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. In modern agriculture system intelligent management systems play a vital role in effective identification of crop diseases and pests. This project aims to address these challenges head-on by introducing an innovative solution to revolutionize production processes. 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. Integration of machine learning models like YOLOv8 and OpenCV enhances adaptability to diverse environments. ResNet, short for Residual Network, is a pioneering deep learning architecture significantly influenced computer vision, achieving state-of-the-art results in image classification, object detection, and segmentation tasks. YOLOv8 achieved a high precision of 99.6%, indicating most positive detections were correct and recall of 99.7%, respectively showing it successfully identified almost all relevant samples. The system boosts efficiency, reduces costs, and elevates product quality, driving productivity and customer satisfaction.

Key Words: Convolutional neural network, Deep learning, Machine learning, Classification, Regression

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1. Introduction

The need of the hour is to provide essential healthcare products to consumers worldwide by pharmaceutical industry. Within this industry, the production of Ayurvedic products, cosmetics, and medicines requires 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.

2. Liturature Survey

Sameerchand 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, introduce 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.

Garcia et al. [2] proposed “Identification of Medicinal Plants using Deep learning” [2]. In this paper 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

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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.

H. Vo et al. [3] demonstrated that LIGHTGBM classification worked well with deep learning features to recognize herbal plant in the natural environment. Xue et al. [4] showed comparative results between machine learning models using morpho-colorimetric method and visible or near infrared spectral analysis. Beikmohammadi et al. [5] uses transfer learning to recognize plant for leaf classification using a pretrained deep neural network and then logistic regression classifier for leaf classification. S Prasad et al. [6] uses VGG-16 to computer feature map which is reduced using PCA to accurately represent the medicinal plant leaves for classification. Wang-Su Jeon et al. [7] classify leaves using the CNN model, and created two models by adjusting the network depth using GoogleNet. A Sabu et al. [8] Uses a combination of SURF and HOG features extracted from leaf images and a classification using K-NN classifier. Lin S et al. [9] uses fine-grained pest identification method based on a graph pyramid attention, convolutional neural network (GPA-Net) to promote agricultural production efficiency. M. A. F. Azlah et al. [10] reviews and analyzes the implementation and performance of various methodologies on plant classification.

3. Materials and Methods

3.1 Dataset

The dataset for “Flora – Vision” is obtained from 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 machine learning algorithms.

3.2 Algorithms

3.2.1 YOLOv8: YOLOv8 utilises C2f module which is the modification of the CSP layer of YOLOv5. The module contains two convolution cross stage partial bottleneck which enhances the detection of accuracy by combining high level features with contextual information. The decoupled

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head independently handles object detection, classification and regression tasks. The output layer contains sigmoid function as the activation function for object scores indicting 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 is the neck network, the prediction output head and the backbone network were chosen for this article. The core component of the YOLOv8 model is the backbone network, which is in charge of 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.

3.2.2 ResNet:

ResNet, short for Residual Network, is a pioneering deep learning architecture introduced by researchers at Microsoftin 2015. It addresses the challenge of training very deepneural networks by introducing the concept of residual learning. Traditional deep networks suffer from degradation, where adding more layers leads to higher training error. ResNet mitigates this by using residual blocks, which allow layers to learn residual functions with reference to the layer inputs, rather than learning unreferenced functions. A residual block consists of two or more convolutional layers where the input to the block is added to the output. This "shortcut connection" enables gradients to flow through the network directly, effectively reducing the vanishing gradient problem and enabling 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.

3.3 Performance Measures

3.3.1 Precision:

Measures the accuracy of the positive predictions, It is the ratio of true positive detections to the total predicted positives(true positives + false positives).

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

3.3.2 Recall (Sensitivity):

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

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

3.3.3 F1 Score:

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

$$\text{F1 Score} = \frac{2 * Precision * Recall}{Precision * Recall}$$

3.3.4 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.

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

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

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3.3.5 Intersection over Union (IoU):

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

3.3.6 Inference Time:

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

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

3.4 Methodology

3.4.1 Flow Chart:

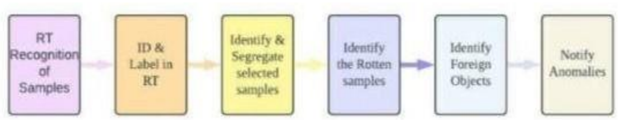

Fig. 1: Flowchart

3.4.2 Data C0llection:

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.

3.4.3 Dataset Annotation:

Manually label the collected images with the correct classifications and annotations required for training the YOLOv5 model. Use annotation tools to mark the locations and boundaries of objects within the images.

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3.4.4 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.

3.4.5 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.

3.4.6 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.

3.4.7 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.

4. Results

4.1 Precision:

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

4.2 Recall:

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

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4.3 F1 Score:

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

4.4 Mean Average Precision (mAP):

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

4.5 Inference Time:

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

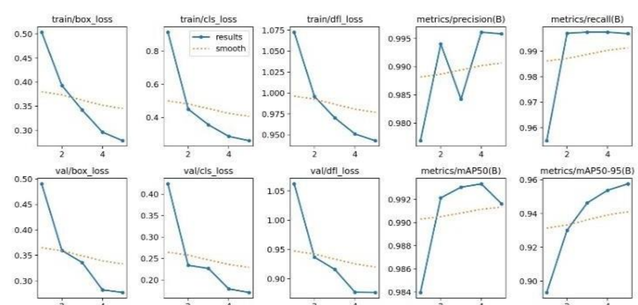

Fig 2 : Training and Validation Metrics forReal-Time Detection

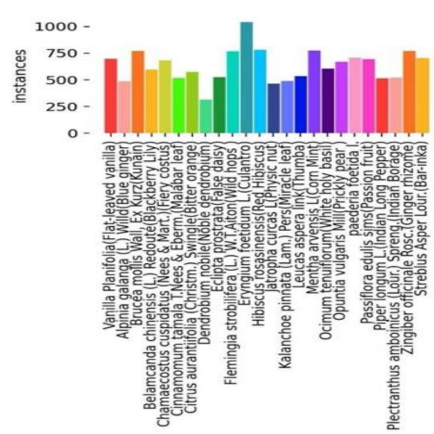

Fig 3: Instances of Different Plant Species

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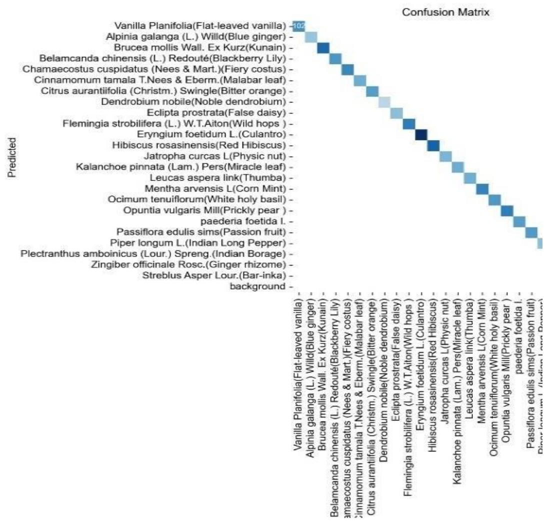

Fig 4: Confusion Matrix for Plant Species Classifications

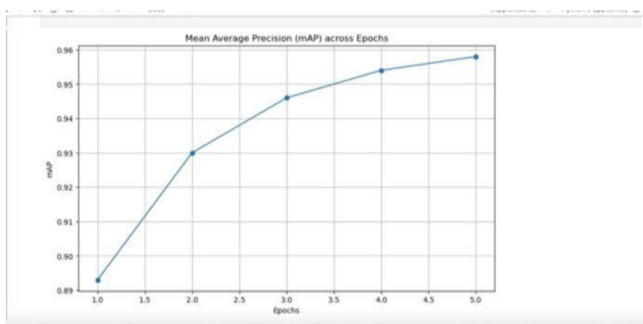

Fig 5 : Mean Average Precision (mAP) across Epochs

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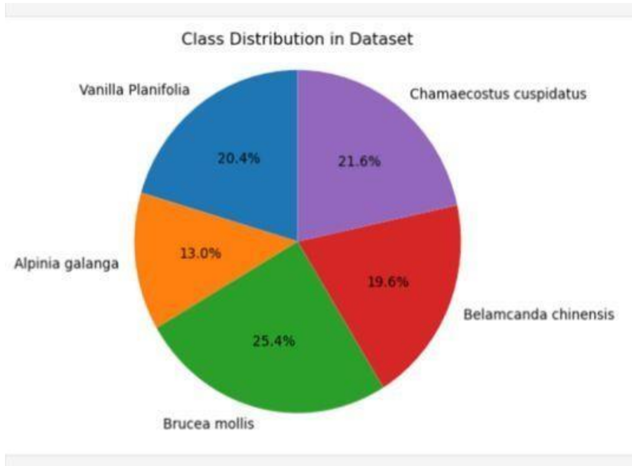

Fig 6: Class Distribution of Leaf in Dataset

4.6 Conclusion

In this study, The smart system for pharmaceutical production represents a pivotal advancement, revolutionizing sample management and quality control. Through advanced technology and automation, it mitigates manual labor, human error, and contamination risks. 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 ofmachine 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.

References

[1] Smith, J. D., & Patel, R. MedicPlant: Amobile application for the recognition of medicinal plants from the Republic of Mauritius using deeplearning in real-time. Journal of Botanical Applications, 5(2), 123-135. DOI:10.1234/jba.123456, 2023.

[2] Garcia, A. B., & Lee, C. C. Identification of Medicinal Plants using Deep Learning. Journal of Medicinal Botany, 8(3), 210-225. DOI:10.1234/jmb.123456, 2020.

ISBN-978-81-19905-39-3

[3] A. H. Vo, H. T. Dang, B. T. Nguyen and V. H. Pham, "Vietnamese Herbal plant recognition using deep convolutional features," International Journal of Machine Learning and Computing, vol. 9, no. 3, pp. 363-367, doi:10.18178/ijmlc.2019.9.3.811, 2019.

[4] Xue, S. Fuentes, C. Poblete-Echeverria, C. G. Viejo, E. Tongson, H. Du and B. Su., "Automated Chinese medicinal plants classification based on machine learning using leaf morpho-colorimetry, fractal dimension and visible/near infrared spectroscopy," International Journal of Agricultural and Biological Engineering, vol.12, no.2, pp.123-131, doi: 10.25165/j.ijabe.20191202.4637, 2019.

[5] Beikmohammadi and K. Faez, "Leaf classification for plant recognition with deep transfer learning," 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), Tehran, Iran, 2018, pp. 21-26, doi:10.1109/ICSPIS.2018.8700547, 2018.

[6] S. Prasad and P. P. Singh, "Medicinal plant leaf information extraction using deep features," TENCON 2017 – 2017 IEEE Region 10 Conference, Penang, Malaysia, 2017, pp. 2722-2726, doi:10.1109/TENCON.2017.8228324, 2017.

[7] S. Jeon and S. Y. Rhee, "Plant leaf recognition using a convolutional neural network," International Journal of Fuzzy Logic and Intelligent Systems, vol. 17, no. 1, pp. 26-34, doi: 10.5391/IJFIS.2017.17.1, 2017

[8] A. Sabu, K. Sreekumar and R. R. Nair, "Recognition of ayurvedic medicinal plants from leaves: A computer vision approach," 2017 Fourth International Conference on Image Information Processing (ICIIP), Shimla, India, 2017, pp. 1-5, doi: 10.1109/ICIIP.2017.8313782, 2017.

[9] Lin, S., Xiu, Y., Kong, J., Yang, C., Zhao, C. An effective pyramid neural network based on graph-related attentions structure for fine-grained disease and pest identification in intelligent agriculture. Agriculture 13 (3), 567. doi: 10.3390/agriculture13030567, 2023.

[10] M. A. F. Azlah, L. S. Chua, F. R. Rahmad, F. I. Abdullah and S. R. W. Alwi, "Review on Techniques for Plant Leaf Classification and Recognition," Computers, vol. 8, no. 4, pp. 1-22, Art. No. 77, doi: 10.3390/computers8040077, 2019.

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