Poisonous Mushroom Detection using YOLOV5

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Abstract: Mushroom is a nutritious food that is grown and consumed in many countries around the world. It is preferred for consumption due to its easy acquisition, the benefit to human health and taste. Although edible ones are beneficial for health, there are also poisonous types. It is difficult for people who are not familiar with this subject to distinguish which mushrooms are edible. Therefore, it will be useful to provide this process automatically. The study aims to identify poisonous mushrooms. In this context, a dataset containing the eight most poisonous mushroom species is created. The dataset created is trained with the fine tuning method using the pre-trained YOLOV5 algorithm. Precision, recall, and mAP metrics are used to demonstrate the performance of the method. The fine-tuned model enables the recognition of eight different types as 0.77 mean Average Precision.

Key words: Object detection, YOLOV5, Poisonous mushroom detection.

YOLOV5 Kullanarak Zehirli Mantar Tespiti

Öz: Mantar dünyadaki birçok ülkede yetişen ve tüketilen besin değeri yüksek bir gıdadır. Kolay edinilmesi, insan sağlığına faydalı olması ve lezzeti sebepleriyle tüketim için tercih edilmektedir. Yenilebilir olanları sağlık açısından faydalı olmakla beraber zehirli türleri de bulunmaktadır. Mantarların hangilerinin yenilebilir olduğunu ayırt etmek bu konuda bilgi sahibi olmayan kişiler için zordur. Dolayısıyla bu işlemin otomatik olarak sağlanması faydalı olacaktır. Çalışma, zehirli mantarların tanınmasını sağlamaktır. Bu kapsamda, en zehirli 8 mantar türünü içeren bir veri seti oluşturuldu. Oluşturulan veri seti, ön eğitimli YOLOV5 algoritması kullanılarak ince ayar yöntemi ile eğitildi. Yöntemin başarımını göstermek için precision, recall ve mAP kriterleri kullanıldı. İnce ayarlanmış model, sekiz farklı türün tanınmasını 0.77 mean Average Precision olarak sağlamıştır.

Anahtar kelimeler: Nesne bulma, YOLOV5, Zehirli mantar tespiti.

1. Introduction

Mushroom is a very nutritious fungus. It contains vitamins B, C, and D, minerals such as copper, beta-glucans, potassium, selenium, sodium, calcium, phosphorus, magnesium and a large amount of protein [1]. They support preventing diseases such as cancer and diabetes. Also, it has benefits such as preventing weight loss and strengthening immunity [2]. There are many types of mushrooms in nature. The number of edible mushrooms is high. There are also types of poisonous mushrooms. Headaches, allergies, anxiety can be seen as side effects of eating poisonous mushrooms. While only a few of the around 80 types of poisonous mushrooms are deadly when eaten, most of these deadly mushrooms have a resemblance to edible species and are therefore particularly dangerous. For these reasons, it is important to distinguish poisonous mushrooms.

Studies have been done to classify poisonous mushrooms. S Alkronz et al. [3] used multilayer sensors to divide mushrooms into two groups as poisonous and edible. Using the "JustNN" software, they achieved 99.25% accuracy in their study with 8124 samples. Y. Wang et al. [4] emphasized the importance of recognizing poisonous mushrooms, Logistic regression, support vector machine and multi-grained cascade forest classifier methods were tried to distinguish poisonous mushrooms. The highest accuracy was achieved as 98% with multi grained cascade forest. P. Maurya et al. [2] used five different classifiers in their study in which they focused on mushroom classification using the texture feature based on a machine learning approach. Among these, SVM provided 76.6% accuracy performance by showing higher accuracy than other classifiers.

In [5], a method using the PCA algorithm is proposed to distinguish edible from inedible mushrooms. The performance of the proposed method showed a success rate of about 85% ~ 96% increasing with the number of training images. S. Beniwal et al. [6], were tested Naive Bayes, ZeroR, and Bayes net classifiers with the WEKA tool to classify the mushroom dataset. Bayes has shown the highest accuracy. I. T. Ayorinde et al. [7] develop a

deep learning model using a multi-layer perceptron neural network. Two different models, the first model with MLP and the model with PCA, were developed and applied using TensorFlow. The result shows that the model with PCA performs better than the first model with 98.34% accuracy. In [8], aimed to classify mushrooms according to whether they are edible or poisonous. In the method in which many classification algorithms are investigated, the decision tree method has shown the highest performance. M.A. Ottom et al. [9] aimed to classify mushrooms using the dataset they created from the internet. In the experiments performed with different machine learning algorithms, their methods showed 87% accuracy with the KNN classifier. In [10], a mobile application has been developed to recognize whether mushrooms are poisonous or not. In the application, the GrabCut algorithm is used for segmentation and probabilistic neural network as a classifier. The method using 133 images achieved 92% accuracy. In the literature, besides classification by looking at an image and numerical feature information, some studies make classification by using smell information. In [11], the authors proposed an electronic nose to classify the amanita mushroom species. Data were analyzed using PCA, LDA, and ANN algorithms. Classification of mushroom species provided 80-100% accuracy.

In the study, images of the 8 most poisonous mushroom species were collected from the internet. These images are manually labeled using the labelImg tool [12]. After the dataset acquisition, the related poisonous mushroom images were classified and localized using pre-trained yolov5 architecture.

The contributions of the study can be listed as follows:

1) To our knowledge, studies in the literature have treated mushrooms by dividing them into two groups as edible and poisonous. We group and detect the most poisonous mushrooms.

2) A dataset of eight categories including the most poisonous mushroom species was generated.

3) The Yolov5 architecture is trained with fine-tuning to enable the recognition of poisonous mushrooms. In addition to classification, location information is also provided with bounding boxes.

The organization of the study is as follows. Section 2 introduces basic object detection algorithms using deep learning methods. Section 3 explains the material and methods including dataset, model development, performance metrics, and experimental results. Finally, section 4 presents the conclusions of the paper.

2. Deep Learning Based Object Detection Approaches

Object detection finds the object in an image or video and then draws a box around the found object. Image classification aims to predict the class of the object in the image. Object localization involves determining the position of an object in an image. Object detection combines these two tasks, localizing and classifying objects in the image. An effective object detection extraction pipeline plays an important role in providing consistent and high quality labeled output [13].

Traditional methods were used before using deep learning algorithms for object detection problems. Methods developed for object detection consisted of the stages of proposal generation, feature vector extraction, and region classification [14]. Impressive results were obtained thanks to the advances in feature vector representations and classification models in the period they were used. However, using light variants of these models over the period 2007-2012 achieved slight gains [13].

Following the success of deep convolutional neural networks in image classification [15], object detection techniques based on deep learning have been developed [16] and have made significant progress in recent years. CNN-based detectors have replaced these detectors as they show better results than traditional detectors.
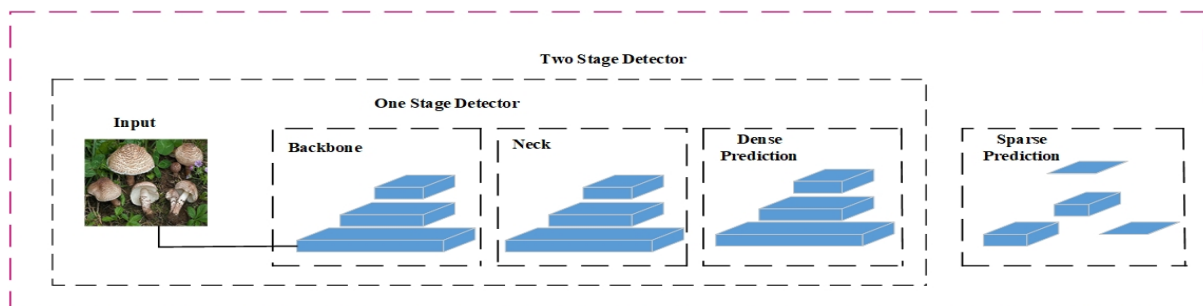

Figure 1. One-stage and two-stage object detectors

Generally, the convolutional neural network-based object detection approaches can be divided into two types. Figure 1 gives a summary of the two different approaches. The first type creates the region proposal network (RPN) as a branch to find category-independent candidate regions of interest (ROIs). The ROI-pooling layer is then added to create fixed-length feature representations. Another branch of the network is learned to classify and localize objects of various classes. These multi-stage detectors always require additional ROI-Pooling operations for better localization performance [17]. RCNN [16], Faster RCNN [17], Mask RCNN [18], Light-head RCNN [19], Cascade RCNN [20] are examples of multi-step object detectors.

The second type, called single-stage object detectors, finds objects in different categories through a sliding window [21]. The input images are gridded and the anchors correspond to spatially localized regions. The CNN outputs of these regions are used to distinguish objects from the background. These detectors are simple and effective in design and training. But there is a problem of unbalanced classification. SSD [21], DSSD [23], FSSD [24], MDSSD [25], DSOD [26], M2Det [27], RetinaNet [28], CornerNet [29], Reppoints [30], YOLO [31], YOLO9000 [32], YOLOV3 [33], YOLOV4 [34], DC-SPP-YOLO [35], YOLOV5 [36] can be cited as some of the one-step object detectors. Yolov5, the latest version of YOLO, one of the single-step object detectors from many existing architectures, was preferred in the study. We prefer it because it provides better performance in terms of accuracy and speed criteria [36].

3. Material and Methods

3.1. Dataset

There are thousands of mushroom species in the world. Although most of these are edible, there are also poisonous species. In the article written by Melissa Petruzzello, a dataset of 7 species [37], which are said to be the most poisonous species in the world, and fly agaric mushrooms, another poisonous species not mentioned in the article, were created. These species are; "Autumn Skullcap (Galerina marginata)", "Destroying Angels", "Conocybe Filaris", "Deadly Dapperling", "Death Cap", " Podostroma Cornu-damae", " Fly Agaric", and "Webcaps". An example of each category of images in the dataset is as illustrates in Figure 2.

Autumn Sculp(Galerina Margina) Destroying Angel Conocybe Filaris Deadly Dapperling

Death_Cap Podostroma Cornu-damae Fly Agaric Webcaps

Figure 2. Sample images of each category in our dataset [37]

Images were obtained from the internet. It is not possible to train images as we first downloaded them. Images of different formats and sizes have been converted to the same format. Then the images are labeled in YOLO format with the labelImg tool. The number of images concerning the classes is not equal. Besides, the number of images given to training and validation for each class was also kept different. In this way, it was aimed to observe the effect of the number of images on the training results. The number of images belonging to each category is as in table 1.

Table 1. The number of images in the dataset

	Autumn Sculp	Destroying angel	Conocybe Filaris	Deadly Dapperling	Death Cap	Podostroma Cornu-damae	Fly Agaric	Webcaps
Train	27	79	23	74	82	80	77	72
Validation	14	19	21	15	17	15	22	7
Total	41	98	44	89	99	95	99	79

3.2. 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. Yolov5 was used in the study. The pipeline consists of three parts: backbone, neck, and head. In the model; CSPNET is preferred as a backbone. It extracts important features from the input image. The neck is used to produce feature pyramids. PANET is used here. The head is used to decide the final part. YOLOv5 uses the same head structure as the previous YOLOV3 [36].

Yolov5 has four different models: yolov5s, Yolov5m, Yolov5l and yolov5x. These models are pre-trained with an 80 class MSCOCO dataset. We used the largest model, Yolov5x, to get more accuracy. We trained the model with our poisonous mushrooms dataset. While 70% of the data was used for the training process, the remaining 30% was used for validation. The training process was carried out in a computer environment with Nvidia Geforce Gtx 950M GPU support. Other details of the training are as shown in table 2.

Table 2. Training details of Yolov5x model

Input Size	Model Parameters	Software Language	Environment	Library	Epoch	Optimizer	Activation Function
640x640	89M	Python	Spyder	Torch	40	SGD	Leaky RELU & Sigmoid

3.3. Performance Metrics

There are many measurement criteria used to evaluate the performance of an object detection model. Intersection over Union (IoU) Precision, Recall, Average Precision (AP), and mean Average Precision (mAP) can be given as examples of the most used criteria [39].

Intersection over Union: A measurement that finds the difference between the ground truth annotations and the predicted bounding boxes. This metric is used in the state of the art object detection algorithms. In object detection, the model predicts multiple bounding boxes for each object and removes unnecessary boxes depending on the threshold value based on the confidence scores of each bounding box. A threshold value is determined according to requirements. If the IoU value is greater than the threshold value, it is taken as an object, otherwise, the box is removed [38]. Metric is calculated as given in equation (1).

IOU = Area of union / Area of intersection (1)

Precision: Precision is the metric used to measure correct predictions. It is calculated as in equation (2).

Precision= TP/(TP+FP) (2)

Recall: Recall is the true positive rate. It measures the probability that exact reference objects will be detected correctly [39]. It is calculated as in equation (3).

Recall= TP/(TP+FN) (3)

Average Precision (AP): AP is another criterion used to evaluate the performance of object detectors. It includes precision and recall. It is a single number metric that summarizes the Precision-Recall curve by averaging the recall values from 0 to 1 [40]. It is calculated with the equation given in 11-point interpolated AP (4).

$$AP = \frac{1}{11} \sum_{r \in (0,0.1,0.2,...,1)} p_{interp(r)} \qquad (4)$$

mAP: If the dataset contains M class category while calculating mAP, it takes AP average over M classes [41]. mAP is calculated as in equation (5).

$$mAP = \frac{1}{M} \sum_{j=1}^{M} AP_j \qquad (5)$$

3.4. Experimental Results

The precision-recall curve obtained after the training is given in figure 3. According to the figure, the mean average Precision value for all classes was found to be 0.778. In addition, AP values of each class are given as 0.818, 0.825, 0.610, 0.737, 0.826, 0.854, 0.993, 0.556, respectively. The images allocated training and validation for each class are given at different rates as can be seen in table 1. For "fly agaric" mushroom showing the highest performance, 77 images were used for training and 22 images for testing. For the "Conocybe filaris" strain showing a low performance with 0.610 AP, 23 were used for training and 22 for validation. Here, both the low number of images and the uneven distribution affected the performance badly.
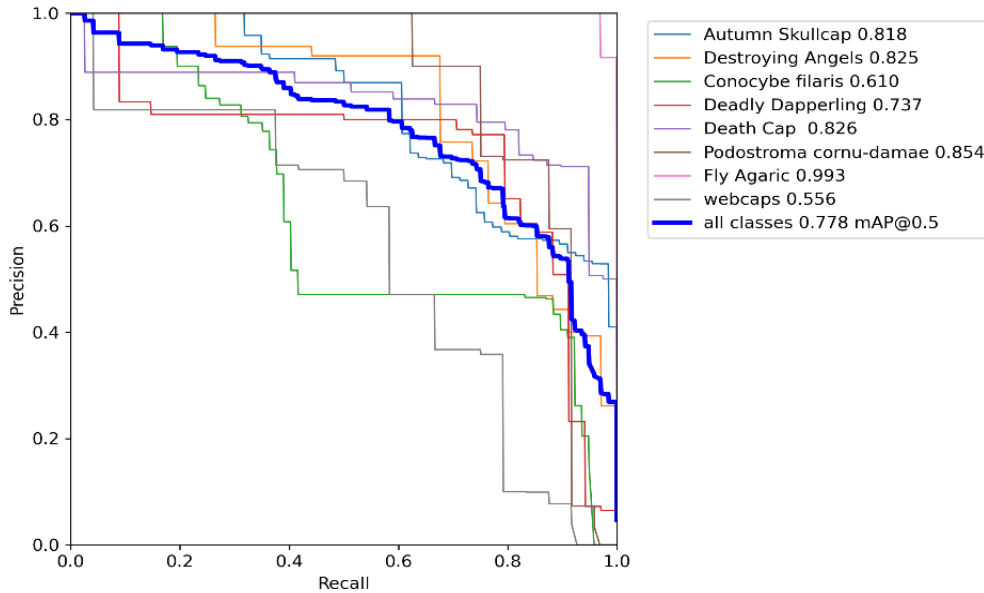

Figure 3. Precision-recall curve of the model

The precision, recall, and mAP curves of the training process are shown in figure 4. The training process is carried out in 40 epochs. Table 3 shows the Average Precision of each class after the training and validation process.

Table 3. Average Precision of each class in dataset

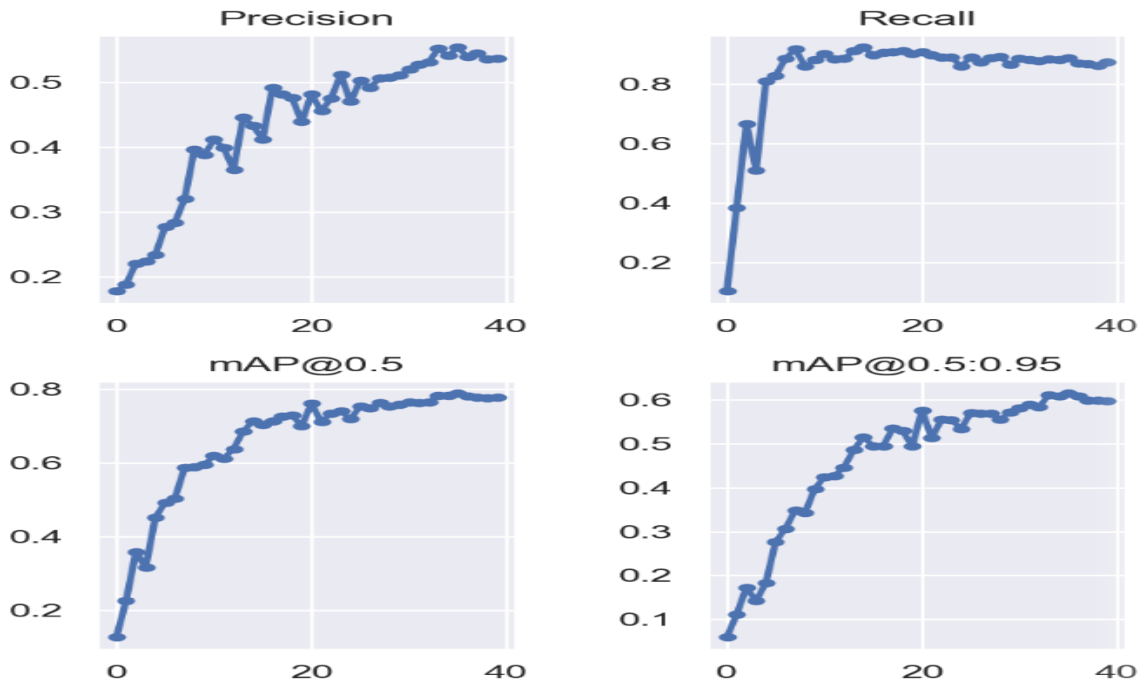| Mushroom Species	Autumn Skullcap	Destroying Angle	Cococybe Filaris	Deadly Dapperling	Death Cap	Podostroma Cornu-Damae	Fly Agaric	Webcaps
AP	0.818	0.825	0.610	0.737	0.826	0.854	0.993	0.556
mAP	0.778 mAP@0.5							

Figure 4. Precision, recall and mAP curve of the model

Figure 5. Images where mushroom species are correctly detected

130 images were used to test the model. Although the mushroom species in these images were mostly predicted correctly, some mushrooms were wrongly predicted or not seen. Figure 5 shows the images containing the correct mushrooms. Figure 6 gives images that are misclassified. Two mushrooms of the "Autumn skullcap" type were found as death cap. In the other image, the death cap mushroom was predicted as destroying angels.

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Figure 6. Images where mushroom species are incorrectly detected

4. Discussions and Conclusions

In the literature, there are some studies made for mushroom classification. According to our knowledge, the studies are for the classification of edible and inedible mushrooms. In [10], authors worked with a ten-class dataset, and their purpose was to decompose edible mushrooms. Existing studies have used classification methods. The comparison of some studies made for mushroom classification is given in Table 4. In the study not only classifies certain types of poisonous mushrooms but also gives location information. YOLOV5 is used in real-time applications due to its speed and high accuracy rate. It is also good at finding small objects. As a future work is to apply our dataset in real-time, after enhancing it via images from internet. YOLOV5 was chosen for these reasons.

In this study where we focused on classifying poisonous mushroom species, a dataset including the most poisonous mushrooms was generated. It was prepared in YOLO format by labeling it with the labelImg tool. The study aimed to identify eight mushroom species known as poisonous species. Trained with yolov5x fine-tuning, the largest YOLOV5 model. As a result of our literature searches, no study classifies poisonous mushrooms according to their species and performs identification. Therefore, it has not had a chance to compare with other studies. But the success of working with a precision-recall curve, Average Precision, and Mean Average Precision metrics has been shown. Mean Average Precision of all classes is 0.77 and AP values of each class are 0.818, 0.825, 0.610, 0.737, 0.826, 0.854, 0.993, 0.556, respectively. The experimental results showed that with the image data used, a high success rate was achieved.

Table 4. Comparison of some studies made for mushroom classification

Ref. No/Year	Dataset/Samples	Number of Class	Method	Performance
[6]/2015	Mushroom dataset/8124	2	MLP+PCA	98.34% Acc.
[5]/2016	Collected from Internet/ 300	10	PCA	85%~96% Acc.
[9]/2019	Collected from Internet/ 380	2	KNN	87%~94% Acc.
[3]/2020	Mushroom dataset/8124	2	Multi-Layer ANN	99.25% Acc.
[4]/2020	Mushroom dataset/8124	2	Multi-Grained Cascade Forest	98% Acc.
Our/2021	Collected from Internet/644	8	Fine-tuned YOLO-V5	0.778 mAP

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