The Prospects of YOLO Algorithm Application in the Sorting of Agricultural Products

Ivana Medojević and Jelena Ilić

***Abstract*—In the contemporary food processing industry, there is a tendency to automatize sorting process along with minimizing the waste. Therefore, the efforts to improve large – capacity industrial systems for the sorting of agricultural products are constant and go from various image processing techniques towards the area of machine learning. Among deep learning techniques, You Only Look Once (YOLO) algorithm offers the potential of recognizing and determining the location of noncompliant products. In this paper, the study that evaluates the performance of YOLOv3 algorithm in sorting of raspberries is represented, together with a logical solution model of a centralized color sorting system and developed web application.**

***Index Terms*—agricultural processing; color sorting; deep learning; YOLO.**

I. Introduction

The essential part of the preprocessing of harvested agricultural products, especially fruits and vegetables, is sorting - separating noncompliant products and foreign materials, such as soil, leaves, animal and insect parts, wood glass, metal …, from compliant products. In standard industrial systems for machine inspection of agricultural products, known as color sorters, an operator generates the recipe i.e., defines the set of criteria that a product should fulfill in order to be classified as compliant [1]. It means that performances of those systems depend on subjective estimation of an operator. In addition to that, the algorithms used in those systems utilize simple image processing techniques, the analysis of image parameters, and make the discrimination between compliant and noncompliant objects mostly on the basis of their color. Along with efforts to improve the objectivity and reliability of sorters, appeared the idea to combine computer vision and machine learning though the application of neural networks, especially convolutional neural networks (CNN) [2,3]. In color sorting applications CNNs are typically trained on large datasets of labeled images using supervised learning techniques. During the training, the CNN learns to recognize patterns and features within images that are relevant to the classification task, such as the color and texture of the product. Recent development of CNN led to supervised deep learning model called You Only Look Ones (YOLO) algorithm [4,5], which is primarily used for object detection tasks, where the goal is to identify and locate objects of interest within an image or video. The YOLO algorithm uses a single convolutional neural network to simultaneously predict the class probabilities and bounding boxes of objects within an image. Unlike traditional object detection methods, which involve running a classifier on multiple regions of an image, YOLO performs object detection in a single pass of the network.

The YOLO algorithm is known for its fast and accurate object detection, making it well-suited for real-time applications. Firstly, YOLO algorithm has been developed for autonomous vehicles and detection of objects and pedestrians [6,7]. Due to significant benefits of YOLO algorithm, the ideas to apply it in various areas of agriculture research appeared. Some of the examples are monitoring of growth stage and yield assessment in an orchard [8], or in a greenhouse [9]. Early detection of weed in wheat field and weed mapping with YOLO algorithm in order to perform site specific weed management is proposed in [10]. The application of YOLO algorithm in fruit and vegetable recognition is reported in [11, 12]. To the best of authors knowledge, the study presented in this paper is the first that proposes the application of YOLOv3 in the sorting of raspberries. The closest to our study is the one presented in [13], where the author test fast region-based CNN in raspberry sorting and present the database of raspberry images that they have created.

However, there are still challenges in the development of practical applications. In this paper, we proposed a logical data model and a beta version of a web application using results from the initial study.

II. The Method

The input data on which the initial research is based are digital images of agricultural products captured by the Optyx3000 color sorter during industrial processing. One of those images is in Fig. 1. Those images were divided into images 224 × 224 pixels and saved in .jpg format. Obtained images were manually labeled, using the program LabelImg (https://tzutalin.github.io/labelImg/, accessed on 10 May 2021). In the labeling process, each image is associated to one of five classes: 1) compliant raspberry, 2) noncompliant moldy raspberry, 3) noncompliant raspberry with a stalk, 4) stalk, 5) foreign (extraneous) objects. Original set of images contained totally 165 images, of which 60% belong to class 1 (compliant raspberries). The whole original set of images is divided into training set, validation set and test set. 12% of all

Ivana Medojević is with the University of Belgrade – Faculty of Mechanical Engineering, Kraljice Marije 16, 11060 Belgrade, Serbia (e-mail: imedojevic@mas.bg.ac.rs), ORCID ID (https://orcid.org/0000-0001-7200-763X)

Jelena Ilić is with the University of Belgrade – Faculty of Mechanical Engineering, Kraljice Marije 16, 11060 Belgrade, Serbia (e-mail: jilic@mas.bg.ac.rs), ORCID ID (https://orcid.org/0000-0001-8258-4801).

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original images are selected for test set in a way that all of five classes are represented in it. Validation set is formed of 12% randomly selected images. The rest of original images are used to create the training set, by the application of various data augmentation techniques: variation of brightness (9 levels), gamma correction (7 values), Gaussian noise (5 degrees), blur (5 levels), rotation (3 additional angles) and mirroring. Thus, the training set of 4000 is obtained.

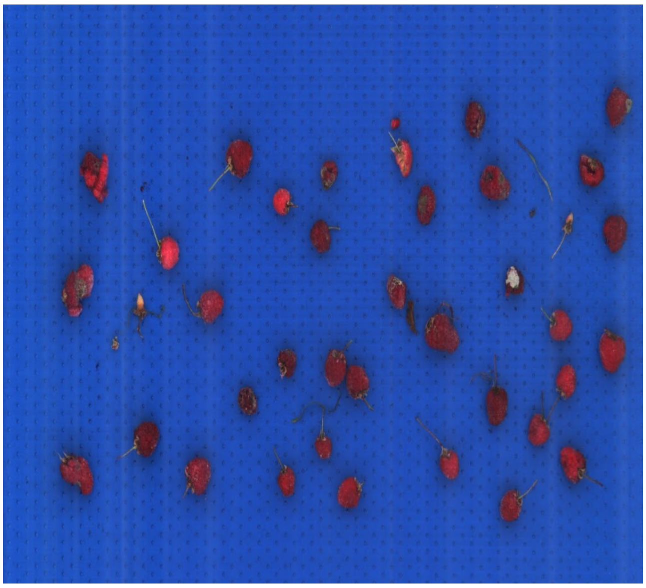

Fig. 1. The example of a testing image from color sorter

The trainings, validation and testing were performed on virtual machine with installed YOLOv3 environment. Virtual machine is chosen because the required graphics card speed is much higher than that of standard desktop computer. Nine trainings, with different hyperparameters (number of epochs 100 – 150, batch size and learning rate), were executed.

III. Results

Based on a comprehensive study, several results can be reported for the application of the YOLOv3 algorithm for detection, localization, and classification on test images of raspberries. The size of the training set yielded excellent results for all training models. The F1 score ranged from 92-97%. Detection and classification of the object such as the stalk represents a significant result of the application of the YOLOv3 algorithm due to its shape, small dimensions, and variations. Detection, localization, and classification of non-matching raspberries with different damage and shapes, which were classified into one class, can also be identified as an exceptional result of the application of the YOLOv3 algorithm. The average detection time on full-resolution images of 1024x1024 is only 0.37s with selected software components that fall into the middle class.

The example of a test image is shown in Fig. 2 where most of the raspberries are noncompliant or have stalk. Results are in Serbian language (nesaglasen - noncompliant, peteljka - stalk, neusaglasen + peteljka - noncompliant raspberry with a stalk). The initial results demonstrate the potential application of the YOLOv3 algorithm in industrial solutions, leading to the idea of a system aimed at reducing the subjectivity of operators when deciding on the correctness of sorted products. Besides YOLOv3, there are YOLOv4 [14] and YOLOv5 (May 2020). The choice between these algorithms ultimately depends on specific needs and use cases. Here are some factors to consider: performance, model size, model complexity, and available pre-trained models. Ultimately, the best choice will depend on specific requirements and constraints. It may be worth trying out all three models and seeing which one works best for a particular use case.

The presented centralized system represents an intelligent solution utilizing modern online technology and deep learning algorithms for object detection, localization, and classification, in this case agricultural products.

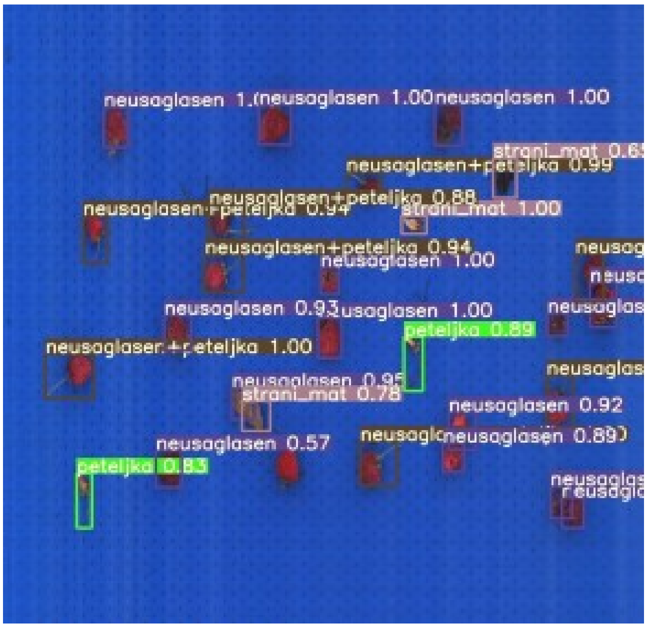

Fig. 2. The example of tested image with results

The schematic diagram of the proposed system is shown in Fig. 3, consisting of a color sorting machine located in an industrial plant with the ability to connect to the internet. The entire connection would be made via an internet connection between the central system and the machine.

The central system consists of a hardware component located in the manufacturer's development center, where training data labeling, algorithm training, and testing are performed. The obtained weight coefficients are sent to the cloud that collects and sends data to the color sorter in real time, which uses a new recipe according to the obtained weight coefficients from that moment on. As an auxiliary option in the industrial plant, there could be a web application for desktop and mobile phones that serve operators or quality controllers to check the current recipe or send additional images for training or class modification to the centralized system. In the meantime, a beta version of such an application has been created, which will be explained further.

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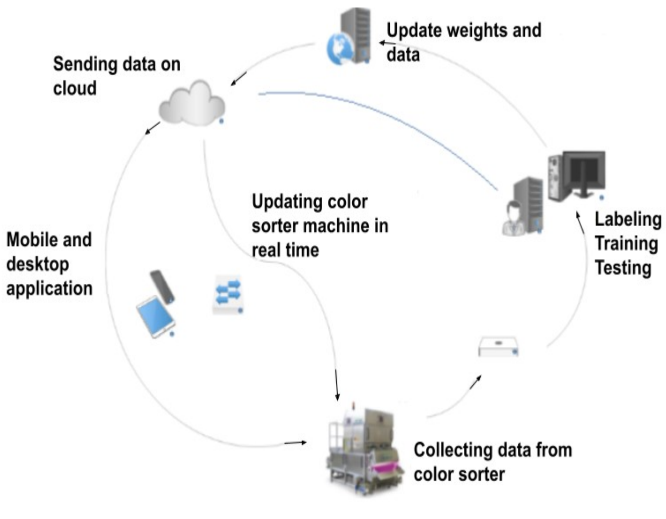

Fig. 3. Conceptual solution of centralized color sorting system

At any given moment, the quality controller can take a picture of a product on the production line at a precisely designated location and receive information about the product class. The application contains pre-defined weight factors trained using the YOLOv3 algorithm and possible classes for products that are sorted on the technological line. The application is open source and is hosted on the GitHub development platform at the following link: https://github.com/ultralytics/yolov3. Image detection using trained weight factors is performed via the command-line interface. After initialization, images are selected from the default input folder. The background algorithm with pre-defined weight factors marks objects of interest in the image and saves the marked image in the default output folder. The input and output folders can be passed as command-line arguments. The web application is written in the Flask web framework based on the Python programming language. The application source code and training configurations are available on the GitHub repository at the following link: https://github.com/IvaMark/YoloV3-Raspberry The application is packaged in a Docker container, so the user does not need to manually install the application and its dependencies. The only requirement is to install Docker software (https://www.docker.com/). Once Docker is successfully installed, the user must clone the GitHub repository and navigate to the docker application directory. Next, the following commands need to be executed in order to create the application in the local environment: *docker-compose build* and *docker-compose up -d.* The application is currently available on the web at the following address: http://localhost:43311/.

In addition to the weight factors trained on the example of raspberries, image detection can also be performed using weight factors trained on the COCO dataset (330,000 images, 80 classes) [8] created for YOLOv3, yolov3-spp, and yolov3-tiny. It is possible to add a greater number of predefined parameters, thereby expanding the range of agricultural products that can be tested. Another feature of the application is the option to select predefined classes for certain agricultural products. Advanced functionality of the application is the upload of new images intended for training. The added image is automatically sent to an email service that is directly connected to the central web server where new images are added to the training set and a new training process is initiated. In this way, the existing weight coefficients are updated and the application is given the ability to update to a new version or to set a new version as one of the offered weight coefficient sets. The developed web application represents a beta version that can be customized for different agricultural products and requirements of both processing and sorting manufacturers. The application can also be intended for quality controllers or other responsible persons in the factory for further analysis and improvement of production. What is the main difference from current systems that achieve an accuracy of almost 98%? The difference would lie in the use of machine and deep learning systems that require minimal involvement of a qualified person, regularly updated data, an algorithm that is constantly improved and can reach the accuracy of a human expert, remembers every case of undesirable products, stores data in the cloud, and is always available on demand.

IV. Conclusion

Using the machine learning method, specifically the YOLOv3 algorithm, in the example of raspberry in the study, provides more than satisfactory results in classification even with a smaller training dataset. Increasing objectivity in decision-making and the ability for constant algorithm updates can be characterized as one of the main advantages of implementing YOLOv3. This method can be useful as a non-destructive method for detecting, localizing, and classifying agricultural products during machine inspection. As theoretically demonstrated in the study, there are also real possibilities for application in industrial plants for processing agricultural products. Therefore, it is very important to further develop this method in the context of this field. With the development of unsupervised learning algorithms, this possibility is further increased, along with the processing of larger amounts of data in real time.

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