



Contents lists available at ScienceDirect

## Data in Brief

journal homepage: [www.elsevier.com/locate/dib](http://www.elsevier.com/locate/dib)

## Data Article

# A novel dataset of annotated oyster mushroom images with environmental context for machine learning applications

Sonay Duman<sup>a,c</sup>, Abdullah Elewi<sup>a</sup>, Abdulsalam Hajhamed<sup>b,\*</sup>,  
Rasheed Khankan<sup>d</sup>, Amina Souag<sup>e</sup>, Asma Ahmed<sup>f</sup>

<sup>a</sup> Computer Engineering Department, Mersin University, 33343 Mersin, Turkey

<sup>b</sup> Faculty of Agricultural Sciences, University of Hohenheim, 70599 Stuttgart, Germany

<sup>c</sup> Software Engineering Department, Toros University, 33140 Mersin, Turkey

<sup>d</sup> Electrical and Electronic Engineering Department, Mersin University, 33343 Mersin, Turkey

<sup>e</sup> School of Engineering, Technology and Design, Canterbury Christ Church University, Canterbury, United Kingdom

<sup>f</sup> Department of Chemical and Environmental Engineering, University of Nottingham, Nottingham NG7 2RD, United Kingdom

## ARTICLE INFO

## Article history:

Received 15 July 2024

Revised 3 October 2024

Accepted 21 October 2024

Available online xxx

Dataset link: [Annotated oyster mushroom images \(Original data\)](#)

## Keywords:

Oyster mushroom

Mushroom maturity

Smart farming

Precision agriculture

Image classification

Feature extraction

YOLO

PASCAL VOC

## ABSTRACT

State-of-the-art technologies such as computer vision and machine learning, are revolutionizing the smart mushroom industry by addressing diverse challenges in yield prediction, growth analysis, mushroom classification, disease and deformation detection, and digital twinning. However, mushrooms have long presented a challenge to automated systems due to their varied sizes, shapes, and surface characteristics, limiting the effectiveness of technologies aimed at mushroom classification and growth analysis. Clean and well-labelled datasets are therefore a cornerstone for developing efficient machine-learning models. Bridging this gap in oyster mushroom cultivation, we present a novel dataset comprising 555 high-quality camera raw images, from which approximately 16,000 manually annotated images were extracted. These images capture mushrooms in various shapes, maturity stages, and conditions, photographed in a greenhouse using two cameras for comprehensive coverage. Alongside the images, we recorded key environmental parameters within the mushroom greenhouse, such as temperature, relative hu-

\* Corresponding author.

E-mail address: [abdulsalam.hajhamed@uni-hohenheim.de](mailto:abdulsalam.hajhamed@uni-hohenheim.de) (A. Hajhamed).

<https://doi.org/10.1016/j.dib.2024.111074>

2352-3409/© 2024 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>)

Please cite this article as: S. Duman, A. Elewi and A. Hajhamed et al., A novel dataset of annotated oyster mushroom images with environmental context for machine learning applications, Data in Brief, <https://doi.org/10.1016/j.dib.2024.111074>

midity, moisture, and air quality, for a holistic analysis. This dataset is unique in providing both visual and environmental time-point data, organized into four storage folders: “Raw Images”; “Mushroom Labelled Images and Annotation Files”; “Maturity Labelled Images and Annotation Files”; and “Sensor Data”, which includes time-stamped sensor readings in Excel files. This dataset can enable researchers to develop high-quality prediction and classification machine learning models for the intelligent cultivation of oyster mushrooms. Beyond mushroom cultivation, this dataset also has the potential to be utilized in the fields of computer vision, artificial intelligence, robotics, precision agriculture, and fungal studies in general.

© 2024 The Authors. Published by Elsevier Inc.

This is an open access article under the CC BY license

(<http://creativecommons.org/licenses/by/4.0/>)

## 1 Specifications Table

Subject	Agriculture Engineering, Computer Vision, Artificial Intelligence
Specific subject area	Machine learning-based mushroom detection and classification
Type of data	Image, Excel File, Annotation File
Data collection	The raw images were captured in an oyster mushroom farm using two TP-Link Tapo C310 IP cameras, each set to full HD resolution of 1920 × 1080, resulting in a minimum of 4–5 images per day during two cultivation cycles from late December 2022 until late April 2023. Environmental parameters were recorded concurrently using various sensors. These include temperature, relative humidity, and air quality inside the greenhouse, in addition to temperature and moisture inside mushroom composite bags. The images and sensor readings were time-stamped to be linked together. Mushroom images were manually extracted from raw images, maturity-labelled and annotated using different annotation formats.
Data source location	City/Region: Mersin/Akdeniz Country: Turkey
Data accessibility	Latitude and longitude for collected samples/data: 36°49'49.8"N 34°43'20.4"E Repository name: Mendeley Data Data identification number: <a href="https://data.mendeley.com/datasets/hf55tkx489.1">10.17632/hf55tkx489.1</a> Direct URL to data: <a href="https://data.mendeley.com/datasets/hf55tkx489/1">https://data.mendeley.com/datasets/hf55tkx489/1</a> Instructions for accessing these data:
Related research article	None.

## 2 1. Value of the Data

- 3 • The diverse features of the mushrooms in this dataset are crucial for any intelligent system,
- 4 as they offer comprehensive information to cover a wide range of mushroom sizes, varied
- 5 shapes, and growth stages.
- 6 • This data can be valuable for researchers in the fields of computer vision, agricultural
- 7 robotics, mushroom classification, and fungal studies.
- 8 • Farmers and agriculturalists engaged in smart farming and precision agriculture, especially
- 9 those working within greenhouses, can harness this data to support their specific needs and
- 10 research endeavors.
- 11 • About 16,000 oyster mushroom images, labelled as “mushroom”, “mature” and “immature”,
- 12 from different shapes, sizes, day times and maturity stages, were manually extracted and
- 13 annotated to help researchers in mushroom classification and growth analysis problems.

- 14 • The dataset of mushroom images was captured from the day of mushroom appearance  
15 through to harvesting, along with the corresponding environmental parameters within the  
16 mushroom greenhouse. This will help researchers identify correlation patterns between the  
17 mushrooms and their surrounding environmental conditions.
- 18 • The dataset includes annotated mushroom images, providing a valuable resource for devel-  
19 oping and refining machine learning models for classification and regression applications.

## 20 2. Background

21 Automated systems often struggle with the classification and growth analysis of mushrooms,  
22 primarily due to the wide range of sizes, shapes and surface characteristics they exhibit. This  
23 inherent diversity has posed a significant challenge for mushroom-related technologies. Recent  
24 research [1] has shown that machine and deep learning technologies hold great promise in over-  
25 coming this challenge, given their high precision and accuracy. However, one of the key lim-  
26 itations has been the lack of diverse and comprehensive image datasets that include labelled  
27 mushrooms across various stages, shapes, and sizes, which are essential for training and val-  
28 idating machine learning models. To bridge this gap, we have curated a dataset that includes  
29 high-quality images of meticulously annotated mushrooms, capturing different shapes, maturity  
30 stages, and conditions. Additionally, we have matched these images with corresponding environ-  
31 mental parameters from the farm, ensuring thorough and extensive coverage of the topic.

## 32 3. Data Description

33 The meticulously gathered dataset has been created with the aim of addressing the existing  
34 challenges in mushroom analysis systems. These challenges revolve around the various states  
35 of mushrooms, including their growth, maturity, surface conditions, and other factors that can  
36 hinder the accuracy of classification systems. Fig. 1 shows an example of raw camera images,  
37 and Fig. 2 shows mushroom images that were extracted from the raw camera images.



Fig. 1. An example of original camera images.



Fig. 2. An example of manually extracted images of the same mushroom during daytime (left) and at night (right).

38 The oyster mushroom dataset comprises 555 raw camera images, approximately 8000  
39 mushroom-labelled images, about 8000 maturity-labelled images, various annotation files, and  
40 sensor data. The images were captured in both day and night-time settings in an oyster mush-  
41 room cultivation greenhouse/farm in Mersin, on Turkey's Mediterranean coast. A remote mon-  
42 itoring and management (RMM) system was designed and implemented in the farm for two  
43 cultivation cycles from late December 2022 until late April 2023. More details about the sys-  
44 tem are available in our previous work [2]. Different internet of things (IoT) platforms, such as  
45 ThingSpeak™ and Arduino IoT Cloud™, were trialled in the first cycle. ThingSpeak platform was  
46 the main IoT platform used in the second cycle due to its superior affordances.

47 All raw camera images and various sensor recording data were time-stamped for correlation  
48 and analysis. The "Sensor Data" folder contains two sub-folders for every cultivation cycle. The  
49 "Cycle I" sub-folder includes 4 .xlsx files for all the first-cycle ThingSpeak data, and a sub-folder  
50 for daily data obtained using Arduino IoT Cloud. The "Cycle II" folder includes 11 .xlsx files of  
51 various environmental sensor values, obtained using ThingSpeak from different sensors during  
52 the second cycle and presented in separate time-stamped Excel files for easy management and  
53 connection with images. For temperature and relative humidity in the greenhouse, DHT21 and  
54 SHT20 sensors were utilised. Several DS18B20 sensors were utilised for measuring temperature  
55 inside mushroom composite bags, while resistive and capacitive moisture sensors were used for  
56 moisture inside bags. For air quality inside the greenhouse, SGP30 and CSS811 sensors were  
57 utilised for measuring the estimated CO<sub>2</sub> (eCO<sub>2</sub>) and total volatile organic compounds (tVOC)  
58 in the mushroom greenhouse. For managing the sensors, ESP8266 and ESP32 microcontroller  
59 boards were utilised. Further technical details can be found in our previous publication [2].

60 The environmental data from different sensors, in addition to mushroom images, allow re-  
61 searchers to observe how environmental values change instantly and how they affect mushroom  
62 growth processes. This comprehensive collection addresses the need for diverse mushroom data,  
63 showcasing various stages of maturity, different environmental conditions, and other factors. By  
64 encompassing a wide range of conditions and times of day, our dataset equips researchers and  
65 practitioners in the field of smart mushroom farming with a valuable resource to enhance the  
66 accuracy and effectiveness of their classification and analysis systems.

67 Within the dataset, numerous mushrooms populate each raw camera image (Fig 2). During  
68 the labelling process, the mushrooms that were clearly visible throughout the growth process in  
69 the raw images were cut from the images from the first day until the day they were collected  
70 and took their place in the annotation file. This ensured that images of each growth period were  
71 included in the dataset. The distribution of the maturity labelled images is 3158 "mature" and  
72 5124 "immature" labelled images. As the images were collected frequently from different times  
73 of the day, both day images (about 4000) and night images (about 3963) were included in the  
74 dataset.



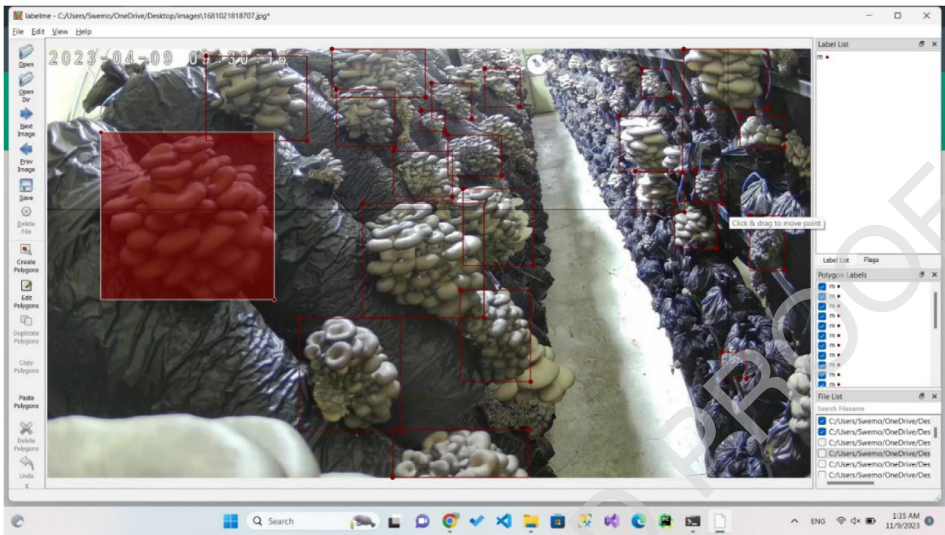


Fig. 3. Labelling with LabelMe software.

75 The images were processed in a manner where they were retained at their original size  
 76 during the labelling phase. We employed the open-source LabelMe software [3] for this pur-  
 77 pose. While labelling the images, we ensured that each bounding box precisely encompassed  
 78 the entire mushroom, minimizing the inclusion of unnecessary background pixels, as depicted  
 79 in Fig. 3. The selected annotation formats (JSON, TXT and XML) are widely used across popular  
 80 object detection environments, providing researchers with an effortless integration of the pro-  
 81 posed dataset into their work. This streamlines the training process for object detection models,  
 82 eliminating the requirement to convert annotation files into various formats.

83 The Pascal VOC (Visual Object Classes) [4] format is an XML file annotation, and it includes  
 84 the information of coordinates (Xmin, Ymin, Xmax, Ymax) of mushroom. According to this in-  
 85 formation, the height and width of bounding box can be calculated. Fig. 4 shows the Pascal VOC  
 86 annotation format.

87 The COCO (Common Objects in Context) format [5] is widely adopted as the standard data  
 88 format for training and inference in object detection tasks, and it is required that all data related  
 89 to object detection tasks conform to the COCO format. The COCO format is a JSON (JavaScript  
 90 Object Notation) structure that governs how labels and metadata are formatted for a dataset,  
 91 and it is one of the most popular datasets for object detection. The JSON file includes the x and  
 92 y coordinates of mushroom and also, the height and width of them, Fig. 5.

93 The YOLO Darknet [6] contains one text (TXT) file per image, which includes the annotations  
 94 and a numeric representation of the label, as well as a label map that maps the numeric IDs  
 95 to human-readable strings. The annotations are normalized to lie within the range [0,1], making  
 96 them easier to work with even after scaling or stretching images. Its popularity has grown due to  
 97 its alignment with the Darknet framework implementations of the various YOLO models. Fig. 6  
 98 shows the YOLO Darknet annotation format on an example image.

99 The collected and processed data was organized into four separate folders: raw images,  
 100 mushroom labelled images, maturity (mature and immature) labelled mushroom images, sen-  
 101 sior data of the farm. Table 1 shows a brief description of the dataset folders and files.

## 102 I. Raw Images

103 This folder contains 555 images in JPG format. These images were selected from 1200 images  
 104 taken by the two cameras, when the image contains mushrooms in it.

## 105 II. Mushroom Labelled Images and Annotation Files

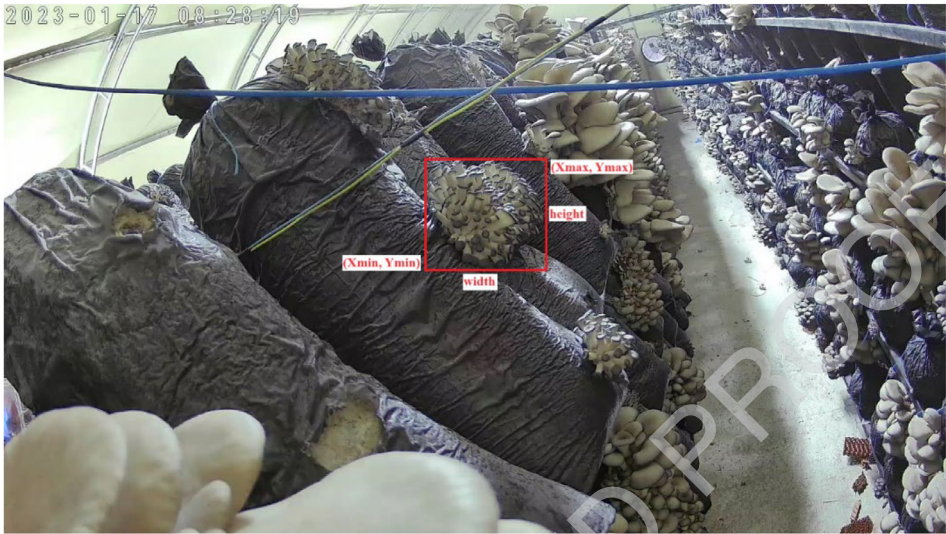


Fig. 4. Pascal VOC annotation format.

```
{
  "image": "1673327464853.jpg",
  "annotations": [
    {
      "label": "mushroom",
      "coordinates": {
        "x": 1123.1195335276966,
        "y": 261.07871720116617,
        "width": 76.67638483965038,
        "height": 88.33819241982508
      }
    },
    {
      "label": "mushroom",
      "coordinates": {
        "x": 1231.428571428571,
        "y": 313.265306122449,
        "width": 61.80758017492735,
        "height": 60.34985422740522
      }
    }
  ]
},
```

Fig. 5. COCO annotation format.

106 This folder contains a sub-folder with 7963 images in JPG format, in addition to 3 subfolders  
 107 for JSON, XML, and TXT formatted annotation files of all raw images. The raw images were  
 108 cropped to get mushroom images only and labelled as "mushroom" using LabelMe software,  
 109 Fig. 5.

### 110 III. Maturity Labelled Images and Annotation Files

111 This folder contains 5 sub-folders; the first one contains 5124 images of mushrooms labelled as  
 112 "immature", and the second one contains 3158 images of mushroom labelled as "mature".  
 113 Additionally, there are 3 sub-folders for JSON, XML, and TXT formatted two-class annotation  
 114 files of all raw images.

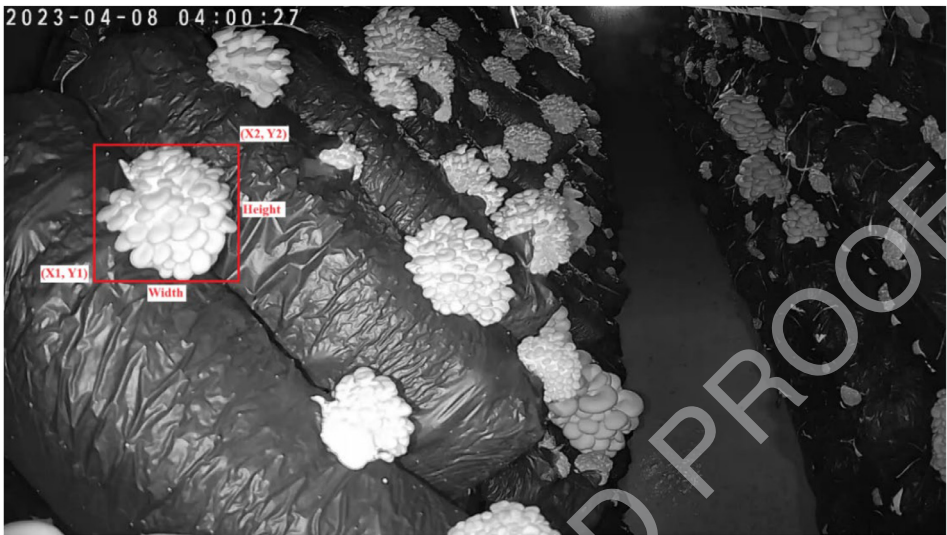


Fig. 6. YOLO Darknet annotation format representation.

#### 115 IV. Sensor Data

116 This folder contains two sub-folders of environmental data, obtained from different sensors  
 117 during two cycles. The Cycle I folder contains 4 Excel files and 388 .csv files representing  
 118 time-stamped sensor data. Cycle II contains 11 Excel files to represent the sensor values by  
 119 date and time. These environmental data include temperature (DHT Temp, SHT Temp), rela-  
 120 tive humidity (DHT Hum, SHT Hum), and air quality (SGP ECO2, SGP TVOC, CSS ECO2, CSS  
 121 TVOC) in the mushroom greenhouse, in addition to temperature (DS Temp) and moisture  
 122 (Cap Moist, Res Moist) inside some mushroom composite bags.

#### 123 4. Experimental Design, Materials and Methods

124 Fig. 7 shows the structure and construction methodology of our dataset of annotated mush-  
 125 room images with their environmental context.

126 The original raw images were taken using two IP cameras with night and day vision in an  
 127 oyster mushroom cultivation farm in Mersin, Turkey, on the northern Mediterranean coast. There  
 128 were at least 4-5 images per day, in addition to associated environmental data obtained using  
 129 an IoT-based system [2] in the farm for two mushroom cultivation cycles from late December  
 130 2022 until late April 2023.

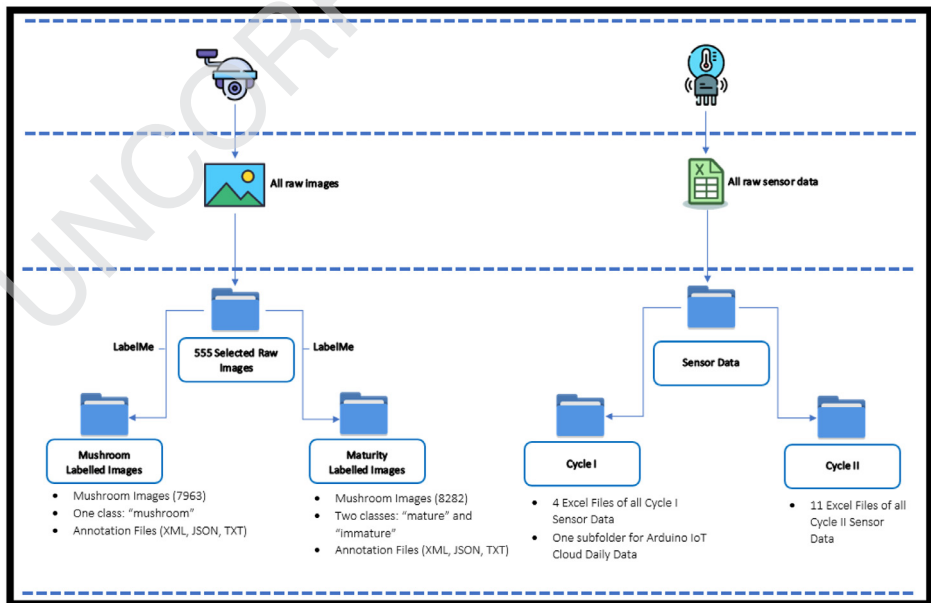
131 In this study, mushroom clusters in the raw images, Fig. 1, were manually selected and  
 132 turned into separate images, such as those shown in Fig. 2. At the same time, annotation files  
 133 with three different (XML, JSON, and TXT) formats, which are widely adopted in object detectors,  
 134 were created for all raw images. With YOLO Darknet, COCO and PASCAL VOC formats, researchers  
 135 will be able to use this dataset for different machine learning and deep learning studies.

136 In a similar dataset of oyster mushroom images published by Sujatanagarjuna et al. [7], a  
 137 total of 34,400 raw, unannotated mushroom images were collected in an amateur cultivation  
 138 environment using plastic buckets. However, only 3300 mushrooms were annotated (2759 for  
 139 training and 541 for testing) using the COCO (JSON) annotation format. In contrast, this dataset  
 140 contains 7963 annotated mushrooms and 8282 maturity-labelled mushrooms using three differ-  
 141 ent annotation formats. Additionally, and more importantly, the associated environmental data,  
 142 such as temperature, relative humidity, air quality inside the greenhouse, as well as temperature

**Table 1**

Brief description of the dataset folders/files.

No.	Name	Type/Format	Description	Size
1	Full Dataset	Root folder	Conveniently packaged for download	476 MB
2	Raw Images	Compressed (.rar) folder: 555 JPG images	Original camera images with a lot of mushrooms	268 MB
3	Mushroom Labelled Images and Annotation Files	Compressed (.rar) folder: Mushroom images sub-folder with 7963 JPG images- Three sub-folders: COCO, PASCAL VOC, and YOLO for one-class annotation files of all raw images	Using LabelMe, raw images were cropped to get mushroom images and labelled as "mushroom" in annotation files of different (JSON, XML and TXT) formats	80 MB
4	Maturity Labelled Images and Annotation Files	Compressed (.rar) folder: Two mature and immature sub-folders with 8282 JPG images- Three sub-folders: COCO, PASCAL VOC, and YOLO for two-class annotation files for all raw images	Using LabelMe, the images initially taken from raw images were classified into two classes and labelled as "mature" and "immature" in annotation files of different (JSON, XML and TXT) formats	80 MB
5	Sensor Data	Compressed (.rar) folder: Sub-folders (Cycle I & Cycle II): -15 Excel .xlsx files- Sub-folder with a .txt notes file and 97 .zip files for daily data.	Sensor environmental values of the farm: Excel .xlsx files for ThingSpeak data- Compressed .zip files for Arduino IoT Cloud daily data with 388 .csv files and 97 .txt readme files	53 MB

**Fig. 7.** Construction and annotation of dataset.



143 and moisture inside mushroom composite bags were recorded at one-minute intervals using  
144 various sensors to assess their impact on mushroom growth using machine learning techniques.  
145 This dataset serves as an invaluable resource for researchers aiming to develop high-  
146 performance machine-learning models for intelligent oyster mushroom cultivation. Beyond its  
147 immediate application, the dataset holds promising aspects for exploration in diverse fields, in-  
148 cluding computer vision, precision agriculture, robotics, and broader fungal studies. Overall, this  
149 initiative contributes significantly to advancing mushroom-related research and technology.

## 150 Limitations

151 Environmental data were collected over two cultivation cycles. In the first cycle, the tempera-  
152 ture and relative humidity inside the mushroom greenhouse were measured using cost-efficient  
153 DHT21 sensors. In the second cycle, the more reliable SHT20 sensor was added, along with air  
154 quality sensors, for more trustworthy and comprehensive environmental data. More technical  
155 details are available in [2].

## 156 Ethics Statement

157 The expected standards of ethical behaviour in scientific publishing were generally adhered  
158 to by the authors throughout the construction of the article. The work did not entail the use or  
159 involvement of human subjects or animals, thereby aligning with ethical guidelines for research  
160 conduct.

## 161 CRediT Author Statement

162 **Sonay Duman:** Writing – original draft, Software, Data curation, Investigation. **Abdullah**  
163 **Elewi:** Writing – review & editing, Validation, Resources, Project administration, Methodol-  
164 ogy, Conceptualization. **Abdulsalam Hajhamed:** Validation, Resources, Conceptualization, Fund-  
165 ing acquisition. **Rasheed Khankan:** Software, Data curation, Investigation. **Amina Souag:** Writ-  
166 ing – review & editing, Validation, Methodology, Conceptualization, Supervision. **Asma Ahmed:**  
167 Writing – review & editing, Conceptualization, Supervision.

## Data Availability

Annotated oyster mushroom images (Original data) (Mendeley Data).

## 168 Acknowledgements

169 This work was supported by the Council for At-Risk Academics (Cara) [Apr22URN15 grant].  
170 The authors would also like to thank Dr. Denise De Pauw from University of Leeds Language  
171 Centre for providing language support.

## 172 Declaration of Competing Interest

173 The absence of any known competing financial interests or personal relationships that could  
174 have been perceived to influence the work reported in this paper is declared by the authors.

175 The authors declare that they have no competing interest.

176 **References**

- 177 [1] H. Yin, W. Yi, D. Hu, Computer vision and machine learning applied in the mushroom industry: a critical review,  
178 Comput. Electron. Agricult. (2022), doi:[10.1016/j.compag.2022.107015](https://doi.org/10.1016/j.compag.2022.107015).
- 179 [2] A. Elewi, A. Hajhamed, R. Khankan, S. Duman, A. Souag, A. Ahmed, Design and implementation of a cost-aware  
180 and smart oyster mushroom cultivation system, Smart Agricult. Technol. 8 (2024) (2024) 100439, doi:[10.1016/j.atech.  
181 2024.100439](https://doi.org/10.1016/j.atech.2024.100439).
- 182 [3] Labelmeai. Labelmeai/labelme: Image polygonal Annotation with Python (polygon, rectangle, circle, line, Point and  
183 Image-Level Flag Annotation). GitHub. Available at: <<https://github.com/labelmeai/labelme>> [Accessed 1 February  
184 2024].
- 185 [4] PASCAL VOC. [online] Available at: <<https://opencv.github.io/cvat/docs/manual/advanced/formats/format-voc/>>  
186 [Accessed 25 May 2024].
- 187 [5] COCO. [online] Available at: <<https://opencv.github.io/cvat/docs/manual/advanced/formats/format-coco/>> [Accessed  
188 25 May 2024].
- 189 [6] YOLO Darknet. [online] Available at: <<https://docs.plainsight.ai/labels/exporting-labels/yolo/>> [Accessed 1 February  
190 2024].
- 191 [7] A. Sujatanagarjuna, S. Kia, D.F. Briechele, B. Leiding, MushR: a smart, automated, and scalable indoor harvesting system  
192 for gourmet mushrooms, Agricult. (Switzerland) 13 (8) (2023), doi:[10.3390/agriculture13081533](https://doi.org/10.3390/agriculture13081533).