degradation has made it a foundational model in the field, inspiring many subsequent architectures and applications in various domains including medical imaging, autonomous driving, and more [6].

PERFORMANCE MEASURES

Precision

Accuracy of the positive prediction is measured as precision, and it is calculated by the ratio of true positive detections to the total predicted positives (false positives + true positives).

$$\text{PRECISION} = \frac{\text{True Positives (TP)}}{\text{True positives (TP)} + \text{False Negatives (FP)}}$$

Recall (Sensitivity)

Measures the ability of the model to detect all relevant samples. The ratio of true positives to the total actual positives is considered as RECALL (true positives + false negatives).

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True positives (TP)} + \text{False Negatives (FP)}}$$

F1 Score

The harmonic means of precision and recall, providing a single metric that balances both concerns.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall True Positives (TP)}}{\text{Precision} * \text{Recall}}$$

Mean Average Precision (mAP)

A common metric for object detection models, mAP considers the precision-recall curve and calculates the average precision across different recall levels.

$$mAP = 1/n \sum_{i=1}^{n} API$$

where, (AP_i) is the average precision for each class (i) and (N) is the number of classes.

Intersection over Union (IOU)

$$\text{IoU} = \frac{\text{a of Overlap}}{\text{Area of Union}}$$

Inference Time

The time it takes for the model to process an image and make predictions. This is crucial for real-time applications.

$$\text{Inference time} = \frac{\text{Total Processing Time}}{\text{Number of images}}$$

METHODOLOGY

Flow Chart

Initiate RT sample recognition and labeling, identify and segregate the hottest samples and foreign objects, and report any anomalies (Figure 1).

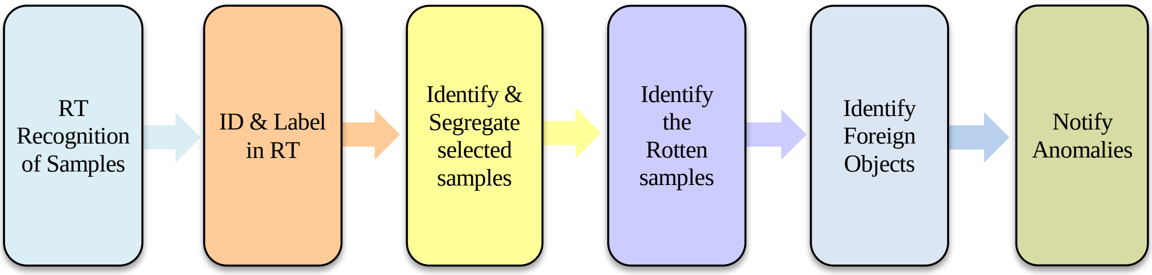

Figure 1. Processing flow diagram.

Data Collection

Gather a comprehensive dataset of images representing various samples used in pharmaceutical production. Ensure diversity in the dataset to cover all possible sample types and conditions, including rotten and foreign objects [11].

Dataset Annotation

Manually label the collected images with the correct classifications and annotations required for training the YOLOv5 model. To mark the boundaries and locations of objects within images annotation tools were used [7–10].

Training The Model

Utilize the annotated dataset to train the YOLOv5 model, optimizing it for accurate object detection and classification. Monitor the training process, adjusting hyperparameters and configurations to improve model Performance (Figures 2–6).

Testing the Model

Evaluate the trained YOLOv5 model using a separate testing dataset to validate its accuracy and reliability. Perform various tests to ensure the model's robustness and ability to generalize across different sample types.

Integration with UI

Integrate the trained YOLOv5 model into the user interface using Flask, enabling real-time recognition and classification of samples. Ensure seamless communication between the frontend UI and the backend model for efficient processing [12, 13].

Anomaly Detection with ResNet

Incorporate a ResNet model into the system for detecting anomalies such as rotten samples and foreign objects. Use the ResNet model to analyze embeddings and compare them with database images, triggering alerts for detected anomalies.

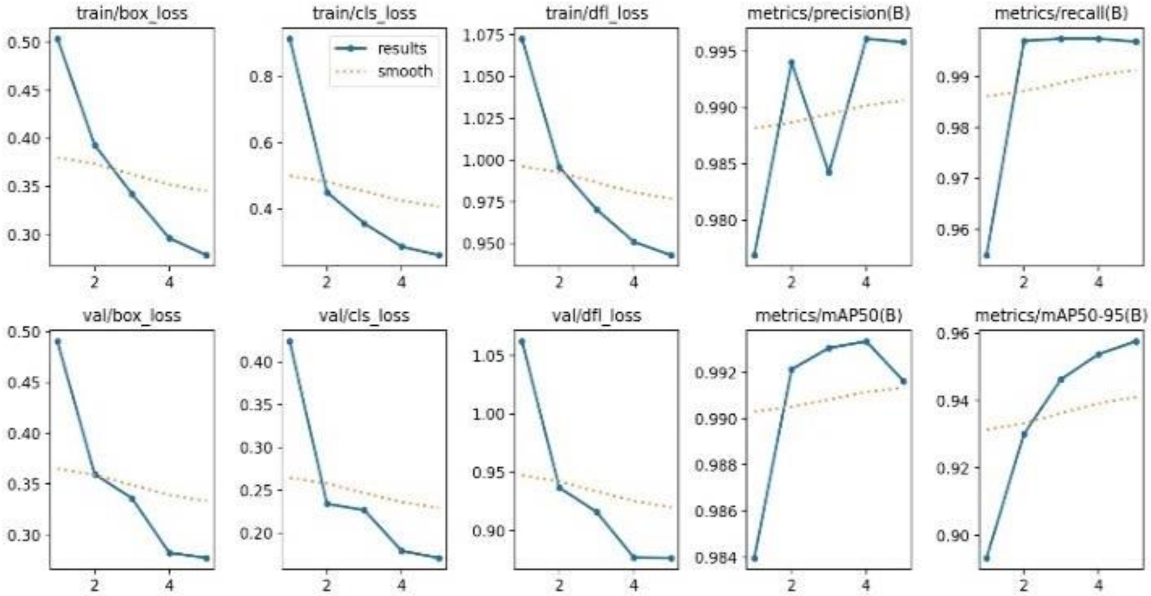

Figure 2. Training and validation metrics for real-time detection.

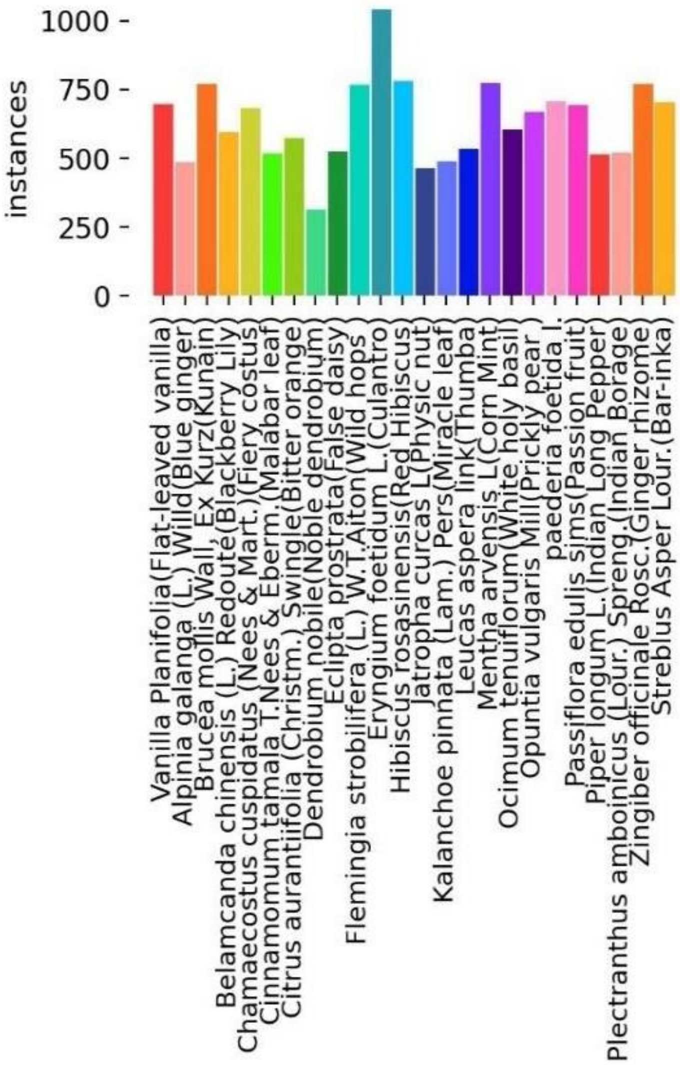

Figure 3. Instances of different plant species.

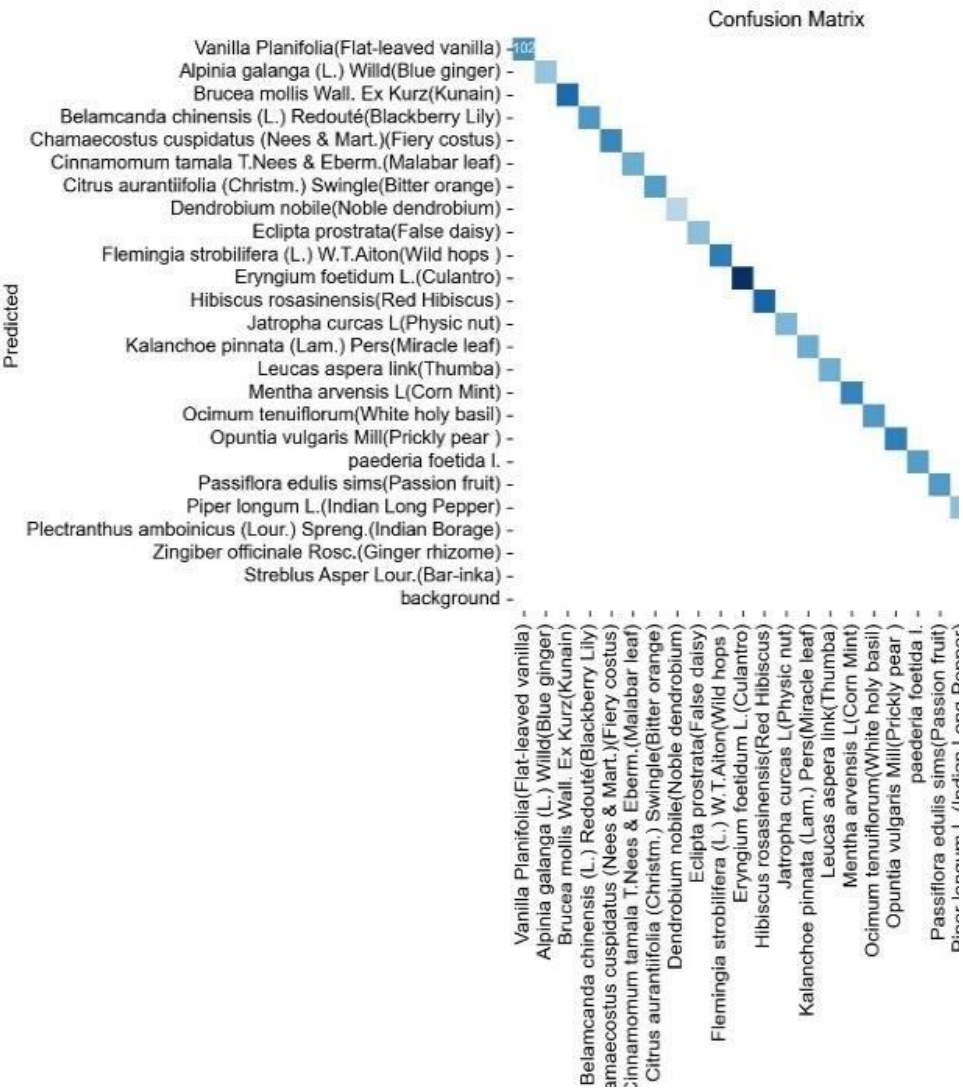

Figure 4. Confusion matrix for plant species classifications.

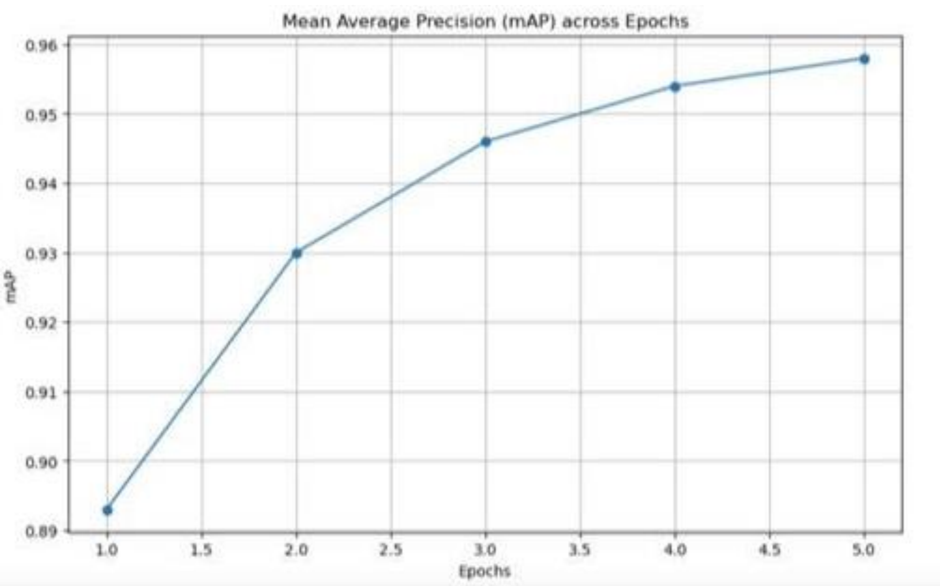

Figure 5. Mean average precision (mAP) across Epochs.

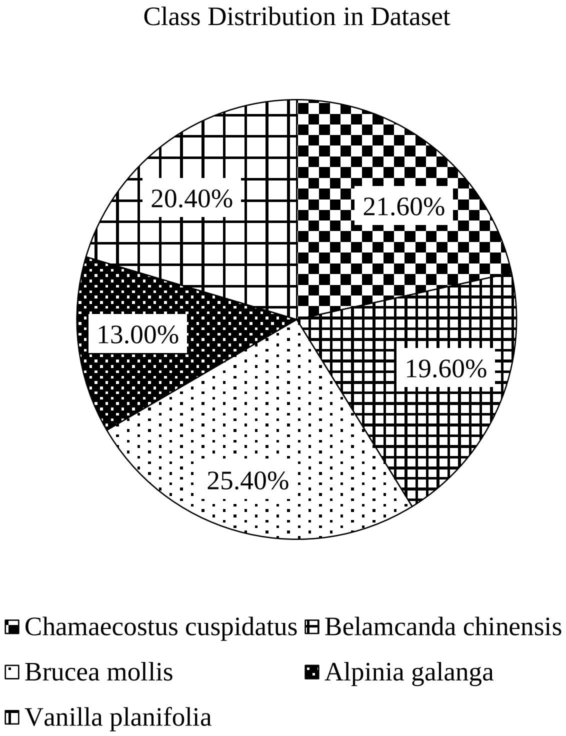

Figure 6. Class distribution of leaf in dataset.

RESULTS

Precision

YOLOv8 achieved a high precision of 0.996, indicating the most positive detections were correct.

Recall

YOLOv8 demonstrated a recall of 0.997, showing it successfully identified almost all relevant samples.

F1 Score

Given the high precision and recall, the F1 score for our model would be close to 0.997, indicating excellent overall performance.

Mean Average Precision (mAP)

Model achieved an mAP50 of 0.992 and mAP50-95 of 0.957, showcasing its robust detection capabilities.

Inference Time

The YOLOv8 model processed images in approximately 508.1ms per image, making it suitable for real-time applications in our project.

CONCLUSION

In this study, the smart system for pharmaceutical production represents a pivotal advancement, revolutionizing sample management and quality control. The challenges posed in manual labor, human error and contamination risks can be mitigated by advanced technologies. Real-time recognition and quality checking algorithms streamline sample identification and enhance product safety. User-friendly interfaces and alert mechanisms empower informed decision-making. Integration of machine learning models like YOLOv8 and OpenCV enhances adaptability to diverse environments. This system boosts efficiency, reduces costs, and elevates product quality, driving productivity and customer satisfaction. Its scalability and flexibility ensure widespread adoption. Continuous refinement is crucial to meet evolving industry needs and technological advancements, solidifying its role as a cornerstone in pharmaceutical manufacturing.

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