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Automated Mushroom Classification System using Machine Learning

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ABSTRACT

The mushroom farming industry is on the rise and there is a growing demand for high-quality, sustainable production methods. However, mushroom cultivation can be challenging for growers, as it requires careful environmental control and can be labour-intensive. This paper presents the results and analysis of a mushroom classification system, designed to accurately classify two types of mushrooms: Shiitake and oyster mushrooms. The system utilizes advanced machine learning algorithms and an extensive dataset to achieve accurate classification results. Technology replaces human inspection with computer vision, providing farmers with a quick and precise tool for classifying various mushroom species. The augmented and labelled mushroom dataset is divided into three distinct subsets: validation, testing and training. In this study, 80% of the data is allocated for training, while 20% is reserved for testing. The outcomes have proven the efficacy of You Only Look Once version 8 (YOLOv8) model, with an astounding accuracy of over 90%. This study suggests that the YOLOv8 model has the potential to be an accurate method for distinguishing different varieties of mushrooms. Farmers can significantly reduce the time and effort they previously expended on manual inspections by utilizing this approach.

1. Introduction

Mushroom farming has experienced a substantial surge in popularity in recent times and has become a swiftly expanding industry [1-3]. It offers not only profitability but also sustainability and eco-friendliness in agricultural practices. Nonetheless, mushroom cultivation poses challenges for growers, such as the requirement for meticulous environmental management and the labour-intensive nature of the procedure. The classification of mushrooms, particularly Shiitake mushrooms (often referred to as black mushrooms) and oyster mushrooms, poses a significant challenge due to their subtle visual differences and overlapping features. Existing manual classification methods are time-consuming, subjective and prone to errors. Therefore, there is a need for an accurate

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mushroom classification system that can efficiently differentiate between Shiitake mushrooms and oyster mushrooms based on objective criteria, contributing to improved efficiency and reliability in mushroom farming and research.

Large amounts of data about mushrooms have been gathered over the years and programs have been created to classify mushrooms. To provide more accurate decision-making, many classification systems have been created and improved [4]. Classification represents a form of supervised learning, involving the segmentation of data into pre-established categories or classes that are predetermined before analysing the data. The significance of classification lies in its ability to predict data values by drawing upon established results derived from a wide array of data collections [5]. In previous research, researchers used classification algorithms to make predictions. For example, in forecasting the behavioural features for mushroom classification, Ismail *et al.,* [4] used a Decision Tree classification system. Yadav's work involved the utilization of Decision Tree and Bayesian Network techniques to ascertain the optimal classifier for predicting student performance [6]. Another investigation focused on the identification of behavioural malware through the application of Nave Bayes classification methods [7]. The outcomes highlighted that data mining proves to be more efficacious in detecting malware. The experimental findings endorsed the viability of classifying behavioural attributes of malware as a pragmatic approach in the development of behavioural antivirus solutions.

The availability of huge data and processing power has resulted in significant success in the field of Artificial Intelligence (AI) [8-10]. Machine Learning (ML) has emerged as a major highlight in AI due to its ability to self-improve as it is fed new data. It saves time, reduces expenses and adds value [11,12]. Contrary to popular belief, artificial intelligence (AI) is not a new idea. McCarthy proposed it in 1956 at the first summer workshop at Dartmouth College in New Hampshire, US [13]. For many years, AI was either a scholarly topic or a source of inspiration for science fiction writers. However, there has been a dramatic acceleration in recent years in areas such as data availability, processing power and algorithm efficiency [14]. One of the highlights of this AI revolution is the ability of machine learning algorithms, software that self-improves as it is fed more and more data, to identify mushrooms as edible or deadly. A dataset containing 8124 instances and 22 mushroom features was downloaded from the UCI Machine Learning Repository in order to classify the mushrooms as edible or poisonous [15]. Werapan *et al.,* [16] in their study has proposed You Only Look Once version 8 (YOLOv8) to classified between poisonous and edible mushrooms. Additionally, YOLOv8 has been employed in previous works for classification tasks involving tomatoes [17], fruits [18] and other agricultural products [19].

This project aims to develop a computer vision-based mushroom classification system using YOLOv8 to address the lack of a reliable and standardized system for categorizing and differentiating between mushroom types. The incorporation of deformable convolution layers in the YOLOv8 architecture aims to overcome the limitations of traditional convolutional layers when dealing with objects of different scales and aspect ratios. The current absence of such a system poses challenges for professionals in accurately identifying and classifying mushrooms based on their characteristics. This project intends to simplify and streamline the process, providing a solution for accurate mushroom classification through computer vision technology.

2. Methodology

The methodology employed for the classification of oyster and Shiitake mushrooms using a machine learning approach is shown in Figure 2 below. The methodology encompasses various steps including image acquisition, image annotation, image augmentation, data splitting, model training,

evaluation and recognition output. This systematic process ensures accurate classification and reliable performance of the trained model. The steps for classification of mushrooms are as following:

i. Mushroom selection: This study focuses on two types of mushrooms, namely oyster and Shiitake mushrooms. These mushrooms have been chosen due to their distinct characteristics and prevalence from the 300 samples. Figure 1 provides a representation of the target classes for classification.

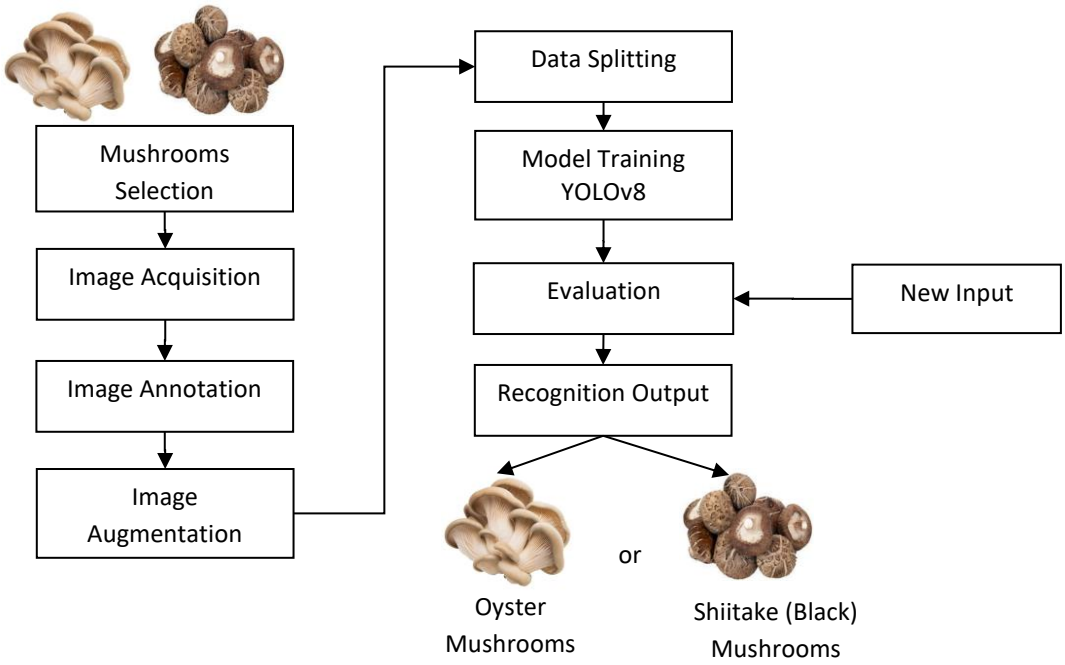


Fig. 1. Classification block diagram of oyster and Shiitake mushrooms

ii. Image acquisition: The initial step involves acquiring images of Shiitake and oyster mushrooms from 300 samples. The Logitech C920 camera was utilized to capture high-resolution images of the mushroom samples. The camera was set up in a controlled environment with consistent lighting conditions to ensure high-quality images. Each mushroom was photographed from multiple angles to capture comprehensive visual data.

iii. Image annotation: The acquired images are annotated by assigning labels corresponding to their respective mushroom types (Shiitake or oyster). Image annotation creates a labelled dataset that serves as the foundation for model training and evaluation. Each image is associated with its designated class, facilitating the learning process for the machine learning model.

iv. Image Augmentation: Image augmentation is employed to increase the diversity and generalization capability of the dataset. Annotated images undergo augmentation by applying transformations such as rotation, scaling or flipping. By introducing these variations, the dataset captures a wider range of mushroom characteristics, enabling the model to better handle unseen data and improve classification performance. This step is crucial in developing a robust and accurate classification model. Through the utilization of computer vision, the system obviates the necessity for human inspection and provides producers with a streamlined and precise instrument to evaluate the quality of their crops. The YOLOv8 model autonomously evaluates visual signals in order to identify

indications of damage in individual mushrooms crops. The dataset used for assessing the crop classification system was specifically created for this project. Initially, we captured 300 mushroom samples using a Logitech C920 camera. To enhance the dataset, various data augmentation techniques such as rotation, scaling, flipping and colour adjustments were applied. This process increased the dataset size from 300 to 1009 samples, providing a more diverse set of images for training the classification model.

v. Data splitting: To evaluate the performance, the augmented dataset is divided into training and testing subsets. The data splitting process ensures the model is trained and evaluated on independent datasets. The training subset is used to train the classification model, enabling it to learn distinguishing features of Shiitake and oyster mushrooms. The testing subset is used to assess the performance and evaluate its effectiveness.

vi. Model training: The training subset is employed to train a machine learning model, specifically a convolutional neural network (CNN). The CNN is capable of learning intricate patterns and features from the annotated images.

vii. Evaluation: The trained model is evaluated using the testing subset to assess its performance and effectiveness. Various evaluation metrics, such as accuracy, precision, recall and F1 score, are utilized to measure the model's classification accuracy and overall effectiveness. This step provides insights into the model's strengths, weaknesses and potential areas for improvement.

viii. Recognition Output: In the final stage, the trained model is deployed for recognition output. New and unseen images of mushrooms are presented to the model for classification. The model processes each image and produces the predicted mushroom type (Shiitake or oyster) as the output. This step demonstrates the model's ability to classify mushrooms accurately in real-world scenarios.

The flowchart, depicted in Figure 2, illustrates the sequential process of a mushroom classification system. The flowchart summaries the steps involved in the system, beginning with webcam camera initialization, followed by input reception and concluding with mushroom identification and classification.

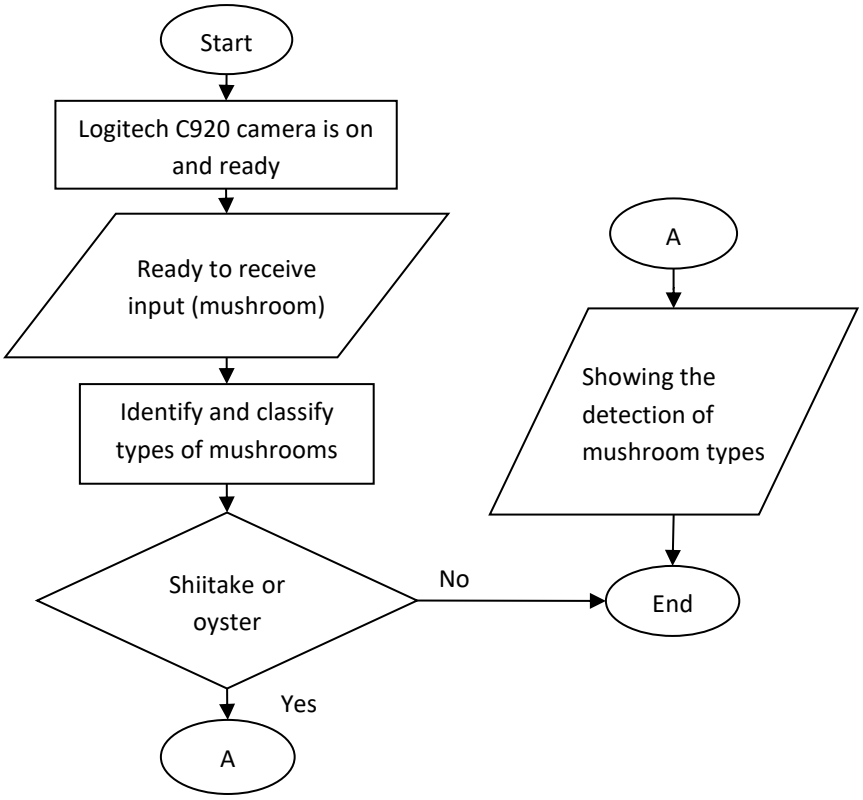


Fig. 2. Flowchart of mushroom classification system

Start is the initial step of the flowchart, indicating the beginning of the process or program. "Camera is on and ready," indicating that the webcam camera is powered on and in a state of readiness to capture images. The Logitech C920 camera was mounted on a tripod and positioned approximately 30 cm away from the mushrooms. Images were captured at a resolution of 1920x1080 pixels. Consistent lighting was maintained to avoid shadows and reflections, ensuring the clarity and quality of the images. This step signifies the initial setup where the webcam camera is operational and prepared for image acquisition.

The subsequent step, "Ready to receive input (mushroom)," represents the program or process waiting to receive input in the form of an image of a mushroom. The webcam camera remains in a waiting state, expecting the user to provide the mushroom image. The flowchart then proceeds to the step "Identify and classify types of mushrooms." This step represents the core functionality of the program or process. After the Logitech C920 camera is activated, video input and a pre-trained model utilizing YOLOv8 to detect mushrooms are received by the system. The aforementioned model plays a pivotal role in facilitating the ensuing stages of the procedure. Subsequently, the pre-trained model is employed in conjunction with the video input to perform mushroom detection, localization and classification. By harnessing the capabilities of YOLOv8, the system conducts an analysis of every frame in the video, discerning the existence of mushrooms and pinpointing their precise positions within the frame.

Following the identification and classification step, the program or process decides based on the determined mushroom type. The decision is binary in this case, limited to categorizing the mushroom as either a Shiitake mushroom or an oyster mushroom. Showing the detection of mushroom types is a step that implies the program or process to provides some form of output or display to show the detected mushroom types. It could be visual feedback, such as highlighting or labelling the identified mushrooms on a screen or providing text-based information about the detected types. Lastly, the end process is the final step of the flowchart signifies the conclusion of the process or program. It

indicates that the flowchart has reached its conclusion and the program may terminate or continue with further actions as required.

2.1 Model Development

The YOLO algorithm is one of the one-step object detectors. Many versions of the algorithm have come out since the day it was published. YOLOv8 was used in the study. The pipeline consists of three parts: backbone, neck and head. The model was trained with using two types of mushrooms which is Shiitake and oyster mushrooms. At present, the augmented and labelled mushroom dataset is partitioned into two distinct subsets, namely validation, testing and training. In order to train the model, assess its performance and optimize its parameters, the data is partitioned. In general, training is allocated 80% of the data, testing 20%. During the training phase, the YOLOv8 algorithm is provided with the labelled and augmented mushroom images. The training process was carried out in an environment with NVIDIA GeForce MX150 support. Other details of the training are as shown in the Table 1 below:

Table 1
Training details of YOLOv8 model

Input Dimension	Software Language	Environment	Library	Epoch	Optimizer
756 (Width) x 1008 (Height)	Python	Anaconda	Ultralytics	140	YOLO

2.2 Performance Metrics

Several measurement criteria are commonly employed to assess the performance of an object detection model. Among them, some notable examples include Precision, Recall, Average Precision (AP) and mean Average Precision (mAP). When calculating performance criteria, TP, FP and FN values are examined [20,21].

i. TP: The actual class of the data and the predicted class true.
ii. FP: The actual class of the data is incorrect and predicted class correct,
iii. FN: The actual class of the data is accurate and predicted class is incorrect

Precision is the metric used to measure correct predictions. It is calculated as in Eq. (1).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall also known as the true positive rate, quantifies the likelihood of correctly detecting exact reference objects. It is computed using Eq. (2), which is given as follows:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Average Precision (AP) is an additional metric employed for assessing the performance of object detectors. It combines precision and recall and provides a single numerical value that summarizes the Precision-Recall curve. AP is calculated by averaging the recall values from 0 to 1. This is typically done using the equation provided in the 11-point interpolated AP method given in the Eq. (3) below.

$$AP = \frac{1}{M} \sum_{r \in (0,0.1,0.2,...1)} P_{interp}(r) \tag{3}$$

Mean Average Precision (mAP) is a metric used when evaluating object detection models. When calculating mAP, if the dataset consists of M class categories, it takes the average precision (AP) over all M classes. The mAP value is calculated using Eq. (4), which is given as follows:

$$mAP = \frac{1}{M} \sum_{j=1}^{M} AP_j \tag{4}$$

3. Results and Discussion

The confusion matrix is a straightforward and intuitive method used to determine the accuracy of a model. It provides valuable information about instances of misclassifications and confusion with the "background" category, enabling an assessment of the overall effectiveness of the model. In the context of AI predictions, a confusion matrix comparing Shiitake and oyster mushrooms with the background is shown in Figure 3.

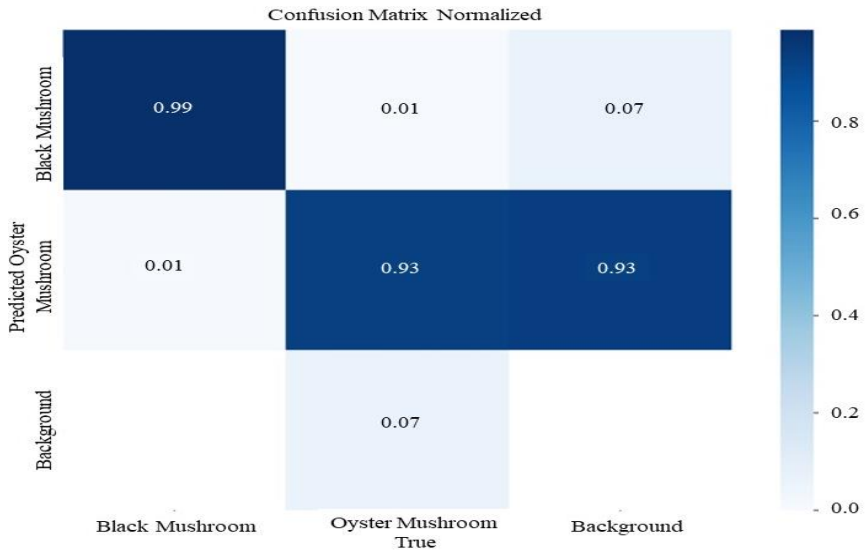
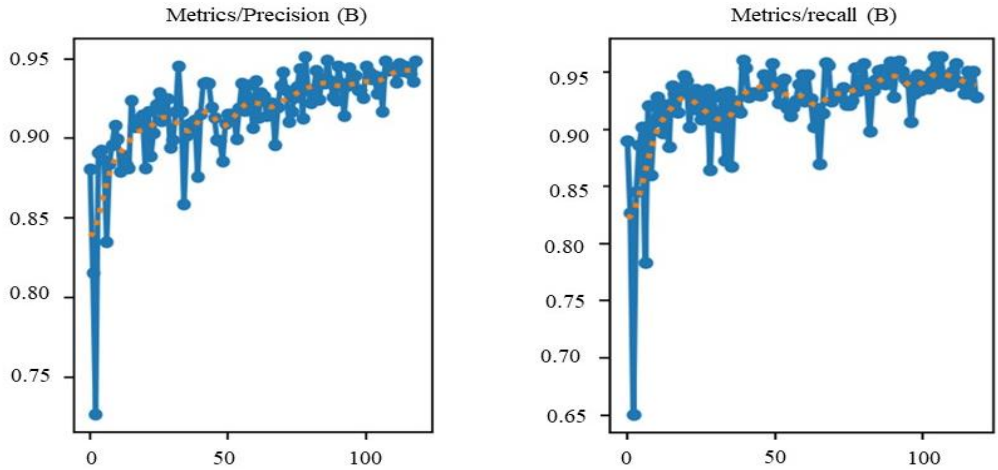


Fig. 3. Confusion matrix of the proposed model

The purpose of this evaluation is to assess the performance of the system based on the available data. The findings indicate that the system achieves a reliable detection rate of 99% for Shiitake mushrooms and 93% for oyster mushrooms. These results indicate that the AI model has developed the capability to accurately distinguish and identify both Shiitake and oyster mushrooms from the background. These positive outcomes demonstrate the system's potential to support precise and efficient mushroom classification procedures.

The precision and recall curves of the training process are shown in Figure 4(a) and 4(b), respectively. Based on Figure 4(a), achieving precision of more than 0.90 on epoch 100 indicates the ability of the model to accurately identify and classify objects has significantly improved. This result highlights the capability of the model to make reliable and accurate predictions, making it a valuable tool for object detection tasks. Besides, achieving a recall of over 0.90 on epoch 140 after raining

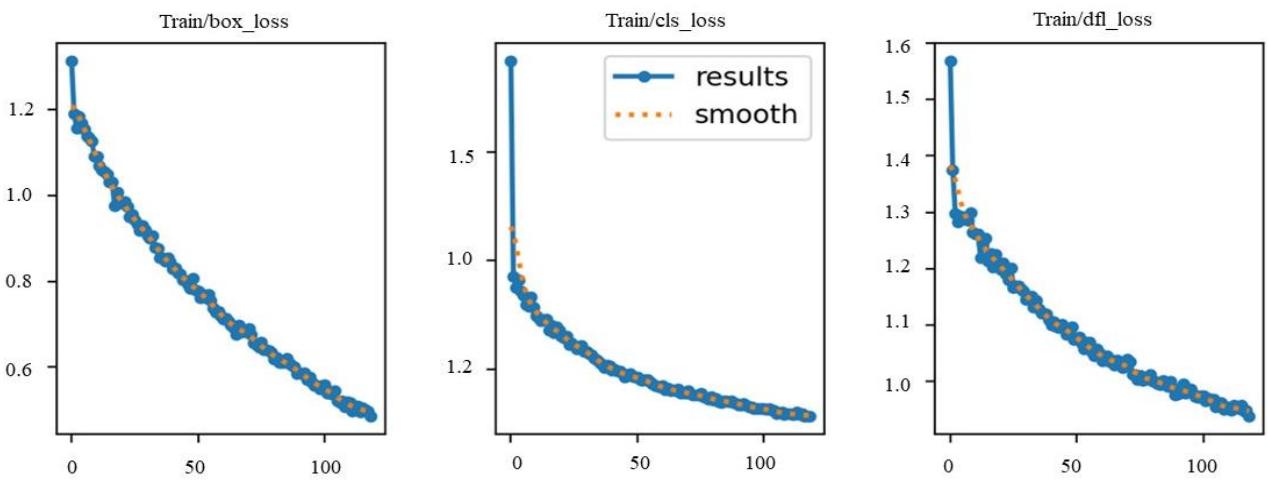
with YOLOv8 indicates the model has strong ability to accurately detect and capture a high proportion of the actual positive instances in the dataset.



(a) (b)

Fig. 4. The curve of (a) precision (b) recall

Figure 5 shows the training graphs of the model for 140 epochs are presented. In Figure 6(a), the result specifically shows the graph of bounding box regression loss, which measures the error in the predicted bounding box coordinates and dimensions compared to the ground truth. As the number of epochs increases, the box loss decreases, indicating that the accuracy of the predicted bounding boxes improves over time. Subsequently, the ability of the model to accurately localize objects or regions of interest becomes more refined, resulting in more precise bounding box predictions. Figure 5(b) illustrates the graph of classification loss which assesses the deviation between the predicted class probabilities for each object in the image and the corresponding ground truth values. The results show that the number of epochs increases, if the classification loss decreases, which suggests that the model is improving its ability to classify objects correctly, refining its understanding of the different object categories within the data.



(a) (b) (c)

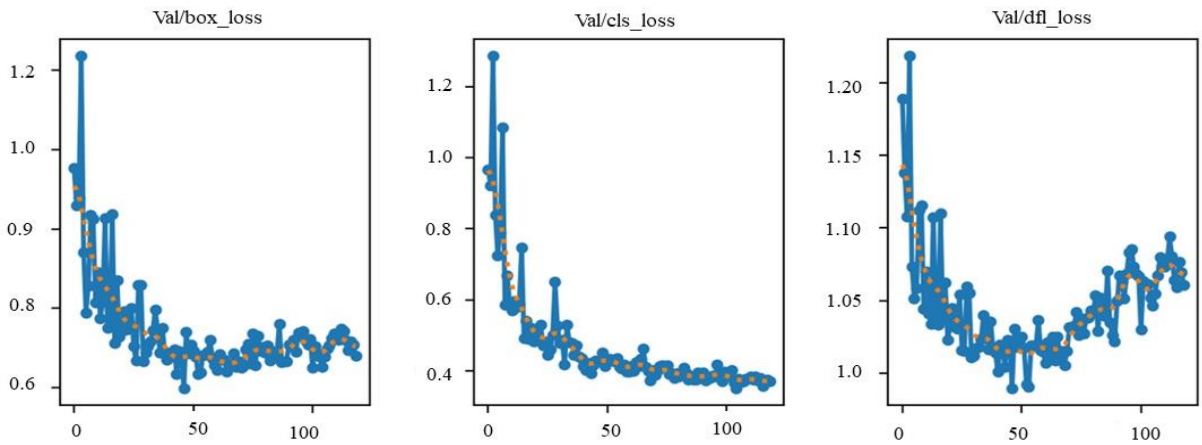
Fig. 5. Train graphs of (a) bounding box regression (b) classification (c) deformable convolution layer losses

Figure 5(c) specifically presents the graph of deformable convolution layer (dfl) loss, which evaluates the disparity performance in the deformable convolution layers. These layers are

incorporated in the YOLOv8 architecture to enhance the capability of the model to detect objects with different scales and aspect ratios. As observed in the results, the dfl loss decreases as the number of epochs increases, which proved that the system is proficient in handling object deformations and variations in appearance. This signifies that the model has successfully adapted to diverse object shapes, sizes and orientations, leading to improved object detection accuracy for objects with varying characteristics.

Figure 6 below shows the plots of the performance loss of a model during validation phase validation over a series of 140 epochs. From the results, the validation loss goes below 0.8, 0.6 and 1.05 for the bounding box regression loss, classification loss deformable convolution layer loss, respectively. In Figure 6(a), the bounding box regression loss goes below 0.8, indicating that the model is able to accurately predict the position or size of bounding boxes with relatively low error.

In Figure 6(b), The classification loss goes below 0.6, suggesting that the model is performing well in classifying objects or entities within the given data. The deformable convolution layer loss in Figure 6(c) goes below 1.05, indicating that the deformable convolution layer is successfully learning and adapting to the input data. However, as the training progresses, the deformable convolution layer loss start to increase after 50 epochs which shows instability in learning accuracy. By implementing techniques to prevent overfitting, such as regularization methods, dropout or early stopping may help the model generalize better and reduce the increase in the loss over time.



(a) (b) (c)

Fig. 6. Validation graphs of (a) bounding box regression (b) classification (c) deformable convolution layer losses

Figure 7 shows the results of detected mushrooms with different samples of oyster and Shiitake mushrooms.

Fig. 7. Different samples of oyster and Shiitake (black) mushrooms detected using Logitech C920 camera

From the figure, the results show that the system achieved outstanding accuracy, surpassing 90% in accurately differentiating between Shiitake mushrooms and oyster mushrooms. Specifically, the system achieved an accuracy rate up to 92.5%, demonstrating its reliability in classifying the two mushroom types. The high accuracy results obtained by system are noteworthy and indicate its robustness in correctly categorizing Shiitake mushrooms and oyster mushrooms. The factors contributed to the exceptional performance of the system are:

i. Feature Extraction: The system employed an extensive range of features, including colour, shape and texture, to capture the distinctive characteristics of Shiitake mushrooms and oyster mushrooms. By utilizing a diverse set of features, the system was able to extract relevant information and make accurate classifications. This comprehensive feature extraction approach played a significant role in achieving high accuracy results.

ii. Dataset Quality: The performance of the system was assessed on an independent dataset comprising 300 mushroom samples, which was then augmented to 1009 samples. The dataset used for training and evaluation was carefully compiled and labelled to ensure accuracy and diversity. It encompassed a wide variety of Shiitake mushrooms and oyster mushrooms, capturing the nuances and variations within each type. The inclusion of such

a high-quality dataset enabled the system to generalize well and achieve accurate classifications. The achieved accuracy of above 90% for differentiating between Shiitake mushrooms and oyster mushrooms underscores the effectiveness and practical applicability of the Mushroom Classifying System. The high accuracy rate ensures reliable classification results, which can be invaluable for mushroom growers, distributors and consumers, researchers and others.

4. Conclusions

The classification of mushrooms poses a significant challenge due to their subtle visual differences and overlapping features. In this study, a mushroom classifying system has been developed with the capability to accurately differentiate between two types of mushrooms: Shiitake mushrooms and oyster mushrooms. The system has achieved impressive results, surpassing a 90% accuracy rate in correctly classifying these mushroom varieties. This high accuracy rate demonstrates the effectiveness and reliability of the system in accurately identifying Shiitake mushrooms and oyster mushrooms using YOLOv8.

The success of the system can be attributed to the utilization of advanced machine learning algorithms and a carefully curated dataset that encompasses diverse samples. By incorporating a wide range of variations in colour, shape, texture and other relevant features, the system was able to extract meaningful features and capture the unique characteristics that distinguish Shiitake mushrooms from oyster mushrooms. This comprehensive approach played a vital role in the ability of the system to achieve accurate classifications.

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