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Short Communication

Detection of mold on the food surface using YOLOv5

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ABSTRACT

The study aimed to identify different molds that grow on various food surfaces. As a result, we conducted a case study for the detection of mold on food surfaces based on the “you only look once (YOLO) v5” principle. In this context, a dataset of 2050 food images with mold growing on their surfaces was created. Images were obtained from our own laboratory (850 images) as well as from the internet (1200 images). The dataset was trained using the pre-trained YOLOv5 algorithm. A laboratory test was also performed to confirm that the grown organisms were mold. In comparison to YOLOv3 and YOLOv4, this current YOLOv5 model had better precision, recall, and average precision (AP), which were 98.10%, 100%, and 99.60%, respectively. The YOLOv5 algorithm was used for the first time in this study to detect mold on food surfaces. In conclusion, the proposed model successfully recognizes any kind of mold present on the food surface. Using YOLOv5, we are currently conducting research to identify the specific species of the detected mold.

1. Introduction

Mold is dangerous to human health and a serious threat to food supply chains. They can grow on a wide range of acidic products, such as fruits or fruit juices, as well as foods with intermediate moisture content, like breads and bakery products, that many other microorganisms, such as bacteria, cannot (Dagnas et al., 2013). Mold spoilage of food products causes significant economic losses as well as diseases by inducing allergies or asthma, or it may be associated with hypersensitivity diseases like allergic bronchopulmonary aspergillosis or allergic fungal sinusitis (Borchers et al., 2017). The prompt detection of fungal presence to prevent further harmful effects is very important in food processing.

Object detection is a significant branch in the field of computer vision and image processing. Object detection is the process of identifying occurrences of a specific type of object in images and videos. Object detection algorithms have received a lot of attention in deep learning (Pan et al., 2020). Deep learning-based object detection algorithms have advanced rapidly in recent years. These can roughly be subdivided into two categories. The first is the R–CNN (region-based convolutional neural network) family algorithms, which are based on regional proposals and have representative networks such as R–CNN, Fast R–CNN, Faster R–CNN, Mask R–CNN, and so on. They are characterized by the use of two-stage methods. Another one is the one stage algorithms and its representative network, such as the YOLO (you only look once) series (Wang and Yan, 2021). As object detection technology has evolved, the YOLO series of algorithms with very high precision and speed have been used in various scene detection tasks (Kuznetsova et al., 2020). At the same time, the YOLO system computes all of the image’s features and predicts all of the objects. YOLOv5 is the fifth generation of YOLO, written in Python programming language (Thuan, 2021). According to various studies YOLOv5 outperforms the rest of the YOLO model in terms of accuracy and speed (Kuznetsova et al., 2020; Thuan, 2021; Cengil and Cinar, 2021). In some recent studies, YOLOv5 was used to detect various objects. The YOLOv5 model was used by Yan et al. (2021) and Kuznetsova et al. (2020) to detect apples in orchards by harvesting robots. In both studies, the detection speed and accuracy were notable compared to other YOLO models. In another study, Cengil and Cinar (2021) used a pre-trained YOLOv5 algorithm and a dataset of eight poisonous mushroom species to detect poisonous mushroom detection. In a number of researches YOLOv5 has been used to detect

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vehicles (Kasper-Eulaers et al., 2021) and ships (Chen et al., 2021). Kasper-Eulaers used YOLOv5 to detect heavy goods vehicles at rest areas during the winter, allowing for real-time parking spot occupancy prediction. Some recent studies focused on using the YOLOv5 during the COVID-19 period to check for social distancing (Shukla et al., 2021) and face mask (Yang et al., 2020) from video and still images to replace the manual inspection process. There are some other studies that used the same model for the detection of safety helmets (Zhou et al., 2021) and tree leaves (Wang and Yan, 2021). Again, the YOLOv5 outperformed the R–CNN and other YOLO in terms of speed and accuracy in a number of studies (Yan et al., 2021; Wang and Yan, 2021; Chen et al., 2021; Kuznetsova et al., 2020). As a result, we decided to convey the current research using the YOLOv5. However, to the best of our knowledge, no study has used YOLOv5 to detect mold on food surfaces, as was done in the current study. Hence, the aim of this study was to detect the molds from the captured images using the YOLOv5.

2. Experimental design, materials and methods

2.1. Data description

There are two types of data file in the dataset. A) Raw digital images which contain a total of 2050 images with a high diversity of poses, angles, lighting conditions, weather conditions, and backgrounds. The images are all in JPG format. B) Image annotation files containing 2050 images. These files specify the precise locations of the objects with labels in the corresponding images. The annotation was done manually, and the annotated values were saved in txt files as well. The data files were divided into two folders: images & labels. Each folder was then divided into two subfolders: train and valid. On the other hand, the dataset preparation consists of four steps: 1) data collection, 2) data preprocessing, 3) data annotation, and 4) data augmentation. The Model building and detection consist of eight steps: 1) importing libraries, 2) importing dataset, 3) cloning YOLOv5 repository, 4) installing required libraries for YOLOv5, 5) training YOLOv5 model with mold dataset, 6) plotting metrics in tensor board, 7) detecting mold in images using trained model, and 8) plotting detected images.

2.2. Importing and installing libraries

Some popular Python libraries were imported for matrix operations, plotting, and file handling.

```
import numpy as np
import matplotlib. pyplot as plt
from glob import glob
```

There is a ‘requirements.txt’ file in the YOLOv5 directory that lists the required libraries and versions to run the YOLOv5 model. Required library was installed using the bash command ‘!pip install -qr <directory>‘. It is good to mention that ‘pip’ is a python package manager.

```
!pip install -qr '/content/yolov5/requirements.txt'
```

2.2.1. NumPy

NumPy's data formats include matrix and multidimensional arrays. NumPy can perform mathematical operations on arrays such as statistical, algebraic, and trigonometric routines. It provides a highly functional multidimensional array and even the necessary tools for computing and regulating the arrays (Sharma, 2020).

2.2.2. Matplotlib

Matplotlib is a portable 2D plotting and imaging package largely used to visualize scientific, engineering, and financial data. The software is free to download, use, and distribute. It has a wide range of applications. Most users are familiar with the command-line interface for creating plots and images interactively. This interface displays and manipulates data in a simple pop-up window (Barrett et al., 2005).

2.2.3. Glob

It finds all path names that match a given pattern.

2.3. Data collection

Images of foods with mold growing on their surfaces were collected accordingly. 850 images of various foods stored in the laboratory of Department of Food Engineering and Technology of Sylhet Agricultural University, Sylhet, Bangladesh were collected. The images were captured using an action camera (GoPro HERO 9 5K Ultra HD). The remaining images (1200) were obtained from various internet sources. Both paid and free stock photos were used in this case.

2.4. Data pre-processing and annotation

After taking photos of various mold-affected food surfaces, the images were all converted to JPG format. Tzutalin's, 2018 popular annotation tool LabelImg was used to cautiously label the images in this final phase. First, each image is opened in this tool one at a time. Then, a rectangular shape was manually drawn to the boundary of an object in order to specify its exact location in that image by x_center y_center width height. Finally, each object has been given a label, such as ‘bread mold’, or, ‘cake mold’ etc. In LabelImg, annotated values were saved as txt files in YOLOv5 format.

2.5. Data augmentation

Following labeling, the images were uploaded to ‘Roboflow’ for augmentation. Data Augmentation was done in order to increase the quantity and diversity of data. It aided in the reduction of over fitting in small datasets. To generate new images from the mold dataset, a few data augmentation techniques such as flipping, cropping, and color space transformation were used. The datasets were also uploaded to the roboflow web tool for data augmentation, preprocessing, and train-test split.

2.6. Importing dataset

Google Colab was used for model training and evaluation purpose. The dataset was downloaded to colab using the roboflow generated url as a zip folder. The zip folder has been unzipped and deleted.

```
!curl -L "https://app.roboflow.com/ds/r7gxbFXmxO?key = P4RWGf2c2R" > roboflow. zip; unzip roboflow. zip; rm roboflow. zip
```

2.7. Cloning YOLOv5 repository

YOLOv5 repository was cloned from GitHub using ‘git clone <url>‘.

```
!git clone 'https://github.com/ultralytics/yolov5. git'
```

2.8. Plotting detected images

After running inference, images was saved in ‘runs/detect/exp/’ directory. Using ‘matplotlib’ images were plotted.

```
disp_images = glob ('runs/detect/exp/*') # taking location of all file
fig = plt.figure (figsize=(20, 28))
columns = 3
rows = 5
```

```
for i in range (1, columns*rows +1):
    img = np. random.choice (disp_images)
    img = plt. imread (img)
    fig.add_subplot (rows, columns, i)
    plt.imshow (img)
plt.show ()
```

2.9. Training YOLOv5 model with mold dataset

The mold dataset was designed to train by using Google Colab, which provides free access to powerful GPUs. We used a notebook developed by Roboflow. ai (Roboflow, 2016) which is based on YOLOv5 (Jocher et al., 2021) and uses pre-trained COCO weights. Suitable number of epochs was chosen to train newly developed mold dataset. To train the model 205 epochs was selected which was taken approximately 40 min. In YOLOv5 directory there is a 'train.py' file for training YOLOv5 model. Using bash command '!python train. py <parameters>' the model was trained accordingly.

The details of training the YOLOv5 model are as follows.

- Image size: 640
- Batch size: 10
- Data description: data. yaml
- Yolo model: YOLOv5s.yaml
- image: height and width of images.
- batch: size of mini batch of images to feed in one iteration.
- epochs: the number of training iteration.
- data: (train, validation) data directory and number of class and class name was described in this YAML file.
- cfg: models are described in YAML model configuration files in 'model' directory. There is four version of model of different size. 'YOLOv5s.yaml' has been used to train.
- name: a model name has been given.

```
%cd yolov5/# change directory to 'yolov5' using magic command
!python train. py –img 640 –batch 10 –epochs 205 –data/content/data.yaml –cfg models/yolov5s.yaml –name FoodMold
```

2.10. Plotting metrics in tensor board

Tensor Board is a helpful tool for visualizing metrics related to planning, validation, and testing. To visualize mAP, recall, precision metrics 'tensorboard' was loaded using magic command '%load_ext tensorboard'. And '%tensorboard –logdir runs/' was used to visualize metrics from log directory.

```
%load_ext tensorboard
%tensorboard –logdir runs/
```

2.11. Mold detection and confirmation in the laboratory

A laboratory test was also performed to confirm that the microorganism that had grown on food surfaces was mold. Mold detection was carried out in accordance with the AOAC method (AOAC Official method 997.02, 1998).

3. Experimental outcomes

3.1. Detecting mold in images using trained model

After the training, different types of new and previously unseen images were used to test the model performance to detect the mold on the food surface. We took over 100 images as a test dataset. There is a 'detect.py' file 'yolov5' directory to run inference on images. Inference was performed on the image source directory using '!python detect. py parameters>'.

```
!python detect. py –source/content/valid/images –weights 'runs/train/FoodMold/weights/best.pt
```

Fig. 1 shows that the model can detect molds on food surface to a higher degree of certainty.

3.2. Model performance and comparison

The YOLOv5 model performed very well with 150 epochs. After that with the increase of epochs all the losses like classification loss, box loss, and objectness loss were increased. And the model performance was decreased. YOLOv5 was tested to detect mold on various food surfaces after the data set was created. To train the model, various image resolutions were used, and a suitable image resolution of 500 × 500 pixels was chosen. Before creating the data set, the images were labeled to attain the optimum mold detection. The detected molds' precision, recall, and average precision (AP) were calculated and compared to other models. Results are shown in Table 1. Metrics are calculated with the help of following equations [7].

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$
$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$$
$$\text{F1} = [2/(1/\text{Precision}) + (1/\text{Recall})]$$
$$\text{AP} = 1/11^{*} \sum_{r\in(0,0.1,0.2,\ \ldots..1)} p\text{interp}(r)$$

As a YOLOv5 feature enhancement, the model is better at detecting small to large molds. The activation of Mish + SPP in the models showed an increase in precision, recall, F1-score and AP. It was also discovered that when the image quality was high, the performance was better.

4. Discussion

Although tremendous progress has been made in the field of object detection recently, it remains a difficult task to detect and identify objects accurately and quickly. Yan et al. (2021) named the YOLOv5 as the most powerful object detection algorithm in present times. In the current study, the overall performance of YOLOv5 was better than YOLOv4 and YOLOv3. This finding is in line with some previous researches, as we found several studies comparing YOLOv5 to previous versions of YOLO, such as YOLOv4 or YOLOv3. According to Thuan (2021), YOLOv5 is more accurate and faster than YOLOv4. YOLOv5 was compared to YOLOv3 and YOLOv4 for picking apples by robots, and the mAP was increased by 14.95% and 4.74%, respectively (Yan et al., 2021). Similar results and comparisons with other YOLO models were demonstrated by Kuznetsova et al. (2020) while using YOLOv5 to detect and pick apples by robots. The recall (0.73) and precision (0.62) of YOLOv5 was better compared to YOLOv3-timy (0.57 and 0.45, respectively) for ship detection in satellite remote sensing images (Chen et al., 2021). On the other hand, we encountered various studies that showed that YOLO outperforms CNN in object detection deep learning methods. In tree leaf detection, YOLOv5 was nearly 32 times faster in training, nearly 39 times faster in execution, and nearly 8 times smaller in memory occupancy than Faster R–CNN (Wang and Yan, 2021). Moreover, computational time of YOLO (5.48 ms) was found much faster than the mask R–CNN (67.63 ms) in detecting human figures from specific images (Sumit et al., 2020). In this study, the mask R–CNN was unable to detect all figures, whereas the YOLO did that successfully. In a number of studies, previous versions of the YOLO outperformed R–CNN in terms of speed and accuracy (Lee and Kim, 2020; Du, 2018). In addition, in light of the preceding discussion, we believe that selecting YOLOv5 over R–CNN for mold detection on the food surface was a smart move.

5. Conclusion and future research

In the current study, YOLOv5 successfully detected mold on food surfaces. This is a novel study, and there have been no previous studies

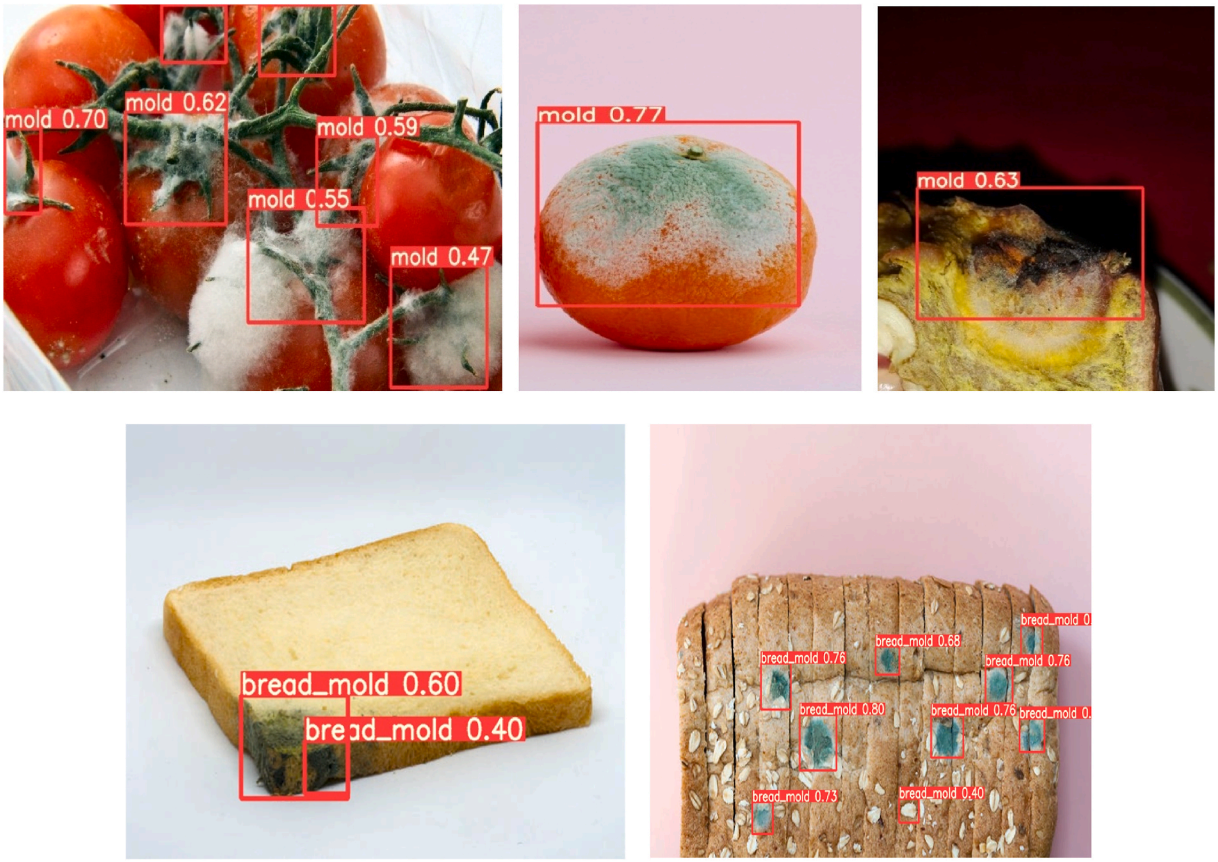

Fig. 1. Images from test data sets by showing mold detection on various foods.

Table 1
Model performance evaluation with raw dataset under 500 × 500 pixels' resolution.

YOLOv3	Leaky	96.00	95.20	9.50	97.00
YOLOv4	Mish + SPP	98.00	99.05	99.00	99.01
YOLOv5	Mish + SPP	98.10	100.00	99.50	99.60

that used YOLOv5 to detect mold as an object on food surfaces. There are still a lot of things that can be done to improve the mold detection system with YOLOv5. We are currently working on improving the model to detect specific species of food mold. Furthermore, once the system detects and declares any type of foodborne mold, we will attempt to make the entire system more convenient for food industry applications. Furthermore, we intend to increase the number of images to a greater extent in order to reach a better and more precise conclusion.

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Data availability statement

Data are available upon reasonable request.

CRediT authorship contribution statement

Fahad Jubayer: Conceptualization, supervision, writing original draft. **Janibul Alam Soeb:** Conceptualization, supervision, writing original draft. **Abu Naser Mojumder:** Formal analysis, writing and reviewing. **Mitun Kanti Paul:** Formal analysis, algorithm development, review and editing. **Pranta Barua:** Formal analysis, algorithm development, review and editing. **Shahidullah Kayshar:** Writing, reviewing, and editing. **Syeda Sabrina Akter:** Writing, reviewing, and editing. **Mizanur Rahman:** Image collection and laboratory works. **Amirul Islam:** Image collection and laboratory works.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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