Berries Quality Detection In Visual Spectrum Using Neural Networks

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Abstract. The paper presents the raspberry quality detection approach based on a convolutional neural network with U-net architecture. The relevance of the study is determined by the limited possibility to use manual labor when growing, sorting, processing vegetables, fruits and berries in the face of increasing risks of new pandemics. For the research, a neural network of the U-net architecture has been chosen based on the narrow focus of the task and repetitive small patterns. The neural network of the U-net architecture has proven itself well in solving problems of image segmentation in biomedical researches. The authors decided to expand the scope of this tool to a new area of investigation. The research is carried out on the data that has been collected by the researchers for the experiment. The dataset for the experiment has been generated manually based on photographs of different varieties of raspberries and various states of raspberry fruit. This research is expected to become a part of the complex robotic system for solving the problem of manual berry fruits sorting.

Keywords: computer vision, deep learning, machine learning, convolutional neural networks, images segmentation, U-Net architecture, berries quality detection

1 Introduction

Being rich in vitamins, microelements, and fibers, berries are a real superfood and currently the fastest-growing segment of the world fruit market.

Berries are chosen for this research since the cultivation of berries is rapidly expanding around the Globe.

In Ukraine and almost all Eastern European countries, the primary producers are small private households. In Western Europe and North America, the share of small producers fell sharply. Large companies that can compete in the market replaced them. For example, in Great Britain and Northern Ireland, many fruit growers became part of the large cooperative K.G. Fruits / Berry Growers. The leading producer of fresh berries in North America is the DSA Driskol Raspberry Growing Partnership (Watsonville, Calif.), which markets up to 80% of raspberry production.

Berry fruit production in the Western world has changed significantly over the past 30 years. If earlier berries were grown mainly for processing, now most of the products are sold fresh. For example, in Scotland, about 80% of the berry crop goes to the fresh market. It became possible thanks to the creation of varieties with hard berries, special refrigeration units and storage facilities, small-capacity containers, air transportation, a streamlined logistics system, and sales of products to consumers through a supermarket chain. But growing and sorting berries is a labour-intensive process.

The world is entering an era of pandemics now. In particular, the spread of coronavirus limits the ability to use human workers' work in berry growing and berry processing [13]. The shelf life of many berries is limited to a few days after harvest. For instance, a raspberry fruit structurally is very fragile when compared to other fruits and berries. It restricts sales and increases processing and storage costs for producers and retailers.

Furthermore, raspberries being a very perishable product, succumb easily to mildew as the fruit bruises easily. Berry fruits of low quality, as well as unripe ones, provokes a stomach disorder. Mold can spoil a whole lot of raspberries. To be sold, frozen or canned berries should be even, free from spoiled areas and signs of disease and rot. Therefore, the producers and retailers are interested in detecting damaged fruit at an early stage and must inspect the large batches of berries every day. This is a labour-intensive and time-consuming procedure. Humans` ability to recognize defects becomes inconsistent as they get tired or become distracted. It determines the relevance of the research in detecting the quality of food products using optical non-destructive techniques.

Therefore, the contribution of this study is to introduce deep learning technology into the agricultural engineering practice of non-destructive fruit damage detection based on visual spectrum imaging. Compared to traditional or manual methods, the implementation of deep learning will reduce time costs, labour inputs, and improve detection accuracy.

In this study, we attempt to use a newly developed CNN architecture for the detection of raspberry damage. We are exploring the ability to recognize damaged fruit in the visible spectrum using common and affordable RGB cameras

The paper is organized in the following sections:

1. Introduction
2. Literature review
3. Problem setting and approach to the solution
4. Early results and discussion
5. Summary and future work

2 Literature review

For this research, previous studies have been obtained from abstract and citation databases. The academic peer-reviewed papers have been searched using an online bibliographic service.

This review revises literature on optical non-destructive techniques and highlights how it can be used to detect berries' quality.

All searches were carried out on the Microsoft Academic database. The utilization of the Microsoft Academic database provides a better advantage of semantic-based searches as well as more comprehensive coverage of the latest literature.

Twenty-one articles were identified, using the first combination of keywords in the search. In the second search, twenty-two articles were identified. After the exclusion of repeated articles (articles that appeared in both examinations), the total number identified was twenty. And then, they were refined by document type: research paper, conference proceedings, dissertation. Finally, ten studies were selected as “seed” publications (Nine publications have sufficient citation count and are not older than ten years from their publication date. Despite the lack of citation, the contemporary work by Karthik Kuchangi Jothi Prakash is also included in this review since it correlates with the chosen research subject.

Based on this literature, deep machine learning algorithms combine different types of neural networks, which can be used to solve application tasks in multiple areas. As it is pointed out in [1; 4] neural networks can be classified into the following different types: 1) feed-forward neural network; 2) recurrent neural network (RNN); 3) radial basis function neural network 4) Kohonen self-organizing neural network; 5) modular neural network.

In its turn, by structure, the following main types of neural networks are distinguished:

- deep (DNN), provide multivariate data analysis;
- recurrent (RNN), analyze speech and other streaming data;
- convolutional (CNN), used in image recognition systems;
- generative adversarial (GAN), the creation of new content from existing examples.

Table 1 provides a summary and comparison of the advantages and disadvantages of common optimization techniques.

Table 1. Optimization techniques comparison table [1; 8; 10].

Optimization techniques	Advantages	Disadvantages
(Batch) Gradient Descent	Scales well after optimizations	It takes a long time to converge as weights are updated after the entire dataset pass
		Local minima

Stochastic Gradient Descent	Scales well after optimizations	Noisy error rates since it is calculated at every sample; Accuracy requires random order
		Local minima
Back Propagation through Time	Performs better than metaheuristics (e.g., genetic as the algorithm)	Hard to be used in the application where online adaption is required entire time series must be used
Contrastive divergence	Can create samples that appear to come from input data distribution; Generative models; Pattern completion	Difficult to train
Evolutionary Algorithms	Is able to explore and Exploit solutions Space effectively	It takes a long time to run as it needs to test different combinations

Thus, it follows from the table that gradient descent-based training has the most widespread use. Backpropagation through time is tailored for the recurrent neural network. Contrastive divergence finds its use in probabilistic models such as RBMs. Evolutionary algorithms can be applied to hyperparameter optimizations or training models by optimizing weights. Reinforcement learning could be used in-game theory, multiagent systems, and other problems where both exploitation and exploration need to be optimized. Moreover, as it is shown in the studies [6-7; 10-12], machine learning algorithms can be widely used in agriculture, in particular, to identify spoiled berries.

The review of literature sources [3; 4; 12] proves that the conventional approaches to berry fruits detection are developing in the following directions (Fig. 1).

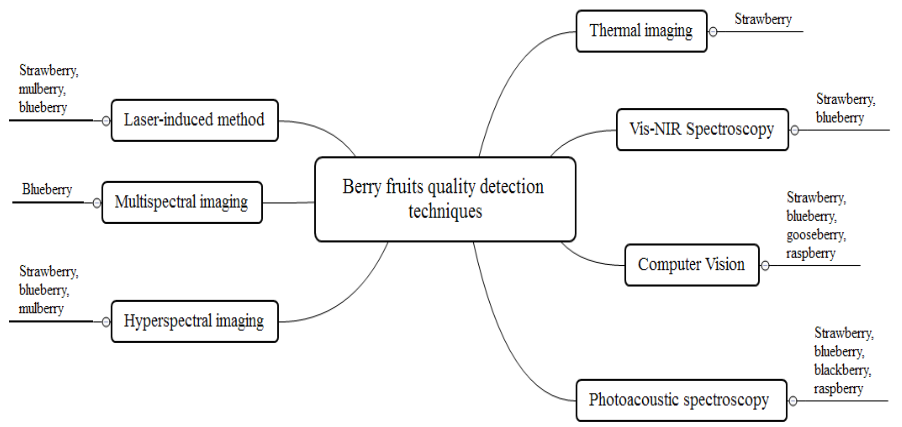

Fig. 1. Mind-map on berry fruits detection techniques

Berry fruits in [3-4; 6-7; 11-12] are examined based on general indicators of the commercial quality such as appearance, size, smell, taste, and tolerances. Appearance as a complex indicator of fresh fruits includes freshness, integrity, color, shape, surface condition, and ripeness or maturity.

The literature overview of techniques and algorithms applied to berry quality detection is presented in Table 2.

Table 2. Types of berry fruits and techniques applied for their detection

Berry Fruit	Applied technique and algorithm	Parameters for detection	Prediction set or result	Reference
Grapes	A connected component algorithm	Quantitative detection	Accuracy from 0.86 to 0.94	[6]
Blueberry	Mask R-CNN	Maturity and other relevant traits	Avg RMSE = 0.75 Avg $r2$= 0.886	[11]
Strawberry	Partial least square discriminant analysis	Soluble solid content	$rp2$=0.733, RMSEP = 0.66, RPD = 1.96	[3]
Strawberry	Convolution neural network	Disease	Accuracy = 92%	[12]
Strawberry	Otsu algorithm, HOG, H component variance	Shape and color	Rate of mature strawberries by 95%	[7]
Blueberry	The active learning algorithm, SVM	Damage	Accuracy = 0.87, precision = 0.93, recall = 0.78	[4]

Researchers most often use blueberries and strawberries in their experiments to recognize the qualitative and quantitative characteristics of berries. Raspberry quality detection is not enough presented in the research literature, although this berry ranks second in the world market's sales structure. Moreover, workers sort it by hand in rooms with a temperature of two degrees below zero Celsius.

Research gap and refined motivation to perform the research work. The literature review has revealed that apart from image classification, convolutional neural networks [9] can be applied for image segmentation and object detection, which are more advanced problems. The image segmentation process takes place in computer vision, where the image is separated into different segments representing each different class in the image.

Segmentation helps to identify where objects of different classes are located in the image. U-Net is a convolutional neural network architecture that expanded with few changes in the CNN architecture. It was invented to deal with biomedical images where the target is not only to classify whether there is an infection or not but also to identify the area of infection.

The comparative result of different state-of-the-art semantic segmentation models on various datasets is presented in table 3. The performance metric used here is mean average precision (mAP) as Intersection over Union (IoU) threshold.

Table 3. Comparative accuracy of different semantic segmentation models in terms of mean average precision (mAP) as Intersection over Union (IoU) [14]

Model	Year	Used Dataset	mAP as IoU
FCN-VGG16	2014	Pascal VOC 2012	62.2%
DeepLab	2014	Pascal VOC 2012	71.6%
Deconvnet	2015	Pascal VOC 2012	72.5%
U-Net	**2015**	**ISBI cell tracking challenge 2015**	**92% on PhC-U373 and 77.5% on DIC-HeLa dataset**
DialatedNet	2016	Pascal VOC 2012	73.9%
ParseNet	2016	ShiftFlow PASCAL- Context Pascal VOC 2012	40.4% 36.64% 69.8%
SegNet	2016	CamVid road scene segmentation SUN RGB-D indoor scene segmentation	60.10% 31.84%
GCN	2017	PASCAL VOC 2012 Cityscapes	82.2% 76.9%
PSPNet	2017	PASCAL VOC 2012 Cityscapes	85.4% 80.2%
FC-DenseNet103	2017	CamVid road scene segmentation Gatech	66.9% 79.4%
EncNet	2018	Pascal VOC 2012 Pascal Context	85.9% 51.7%
Gated-SCNN	2019	Cityscapes	82.8%

As it is shown in the table 3, U-net architecture demonstrates one of the highest accuracy level.

Therefore, at the next stages of the study, convolutional neural networks based on U-Net architecture [9] will be applied to recognizing and sorting of raspberries. The U-net is the architecture for fast and precise segmentation of images. It provides higher accuracy for image recognition. The proposed approach differs from those considered in [3; 4; 6; 7] that it allows analyzing at once a whole complex of characteristics of berries. For example, ripeness, size, damage condition. Analysis of these parameters makes it possible to sort the berries for different uses: freezing, processing, and fresh consumption.

Also, the studies considered do not highlight the possibility of automating the process of sorting fruit berries. Therefore, the prospect of further research is the combination of computer vision and robotics with the use of a real-time algorithm-based model for solving problems of detecting the quality of raspberries and sorting them.

3 Problem Setting and Approach to Solution

The project aims at training a Deep learning model using a Convolutional Neural Network based on U-net architecture and detecting the raspberry fruit condition. The dataset consists of the images obtained from raspberry fruits which were collected over a time span of fourteen days using a digital camera. This is a supervised learning technique that has independent and dependent variables. The three channels of the image, namely Red, Green, and Blue (RGB), which is made up of pixels, are the independent features, with the dependent feature being the condition of the fruit (either good or bad). The research question, research objectives, and hypotheses of the research are presented in Fig. 2

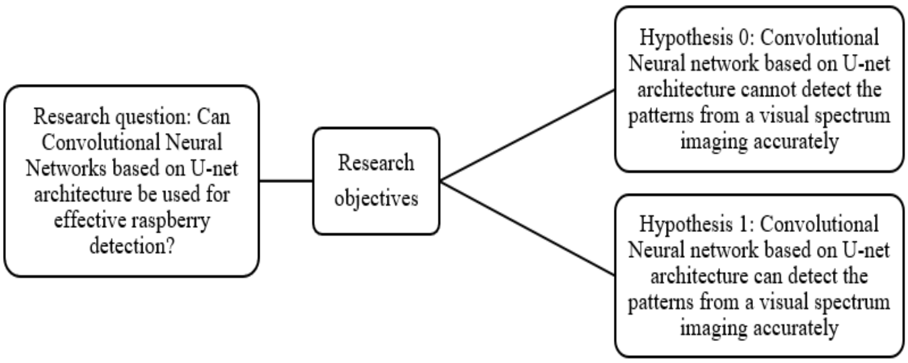

Fig. 2. Research question and hypotheses

The ultimate research goal is to design and execute experiments that seek to reject the null hypothesis. The experiment consists of five steps (Fig. 3)

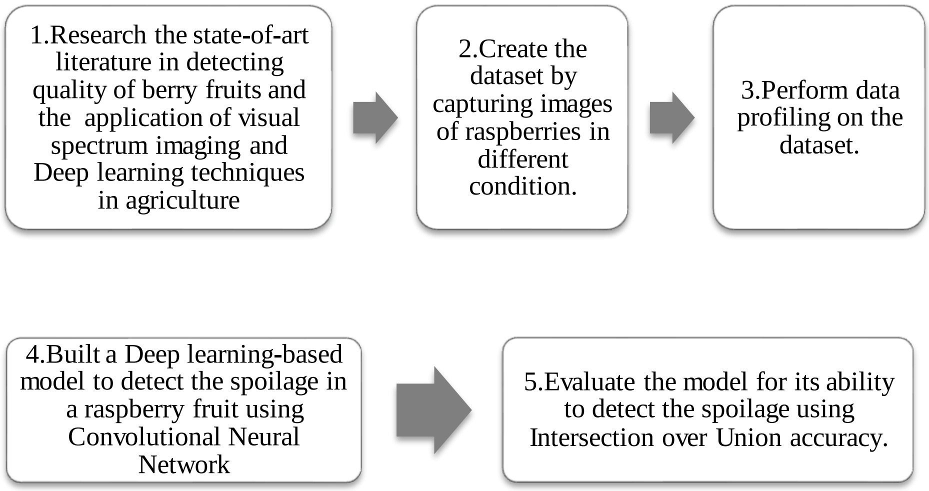

Fig. 3. Steps of experiment

The result obtained from this study would be a proof of concept for the use of Convolutional neural networks based on U-net architecture along with spectrum imaging in the detection of fruit spoilage.

4 Early Results and discussion

Technologies and hardware used in the experiments are as follows: Tensorflow 2.2.1, OpenCV 4.4.0, Computer Vision annotation Tool 1.13.1, NVIDIA GeForce RTX 2070 Super. The preliminary results of the first stages of the experiment look encouraging. The stages of the study and the results obtained are described below:

- Images dataset preparation: a dataset of images was prepared and composed by the researcher with the use of the digital camera. It includes around 1000 unspoiled, spoiled, and damaged raspberry fruits. In the dataset, we use only berries in one layer. While for this experiment, only 50 images and corresponding masks were used.
- Preparation of masks of images: they contain the segmented masks of each berry. Masks are not allowed to overlap (no pixel belongs to two masks). Three classes were used in the segmentation: pixel belonging to the unspoiled berry, pixel belonging to the spoiled berry, none of the above.

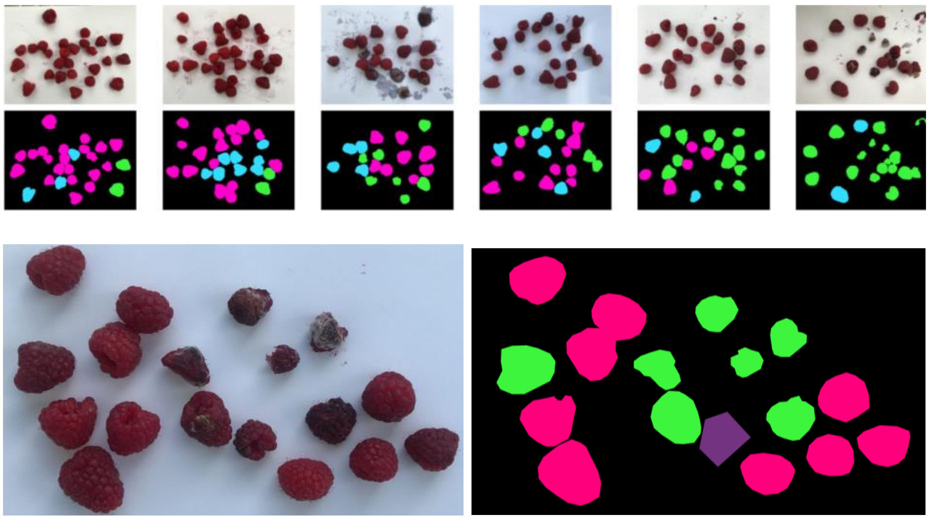

Fig. 4. Examples of the input image and its corresponding map

- Defining and training the model. The U-net architecture was used for the model. It consists of two parts: the encoder part that usually is a pre-trained classification network where convolution blocks are applied, followed by a max pool downsampling to encode the image into feature representations at multiple different levels; the decoder is the second part. Its target is to semantically project the discriminative features learned by the encoder onto the pixel space (to get a dense classification).

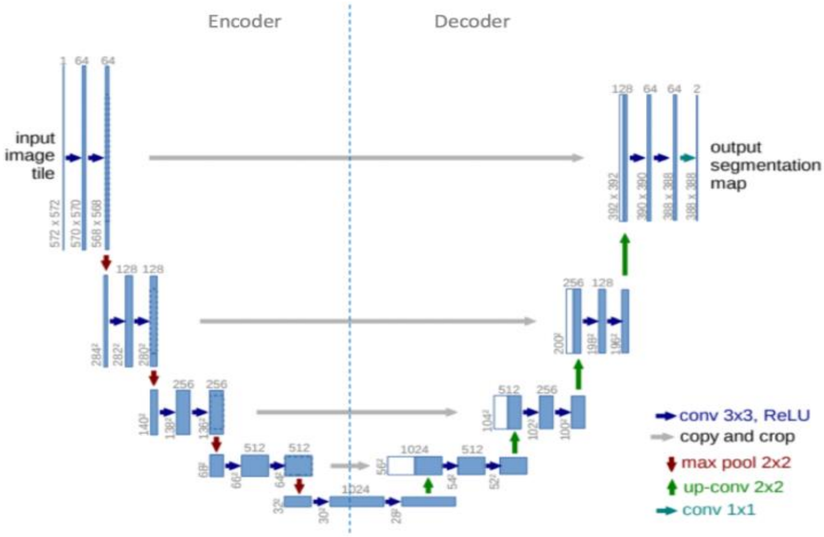

Fig. 5. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations. [9]

The images with their corresponding segmentation maps were used to train the neural network with the stochastic gradient descent. The model was training relatively fast. It took just around 45 minutes to pass 150 epochs.

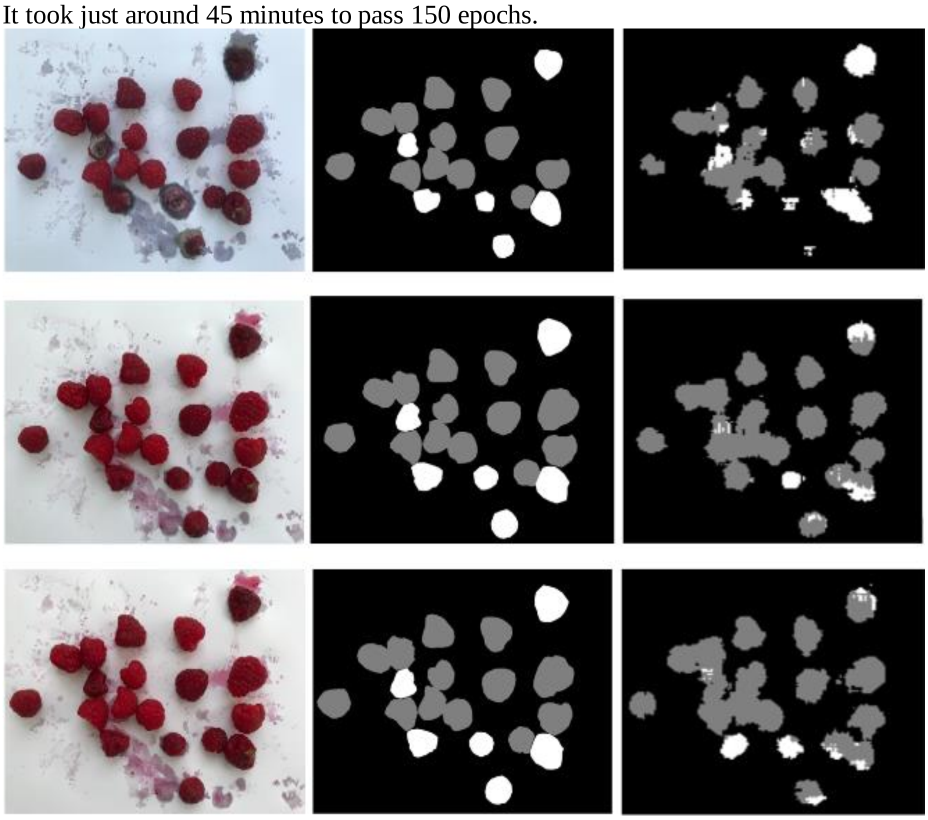

Fig. 6 Input image, ground truth mask, predicted result

White color depicts the spoiled raspberries; grey color depicts non damaged raspberries.

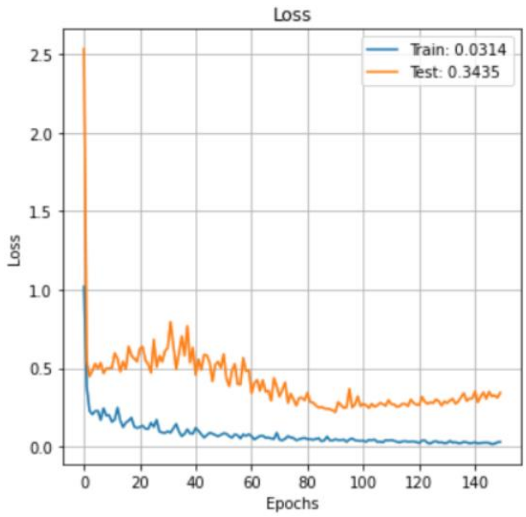

Fig. 7. Loss values during the model training process

As was expected, we received an overfitted model on the low value of the data set, and we are going to excide it in our future iterations to get better results.

5 Summary and Future Work

In this paper, we provided an overview of the raspberry quality detection approach based on the convolutional neural networks with U-net architecture. The following stages of research within the master's thesis include the following steps:

- increasing the dataset from 50 to 1000 images;
- apply data augmentation/data synthesis;
- perform experiments with model layers and kernels;
- image augmentation pipeline;
- apply the model in the more complex system with a camera for live detection;

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