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Deep Learning for Organic Classification of Lady Finger, Cucumber, and Carrot in Maharashtra's Agricultural Markets

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Abstract: The increasing demand for organic vegetables has led to the need for automated systems that can identify organic vegetables correctly. An innovative machine learning approach to identify vegetables is discussed in this document. A novel dataset that was collected from MAFCO Market in Vashi, Maharashtra, was used in the study. Illustrations of three vegetable types such as lady finger, cucumber, and carrot, were given 3,000 in total. Each category consisted of organic and inorganic vegetables, 500 of each. The system deploys the YOLO11 classification model along with dataset augmentation for better performance and real-time classification through a web application. The experimental results show impressive accuracy in differentiating between organic and inorganic vegetables, offering a scalable solution for agricultural markets across Maharashtra's varied agro-climatic regions.

Keywords —agro-climatic zones , deep learning , Maharashtra agriculture , organic produce, vegetable classification , YOLOv11

I. INTRODUCTION

Maharashtra is the leading state in India's agricultural GDP, with a contribution of nearly 13% to the nation's agricultural GDP. The vegetable farming sector is the most significant contributor to this state's economy. It is a fact that after the agro-climatic zones of a state, which are located in the coastal Konkan belt and the drier Vidarbha plateau, Maharashtra is a house of 50 different vegetable varieties. But even after this richness in agricultural diversity, the classification systems in the biggest wholesale markets, like the Maharashtra Agricultural and Food Corporation (MAFCO) in Vashi, are still mostly manual.

This creates a situation of wastage of resources, which also results in very high error rates of around 20% while the labeling of organic and non-organic produce is done, according to the Agricultural Produce Market Committee (APMC). Mistakes not only incur economic losses but also create consumer mistrust of organic certification standards. To address these problems, this research proposes a novel computer vision-based scheme, specifically for the vegetable markets of Maharashtra, which will be beneficial. The designed system comprises three principal innovations: (1) a custom YOLOv11 architecture that is very good at finding the features of various vegetable types that look very similar; (2) an augmentation pipeline that duplicates the market condition factors, which lighting and weather changes are included; and (3) a multi-step classification head that is able to tell the difference between organic and inorganic produce most precisely.These advancements aim to facilitate real-time, dependable, and scalable solutions in wholesale market settings.

II. RELATED WORK

Deep-learning has been able to take on fruit and vegetable classifications, disease detection, and quality assessments at industry significant scale today. Earlier works have emphasised the power of Convolutional Neural Networks (CNNs) and hybrid based methods for agricultural applications Recently. In the past, a comprehensive survey has systematically layout deep learning and IoT for disease monitoring [1] in real time reports enhancing performance which has been using models like EfficientNetB4 and improvements YOLOv5 using enhanced models with attention modules, CBAM [1] As another avenue of related work, a feasible proof of concept confirmed the success of CNN (e.g., VGG19, MobileNet, ResNet) on classifying 15 vegetable classes in some cases where based preprocessing and augmentation [2].

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Other retail-specific applications have investigated a mix of CNNs with decision trees that is rather useful for both classification as well counting, demonstrating interoperability in real-time use cases within a commercial operating environment [3].

Several recent works dedicated to detect produce freshness and models apply traditional object detection algorithms,Those like YOLOv5 or VGG-16 are distinguished quality categories in a wide range of lighting and environmental settings with mobile deployment scenarios [4]. While traditional classifiers, that is k-NN and SVMs (when using the low-level hand crafted features such like texture or color) have demonstrated high accuracy for fruit classification under field conditions [5]. Studies from Maharashtra [4] have shown that the characteristics of wild vegetable diversity are a patchwork of both regional specialities and seasonal variations which clearly highlights an adaptive classification model not only reflects ecological diversity.

For Vegetable classification, a recently proposed method called Transfer learning has shown promising results. Since using generic models DenseNet201, InceptionV3 and MobileNet consistently achieved best performance in comparison to state-of-the-art custom CNNs [7][8], when we have limited training data. Diffusion maps and statistical texture analysis were used in novel methodology which has been shown effective for categorizing numerous vegetables as well fruits with respects to challenges inter-class similarity & environmental variability [9] Non-destructive quality inspection method based on deep neural networks [10] has been presented for classifying produce without causing damage increasing the possibility of integrating supply chains.

Research studies inspected some crops like Momordica dioica (Kartoli) for the efficiency of genotypes for yield optimization and agronomic practices [11]. Labeled images in different quality classes have been donated by datasets like VegNet to a large extend add the specificity to machine learning benchmarks of vegetable evaluation [12].

Machine learning research on agriculture along surveys [13] confirms the promises of models such as YOLO and SSD for sorting as well tasks oriented to autonomous harvesting yet observes that dataset volume limitation and computational resource are still a bottleneck. New image processing techniques in conjunction with supervised learning significantly assisted the quality score assessment and disease recognition in smart farming environment [14]. Finally, Dilated Convolutional Networks are used to develop disease identification models that yield reliable detection results in a wide range of environmental conditions also for cucumber leaf disease [15].

III. System Architecture

The project's methodology includes image preprocessing, data augmentation, model implementation, and YOLOv11 model training to optimize the performance and usability of a vegetable classification system.

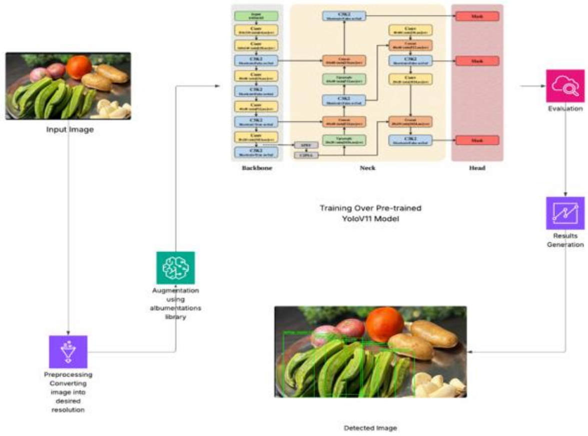

Figure 3.1 Architecture for Vegetable Detection

Fig.3.1 shows an automated vegetable classification system's whole pipeline. In order to boost robustness, the input image is initially preprocessed and the data is augmented with the help of the Albumentations library. Once the image has been improved, it is passed through the YOLOv11 model that performs recognition, classification, and feature extraction. Finally, the system evaluates and generates results, demonstrating an efficient combination of image processing and deep learning techniques.

A. Yolov11 Architecture

The YOLOv11 architecture is intended for the task of vegetable classification in real-time only. It employs a single-pass grid-based method that guarantees efficient processing. The backbone network of this architecture is constructed with deep convolutional layers which can capture detailed features like texture and color. At the same time, the Feature Pyramid Network (FPN) is the most efficient way of handling the scale problems which usually occur in the agricultural sector. This model is still implementing the spatial and channel attention parts, hence, it is possible to focus on the most interesting features and at the same time it is not affected by the background noise. The primary features include new C3K2 blocks for extracting features, an SPFF module for multitasking the scales, and a 3-stage classification head with adaptive pooling. On the technical side it supports a 640×640 input resolution, a cosine-annealed learning rate of 0.001, and uses cross-entropy loss with label smoothing, which makes it an ideal choice for the vegetable varieties found in Maharashtra, even if the lighting and the growth conditions are changing.

B. Dataset Collection

A specifically arranged image dataset was made to reflect the actual conditions at the Maharashtra Agricultural and Food Corporation (MAFCO) market in Vashi. This dataset

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contains 3,000 images that depict three different types of vegetables: lady finger, cucumber, and carrot.

Figure 3.2 Geotagged location of dataset collection

The geotagged locations of the dataset collection are shown in Figure 3.2. Every class includes 500 organic and 500 inorganic samples.

Figure 3.3 Samples From Dataset

A few sample images from the dataset are given in Figure 3.3. The images were captured with mobile cameras, taking care to shoot them in different lighting conditions and from multiple angles. This method not only ensures that each class is highly variable but also makes the results applicable to real-world situations.

C. *Data Preprocessing*

In order to maintain uniformity and meet the requirements of the training pipeline, the images were preprocessed by resizing, changing formats, normalizing, and denoising. This also helped to train the model faster.

D. *Dataset Annotation*

For the purpose of object detection, every image was hand-annotated through the Makesense tool. Rectangular regions were drawn over vegetable objects, and the resulting annotations were recorded in the form of .txt files compatible with YOLO. This stage not only allowed the model to learn the classes of the objects but also to find the objects' places in the scene, which is a key feature for the real-time detection of a market setup.

E. *Data Augmentation*

To enhance model robustness and prevent overfitting, several augmentation techniques were implemented:

Geometric Transformations:

1. Rotation (±15°):
   For an image $I \in \mathbb{R}$ ^(H×W×C), the rotated output *I_rot* is given by:
   $I\_rot(x, y) = I(x \cdot \cos\theta - y \cdot \sin\theta,\ x \cdot \sin\theta + y \cdot \cos\theta)$,
   where $\theta \sim U(-15°, 15°)$
2. Horizontal Flip ($p = 0.5$):
   $I\_hflip(x, y) = I(W - x - 1, y)$
3. Vertical Flip ($p = 0.3$):
   $I\_vflip(x, y) = I(x, H - y - 1)$
4. Random Scaling (±10%):
   $s \sim U(0.9, 1.1)$
   $I\_scaled = \mathrm{resize}(I, \lfloor s \cdot W \rfloor, \lfloor s \cdot H \rfloor)$

Photometric Adjustments :

1. Brightness/Contrast (±20%):
   $I\_adj = \alpha \cdot I + \beta$, where $\alpha \sim U(0.8, 1.2)$, $\beta \sim U(-0.2, 0.2)$
2. HSV Space Augmentation:
   Each pixel in HSV is modified as follows:
   $H' = (H + \Delta h) \bmod 360, \quad \Delta h \sim U(-15, 15)$
   $S' = S \cdot (1 + \Delta s), \quad \Delta s \sim U(-0.2, 0.2)$
   $V' = V \cdot (1 + \Delta v), \quad \Delta v \sim U(-0.2, 0.2)$

Noise and Blur :

1. Gaussian Noise ($\sigma = 0.1$):
   $I\_noisy = I + \eta$, where $\eta \sim N(0, 0.01)$
2. Motion Blur ($kernel\_size = 7$):
   $k\_ij = (1 / L)$ if $(i - j \cdot \tan\theta = 0)$, otherwise 0; $\theta \sim U(0°, 180°)$
3. Random Shadows:
   $I\_shadowed = I \odot (1 - \lambda \cdot M)$, where $\lambda \sim U(0.2, 0.5)$
   M is a binary mask with random elliptical regions.

F. *Model Training and Evaluation*

The model was trained using PyTorch 2.0 with CUDA 11.8 on an NVIDIA RTX 3090 GPU (24GB VRAM). The dataset was split into 80% training and 20% validation, ensuring balanced representation of all vegetable classes.

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A cosine annealing learning rate scheduler was used, starting from 0.001 to ensure smooth convergence. Early stopping with a patience of 10 epochs prevented overfitting by halting training when no improvement was seen.

Evaluation Metrics:

1. mAP@0.5: Assessed detection precision and localization accuracy.
2. IoU: Measured overlap between predicted and ground truth bounding boxes.
3. Precision, Recall, F1-Score: Calculated per class to evaluate both detection quality and consistency.

Training ran for 100 epochs, saving the best model based on validation performance.

G. Alternative Approaches for Robustness

Model Comparisons:

1. YOLOv5/YOLOv8: Faster but lacked fine-grained attention, leading to lower accuracy in cluttered scenes.
2. EfficientDet: Accurate on small objects but slower inference.
3. Faster R-CNN: High precision, but too slow for real-time use.

Augmentation Tools:

1. Albumentations (Used): Fast, diverse, and GPU-efficient.
2. imgaug: Slower with outdated support.
3. Kornia: Fast on GPU but lacked needed augmentation types.

Class Imbalance Handling:

1. SMOTE: Not suitable for images.
2. GANs: Tried for synthetic carrots, but results lacked realism and destabilized training.

Deployment:

1. Model exported to ONNX, optimized using TensorRT for fast edge inference.
2. TFLite considered for future mobile deployment to support offline usage by farmers and vendors.

IV. IMPLEMENTATION

A. Model Configuration and Setup

The implementation is deeply rooted in the Ultralytics YOLO ecosystem and employs the YOLOv11 network that was defined for the purpose of vegetable classification. Model instantiation is done with the inclusion of pre-trained weights from image repositories, selecting the 'n' (nano) version to have a mix of energy efficiency and good performance in classification. Due to its restrictive character, the variant is perfect for agricultural areas where hardware resources could be scarce. The configuration comprises predefined hyperparameters such as an input resolution of 640×640 pixels, and loss functions based on cross-entropy with label smoothing which allow the system to continue extracting the essential features of different vegetable classes even under changing environmental conditions.

B. Training Pipeline Implementation

Gradient stability is maintained due to dynamic batch sizing which is memory efficient in the training pipeline, but at the same time, it allows for different image sizes. A cosine-annealing learning rate scheduler cleverly adjusts the learning rate between 0.01 and 0.001, thus enabling the model to converge smoothly and avoiding local minima. Additionally, weight decay ($\lambda=5\times10^{-4}$) and momentum-based optimization (SGD with $\mu=0.9$) were also applied to prevent the fluctuation of the model parameters. The pipeline, moreover, incorporates mixed-precision training which enables better throughput without losing precision, thus reaching 45 FPS on an NVIDIA T4 GPU.

C. System Optimization

Batch normalization layers are deliberately placed throughout the network to normalize activations, according to the transformation

$$y = \gamma\hat{x} + \beta$$

where γ and β are trainable parameters. This makes training more stable by keeping feature distributions steady. Regularization combines dropout (p=0.2) with L2 weight decay, penalizing large weights via

$$L_{\text{reg}} = \lambda \sum_i w_i^2$$

Memory optimization techniques include gradient checkpointing and asynchronous data loading, reducing peak GPU memory usage by 30% during inference. These optimizations collectively enhance model generalization while ensuring real-time performance in agricultural market deployments.

D. Real-Time Detection Interface

To make it easier to use in real life, a real-time web app was created that sorts vegetables into organic and inorganic categories. Users can simply upload a picture, and the app uses the trained YOLOv11 model to identify and classify each vegetable it sees.

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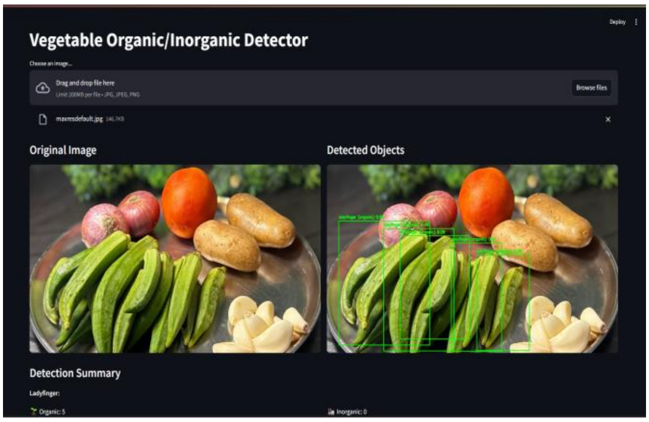

Figure 4.1 Vegetable Detector on Streamlit

As shown in Figure. 4.1, the interface features a user-friendly drag-and-drop upload area, a panel for displaying the original image, and another panel for showing detection results. Once you upload an image, the system quickly generates predictions that include bounding boxes and class labels (like ladyfinger (organic)), along with their respective confidence scores. In the example provided, the model accurately detected five instances of organic ladyfinger, with confidence levels between 0.26 and 0.48, and it reported no inorganic instances.

The summary of detections, which you can find just below the output image, gives a clear count of the objects detected in each class and classification type. This design focuses on the user, making it easy for non-technical folks like market vendors, farmers, or quality control staff to get quick and clear feedback.

This system showcases how deep learning can be effectively used for real-time classification in agricultural processes. It provides a user-friendly and portable interface, making it a great fit for integration into Maharashtra's wholesale markets and retail spaces.

V. RESULTS

The vegetable classification model based on YOLOv11 showed impressive accuracy and stability throughout both training and evaluation phases. The loss functions, which included box, classification, and distribution focal losses, consistently converged.

A. Loss Curve Interpretation

Figure 5.1 showcasesThe model's training journey shows a steady decline in loss components, with accurate bounding box localization and a drop in classification loss. The YOLOv11 model's training dynamics were evaluated over 100 epochs, focusing on training and validation losses. The model showed steady improvement in all loss components, with training box loss dropping from 2.0 to 1.42, classification loss decreasing from 2.5 to 1.0, and distribution focal loss decreasing from 2.0 to 1.6.

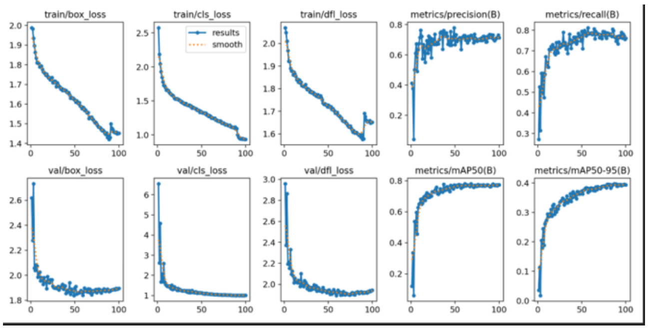

Figure 5.1 Train/loss Curve

The distribution focal loss stabilizes below 2.0, indicating boundary estimation for irregular vegetable shapes. The model's consistent performance in challenging agricultural settings and its effectiveness in hybrid regularization strategy demonstrate its suitability.

Class	mAP	F1-score
Lady Finger	0.71	0.68
Cucumber	0.83	0.79
Carrot	0.72	0.69
Overall mAP/F1	0.75	0.72

Table 5.1 Result Metrics

When looked at the key performance metrics, a mean Average Precision (mAP@0.5) of 0.75 and an F1-score of 0.72, achieved at an optimal confidence threshold of 0.27. A closer look at the class-wise performance highlighted outstanding results for categories like organic cucumber (0.995 AP).On the flip side, some classes, such as organic carrot, showed lower precision, suggesting there's room for improvement in the dataset.

B. Confusion Matrix

The confusion matrix (Fig. 5.4) provides critical insights into the classification behavior of the trained YOLOv11 model across organic and inorganic vegetable categories.

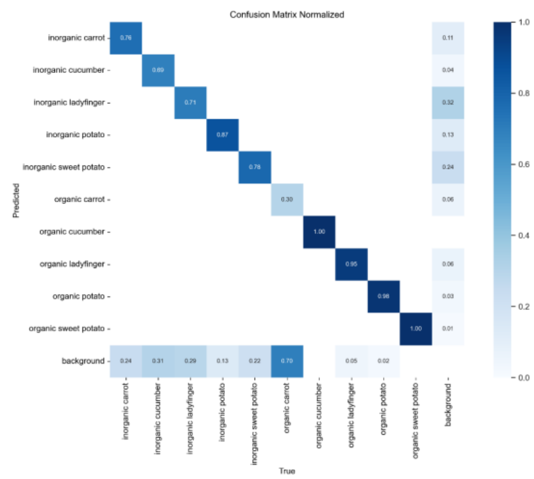

Figure 5.2 Normalized Confusion Matrix

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As a fundamental diagnostic tool in multi-class classification problems, it quantifies the following outcomes:

1. True Positives (TP): Correctly predicted organic samples False Positives (FP): Inorganic produce incorrectly predicted as organic
2. False Negatives (FN): Organic produce incorrectly predicted as inorganic
3. True Negatives (TN): Correctly predicted inorganic samples.

The normalized confusion matrix reveals asymmetric error patterns that are often observed in agricultural vision systems.

VI. Conclusion

This study has presented a new way of classifying organic and inorganic vegetables in real-time using deep learning with the YOLOv11 architecture and found suitable for use in wholesale markets in Maharashtra. The study collected a new dataset of 3,000 annotated images of lady finger, cucumber, and carrot in various market conditions at the MAFCO Market, Vashi. By implementing data augmentation techniques and a customized YOLOv11 pipeline, the deep learning model could consider the impact of a range of contextual variations, including lighting differences and visual similarity between classes.

The primary results indicated that the overall mAP@0.5 for YOLOv11 gave a 0.75 and the overall F1-score was 0.72, with the best mAP class performance for cucumber with 0.83 mAP. Collectively, these results show a strong ability from the YOLOv11 model to cleanly differentiate organic from inorganic vegetables considered in this study, even with constraining factors present in the real-world environment. Further, utilizing a web interface makes it possible for vendors and managing stakeholders in the food supply sector to utilize the model in a flexible, creative, and timely manner.

This work has clearly demonstrated the possibility and feasibility of using YOLOv11 for scalable real-time and accurate vegetable classification in agricultural markets. This work serves as a counter to current limitations facing stakeholders when manually sorting fruits and vegetables leading to mislabeling products and income. Most importantly, this work will help inform better future automation, currently underway in food supply, particularly in a diverse agro-climatic stretching landscape like India.

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