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INVESTIGATING THE EFFECT OF OZONATION ON MECHANICAL PARAMETERS OF *LONICERA CAERULEA* L. FRUITS USING MACHINE LEARNING

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ABSTRACT

Lonicera caerulea L. - well - known in Poland as Kamchatka berry, has been gaining increasing popularity in recent years. The tests carried out on newly established Japanese haskap clones aimed at demonstrating the suitability of the fruits for mechanical harvesting and storage. This study focused on evaluation of mechanical properties and assessment of three distinct machine learning techniques to create predictive models that elucidate the connection between key mechanical attributes of the fruit and storage conditions of *L. caerulea*. The average force needed to puncture the fruits skin and flesh of *L. caerulea* var. *emphyllocalyx* varieties is 16.91% higher than that required for the tested *L. caerulea* var. *kamtschatica* varieties. *L. caerulea* var. *emphyllocalyx* fruits exhibited a significantly higher respiration rate, with C_2H_4 and CO_2 levels during storage being 25.5% and 10.5% higher, respectively, compared to *L. caerulea* var. *kamtschatica* varieties. The machine learning algorithms tested yielded accurate models for deformation and energy prediction. The mean absolute percentage error (MAPE) of these models was determined to be between 14.87 and 20.65%. Models with significantly lower accuracy were obtained for force prediction, with the MAPE reaching 28.95% for *L.* var. *kamtschatica* fruit and 42.33% for *L. emphyllocalyx* fruit. The cultivation and improvement of *Lonicera caerulea* L. varieties is of great importance for the advancement of mechanized harvesting methods and the development of improved storage technologies for this species. The creation of machine learning methods will facilitate the development of predictive models that can serve as a predictive tool for the relationship between selected mechanical properties

Introduction

Originating from cold lands of central Asia and Far East, *Lonicera caerulea* L. belongs to the 200 species of Caprifoliaceae family. Most species in this family are ornamental, with only approximately 17 fruit-bearing plants classified as edible (Senica et al., 2018). *Lonicera caerulea* L. includes several botanical varieties originating from different regions, which may differ in terms of chemical composition or mechanical properties of the fruit. There are varieties which come from Russia such as *L. caerulea* var. *kamtschatica*, commonly known in Poland as 'Kamchatka berry', *L. caerulea* var. *altaica, L. caerulea* var. *edulis*, and *L. caerulea* var. *boczkarnikovae,* and, *L. caerulea* var. *emphyllocalyx* originating in Japanese island of Hokkaido which is known in Poland as Japanese haskap (Kula and Krauze-Baranowska, 2016). These varieties are adapted to their climates and represent some of the primary types of *Lonicera caerulea* L. grown for their edible fruits. Additionally, it is cultivated in Poland, Romania, and Estonia. Research is ongoing to explain its biological properties. Blue honeysuckle berries, highly valued in the processing industry for their flavor and rich content of bioactive compounds like anthocyanins, phenolic acids, and vitamin C, are a popular fruit for desserts (Becker and Szakiel, 2019; Gawroński et al., 2014). The cultivation and storage possibilities of *Lonicera caerulea L.* face several challenges due to various influencing factors. Depending on the variety, fruits have a short ripening period, are difficult to detach from the plant during ripening, and their ripening is uneven, which may significantly affect the efficiency and profitability of production (Leisso et al., 2021a; Ren et al., 2023). A key to maintain the quality of blue honeysuckle fruit for consumers is harvesting the berries at the optimal stage of ripeness while avoiding any mechanical damage during the process. *Lonicera caerulea* L. fruit is typically harvested by hand, though mechanical methods can also be used (Yu et al., 2023). Farmers often modify equipment designed for harvesting other soft fruits to handle blue honeysuckle berries. However, these adaptations can result in mechanical damage due to low resistance of berries, which makes them more susceptible to bruising and other forms of physical harm during the harvesting process. This challenge highlights the need to apply specialized machinery, techniques or software to minimize damage and maintain fruit quality. Damage to the fruit increases ethylene production, which subsequently speeds up the aging process and reduces the firmness of the berries, thereby reducing the storage capacity of the fruit (Martinez et al., 2007; Dziedzic et al., 2020; Gorzelany et al., 2022).

Ozone (O_3) is a powerful oxidizing agent used to disinfect plant materials, thereby extending their freshness. O_3 can be used in either in gaseous or aqueous form, with research showing that the gaseous ozone has better effect on fruit (Zapałowska et al., 2021). Ozonation is a non-thermal food preservation method that improves food safety without compromising quality or causing environmental pollution, and it is particularly favored by the fruit and vegetable industry because it decomposes rapidly into oxygen, leaving no residue. Although O_3 can react with certain organic compounds in food, potentially producing byproducts such as aldehydes, ketones, and carboxylic acids, it remains highly valued for its disinfectant and biocidal properties (Contigiani et al., 2018; Lv et al., 2019). Using a correct dose of ozone can greatly enhance the storage potential of fruit.

The optimisation of storage of agricultural products is significant, given the necessity to minimise food waste. Modern data analysis methods, including machine learning, can be instrumental in achieving effective optimisation. The development of accurate models of the dependence of selected mechanical features of biological materials on storage-related parameters is essential for optimal planning of postharvest operations. Modern artificial intelligence methods are increasingly being used in this area, as evidenced by the growing number of publications reporting on the use of machine learning for agriculture, including in the food processing industry (Niedbała et al., 2022; Clay et al., 2024). One of the key challenges in the application of machine learning techniques is the selection of an appropriate algorithm for the data to be modelled, followed by optimization of the algorithm's hyperparameters. Some publications deal with the prediction of the parameters of fruit and vegetables important in storage process. Saeidirad et al. (2013) employed an artificial neural network (ANN) to predict the stress relaxation of three cultivars of pomegranate based on relaxation time. They also compared the accuracy of the ANN model with that of the Maxwell model and found that both models have the capacity to produce accurate and reliable predictions for stress. The prediction of apple hardness was conducted by Pan et al. (2015), who developed an ANN model with high accuracy using mechanical properties index test results as input parameters. The machine learning models were developed by Ropelewska (2022) for the purpose of analysis of mechanical properties of red currant fruit under a variety of storage conditions. Support vector machines (SVM) have been demonstrated to be a valuable tool for estimating the texture profile and puncture parameters of blueberries (Hu et al., 2016), the mechanical characteristics of apples (Peipei et al., 2022) and the firmness of kiwifruit (Mohsen et al., 2024).

The aim of this study is to compare the mechanical properties of 3 varieties of *L.* var. *kamtschatica* and 3 varieties of *L.* var. *emphyllocalyx* and the potential application of *L. emphyllocalyx* fruit and ozone fumigation in food processing. The fruits of *Lonicera caerulea* L., known for their rich chemical composition, are also known for their limited storage capacity. The O_3 and its use can significantly extend storage time by affecting the mechanical properties of fruit and the number of gases released. Furthermore, three machine learning methods were evaluated in the context of developing predictive models of the relationship between selected mechanical parameters of fruit and storage conditions.

Materials and Methods

Material

The study was conducted between 2022 and 2024 on fruits obtained from a nursery crop located in Tyczyn (49º 57'52'' N 22º2'47'' E, Subcarpathian Voivodship, Poland) The study involved *Lonicera caerulea* var. *kamtschatica*, hereinafter referred to as LK, varieties 'Vostorg', 'Jugana', 'Aurora', as well as newly created clones 'Lori', '21-17' and '139-24' of *Lonicera caerulea* var. *emphyllocalyx*, hereinafter referred to as LE (Fig. 1).

The berries were hand-harvested at full maturity, with 1000 g collected from each variety, and the optimal harvest date was determined by the color and drop of the fruit. The harvest date and meteorological conditions prevailing in each experimental year have been previously published (Basara et al., 2024). Both species were grown in pots containing a peat substrate comprising perlite and sand (20:1:1). In 2022, Osmocote Exact 3-4 m (ICL, Sydney, Australia) fertilizer was added at the concentration of 2.0 kg·m^{-3} of substrate. In 2023-2024, Kristalon Blue (Yara, Oslo, Norway) in concentration of 0.4 kg·m^{-3} was periodically used to fertilize plants.

Figure 1. The botanical varieties of Lonicera caerulea L. used in this study: (A) L. var. kamtschatica (LK) and (B) L. var. emphyllocalyx (LE).

Ozone Treatment of Berries

Before measuring mechanical properties, LK and LE fruits were subjected to the ozonation process. The fruits were randomly divided into four batches, each containing 50 berries. Measurements were taken on the 1st, 3rd, and 5th day of storage each year after the ozonation treatment, where gaseous ozone was applied at the concentration of 5 ppm for durations of 1, 3, and 5 minutes, with a flow rate of 40 g O_3·h^{-1} at 20°C. Ozone was generated using a KORONA A 40 Standard (Korona, Piotrków Trybunalski, Poland) along with a 106 M UV Ozone Solution detector (Ozone Solution, Hull, MA, USA). During each year of the study, the ozonation treatment was consistently applied at the stage when the fruits reached harvest ripeness.

Determination of Morphological Characteristic

The sample size consisted of 10 fruits for each variant. The length and width of individual fruits were measured with an accuracy of 0.01 mm, while mass was measured with an accuracy of 0.001 g. The density (kg·m^{-3}) of each fruit was calculated as the ratio of its weight to the volume of a sphere with diameter d (Gorzelany et al., 2022).

Water content measurement

Water content in fresh *Lonicera caerulea* berries and those kept in cold storage was determined using the dryer method (105°C), following PN-90/A-75101-03:1990. Ten randomly selected berries were placed in a laboratory moisture analyzer (Radwag, Polska), with measurements performed in three replications.

Determination of the Mechanical Properties

The selected mechanical properties of the LK and LE fruits were measured in the compression test using Brookfield CT3-1000 texture analyser (AMETEK Brookfield, Middleboro, MA, USA), with software assistance - TexturePro CT. Each sample was punctured using 2 mm diameter steel plunger. The compression velocity was 0.2 mm·s^{-1} and initial tension force of the measurement was 0.05 N. The plunger penetration depth after puncture was 1 mm. To determine the mechanical resistance of skin and flesh, peak destructive force (N), degree of deformation and destructive energy (mJ) were recorded after each measurement. Each measurement was performed in ten replications.

Statistical Analysis

The Statistica 13.3 program (TIBCO Software Inc., Tulsa, OK, USA) was used to perform a statistical evaluation of the results, including analysis of variance (ANOVA) and the significance of the LSD test at a significance level of $\alpha = 0.05$.

Machine learning methods

Three machine learning methods were employed to model the relationship between the mechanical parameters of LK and LE berries and storage conditions. These were two types of artificial neural networks, namely the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) and Support Vector Machines (SVM). Neural networks are a tool that has been modelled on the operation of the biological nervous system. The fundamental unit of ANN is the artificial neuron, which calculates the weighted sum of the input signals and then transforms this value using an activation function. ANNs are composed of a layered structure of artificial neurons. ANNs do not require programming; instead, they are trained using a training set. After training, the model is tested on a separate dataset to assess its ability to generalise the information contained in the training set. Prior to training the neural models, it is essential to define their structure, specifically the number of neurons in the hidden layer. The concept of SVM is founded upon the notion of support vectors, which are defined as points within the data set that serve to determine the solution. In the context of a classification problem, the solution is represented by a hyperplane that separates groups of data. In the case of a regression problem, the solution is expressed as a function. Support vectors exert a profound influence on the positioning of the hyperplane or regression function. In this study, an epsilon-insensitive support vector machine (ε-SVM) regression was employed. The objective of the algorithm is to identify a function, that deviates from the targets by a value no greater than ε for each point in the training data set. The Gaussian radial basis function (RBF) kernel function was used due to its capacity to effectively model non-linear relationships in the data.

In this study, two distinct models were constructed from datasets pertaining to LK and LE berries, comprising 1081 and 1079 data vectors, respectively (after removal of outliers). The iindependent variables were: variety, year of harvest, storage time, and time of gaseous ozonation. Separate models were generated for each mechanical parameter, namely force, deformation, and energy. The machine learning environment was the Statistica v. 13 software (TIBCO Software Inc., Tulsa, OK, USA). For ANNs the dataset was randomly divided into three subsets: training, validation, and test. The ratio of the three subsets was 70:15:15, respectively. For SVM the dataset was randomly divided into a training set and a test set in a ratio of 75:25. An MLP network with a single hidden layer was employed. The number of neurons in the hidden layer of the MLP and RBF networks was varied from 10 to 50. The MLP network employed linear, sigmoid, hyperbolic tangent, or exponential neuron activation functions. A total of 20,000 distinct neural network configurations were evaluated for each model. These configurations exhibited variability in structure, activation functions, and initial synaptic weight values, which were randomly generated. The testing was conducted using an automated neural network generator within the Statistica environment. The SVM hyperparameters, namely C (inverse regularisation parameter), ε and γ (the width of the RBF kernel), were adjusted by grid search. The ten-fold cross-validation method was used. The accuracy of the models was evaluated using the following metrics:

The root-mean-square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_p - Y_t)^2} \tag{1}$$

The mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_t - Y_p}{Y_t}\right| \tag{2}$$

In addition, the generalization ability (GA) was calculated using the following formula:

$$GA = \frac{RMSE_{test}}{RMSE_{train}} \tag{3}$$

where:

Y_p – is the absolute value predicted by the model,
$\bar{Y}_p$ – is the mean value predicted by the model,
Y_t – is the absolute target value,
$\bar{Y}_t$ – is the mean target value,
n – is the number of vectors in a data set.

In the recent study, El Bilali et al. (2022) proposed a novel classification system for predictive models based on the GA metric. According to this system, models with a GA value within the range of 0.75–1 or 1–1.35 are considered to exhibit excellent performance.

The ANN models enable the implementation of sensitivity analysis, which in turn allows for determination of the extent to which individual model input parameters exert influence on the output parameter. Many sensitivity analysis methods have been proposed in the literature, including the partial derivatives method and the weights method. In this research, the sensitivity analysis algorithm implemented in Statistica v. 13.3 software was utilised. In this method, a specific independent variable is replaced by its mean value calculated for the training data set. The impact of this variable is assessed by the model error in two cases: with the original value of the variable and after it has been replaced by the mean value.

Results and Discussion

Changes in the morphological properties of Lonicera caerulea berries

Extended cooling and storage of vegetables and fruits at low temperatures can negatively affect their water content. These conditions may lead to increased transpiration, resulting in greater water loss and a faster decline in turgor during storage (Lufu et al., 2020; Geasa 2022). Refrigeration of *Lonicera caerulea* L. may affect not only the morphological properties of berries but also the moisture content of the fruits, thereby reducing their biological value and decreasing the value of the raw material., The examined fruits of *Lonicera caerulea* L. varieties from different years of cultivation, subjected to ozonation, differed significantly depending on the day of fruit storage (Tab. 1).

Table 1.
The morphological characteristics and water content of LK and LE are influenced by factors such as variety, harvest year, storage duration, and ozone exposure time

Variable		Length (mm)	Width (mm)	Mass (g)	Density ($g \cdot cm^{-3}$)	Sphericity coefficient (%)	Moisture content (%)
Variety		*L. caerulea* var. *kamtschatica*					
	Vostorg	19.49c±2.80	9.57a±1.58	1.46a±0.49	0.66b±0.14	62.50a±7.02	87.49d±2.18
	Jugana	16.82a±1.99	10.32bc±1.60	1.52b±0.45	0.63a±0.11	72.41c±8.08	86.54c±3.02
	Aurora	20.29c±2.67	10.46c±1.68	1.68de±0.54	0.71d±0.15	64.53b±7.34	78.65b±4.96
		L. caerulea var. *emphyllocalyx*					
	Lori	17.24b±2.11	11.16d±1.59	1.71e±0.48	0.67bc±0.12	75.06d±7.66	77.91a±3.83
	21-17	20.63d±2.73	10.25b±1.56	1.63c±0.48	0.72d±0.16	62.91a±6.15	87.95d±2.66
	139-24	17.59b±2.15	10.98d±1.54	1.65cd±0.43	0.69c±0.13	73.21c±6.53	88.78e±3.15
SL		***	***	***	***	***	***
Year of harvest	2022	18.44a±2.99	10.99b±1.56	1.69ab±0.48	0.71b±0.15	71.47c±8.79	84.77a±5.69
	2023	18.84b±2.79	9.57a±1.50	1.45a±0.44	0.64a±0.14	64.09a±7.64	84.63a±5.65
	2024	18.78b±2.80	10.81b±1.60	1.69ab±0.51	0.70b±0.14	69.75b±8.36	84.92a±5.31
SL		*	*	*	*	**	ns
Storage time (days)	1	18.84b±3.00	10.46a±1.66	1.64b±0.49	1.12a±0.41	68.17a±9.19	83.84a±5.61
	3	18.63a±2.86	10.47a±1.55	1.60a±0.45	1.10a±0.39	68.70a±8.83	85.25b±5.37
	5	18.57a±2.72	10.45a±1.81	1.59a±0,51	1.11a±0.46	68.46a±8.53	84.24b±5.54
SL		*	ns	*	ns	ns	*
Time of gaseous ozonation (min)	0	18.58b±2.86	10.52b±1.82	1.13b±0.48	0.69a±0.15	68.72b±8.16	83.40a±5.87
	1	19.10c±3.14	10.44ab±1.63	1.13b±0.42	0.69a±0.14	67.55a±9.34	86.59d±5.11
	3	18.76b±2.77	10.55b±1.56	1.13b±0.39	0.68a±015	68.67b±8.78	84.15b±1.33
	5	18.28a±2.62	10.33a±1.67	1.06a±0.40	0.68a±014	68.82b±9.05	84.97c±9.55
SL		***	*	*	ns	*	**

All analyzed data are expressed as mean values (n = 3) with different letters as significantly different ($p < 0.05$) ± SD; SD: standard deviation. SL- level of significance: ns - not significant, ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$

The fruit dimensions - length of 18.7–23.7 mm and width of 8.7–12.3 mm are comparable to those obtained in the study of Ochmian et al. (2012), in which the fruit *L. kamtschatica,* depended on cultivar and harvest time, . In the study of Česonienė et al. (2021), fruits of different *Lonicera caerulea* L. varieties had dimensions ranging from 8.3 to 10.8 mm in width and 13.1–26.3 mm. The fruit weight was found to be comparable to the results obtained in the study conducted by Bożek (2012), where the fruit weight was within the range of 0.31–1.42 g, depending on the variety, year of harvest and pollination type. The water content was comparable to the findings of the study conducted by Auzanneau (2018), where it was in the range of 76%–85%, depending on the variety and year of cultivation. In our study, in the LK and LE cultivars, the differences between the berries were characterized at the significance level of - *** ($p < 0.001$), for all tested variables. The fruits of LE were found to be significantly shorter and of greater width and mass than those of the tested LK varieties. In comparison to the other tested varieties, the fruits of clone '21-17' were observed to be significantly longer, measuring 20.63 mm on average. Additionally, among the tested varieties, clone 21 was found to have a significantly higher density, at 0.72 $g \cdot cm^{-3}$. The 'Lori' variety exhibited significantly wider and heavier fruits, with mean diameters of 11.16 mm and 1.71 g, respectively. These berries were distinguished by a markedly higher sphericity coefficient, reaching 75.06%. The highest average moisture content was found in the fruits of clone ‘139-24’ – 88.78%. Depending on the harvest year, the differences between the berries were characterized at the significance level of - * ($p < 0.05$), except for sphericity - ** ($p<0.01$) and moisture content – ns (not significant). Compared to the other years of cultivation, in 2023, the fruits of the tested *L caerulea* varieties were characterized by a significantly smaller width – 9.57 mm, weight – 1.45, density – 0.64, sphericity – 64.09% and moisture content – 84.63%. The differences between the berries were characterized at the significance level of -* ($p < 0.05$) depending on the duration of storage. In the case of length, mass and moisture content, the rest of the variables were characterized at the significance level of – ns (not significant). The fruits stored for five days exhibited a significantly reduced length (18.57 mm) and weight (1.59 g) in comparison to the fruits stored for one day. Additionally, the moisture content of the five-day stored fruits was significantly higher (84.24%) than that of the one-day stored fruits. The extent of the differences between the berries varies depending on the length of ozonation time, except for density, where no significant differences were observed. Among the factors studied and the influence of ozonation, the most important is the influence on the moisture content of the fruit. The higher average moisture content in fruits of LE varieties contributes to their increased firmness which reduces the mechanical damage during handling and transportation. Greater firmness enhances the fruit's structural integrity, making it more resistant to deformation and bruising under pressure (Satitmunnaithum et al., 2022). The lower sphericity coefficient observed in LK fruit varieties could have a notable influence on their storage properties. Increased adhesion elevates the risk of mechanical damage, due to the compression forces during the storage or transit (Aliasgarian et al., 2015; Elibox et al., 2017). An important factor that may determine the storage process may be the geometrical features of the fruit. Fruits with a higher sphericity coefficient often have a smaller surface-area-to-volume ratio in certain orientations, which can create uneven airflow during cooling or storage, leading to hotspots where decay is more likely (Ngcobo et al., 2012). This highlights the importance of considering both firmness and shape when evaluating fruit varieties for their mechanical properties, post-harvest handling and storage characteristics.

Changes in the mechanical properties of Lonicera caerulea berries

Extended periods of low temperature storage lead to water loss of fruits, which may change mechanical properties, thereby increasing risk of mechanical damage. Due to long refrigeration, biological value of *Lonicera caerulea* L. berries may change (Duarte-Molina et al., 2016, Moggia et al., 2017). The fruits of the two tested botanical varieties of *Lonicera caerulea* L. differ depending on the variety, year of production, storage time and ozonation treatment (Tab. 2).

Table 2.
Mechanical features and apparent modulus of elasticity of L. kamtschatica and L. emphyllocalyx depending on the variety, year of harvest, duration of storage and ozone exposure time

Variable		Force (N)	Deformation (mm)	Energy (mJ)
	L. caerulea var. *kamtschatica*			
Variety	Vostorg	0.70b±0.23	3.86c±0.92	1.88ab±0.24
	Jugana	0.54a±0.15	3.71b±0.84	1.84a±0.24
	Aurora	1.02d±1.45	3.68b±0.77	2.39d±0.89
	L. caerulea var. *emphyllocalyx*			
	Lori	0.93d±0.45	3.52a±0.65	2.22c±0.68
	21-17	1.02d±1.47	3.66b±0.79	2.43d±0.89
	139-24	0.77c±0.38	3.84c±0.80	1.95b±0.52
SL		***	***	***
Year of harvest	2022	0.84b±0.43	3.46a±0.66	2.21b±0.77
	2023	0.83ab±0.38	4.17b±0.86	2.10a±0.64
	2024	0.81a±0.41	3.51a±0.68	2.06a±0.62
SL		*	*	*
Storage time (days)	1	0.78a±0.38	3.74ab±0.79	2.08a±0.65
	3	0.87b±0.42	3.65a±0.77	2.14ab±0.68
	5	0.84b±0.44	3.77b±0.86	2.16b±0.73
SL		*	*	*
Ozone exposure time (min)	0	0.82ab±0.36	3.68ab±0.80	2.07a±0.54
	1	0.84b±0.45	3.67a±0.74	2.17b±0.73
	3	0.85b±0.44	3.76b±0.83	2.20b±0.86
	5	0.79ab±0.38	3.73ab±0.85	2.07a±0.55
SL		*	**	**

All analyzed data are expressed as mean values (n = 3) with different letters as significantly different ($p < 0.05$) ± SD; SD: standard deviation. SL- level of significance: ns - not significant, ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$

In the study conducted by Leisso et al. (2021b), the flesh firmness of *Lonicera caerulea* L. varieties, was tested using a 2 mm tip, with results ranging from 0.11 to 0.35 N. In the study by Zhu et al. (2022), the flesh firmness of two varieties of *Lonicera caerulea* L., ranged from 1.38 to 2.78 N. In our study, in the LK and LE cultivars, the differences between the berries of the LK and LE cultivars were characterized at the significance level of -*** ($p<0.001$) for all tested variables. The force required to puncture was ranging from 0.54 to 1.02 N depending on the botanical variety and cultivar. The mean force necessary to puncture the fruits of LE varieties is 16.91% greater than that required for the tested LK varieties. A similar relationship can be observed for Energy, LE varieties were characterized by an average higher energy requirement by 7.42%. LK fruits exhibited a markedly elevated incidence of fruit deformation, with an average degree of deformation that was 2.04% lower in LE fruits. The observed differences between the harvest year reached a level of statistical significance - * ($p<0.05$), for all tested variables. In 2023, the fruit was characterized by significantly greater force – 0.84 N, and energy – 2.21 mJ, required for fruit deformation, compared to the rest of the years of the study. The highest degree of deformation was recorded in 2023, with an average increase of 16.5% in comparison to other years. In case of the storage time, differences were characterized at the significance level of - * ($p<0.05$). The storage of the fruit for a period of five days resulted in a significantly greater force (0.84 N) and energy

(3.77 mJ) being required for puncture, as well as a greater degree of deformation (3.51 mm) in comparison to the storage of berries for the period of one day only. The differences between the ozone exposure time were characterized at the significance level of - * ($p < 0.05$), for Force (N), and level of - ** ($p < 0.005$), for Deformation (mm) and Energy (mJ). Fruits subjected to the ozonation process were characterized by significantly higher values of the tested parameters. The application of ozonation for a period of three minutes was found to result in the greatest force (0.85 N) and energy (2.20 mJ) required for deformation. The shelf life and quality of fresh-cut products are significantly shortened by various decay processes initiated by physical damage, such as moisture loss (Tappi et al., 2017). The soft fruits of *Lonicera caerulea* L. poses a major limitation for adopting mechanical harvesting methods, as these fruits are highly susceptible to damage during handling. LE fruits demonstrate significantly greater resistance compared to LK varieties, making them more suitable for mechanical harvesting and storage. The development and use of LE varieties, with their enhanced firmness, could play a critical role in advancing mechanized harvesting technologies for this species. Increased water content contributes to the structural integrity of the fruit, making it less prone to damage due to compression or impact forces (Zhu et al., 2023). This mechanical resistance of LE varieties aligns well with the mechanical requirements of automated harvesting systems, where fruit durability is essential for minimizing losses and maintaining quality. As such, selecting and cultivating appropriate LE varieties could significantly enhance both the efficiency and economic viability of mechanized harvesting in *Lonicera caerulea* L. production. The observed difference in mechanical properties of berries is also influenced by exposure to ozone (Kuźniar et al., 2022). These findings indicate that the ozone treatment enhances the fruits resistance to deformation, making skin and flesh more durable during handling and storage. This could be connected to changes in cell wall composition or other physicochemical alterations induced by ozonation. Oxidative stress caused by ozone exposure could activate enzymatic processes that modify the mechanical properties of the cell walls (Miller et al., 2013). Enzymes like peroxidases or polyphenol oxidases might catalyze the formation of lignin-like compounds, further enhancing the cell wall (Ranieri et al., 2000). However, the use of gaseous ozone can pose some challenges due to its high cost of implementation and short-term effect. The use of gaseous ozone on such fruits can pose problems due to the aggressive reaction of ozone with cell walls, it requires the use of appropriate concentration for the conditions of cultivation and storage.

Machine learning models

In the case of models based on neural networks, 2,000 independent models were generated for each output parameter. This was achieved by varying the number of neurons in the hidden layer, the neuron activation functions (in the case of MLP) and the values of the initial weights. In the case of SVM models, a ten-fold cross-validation method was used to adjust the values of hyperparameters. The details and error metrics for the best models are presented in Tables 3 and 4.

In the case of the dataset pertaining to the LK berries , the most optimal force prediction was achieved through utilisation of a MLP network comprising 48 neurons in the hidden layer. The model yielded a mean absolute percentage error (MAPE) of 28.95% for the test data set. The application of an RBF network and SVM algorithm yielded models with slightly reduced accuracy. Regarding the deformation, the SVM algorithm generated the optimal model, with a MAPE error for the test data set of less than 15%. The most accurate energy prediction was achieved using an MLP network with 17 neurons in the hidden layer, with a MAPE error for the test data set of less than 15%. All models can be classified as excellent in terms of their generalisation ability.

Table 3.
Structures and error metrics of best MLP, RBF and SVM models for LK fruits

Model	Model structure or hyperparameters	Train		Validation		Test		GA
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	
Force								
MLP	4-48-1	0.28	29.90	0.32	35.72	0.25	28.95	0.88
RBF	4-50-1	0.29	32.06	0.32	37.06	0.27	33.40	0.93
SVM	C=4, ε=0.1, γ=0.25	0.29	30.73	-	-	0.31	31.61	1.05
Deformation								
MLP	4-39-1	0.66	14.35	0.69	14.86	0.70	15.71	1.07
RBF	4-29-1	0.69	15.21	0.67	14.45	0.77	17.16	1.11
SVM	C=8, ε=0.3, γ=0.25	0.69	15.70	-	-	0.70	14.87	1.01
Energy								
MLP	4-17-1	0.50	15.24	0.57	15.77	0.54	14.88	1.07
RBF	4-40-1	0.60	17.47	0.64	17.39	0.65	18.18	1.08
SVM	C=9, ε=0.2, γ=0.25	0.54	16.87	-	-	0.55	17.12	1.02

The structure of MLP and RBF models means: the number of input nodes-the number of neurons in hidden layer-the number of neurons in output layer

The models generated from the dataset for the LE exhibited a lower error rate for deformation compared to the dataset for the berries LK. The optimal model was identified as an MLP network comprising 18 neurons in the hidden layer. The mean absolute percentage error (MAPE) for this model was 16.49% for the test data set. In terms of force prediction, the optimal model was identified as the SVM algorithm. However, the accuracy of this model is limited, as evidenced by a MAPE error exceeding 40% for the test data set. The most precise model for energy prediction was developed using an MLP network with 29 neurons in the hidden layer, exhibiting a MAPE error of 20.65%. Additionally, all generated models demonstrated excellent generalisation ability for this dataset.

A sensitivity analysis enables evaluation of the degree of influence exerted by explanatory variables on the dependent variables. In this study, a sensitivity analysis was conducted on MLP models. For LK fruits, the analysis was performed on all mechanical parameters. For LE fruits, however, the analysis was limited to deformation and energy, as the MLP model for force exhibited low accuracy (MAPE = 47.52), rendering the analysis results for this model unreliable. The results of the sensitivity analysis are presented in Figures 2 and 3.

Table 4.
Structures and error metrics of best MLP, RBF and SVM models for LE fruits

Model	Model structure or hyperparameters	Train		Validation		Test		GA
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	
Force								
MLP	4-48-1	0.28	29.90	0.32	35.72	0.25	28.95	0.88
RBF	4-50-1	0.29	32.06	0.32	37.06	0.27	33.40	0.93
SVM	C=4, ε=0.1, γ=0.25	0.29	30.73	-	-	0.31	31.61	1.05
Deformation								
MLP	4-39-1	0.66	14.35	0.69	14.86	0.70	15.71	1.07
RBF	4-29-1	0.69	15.21	0.67	14.45	0.77	17.16	1.11
SVM	C=8, ε=0.3, γ=0.25	0.69	15.70	-	-	0.70	14.87	1.01
Energy								
MLP	4-17-1	0.50	15.24	0.57	15.77	0.54	14.88	1.07
RBF	4-40-1	0.60	17.47	0.64	17.39	0.65	18.18	1.08
SVM	C=9, ε=0.2, γ=0.25	0.54	16.87	-	-	0.55	17.12	1.02

The structure of MLP and RBF models means: the number of input nodes-the number of neurons in the hidden layer-the number of neurons in the output layer

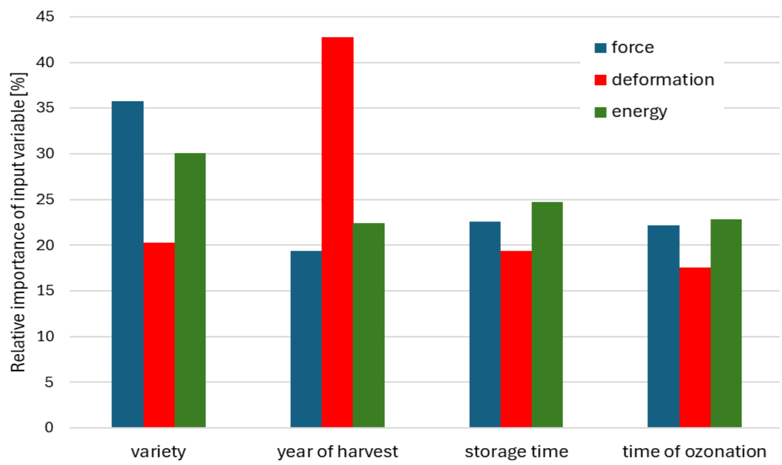

Figure 2. Relative importance of input variables of MLP model on mechanical parameters of LK fruits

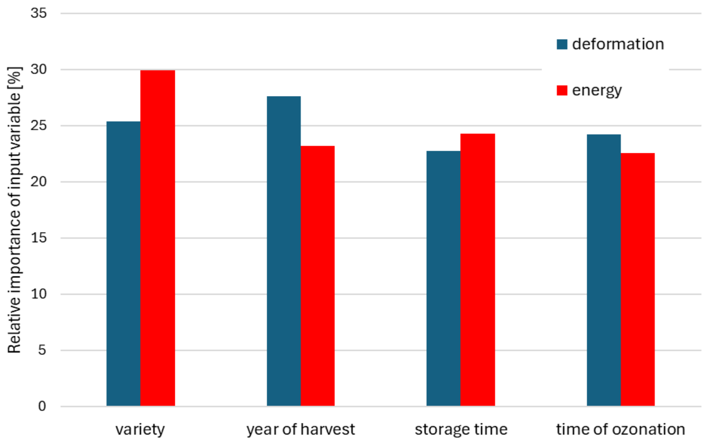

Figure 3. Relative importance of input variables of MLP model on mechanical parameters of LE fruits

In the case of LK fruit, the greatest influence on force and energy is attributed to the variety (35.8% and 30.1%, respectively). The other parameters comparably influence the mechanical parameters, with the maximum impact of 25%. Conversely, the year of harvest exerts the greatest influence on deformation (42.8%). The other parameters in the model affect deformation to a similar degree, with an impact of approximately 20%. For LE fruits, all the independent variables exert a comparable influence on deformation and energy (22-30%).

The application of machine learning is becoming increasingly important in the construction of predictive models that are useful in agriculture. A plethora of algorithms are available for the generation of these models. The optimal modelling method for a given data set is contingent upon the specific relationship between the input and output parameters of the model. Consequently, it is often necessary to employ a combination of methods and conduct a comparative analysis of the resulting data. The methods employed in this research, namely MLP and RBF neural networks and support vector machines, are among the most prevalent algorithms utilized for agricultural data. Hosseini Monjezi et al. (2023), developed RBF and SVM models for the purpose of predicting greenhouse indoor air temperature. The RBF method demonstrated superior accuracy compared to the SVM model, with a lower MAPE error of 1.3% for the test data set compared to 3.7% for the SVM. Bolandnazar et al. (2019) compared the performance of MLP, RBF and SVM models for the prediction of energy consumption in potato production. The RBF model demonstrated superior performance compared to the MLP and SVM models, with a MAPE error of less than 1% on the test data set. Nawaz and Babar (2024) employed the MPL, RBF and SVM methodologies to develop predictive models for the purpose of forecasting reference evapotranspiration to meet crop water requirements in the context of smart agriculture. The study demonstrated that MLP and SVM models exhibited superior predictive capabilities, whereas the RBF model demonstrated significantly lower accuracy. Son et al. (2022) conducted a comparative analysis of ANN and SVM models for rice crop yield prediction based on image composites from Sentinel-2. The findings revealed that the accuracy of SVM models was marginally higher than that of ANN models.

The application of machine learning methodologies is facilitating the development of models with the potential for real-world applications in the optimisation of fruit and vegetable storage procedures. Huang et al. (2023) conducted a comparative analysis of MLP, RBF and SVM models for the prediction of blueberry fruit freshness based on multi-sensing data. The SVM model demonstrated the highest level of efficiency, with the accuracy rate of 94.01%. Hu et al. (2016) employed least squares support vector machines (LS-SVM) to forecast texture profile analysis and puncture analysis parameters of blueberry fruit based on hyperspectral interactance spectra coupled with the Monte Carlo uninformative variable elimination. The SVM algorithm yielded models of high accuracy for most parameters under study, with correlation coefficients R between target and predicted values of 0.91 for cohesiveness, 0.84 for springiness, 0.86 for resilience, 0.65 for maximal force strain, 0.62 for final force, 0.77 for hardness, and 0.71 for maximal force. A variety of neural network configurations were tested to identify optimal models of the pear fruit rupture energy (Cevher et al., 2022), as well as the surface area and volume of the Golden Delicious apples (Ziaratban et al., 2016). The optimal model of pear fruit rupture energy was developed based on mass, water-soluble dry matter, and Magness-Taylor force. An ANN with one hidden layer with five neurons was employed, resulting in the coefficient of determination of $R^2 = 0.94$. The most precise model of the surface area and volume of the Golden Delicious apples, based on the major and minor diameters determined using a computer vision system, was generated using an ANN with one hidden layer containing 15 neurons. The high quality of the model is evidenced by the value of the coefficient of determination $R^2 = 0.99$. The value of the force of the skin puncture and flesh of the analyzed fruits was most influenced by the variety in the case of LK, and the year of harvest in the case of LE. Depending on the selected variable factors, significantly smaller fluctuations of the tested values (deformation, energy) were noted for LE fruits. The analyzed varieties had the greatest influence on the value of the energy needed to pierce the skin and flesh of the fruits.

Conclusions

This study identified differences in fruit morphology, mechanical properties, and gas exchange between *L. caerulea var. kamtschatica* and *L. caerulea var. emphyllocalyx*. The mean force required to puncture the fruits of LE varieties is 16.91% higher than that of the tested LK varieties. A comparable pattern is evident in the energy data, with LE varieties necessitating, on average, 7.42% more energy. The gaseous zone exerted a notable influence on the evaluated characteristics of stored fruit. Ozonation of LK and LE fruits for 3 minutes reduced the ethylene content by 10.8%, while ozonation for 1 minute decreased the carbon dioxide content by 10.9%. During storage, different reactions were observed depending on the length of storage. The ethylene content increased over the course of storage, while the CO_2 content decreased on the fifth day compared to the first day of storage. Due to the large area of cultivation and the significant extension of the process, the use of ozonation may be difficult. The use of ozonation in field production and in the conditions of storage of large quantities of raw material requires the use of appropriate equipment.

The results of the machine learning modelling demonstrate that all three modelling methods, namely MLP, RBF and SVM, yielded models with comparable accuracy. The accuracy of the models derived from the LK fruits dataset is deemed satisfactory for agricultural data, particularly in the case of deformation and energy, where a mean absolute percentage error (MAPE) of several percent was obtained. The LM fruits set yielded models with lower accuracy overall, with the model for force prediction exhibiting insufficient accuracy for practical application. MLP models facilitated the determination of the degree of influence exerted by individual model input parameters on mechanical parameters. The models obtained can be utilized in real-life applications to design the storage processes for *L. caerulea* var. *kamtschatica* and *L. caerulea* var. *emphyllocalyx* fruit using ozonation treatment.

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BADANIE WPŁYWU OZONOWANIA NA PARAMETRY MECHANICZNE OWOCÓW *LONICERA CAERULEA* L. ZA POMOCĄ UCZENIA MASZYNOWEGO

Streszczenie. *Lonicera caerulea* L. – dobrze znana w Polsce pod nazwą jagody kamczackiej w ostatnich latach stała się popularna. Badania przeprowadzone na niedawno wyhodowanych japońskich klonach haskap miały wykazać, że owoce nadają się do mechanicznego zbioru i przechowywania. Niniejsza praca ma na celu ocenę właściwości mechanicznych i trzech odrębnych metod uczenia maszynowego, aby stworzyć modele predykcyjne, które wyjaśniają związek między kluczowymi atrybutami mechanicznymi owoców i warunkami przechowywania *L. caerulea*. Średnia siła potrzebna do przekłucia skóry i miąższu owoca *L. caerulea* var. *emphyllocalyx* wynosi o 16,91% więcej niż ta wymagana dla badanych odmian *L. caerulea* var. *kamtschatica*. Owoce *L. caerulea* odmiany *emphyllocalyx* wykazały istotnie wyższy poziom tempa oddychania, przy poziomach C_2H_4 i CO_2 podczas przechowywania na poziomie 25,5% i 10,5% odpowiednio wyższym, w porównaniu do odmian *L. caerulea* var. *kamtschatica*. Algorytm uczenia maszynowego zbadał wygenerowane dokładne modele do przewidywania deformacji i energii. Średni bezwzględny błąd procentowy (MAPE) badanych modeli wynosił pomiędzy 14,87 a 20,65%. Modele o dużo niższej dokładności uzyskano do przewidywania siły przy średnim bezwzględnym błędzie procentowym wynoszącym 28,95% dla owoców *L.* odmiany *kamtschatica* oraz 42,33% dla owoców *L. emphyllocalyx*. Uprawa i ulepszenie odmian *Lonicera caerulea* L. ma wielkie znaczenie dla rozwoju zmechanizowanych metod uprawy i rozwoju ulepszonych technologii przechowywania tego gatunku. Stworzenie metod uczenia maszynowego poprawi rozwój modeli predykcyjnych, które mogą służyć jako narzędzie predykcyjne dla zależności wybranych cech mechanicznych.

Słowa kluczowe: *Lonicera caerulea* L., cechy morfologiczne, wymiana gazowa, uczenie maszynowe