

Flower Phenotype Recognition and Analysis using YoloV5 Models

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Abstract—Real time detection of flowers based on their growth cycle is called as phenotype. It is one of the most important methods for judging the maturity of flowers and to estimate their yield. Traditional method involves flower detection and classification of varied species. In this paper, we introduce a new dataset based on flower phenotype. The dataset has images of flowers, classified into bud, fresh and stale. The work will help for identification and localization of classes based on flower phenotype. The detection of flowers at various stages of their life will be more important to harvesting in floriculture field. We propose a state of art deep learning-based approach using YOLOV5 model is used for identifying flowers based on flower phenotype. The images are subsequently augmented using rotation transformation, color balance transformation, brightness transformation and blur processing. The augmented images are used for preparing training sets. Using different versions of YoloV5 the flower image dataset is trained and tested. Primarily, flower phenotype considered has stages like bud formation, blossoming and stale flower.

Index Terms— YOLOV5, Deep Learning, Flower Phenotype, Floriculture, Artificial Intelligence.

I. INTRODUCTION

Floriculture is one of the branches of horticulture, where flowers are grown and marketed. The market value of flowers depends on the supply and demand. The primary purpose of the paper is to identify the flowers based on their life cycle, called 'Phenotype'. The paper primarily considers phenotype of flower in three stages namely, bud, fresh and stale type. Bud and fresh flowers have their own importance in the market. Considering the jasmine flower in coastal Karnataka, India, its bud size is small and needs to be stringed and marketed. Bud type flowers are collected at the early stage and have more life. Thus, automatically identifying buds in the plants is a need of the hour. Fresh flowers are directly marketable, which needs to be fresh. Finally, the stale flowers from the plants are to be discarded and of no use in the market, except for storing as seed for some species.

Various research on identifying the flowers species is carried out using different techniques of computers like machine Learning[17], computer vision[22], deep learning[23]. There is no work on identifying the flower based on phenotype. The authors used deep learning techniques for auto identifying the flowers based on flower phenotype. The paper considers primarily the phenotype of flower like bud, fresh and stale.

The proposed work will help in auto identifying the flower based on phenotype. Thus, the floriculturist are direct beneficiaries of this auto identification technique using deep learning. However, based on the flower species the

importance of phenotype is to be considered.

The remainder of this paper is organized as follows. In Section 2, we discuss the related works carried out in agriculture using object detection using deep neural network. Since the dataset was created by the author for the purpose of flower phenotype detection, the process of dataset creation specifically for YOLOV5 model and its annotation format was discussed in section 3. Introduce the proposed model's network configuration and some methods to adopt deep models from large dataset to small ones is discussed in detail. The details of training are discussed in Section 3. Section 4, focuses on methodologies involved in YOLOV5 architecture and various parameters chosen to run the experiment. Experiments results and analysis are given in Section 5. And finally, we draw our conclusions and future work in Section 6.

II. RELATED WORK

The deep learning techniques can be beneficial for floriculture field in terms of grading, classification, decision support system, disease detection, robotic operations etc. This paper targets on flower classification in the field of floriculture. Convolution Neural Network has the capability of extracting features and identify the class type, diseases type, species type, colour type etc.

Grading of four-dimensional flowers using deep learning technique with in-depth information is discussed by authors[1]. The RGBD information of the flower image was considered for grading. Using four different convolution neural network models the RGBD images were trained and the highest accuracy of 98% was achieved for Inception-V3 model [12]. The authors [2] carried out classification of flowers based on Saliency Map and PCANet. Using the PCANet[10] and Saliency Map [11] algorithms, the classification of hard to distinguish flower types were easily able to recognise with the accuracy of 84.15%. However, using the multi-scale principal component analysis network performance could be improved, by enhancing the feature extraction. Flower classification using VGG-16 model with stochastic gradient technology was discussed in [3]. The flower classification was done for the Oxford flower-102 dataset and compared with AlexNet model gaining more performance with the accuracy and loss. [6] proposed saliency map-based technique using HSV (Hue Saturation Value) color space to classify the flower. The model was developed using VGG16. However, using other CNN (Convolution Neural Network) models the testing was to be conducted to compare the performance metrics[8]. The authors compared various CCN networks with transfer learning to check the performance of flower classification. The transfer learning-based models yielded more accuracy as compared to models without transfer learning. The models like VGG-16, VGG-19[13], Inception V3, ResNet-50 were compared[9]. CNN and transfer learning technique for recognition of flower species. The experiment was conducted on 2 datasets of flowers named FLOWERS28, FLOWERS102. Inception V3 model gave good accuracy compared to Xception and Overfeat models[17]. However, more images of flower species datasets are needed for more species recognition and to achieve more accuracy. CNN for detection of colors like yellow, green, red for Orchid flower type species[18]. A comparative study carried out on VGG16, Inception, Resnet50[19], Xception[20], Nasnet models. The results gave good accuracy on ensemble classifier performed well without segmentation technique was used. The attention mechanism for flower recognition using deep learning technique. The technique of attention mechanism increases the learning ability of the network to achieve 85.7% accuracy using FLOWER17 dataset[21]. However, using more species recognition with enhancement of accuracy needed with state of art recognition technique needs to be experimented. Coffee flower identification using multi scale regions using different classifier algorithms was experimented. FSSM method with depression angle of 77.5 degree concluded to be more performing classifier. However, the experiment was concluded with classifier FSS and angel of 52.5 and 27.5 only. More experiments needs to be carried with more angels and other lclassifier as well[24]. Using VGG-16 of deep neural network model flower classification and recognition carried out using grading descent algorithm. For optimization dropout and transfer learning was used. The developed model performed well as compared to the AlexNet and CNN. However the feature extraction was restricted to salient features of the flowers only[25].

The flowers are detected based on phenotype using the state of art object detection algorithm YOLOV5. YOLOV5 belongs to the single shot detector family of algorithms. Using this model, a quick and accurate flower phenotype determination and localization of flower is identified. The developed application has more significance in the field of floriculture for detection and localization and the model can be extended for robotic operations in the agriculture fields.

III. DATASET PREPARATION

A. Image Data Acquisition

The datasets based on phenotype of flowers are not available online. The authors prepared a dataset by searching images over the internet. We used 'Google' and 'Bing' search engine for image collection by giving keywords in Table 1. The images are downloaded automatically using Google Chrome browser extension, 'Image Downloader'. The downloaded images are manually selected for the creation of datasets. Table 1 provides the details of the number of images downloaded for the dataset creation. The dataset consists of unbalanced images of flower classes. The downloaded images are of various resolution types and are of file type'.jpg'.

TABLE I. NUMBER OF IMAGES OF FLOWER PHENOTYPES

Flower Phenotype	Keyword used	Number of images
Bud	'Flower buds'	450
Fresh	'Blossomed flower'	520
Stale	'Stale flower'	350

B. Image Data Augmentation

Flowers appear to be different in different daylight conditions. The intensity of light and angle of sunlight changes throughout the day, the datasets need to be provided with all types of images of flowers for efficient and easy recognition. Table 2 augmentation default setting is used for training in YOLOV5 models to enhance the training sets.

TABLE II. AUGMETATION USED DURING TRAINING ON YOLOV5

Augmentation Parameter	YOLOV5 key	Value	
Hue	hsv_h	0.015	(fraction)
Saturation	hsv_s	0.7	(fraction)
Value	hsv_v	0.4	(fraction)
Translation	translate	0.1	(fraction)
Scale	scale	0.5	(gain)
Flip left to right	fliplr	0.5	(probability)
Mosaic	mosaic	1	(probability)

C. Images Annotation and Dataset Creation

The YOLOV5 model of neural network expects the image datasets to be annotated manually to carryout training for the detection of flower phenotype, the process is called labelling. Various labeling tools are available supporting the model. For YOLOV5 model, the labeling of images is carried out using tool 'LabelImg'[7]. The annotation format to be selected is 'Yolo' while labeling, which is a text document per image. The labeling of images is done manually, since the dataset is custom made. The images are annotated by selecting the appropriate phenotype of flower in the image considered in the form of bounding boxes. The classes considered during annotations for images are 'Bud', 'Fresh', and 'Stale'.

IV. METHODOLOGIES

A. YOLO Network Architecture

YOLO stands for You Only Look Once, and is state of art architecture used in recent times specifically for object detection in deep learning models. It is a one stage object detector technique. YOLO is a regression algorithm for real time object detection in computer vision applications. The YOLO algorithm uses a single bounding box regression, which identifies height, width, center, and object classes. It surpassed Fast R-CNN (Region based Convolutional Neural Networks) (Region based Convolutional Neural Networks), RetinaNet, and Single-Shot MultiBox Detector (SSD), because of its accuracy, speed, and ability to detect objects in a single run. Several notable characteristics like improving the detection time given that it predicts objects in real-time. It provides accurate results with minimal background errors. The model has learning capabilities that enable it to learn the representations of objects and implement them in object detection tasks.

Working of YOLO

YOLO-based models do not scale in terms of space, it uses three fundamental techniques for its operation. Initially, the model divides the input image into $S \times S$ grids, where each grid is responsible for detecting an object or a part of the object that appears inside the grid. Secondly, the objects in each grid are highlighted with a bounding box having properties like weight, height, class, and center. The YOLO model predicts these with a bounding box regression, representing the probability of an object appearing in the bounding box. Finally, the Intersection over Union (IoU), is used which describes the overlap of bounding boxes. Each grid cell is responsible for predicting the bounding boxes and their confidence scores. The IoU is calculated by dividing the area of the overlap by the area of union. The IoU is equal to 1 if the predicted bounding box is the same as the ground-truth bounding box. This way, it becomes easier to eliminate the bounding boxes that are too different from the real box. After dividing the image into grid cells, each cell predicts bounding boxes with probability scores as well as class probabilities for each object. The IoU makes sure that final detection ends up in unique bounding boxes that enclose objects perfectly.

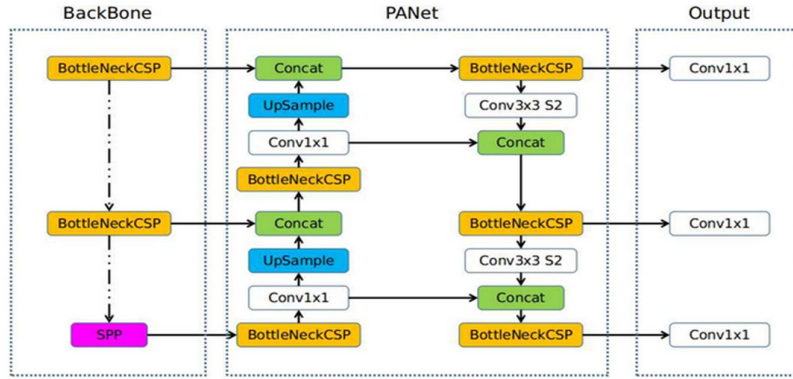


Figure 1: YOLOV5 Architecture [5]. The YOLOV5 network consists of three parts: backbone, neck, and output. The backbone of the network focuses on extracting feature information from input images, neck part extracts the three feature maps, and the output part detects the objects from these generated feature maps

In this paper, we considered the YOLOV5 model for the recognition of flower phenotype. The YOLOV4[4] was the previous version of YOLOV5 model [5]. The YOLOV5 consists of backbone, neck, and head. Using the backbone model, the input image important feature extraction is carried out by CSPDarknet[14]. Using the neck model feature pyramids are generated. Feature pyramids help models to generalize well on object scaling. It helps to identify the same object with assorted sizes and scales. Using PANet the image feature fusion is carried out. The model head is used to perform the final detection part. It applied anchor boxes on features and generates final output vectors with class probabilities, objectness scores, and bounding boxes.

Figure 1, gives the architecture of YOLOv5 having parameters like activation function, optimization function and cost function. An activation function is the one used to decide whether a neuron is to be activated or not. There are various activation functions like Leaky ReLU, mish, swish, sigmoid etc. YOLOV5 uses Sigmoid and Leaky ReLU as activation functions. Optimization function can be of maximizing or minimizing the output from a function, which is a relative term. YOLOV5 uses Stochastic gradient descent (SGD) and Adam as optimization functions, by default SGD is used as optimization function. The cost function is used to get the best result. In the YOLO family, there is a compound loss calculated based on objectness score, class probability score, and bounding box regression score.

B. Experimental Evaluation Indexes

The mean average precision (mAP), precision and recall were adopted as the evaluation indexes of the model to detect and localize the flower phenotypes. The results were assessed as true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Precision estimates how many of a classifier's predictions are actually right. The higher your precision is, the fewer false positives (FP) are generated by your model.

$$Precision = \frac{TP}{TP + FP}$$

Recall indicates how many ground truth labels your classifier is able to pick up. The quality of the model is determined using precision parameter.

$$Recall = \frac{TP}{TP + FN}$$

Mean Average Precision(mAP), is the metric specifically used for multiclass object detection. It incorporates the tradeoffs between precision and recall. Considering both types of errors, false positives (FP) and false negatives (FN). This property makes mAP applicable for most use cases.

Models with high precision and low recall produce very confident predictions but miss a part of the instances. Models with low precision and high recall, can find most objects, but the predictions are false positives to a certain degree, and confidence decreases. The mAP is the mean of the AP over all classes. Perfect models would have an AP of 1.0.

$$MeanAveragePrecision, mAP = \frac{\sum_{c=1}^C AveP(c)}{C}$$

where,

AveP(c) – Average Precision for class ‘c’, C- Total number of classes.

In the experiments we have used mAP_0.5 and mAP_0.5:0.95. The mAP_0.5 indicates mean average precision with IoU (Intersection over Union) of 0.5. Similarly, the mAP_0.5:0.95 indicates, average mAP over different IoU thresholds, from 0.5 to 0.95, in step 0.05.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

F1 score determines the optimum confidence for a given model balancing precision and recall. F1 is a good indicator of overall model performance whose value ranges between 0 to 1.

V. EXPERIMENTAL RESULTS

The experiment was conducted on google Colab environment which uses Tesla K80 GPU machine, using 10GB of GPU memory approximately during experiment. The model having 270 layers, uses 7 million plus parameters with 15.87 GFLOPS.

A. Result of flower phenotype recognition using one of YOLOV5 model

The model was trained up to 150 epochs with auto batch size. The auto batch was selected to speed up the process of training. One of the training batches given for training the dataset in figure 2. The batch selection of images is random and all the classes of phenotypes are visible in the batches created during the training as shown in figure 2.

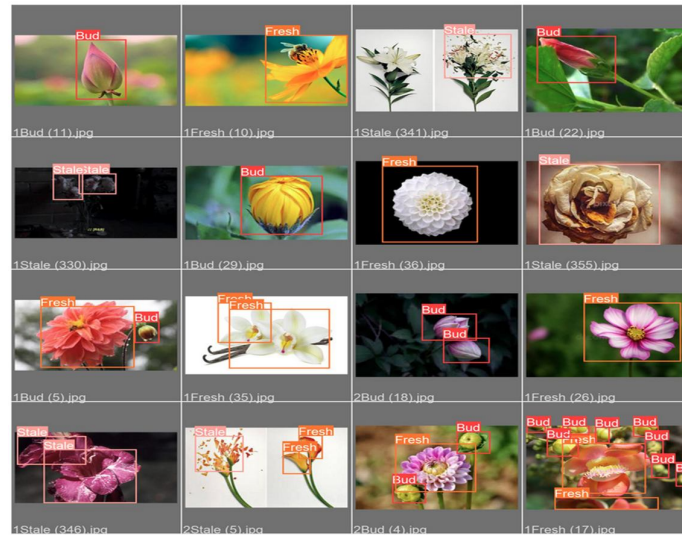


Figure 2: Batch of flowers during training set along with annotation in YOLO format

Figure 3, gives the result of flower phenotype of all class detection using the model of YONOV5s.

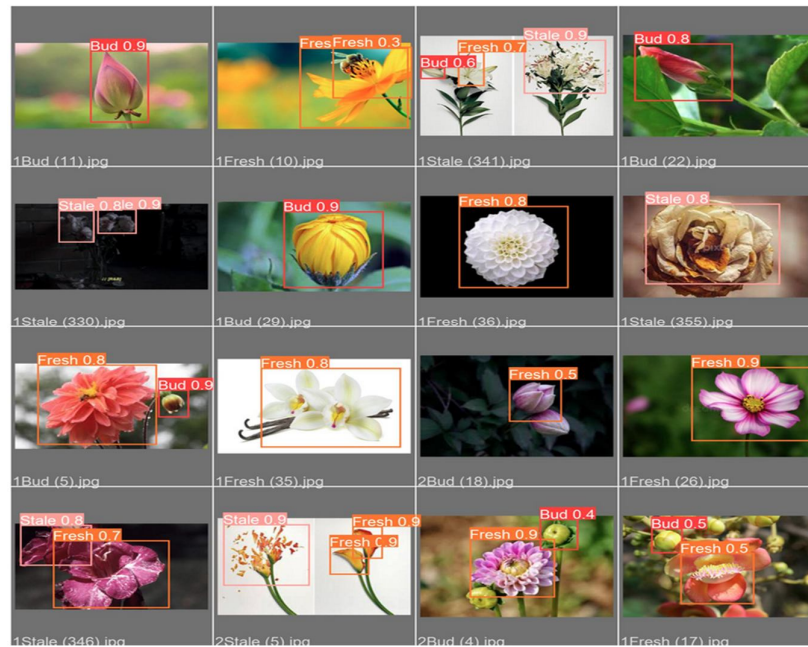


Figure 3: Object detection using YOLOV5s representing localization and flower phenotype recognized

Figure 4, shows the result on testing the images taken randomly from the internet and able to recognize multi class type phenotype using the trained model. The group of stale flowers are recognized in groups. The percentage of the detected phenotype along with the location in image are the result.



Figure 4: Results of Flower phenotype detection for randomly picked images from internet using YOLOV5s model

Metrics like precision, recall and F1 score work together for evaluating the model at various confidence level to determine the performance of the model and what parameter optimizes the performance can be determined. Usually as the threshold of the confidence increase, the precision will increase and the recall starts decreasing. This can be observed in the following figure5 and figure 6.

From the F1 score curve the balance between precision and recall can be seen and decision can be taken using the figure 7. The confidence value that optimizes for precision and recall is at 0.501.

Considering the model YOLOV5s, the optimal confidence value of 0.65 can be considered. Since the F1 value appears to be about 0.65, which is not too far from the maximum value of 0.69 in figure 7. From the figure 5 and figure 6 it can be observed that 0.65 confidence for precision and recall suits well for design. At the point of 0.65 the recall value begins to suffer and precision value exhibiting well.

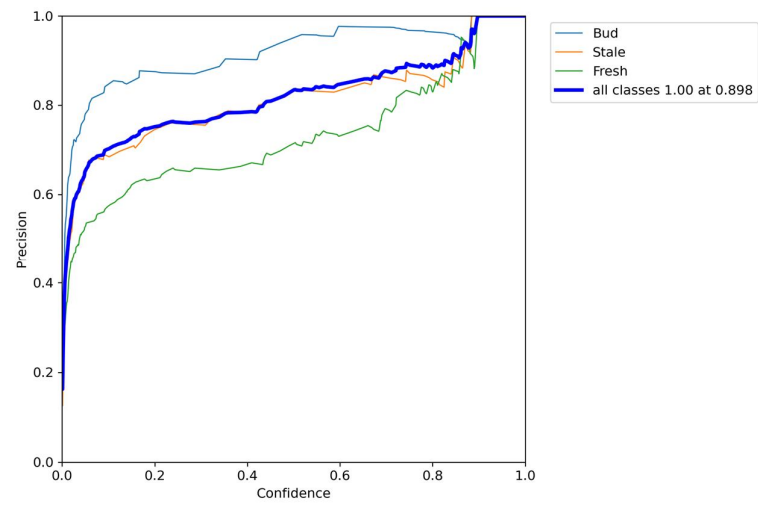


Figure 5: Multi-class precision score for 'flower phenotype' dataset using YOLOV5s object detection model

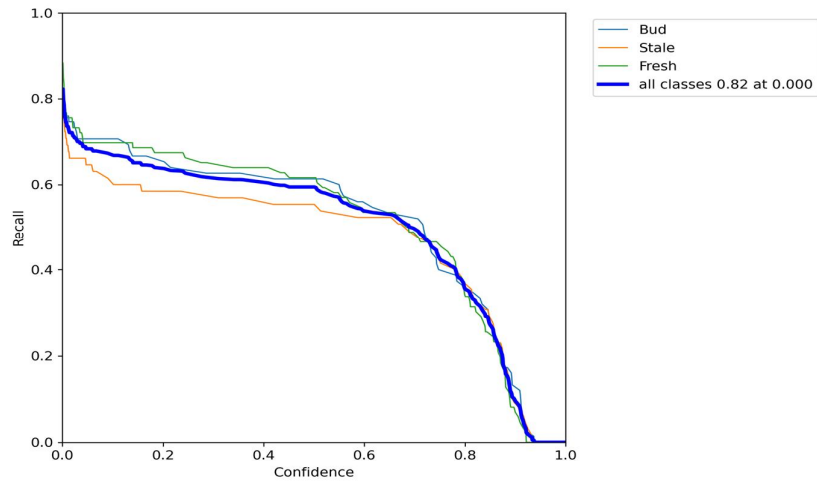


Figure 6: Multi-class recall score for 'flower phenotype' dataset using YOLOV5s object detection model

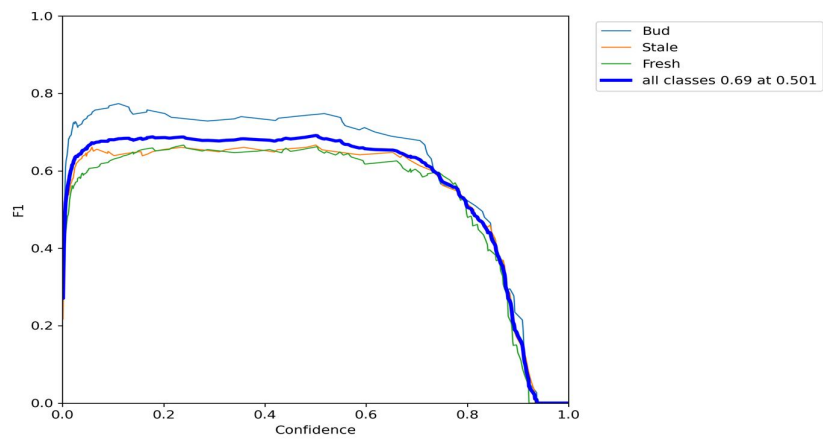


Figure 7: F1 score curve for 'flower phenotype' dataset using YOLOV5s object detection model

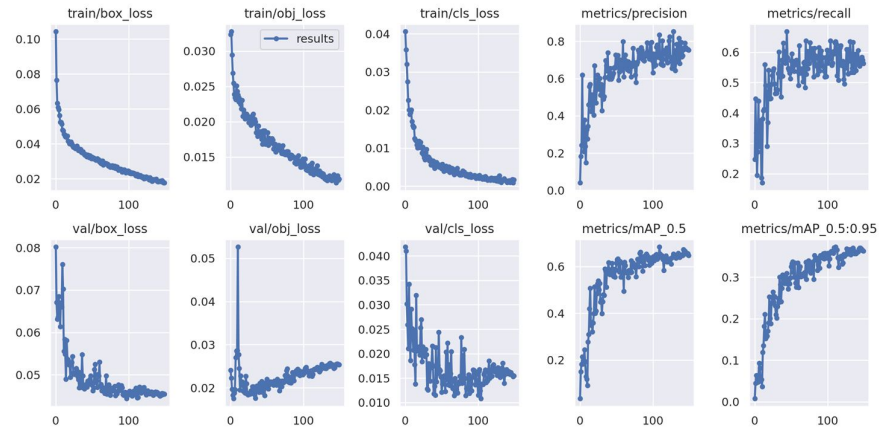


Figure 8: Results of running 'flower phenotype' dataset using YOLOV5s object detection model

Figure 8, shows the various results of running custom made dataset of 'flower phenotype' using YOLOV5s model.

B. Analysis of training 'flower phenotype' dataset on different YOLOV5 models

The dataset was run on different versions of YOLOV5 models such as YOLOV5n, YOLOV5s, YOLOV5m, YOLOV5l and the results like mAP(mean average precision), recall and precision are represented.

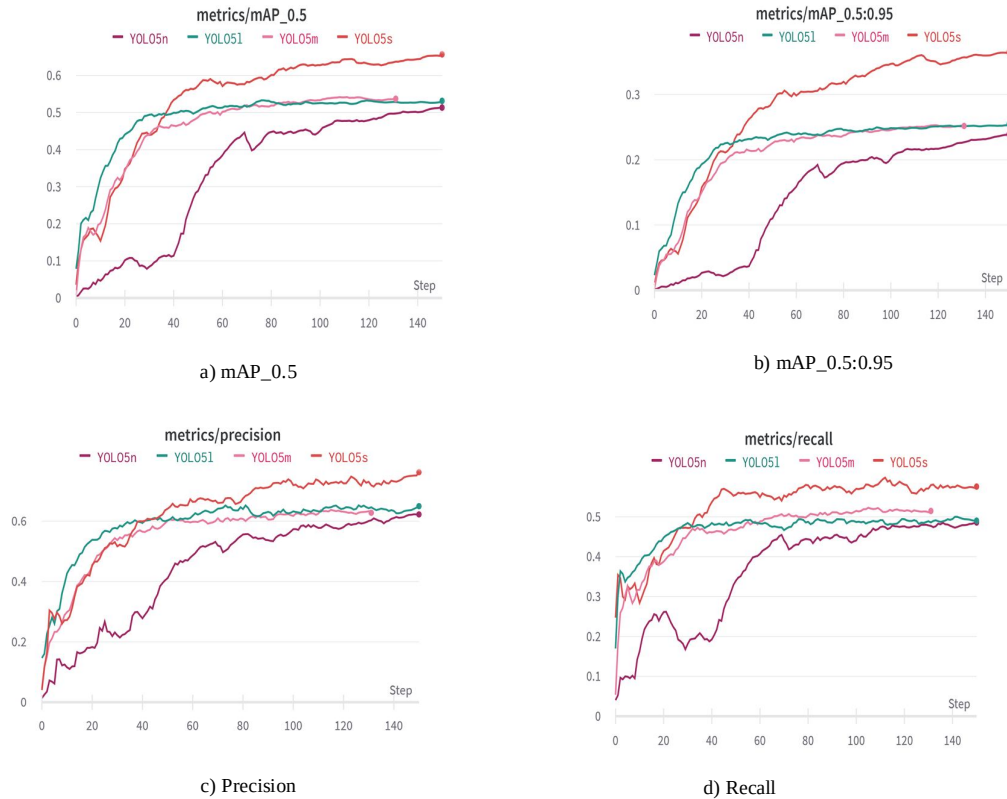


Figure 9: The analysis results of various YOLOV5 models on metrics like (a) mAP_0.5, (b)mAP_0.5:0.95, (c)Precision and (d)Recall.

Table 3, shows various results on running ‘flower phenotype’ custom dataset on various YOLOV5 models. The YOLOV5s model gave superior results as compared to that of other models such as YOLOV5l, YOLOV5m and YOLOV5n. It can be observed from figure 6 that mAP, precision, recall stated showing linear changes after 100 epochs. So, 100 epochs is the point of early stopping for the models indicating no further improvement can be observed further for training.

TABLE III: RESULTS OF RUNNING ‘FLOWER PHENOTYPE’ CUSTOM DATASET ON VARIOUS YOLOV5 MODELS

		Various YOLOV5 models			
		YOLO5n	YOLO5s	YOLO5m	YOLO5l
Metrics for Our dataset of image size= 416	Recall	0.5	0.59	0.54	0.49
	Precision	0.62	0.83	0.59	0.68
	mAP_0.5	0.52	0.68	0.55	0.56
	mAP_0.5:0.95	0.24	0.37	0.25	0.26

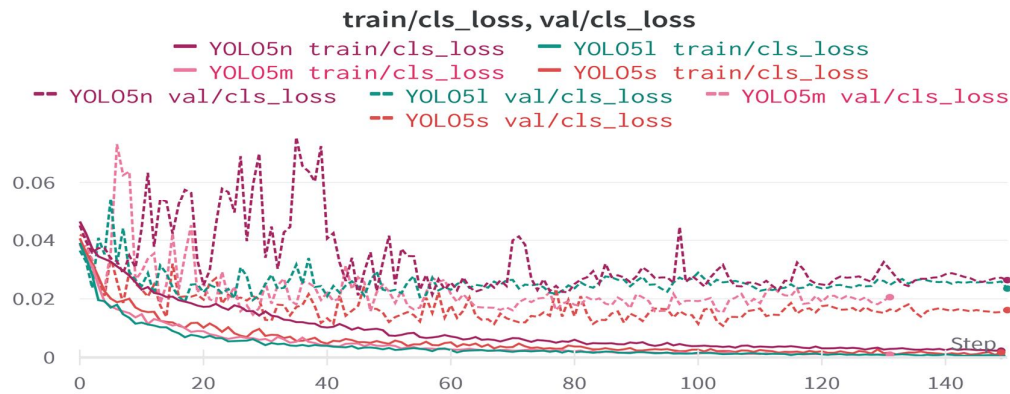


Figure 10: Comparative result of class loss on train and validation for various YOLOV5 models

Figure 10 compares the result of train and validation class loss for various YOLOV5 models. The validation class losses after 120 epochs are almost aligned to single line, but the losses with respect to validation are distinguishable, comparatively less losses are observed at YOLOV5s model.

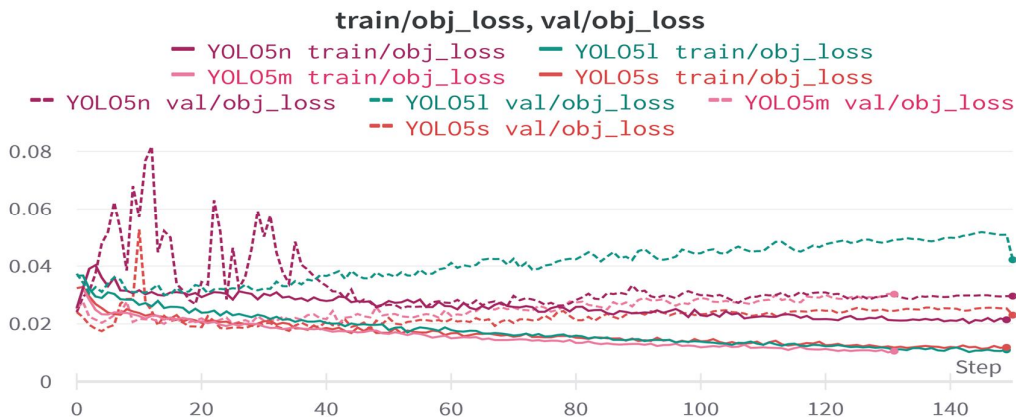


Figure 11: Comparative result of train and validation object loss for various YOLOV5 models

Figure 11, shows the comparative object losses for various models of YOLOV5, it can be observed that the object losses for train for all YOLOV5 models are almost same, whereas the object loss for validations are

clearly distinguishable for each of YOLOV5 models and is more for YOLOV5l model. The very small gap between class loss and object loss for train and validation indicates the non-existence of over-fitting.

VI. CONCLUSION AND FUTURE WORK

Various methodologies using Computer Vision, Machine Learning, Deep Learning were proposed for species classification of flowers. This paper using YOLOV5 model for the detection of flowers based on its phenotype feature. We developed a new dataset of flowers based exclusively on flower phenotype. Using deep learning technique, we trained our model using custom dataset on various YOLOV5 family models. Using YOLOV5s version of the model gave good result for recognition and localization of flower phenotype as compared to that of other versions of YOLOV5. Thus, the state of art YOLOV5s gave superior results for detection of flower phenotype for the dataset created for the purpose. Among the available models of YOLOV5, 'YOLOV5s' gave superior results in terms of the metric parameters considered.

As a future work, the dataset can be enhanced with more images of various image sets along with appropriate annotation formats. Multi-class identification of flowers along with phenotype can be included. The datasets can be compared against other available CNN detection algorithms.

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