Quality classification and shelf life determination of spinach using deep learning methodology

MERAL YILDIRIM YALCIN – ÖZGÜN YÜCEL – FATIH TARLAK

Summary

In this study, a novel deep learning methodology for predicting the shelf life of spinach was proposed. The primary objective of this research was to employ a deep learning approach to determine the shelf life of spinach based on its appearance. The spinach samples were carefully stored at two temperatures, 4 °C and 10 °C, and the appearance of the spinach samples was regularly recorded using imaging techniques, capturing visual data at various wavelengths. Additionally, total bacterial counts, colour properties and sensorial parameters were assessed. Subsequently, a deep learning model was trained using the collected data. The deep learning algorithms achieved excellent accuracy, with all models surpassing 89.4 % accuracy in predicting food categories. Notably, ResNet-101 algorithm outperformed the others, achieving an accuracy of 93.9 %. This study presents an innovative method for determining the shelf life of perishable food, offering potential benefits that could significantly impact industry practices and enhance consumer well-being. The findings of this study may have practical implications for the food industry, allowing for improved inventory management, reduced food waste and better quality control of spinach products.

Keywords

spinach; classification; microbial quality; colour; deep learning

Spinach, being a leafy green vegetable, is prone to microbial growth, which can lead to food-borne illnesses if consumed after the recommended shelf life has passed [1]. When spinach is harvested, it can come into contact with various sources of microbial contamination, including soil, water and handling equipment [2]. If proper hygiene practices are not followed during cultivation, harvesting, processing or storage, these microorganisms can proliferate on the spinach leaves, increasing the risk of food-borne diseases [2].

When spinach is contaminated with microorganisms, they can multiply under favourable conditions, leading to changes in appearance, texture, odour and taste, which signify the deterioration of the vegetable [3]. The presence and growth of bacteria can contribute to the deterioration of spinach [4].

Modelling and predictive microbiology are valuable tools used in determining the shelf life of perishable food items, including spinach [5]. They leverage mathematical models and statistical methods to estimate microbial growth, decay and the overall quality changes over time. By integrating various factors, such as temperature, time and microbiological characteristics, they provide insights into the expected shelf life of a product and aid in decision-making for product quality management [6].

Deep learning, a subfield of machine learning, has found several applications in food science [7]. Its ability to analyse complex data, recognize patterns and make predictions has opened up new possibilities in the food industry [8]. Deep learning can be applied to predict food spoilage by analysing various parameters such as temperature,

Meral Yildirim Yalcin, Department of Food Engineering, Faculty of Engineering, Istanbul Aydın University, Inonu Street 38, 34295 Kucukcekmece, Istanbul, Turkey.
Özgün Yücel, Department of Chemical Engineering, Faculty of Engineering, Gebze Technical University, Cumhuriyet Street 2254, 41400 Gebze, Kocaeli, Turkey.
Fatih Tarlak, Department of Bioengineering, Faculty of Engineering, Gebze Technical University, Cumhuriyet Street 2254, 41400 Gebze, Kocaeli, Turkey.

Correspondence author:
Fatih Tarlak, e-mail: ftarlak@gtu.edu.tr

humidity, time and sensory data [9]. By recognizing patterns in these factors, models can estimate the remaining shelf life of perishable foods, helping to minimize waste and optimize inventory management [10]. There has been no research focusing on assessing the quality of spinach through a deep learning approach for determination of its shelf life based on appearance. Therefore, it is important to create software that can evaluate the quality of spinach.

In this study, the main aim was to determine the shelf life of spinach using a deep learning approach, specifically considering its appearance. To achieve this, spinach samples were obtained and stored at two temperatures, 4 °C and 10 °C, throughout their shelf life. During the storage period, the appearance of the spinach samples was regularly followed at several wavelengths using imaging techniques. The images captured variations in colour, texture and other visual attributes of the spinach samples over time. The captured images served as the input data for the deep learning model. In parallel, various analyses were conducted to assess the quality and freshness of the spinach samples. These included total bacterial counts determination to monitor microbial growth, colour analysis to quantify colour changes and sensorial evaluation to assess sensory attributes taste, odour and texture. Once the deep learning model was trained, it was used to predict the freshness of new spinach samples based solely on their appearance. By inputting images of the spinach samples into the model, the model could analyse the visual attributes and estimate the remaining shelf life of the spinach based on its appearance. The predictions from the deep learning model were then compared to the results obtained on bacterial counts, colour and sensory analyses to evaluate the accuracy and effectiveness of the deep learning approach in determining the shelf life of spinach based on appearance.

MATERIAL AND METHODS

This research was conducted in two primary phases: experimental and computational. In the experimental phase, quantitative data on total mesophilic bacteria in spinach were gathered at temperatures of 4 °C and 10 °C. Additionally, colour and sensory analyses were conducted. The computational phase involved the implementation of deep learning models for classification purposes. The computational steps were performed using Matlab 9.10.0.1710957 (R2021a) software (MathWorks, Natick, Massachusetts, USA). The flowchart showing the steps followed in the study is shown in Fig. 1. More details about each part of the study are provided in the following subsections.

Data collection

The digital image acquisition system employed in this study was custom-designed for capturing images of spinach samples. The system, illustrated in Fig. 1, comprised three primary components: a specially constructed black box, a light source and a digital camera. To ensure minimal light reflection and prevent external light interference, all inner surfaces of the box were coated in black, providing effective insulation [11]. Illumination was facilitated through the utilization of Red Green

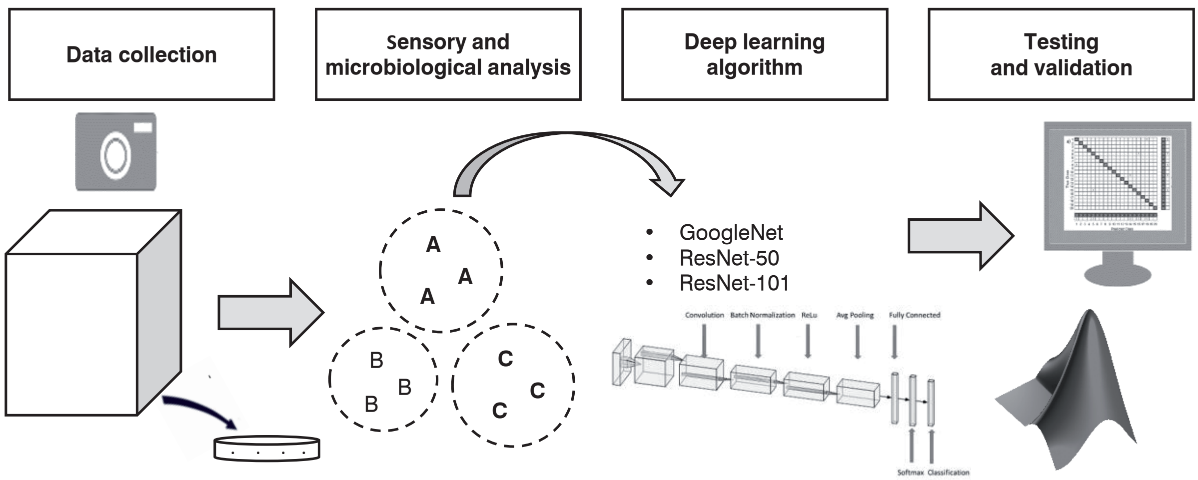

Fig. 1. Flow chart of the steps followed in the current study.

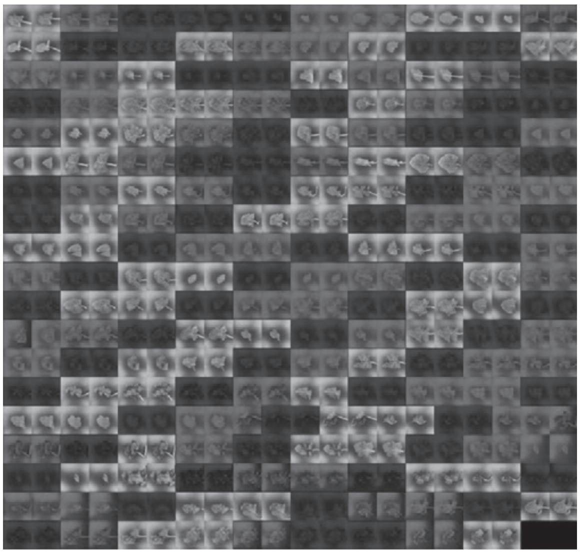

Fig. 2. Sample images of spinach under three different colours (red, green and blue).

Blue (RGB) LED strip lights, controlled remotely. These lights were uniformly positioned at each of the eight corners, ensuring consistent light intensity across the spinach samples. For image capture, digital images were taken using iPhone 7 cameras (Apple, Cupertino, California, USA), placed at a distance of 20 cm from the spinach samples. Spinach images were collected for each of the basic colours (red, green and blue). A sample of the food images used can be seen in Fig. 2.

Samples

Washed and sorted spinach leaves (Eurofresh, Cayirova, Kocaeli) were obtained from a local supplier in Istanbul, Turkey, and promptly transported to the laboratory for storage trials. Spinach leaves are in a polypropylene bag and do not contain preservatives. The products were divided into two groups in their original 700 g packaging, without any pre-treatment and opening the packages, and were placed in incubators set at 4 °C for 288 h and 10 °C for 216 h. The incubators were maintained within a temperature fluctuation range of ± 0.2 °C. A new package was always open for each sampling.

Microbiological analysis

Microbial analyses were done as described previously [12]. During the storage period, total mesophilic bacteria counts were monitored at 24 h intervals. Under aseptic conditions, a 10 g portion of the spinach sample was homogenized in 90 ml of 0.1 $g \cdot l^{-1}$ peptone water (Oxoid, Basingstoke, United Kingdom) for 2 min at high-speed using a stomacher (Bag Mixer 400VW; Interscience, Saint Nom la Bretèche, France). Subsequently, 1 ml of the homogenized mixture was used to prepare serial decimal dilutions ranging from 10^{-2} to 10^{-9}, utilizing tubes containing 9 ml of 0.1 $g \cdot l^{-1}$ peptone water. Enumeration of total mesophilic bacteria was carried out on plate count agar (Merck, Darmstadt, Germany) after incubation at 30 °C for 72 h. Each sampling point at both temperatures was measured in triplicate. The results were reported as the average natural logarithm of colony forming units per gram, derived from these multiple measurements.

Colour analysis

The colour of the spinach samples was measured in CIELab colour space, where L^* is the lightness component or luminance from black (0) to white (100), a^* is a chromatic component from green (–120) to red (+120) and b^* is a chromatic component from blue (–120) to yellow (+120). A chroma meter CR-400 (Konica Minolta, Tokyo, Japan) equipped with a D65 illuminant source was used [13]. Prior to colour measurements, the chroma meter was calibrated with a white calibration tile ($Y = 86.6, x = 0.3188$ and $y = 0.3364$). Total colour difference (ΔE^*) values were calculated using Eq. 1 [14, 15]:

$$\Delta E^* = \sqrt{\left(L_i^* - L_f^*\right)^2 + \left(a_i^* - a_f^*\right)^2 + \left(b_i^* - b_f^*\right)^2} \quad (1)$$

where L_i*, a_i* and b_i* refers to the initial colour values, and L_f*, a_f* and b_f* refers to the final colour values.

Sensory evaluation

Sensory analysis of spinach involved assessing its visual (colour and texture) and olfactory qualities with the input of 10 semi-trained individuals in a laboratory, using a scale from 1 to 3 where 1 signified excellent, 2 moderate and 3 indicated poor [16]. The sensory analysis categorized the spinach samples into three groups: A for fresh, B for moderately fresh and C for not suitable for consumption.

Deep learning algorithms

Deep learning, a branch of machine learning, enables computers to learn and execute tasks by harnessing artificial neural networks to extract significant data features [17]. These networks, composed of interconnected layers of processing units, execute complex computations in parallel, resembling the operations of the biological nervous system [18]. With extensive training on expansive datasets, deep learning models show-

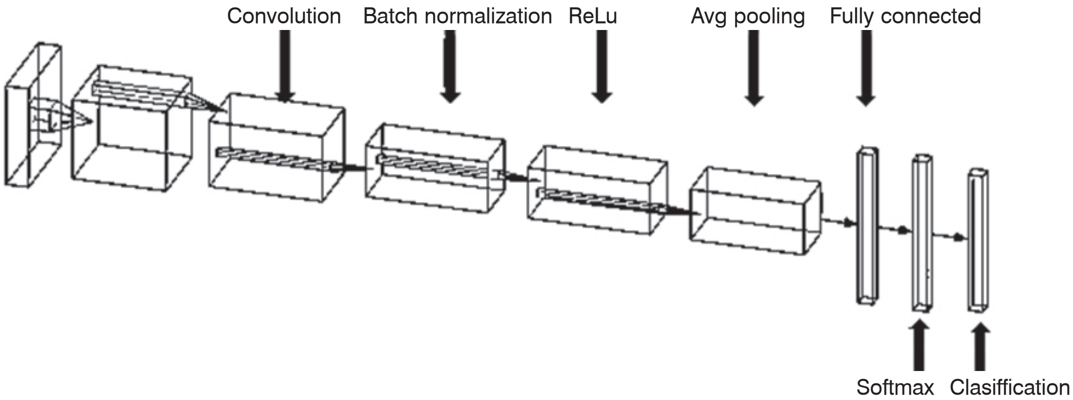

Fig. 3. Main structural components of the used deep learning method.

case exceptional precision levels in tasks such as object recognition, often surpassing human capacities [19]. In the present research, three specific deep learning algorithms, namely GoogleNet, ResNet-50, and ResNet-101, were utilized within the deep learning toolbox of the Matlab software for the purpose of training on food images. These algorithms consisted of 22, 50 and 101 layers, respectively, each playing a fundamental role in the learning process. The fundamental components within these learning structures are visually depicted in Fig. 3.

Evaluation of training and validation process

In the context of classification problems, evaluating the classifier's performance frequently involves examination of the associated confusion matrix [20]. Additionally, it is feasible to compute various metrics, namely, Average accuracy (A_a), Error rate (E_r), Precision (PPV), Recall (TPR) and F-score (F_{score}), by employing Eqs. 2–6, respectively, which are derived from the values within the matrix, as outlined by Sokolova and Lapalme [21]:

$$A_a = \frac{\left(\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}\right)}{l} \tag{2}$$

$$E_r = \frac{\left(\sum_{i=1}^{l} \frac{fp_i + fn_i}{tp_i + fn_i + fp_i + tn_i}\right)}{l} \tag{3}$$

$$PPV = \frac{\left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fp_i}\right)}{l} \tag{4}$$

$$TPR = \frac{\left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fn_i}\right)}{l} \tag{5}$$

$$F_{score} = \sum_{i=1}^{l} \frac{2 \times PPV \times TPR}{PPV + TPR} \tag{6}$$

where A_a refers to average per-class effectiveness of a classifier, E_r refers to average per-class classification error, PPV refers to effectiveness of a classifier to identify positive labels, TPR refers to an average per-class effectiveness of a classifier to identify class labels, F_{score} refers to relations between data's positive labels and those given by a classifier based on a per-class average, tp_i refers to the number of true positives, tn_i refers to the number of true negatives, fp_i refers to the number of false positives, fn_i refers to the number of false negatives and l refers to the number of evaluated classes.

RESULTS AND DISCUSSION

In this experiment, the impact of storage temperatures (4 °C and 10 °C) on the total mesophilic bacteria counts of leafy and sorted spinach samples was investigated. The initial bacterial counts averaged at 7.2 ± 0.1 log CFU·g^{-1}. The storage duration differed based on temperature, leading to a storage period of 12 days at 4 °C and 9 days at 10 °C. Total mesophilic bacterial counts exhibited a slight increase at a higher storage temperature, culminating in levels ranging from 9.65 ± 0.02 log CFU·g^{-1} to 9.95 ± 0.03 log CFU·g^{-1} at the end of the storage period. Colour analysis, utilizing L^*, a^*, and b^* values and computed ΔE^* value, indicated a significant colour change in spinach samples. At 4 °C, ΔE^* exceeded 10 by the 12th day, while at 10 °C, this threshold was reached by the 7th day, signifying an accelerated colour change at the higher temperature. Sensory analysis revealed that spinach samples stored at 4 °C remained edible for seven days, while those at 10 °C became inedible after just five days (Tab. 1). This indicated that the higher temperature accelerated the spoilage process in spinach, corroborating the findings from microbiological and colour analysis.

The deep learning algorithms, GoogleNet, ResNet-50, and ResNet-50, which have 22, 50, and 101 layers respectively, were used to categorize the spinach images in the Matlab software. A total of 378 spinach samples were subjected to the train-validation-test split methodology and divided into training, validation, and testing subsets with the ratio of 80 %, 10 %, and 10 %, respectively. In the scope of supervised machine learning approach, the performance of applied algorithms is assessed with their true and false predictions related to the classes which are defined before. In the context of this research, the true and false predictions were calculated to evaluate the prediction performance of used three algorithms. GoogleNet produced 40 error predictions during the whole process, while ResNet-50 and ResNet-101 produced 24 and 23 false predictions out of 378 spinach samples, respectively. These results showed that ResNet-50 and ResNet-101 performed better than GoogleNet in the training process (Tab. 2).

Tab. 3 presents the statistical evaluation metrics used in this study, including A_a, E_r, *PPV*, *TPR* and F_{score}. The results indicated that A_a of GoogleNet, ResNet-50 and ResNet-101 were 89.4 %, 93.7 % and 93.9 %, respectively. These findings suggested that ResNet-101 performed better than GoogleNet and ResNet-50 in the prediction process. Other statistical metrics, i.e. E_r, *PPV*, *TPR* and F_{score}, further supported the conclusion that ResNet-101 outperformed GoogleNet and ResNet-50 in terms of accuracy and learning capability.

The evaluation of the training, validation and testing phases, encompassing confusion matrices and statistical metrics, consistently indicated that ResNet-101 was the most efficient deep convolutional neural network. However, the elapsed time for the training process varied based on the computational resources. On a system featuring an Intel Core i5-1035G1 CPU @ 1.00 GHz processor (Intel Corporation, Santa Clara, California, USA), GoogleNet, ResNet-50 and ResNet-101 took 26 min, 99 min and 131 min, re-

Tab. 1. Quality of spinach samples during storage.

Time [d]	Temperature [°C]	Total bacterial counts [log CFU·g^{-1}]	Sensory value	Colour parameters				Class
				*L**	*a**	*b**	Δ*E**	
0	4	7.24	1.00	31.21	–7.44	9.44	0.00	A
1	4	8.09	1.00	29.37	–7.56	9.50	1.84	A
2	4	8.05	1.00	29.54	–7.34	8.61	1.87	A
3	4	8.09	1.00	28.86	–7.13	8.77	2.46	A
4	4	8.52	1.50	27.91	–5.06	5.39	5.74	B
5	4	8.55	1.70	26.78	–4.95	5.74	6.29	B
6	4	9.09	1.80	26.45	–5.42	5.63	6.42	B
7	4	9.20	1.90	26.02	–5.45	5.40	6.87	B
8	4	9.00	2.40	24.99	–4.54	4.83	8.27	C
9	4	8.87	2.67	23.07	–4.84	6.35	9.09	C
10	4	9.20	2.67	22.76	–4.74	5.60	9.67	C
12	4	9.67	3.00	20.64	–3.80	5.04	12.01	C
0	10	7.24	1.00	31.21	–7.44	9.44	0.00	A
1	10	8.10	1.00	30.65	–7.82	9.21	0.71	A
2	10	8.18	1.00	28.29	–7.47	8.97	2.96	A
3	10	8.46	1.40	27.28	–6.97	7.66	4.34	B
4	10	8.87	1.70	26.77	–5.03	5.52	6.39	B
5	10	9.20	1.90	25.72	–4.60	4.50	7.91	B
6	10	9.39	2.20	24.59	–3.74	3.39	9.70	C
7	10	9.83	3.00	23.00	–3.50	3.10	11.10	C
8	10	9.83	3.00	21.00	–2.50	2.95	13.07	C
9	10	9.94	3.00	18.15	–1.99	2.85	15.61	C

Sensory value: 1 – excellent, 2 – moderate, 3 – poor.
Class: A – sample is fresh and can be consumed, B – sample is moderately fresh and can be consumed, C – sample cannot be consumed.
ΔE* – total colour difference.

Tab. 2. True and predicted class of spinach samples.

Network	True class number		Predicted class number		
			A	B	C
GoogleNet	A	108	89	18	1
	B	126	16	110	0
	C	144	3	2	139
ResNet-50	A	108	90	18	0
	B	126	2	120	4
	C	144	0	0	144
ResNet-101	A	108	94	14	0
	B	126	1	119	6
	C	144	2	0	142

Class: A – sample is fresh and can be consumed, B – sample is moderately fresh and can be consumed, C – sample cannot be consumed.

Tab. 3. Statistical evaluation for the prediction process.

Network	A_a	E_r	*PPV*	*TPR*	F_{score}
GoogleNet	0.894	0.106	0.888	0.887	0.887
ResNet-50	0.937	0.063	0.940	0.929	0.932
ResNet-101	0.939	0.061	0.941	0.934	0.936

A_a – the average per-class effectiveness of a classifier, E_r – error rate, *PPV* – effectiveness of a classifier to identify positive labels, *TPR* – an average per-class effectiveness of a classifier to identify class labels, F_{score} – relations between data's positive labels and those given by a classifier based on a per-class average.

spectively, for the initial 1 000 iterations. Notably, GoogleNet emerged as the fastest algorithm for the training process, as depicted in Fig. 4. The size of GoogleNet, ResNet-50 and ResNet-101 in the Matlab software's deep learning toolbox was 27 MB, 96 MB and 167 MB, respectively. This discrepancy can be attributed to their varying complexity and network size, preferring GoogleNet for less intricate classification processes. However, considering the entire training image dataset, GoogleNet, ResNet-50 and ResNet-101 demanded approximately 450 min, 300 min and 250 min, respectively. These results demonstrated that, for both accuracy and efficiency in processing, ResNet-101 stood out as the superior deep learning algorithm of the three tested.

Analysing receiver operating characteristic (ROC) curve within the Matlab software's deep learning toolbox for GoogleNet, ResNet-50 and ResNet-101 revealed that area under the ROC curve (*AUC*) values for GoogleNet ranged from 0.89 to 0.99 across each group. ResNet-50 exhibited *AUC* values of approximately 0.98 for groups A and B, while ResNet-101 consistently surpassed 0.99 for each group. These findings clearly demonstrated the superiority of ResNet-101 over GoogleNet and ResNet-50 algorithms.

Based on these results, software development continued for each algorithm to classify spinach samples. The Matlab software interface for computers is shown in Fig. 5 and can be accessed for download [22]. Additionally, a tutorial video explaining how to use the software is available at the same location.

The study included storing spinach samples at two temperatures, capturing their appearance through imaging techniques and performing thorough analyses, involving bacterial count, colour assessment, and sensory evaluation. The

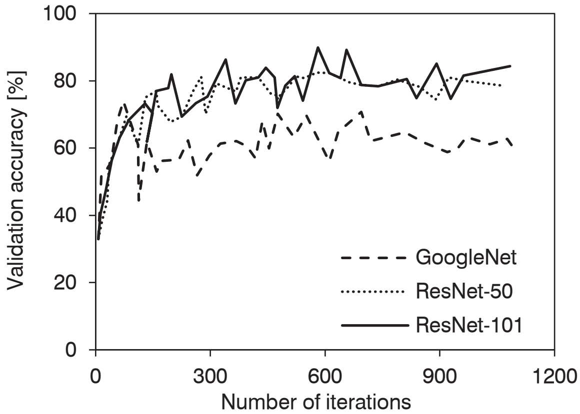

Fig. 4. Accuracy of the deep learning algorithms in the training process by iteration.

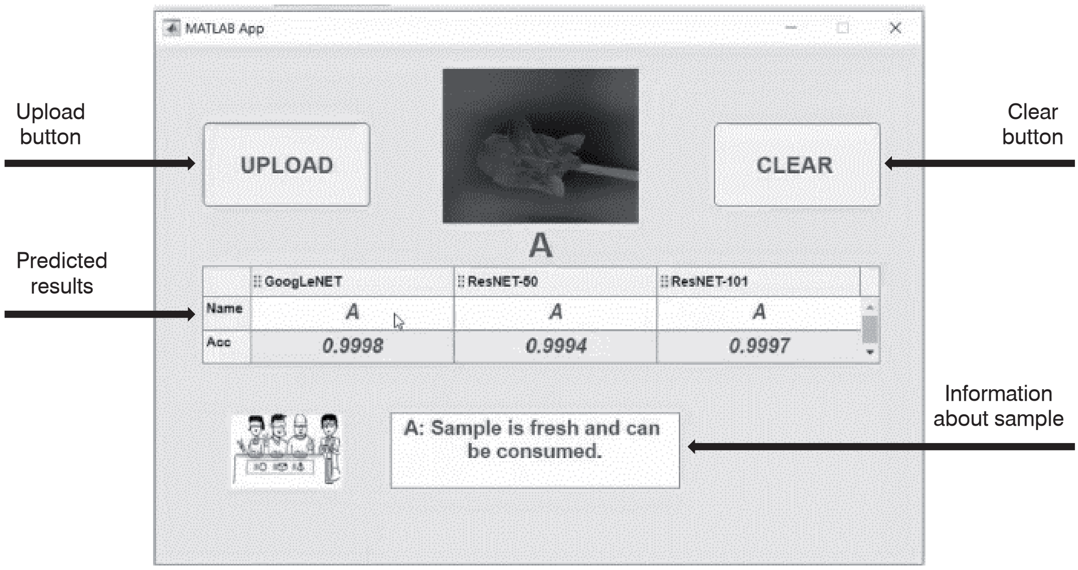

Fig. 5. Illustration of the control panel of the developed software.

ResNet-101 deep learning model demonstrated good accuracy (93.9 %), indicating its effectiveness. The research implied potential benefits for the food industry, such as improved inventory management, decreased waste and enhanced quality control.

CONCLUSION

This study contributed to the development of methods for determination of shelf life of perishable food products, specifically spinach, as a fundamental parameter ensuring quality and safety. Unlike traditional methods that are time-consuming and subjective in nature, the study introduced an innovative deep learning methodology focused on predicting spinach shelf life based on its appearance. Through storage at 4 °C and 10 °C, together with regular imaging, a comprehensive assessment of spinach quality and freshness was conducted, incorporating microbiological analyses of bacterial counts, colour properties and sensory attributes. The deep learning models exhibited remarkable accuracy, surpassing 89.4 %, with ResNet-101 notably achieving the outstanding 93.9 %. With integration of deep learning into shelf life determination, especially emphasizing appearance, it was possible to improve the accuracy and efficiency of spinach quality assessment. Practical implications of the study extend to the food industry, offering prospects for enhanced inventory management, reduced food waste and improved quality control in spinach production management. This study thus introduced a new approach to perishable food shelf life determination, with potential benefits for industry and for consumer well-being.

REFERENCES

1. Mogren, L. – Windstam, S. – Boqvist, S. – Vågsholm, I. – Söderqvist, K. – Rosberg, A. K. – Lindén, J. – Mulaosmanovic, E. – Karlsson, M. E. – Uhlig, E. – Håkansson, Å. – Alsanius, B.: The hurdle approach – A holistic concept for controlling food safety risks associated with pathogenic bacterial contamination of leafy green vegetables. A review. Frontiers in Microbiology, *9*, 2018, article 1965. DOI: 10.3389/fmicb.2018.01965.
2. Park, S. – Navratil, S. – Gregory, A. – Bauer, A. – Srinath, I. – Jun, M. – Szonyi, B. – Nightingale, K. – Anciso, J. – Ivanek, R.: Generic *Escherichia coli* contamination of spinach at the preharvest stage: effects of farm management and environmental factors. Applied and Environmental Microbiology, *79*, 2013, pp. 4347–4358. DOI: 10.1128/AEM.00474-13.
3. Mostafidi, M. – Sanjabi, M. R. – Shirkhan, F. – Zahedi, M. T.: A review of recent trends in the development of the microbial safety of fruits and vegetables. Trends in Food Science and Technology, *103*, 2020, pp. 321–332. DOI: 10.1016/j.tifs.2020.07.009.
4. Zhou, B. – Luo, Y. – Huang, L. – Fonseca, J. M. – Yan, H. – Huang, J.: Determining effects of temperature abuse timing on shelf life of RTE baby spinach through microbial growth models and its association with sensory quality. Food Control, *133*, 2022, article 108639. DOI: 10.1016/j.foodcont.2021.108639.
5. Tsironi, T. – Dermesonlouoglou, E. – Giannoglou, M. –

Gogou, E. – Katsaros, G. –Taoukis, P.: Shelf-life prediction models for ready-to-eat fresh cut salads: Testing in real cold chain. International Journal of Food Microbiology, *240*, 2017, pp. 131–140. DOI: 10.1016/j.ijfoodmicro.2016.09.032.

6. Corradini, M. G.: Shelf life of food products: from open labeling to real-time measurements. Annual Review of Food Science and Technology, *9*, 2018, pp. 251–269. DOI: 10.1146/annurev-food-030117-012433.
7. Lin, Y. – Ma, J. – Wang, Q. – Sun, D.-W.: Applications of machine learning techniques for enhancing nondestructive food quality and safety detection. Critical Reviews in Food Science and Nutrition, *63*, 2023, pp. 1649–1669. DOI: 10.1080/10408398.2022.2131725.
8. Tarlak, F., – Yücel, Ö.: Identification of foods in the breakfast and determination of nutritional facts using deep convolution neural networks. Food Science and Technology, *43*, 2023, article e10323. DOI: 10.5327/fst.10323.
9. Estelles-Lopez, L. – Ropodi, A. – Pavlidis, D. – Fotopoulou, J. – Gkousari, C. – Peyrodie, A. – Panagou, E. – Nychas, G.-J. – Mohareb, F.: An automated ranking platform for machine learning regression models for meat spoilage prediction using multi-spectral imaging and metabolic profiling. Food Research International, *99*, 2017, pp. 206–215. DOI: 10.1016/j.foodres.2017.05.013.
10. Kayikci, Y. – Demir, S. – Mangla, S. K. – Subramanian, N. – Koc, B.: Data-driven optimal dynamic pricing strategy for reducing perishable food waste at retailers. Journal of Cleaner Production, *344*, 2022, article 131068. DOI: 10.1016/j.jclepro.2022.131068.
11. Tarlak, F. – Ozdemir, M. – Melikoglu, M.: Computer vision system approach in colour measurements of foods: Part I. development of methodology. Food Science and Technology, *36*, 2016, pp. 382–388. DOI: 10.1590/1678-457X.11615.
12. Yildirim-Yalcin, M. – Yucel, O. – Tarlak, F.: Development of prediction software to describe total mesophilic bacteria in spinach using a machine learning-based regression approach. Food Science and Technology International, published online 18 April 2023. DOI: 10.1177/10820132231170286.
13. Hussein, J. B. – Oke, M. O. – Abiona, O. O. – Adebayo, Q.: Optimization of processing parameters for drying of tomatoes (*Solanum lycopersicum* L.var) slices using Taguchi technique. Journal of Food Processing and Preservation, *45*, 2021, article e15149. DOI: 10.1111/jfpp.15149.
14. Gibert, J. M. – Daga, J. M. – Gilabert, E. J. – Valldeperas, J.: Evaluation of colour difference formulae. Coloration Technology, *121*, 2005, pp. 147–152. DOI: 10.1111/j.1478-4408.2005.tb00265.x.
15. Wu, D. – Sun, D.-W.: Colour measurements by computer vision for food quality control – A review. Trends in Food Science and Technology, *29*, 2013, pp. 5–20. DOI: 10.1016/j.tifs.2012.08.004.
16. Swegarden, H. – Stelick, A. – Dando, R. – Griffiths, P. D.: Bridging sensory evaluation and consumer research for strategic leafy brassica (*Brassica oleracea*) improvement. Journal of Food Science, *84*, 2019, pp. 3746–3762. DOI: 10.1111/1750-3841.14831.
17. Raschka, S. – Patterson, J. – Nolet, C.: Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. Information, *11*, 2020, article 193. DOI: 10.3390/info11040193.
18. Prieto, A. – Prieto, B. – Ortigosa, E. M. – Ros, E. – Pelayo, F. – Ortega, J. – Rojas, I.: Neural networks: An overview of early research, current frameworks and new challenges. Neurocomputing, *214*, 2016, pp. 242–268. DOI: 10.1016/j.neucom.2016.06.014.
19. Xiao, Y. – Tian, Z. – Yu, J. – Zhang, Y. – Liu, S. – Du, S. – Lan, X.: A review of object detection based on deep learning. Multimedia Tools and Applications, *79*, 2020, pp. 23729–23791. DOI: 10.1007/s11042-020-08976-6.
20. Tarlak, F. – Yücel, Ö. – Yilmaz, O.: Food recognition and nutrition facts determination with deep convolution neural network models. Carpathian Journal of Food Science and Technology, 2023, Special issue, pp. 1–10. DOI: 10.34302/SI/236.
21. Sokolova, M. – Lapalme, G.: A systematic analysis of performance measures for classification tasks. Information Processing and Management, *45*, 2009, pp. 427–437. DOI: 10.1016/j.ipm.2009.03.002.
22. Yildirim Yalcin, M. – Yücel, Ö. – Tarlak, F.: Quality classification and shelf-life determination of spinach. In: GitHub [online]. San Francisco : GitHub, uploaded 13 November 2023 [cited 20 January 2024]. <https://github.com/ftarlak?tab=repositories>

Received 18 November 2023; 1st revised 23 January 2024; accepted 30 January 2024; published online 23 March 2024.