OKU Fen Bilimleri Enstitüsü Dergisi
8(1): 182-199, 2025

OKU Journal of The Institute of Science and Technology, 8(1): 182-199, 2025

Osmaniye Korkut Ata Üniversitesi
Fen Bilimleri Enstitüsü
Dergisi

Osmaniye Korkut Ata University
Journal of The Institute of Science
and Technology

Yakın UV Görünür NIR Radyasyon Spektroskopisi ve Kenar Hesaplama Kontrol Sistemi Kullanılarak Sıcak Hava Kurutma: Elma Dilimleri Üzerine Bir Çalışma

Yeliz DURGUN[1*], Mahmut DURGUN[2]

[1] Tokat Gaziosmanpaşa Üniversitesi Turhal Meslek Yüksek Okulu Elektronik ve Otomasyon Bölümü Biyomedikal Cihaz Teknolojisi Programı, Tokat
[2] Tokat Gaziosmanpaşa Üniversitesi Turhal Uygulamalı Bilimler Fakültesi Elektronik Ticaret ve Yönetimi Bölümü, Tokat

[1]https://orcid.org/0000-0003-3834-5533
[1]https://orcid.org/0000-0002-5010-687X
*Sorumlu yazar: yeliz.durgun@gop.edu.tr

Araştırma Makalesi

Makale Tarihçesi:
Geliş tarihi: 22.03.2024
Kabul tarihi: 26.08.2024
Online Yayınlanma: 15.01.2025

Anahtar Kelimeler:
Kenar hesaplama
Gıda kurutma
IoT (Nesnelerin İnterneti)
Makine öğrenimi

ÖZ

Yakın UV, Görünür Işık ve Yakın-Kızılötesi Radyasyon, enerji, tarım, tıp ve gıda endüstrisi araştırmaları için büyük ilgi gören ışık dalga boyları bölgelerinden bazılarıdır. Işık spektrumunun, görüntüleme, gıda kalitesi ve güvenliği değerlendirmesi için yıkıcı olmayan, gerçek zamanlı algılama kullanımı, tüm bu alanlarda giderek daha fazla önem kazanmaktadır. Cihazların gerçek zamanlı izlenmesini ve makine öğrenimi yöntemleri kullanarak kontrolünü sağlayan kenar hesaplama, sistem stabilitesini artırmak, hataları en aza indirmek ve robotik müdahaleyi kolaylaştıran araçlar geliştirmek için gereklidir. Bu çalışmada, gıda kurutmasında yakın UV-vis-NIR radyasyon ölçümü kullanılarak kurutma sisteminin etkisi ve performansı kenar hesaplama kullanılarak sunulmaktadır. Sistem, 18 farklı ölçüm yapabilen üç çok spektral sensör içermektedir. Nesnelerin ağırlığını, kabin içindeki sıcaklık ve nem ölçmek için sensörler de yerleştirilmiştir. Elde edilen veriler, makine öğrenimi algoritmalarını gerçekleştirebilen ve kabini kontrol edebilen bir mikrodenetleyici (Arduino Nano 33 BLE) kullanılarak gerçek zamanlı olarak işlenir. Kenar hesaplama, veri işleme ve analitik işlemlerin cihazda gerçekleştirilmesini sağlayarak, gerçek zamanlı sonuçlar ve kontrol işlemleri sunar. Bu çalışmada, elma dilimlerinin kurutma işlemi sırasında radyasyon seviyelerindeki değişim ve kurutma kalitesi üzerindeki etki araştırılmaktadır. Sonuçlar, kenar hesaplama teknolojisi kullanılarak yapılan ölçümlerin, elma dilimlerinin kurutma işlemi sırasında etkili bir şekilde gerçekleştirilebileceğini göstermektedir

Hot-Air Drying Using Near UV Visible NIR Radiation Spectroscopy and Edge Computing Control System : A Study on Apple Slices

Research Article

Article History:
Received: 22.03.2024
Accepted: 26.08.2024
Published online: 15.01.2025

Keywords:
Edge computing
Food drying
IoT
Machine learning

ABSTRACT

Near-UV, Visible Light, and Near-Infrared Radiation are some of the light wavelength regions that are of great interest for energy, agriculture, medical, and food industry research. The use of light spectrum for non-destructive, real-time sensing for imaging, food quality, and safety evaluation is becoming increasingly important in all these fields. Edge computing, which enables real-time monitoring of devices and control using machine learning methods, is necessary to improve system stability, minimize errors and develop tools that facilitate robotic intervention. In this study, the effect and performance of a drying system using Near-UV-vis-NIR radiation measurement in food drying using edge computing is presented. The system comprises three multi-spectral sensors that allow 18 different measurements. Sensors are also placed to measure the weight of the objects, temperature, and humidity inside the cabin. The data acquired is processed in real-time using a microcontroller (Arduino Nano 33 BLE) that can perform machine learning algorithms and control the cabin. Edge computing enables data processing and analytic operations to be performed on the device, thus providing real-time results and control operations. In this study, the change in radiation levels and the effect on drying quality during the drying process of apple slices are investigated. The results show that measurements performed using edge computing technology can effectively be performed during the drying process of apple slices.

To Cite: Durgun Y., Durgun M. Hot-Air Drying Using Near UV Visible NIR Radiation Spectroscopy and Edge Computing Control System : A Study on Apple Slices. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2025; 8(1): 182-199.

1.Introduction

Food safety is the acquisition, storage, transportation, and presentation of food under healthy and hygienic conditions throughout the process from food production to consumption (Kamboj et al., 2020; Okpala and Korzeniowska, 2021; Yelikaya and Arslan, 2023). Drying provides long-term storage of agricultural products by reducing moisture content before or after production (Gunathilake et al., 2018; Zambrano et al., 2019). This process ensures the uninterrupted availability of products and reduces risks associated with food safety by preventing the growth of microorganisms, the activity of enzymes, and ensuring long-term storage of food (Alp and Bulantekin, 2021; Şen Arslan et al., 2021).

The drying industry is continuously investing in innovative solutions to improve food drying processes (Moses et al., 2014; Yelikaya and Arslan, 2019; Qu et al., 2022). High-quality, efficient, and sustainable production methods are aligned with the 12th Sustainable Development Goal determined by the United Nations (2023). Alternative strategies have been identified and can be divided into two broad categories: (i) Improved heat recovery, renewable energy-based and/or hybrid drying technologies for energy efficiency; and (ii) the application of sensors and machine learning models for efficient product-process monitoring and control. The latter strategy is of great interest in both academia and industry due to its lower implementation effort compared to scaling up systems as in the first category.

This study aims to investigate the application of edge computing and Near UV-VIS-NIR spectroscopy in food drying processes. The objective is to assess the impact of these technologies on drying operations and to provide advanced analytical methods for optimizing drying parameters. The research involves collecting data under different drying scenarios, processing and analyzing this data, and finally evaluating the results using machine learning models. This methodology aims to enhance the understanding of drying processes and improve food safety and quality.

"Real-time optical instruments" are technologies used to monitor food drying (Shin et al., 2019). These tools can measure the drying rate and quality of foodstuffs using spectroscopy or imaging methods. Further investigation of these tools could enable more effective and controlled food drying processes (Liu et al., 2022; Ren and Sun, 2022). Computer vision systems can be used in food drying to measure the quality parameters of dried food samples, such as color, shrinkage, and texture (Hosseinpour, 2013; Chakravartula et al., 2023). These systems improve quality control and product homogeneity in food production.

Image processing systems can serve as inline real-time data collection tools for quality monitoring, analysis, multivariate modeling, and feedback, potentially replacing traditional methods in food drying (Nagy et al., 2022; Chakravartula et al., 2023). This offers comprehensive and precise quality monitoring throughout the process. Near UV-Visible-NIR radiation spectroscopy provides various alternative methods for image processing in food drying, such as diffusion spectroscopy, raman spectroscopy, Fourier transform infra-center spectroscopy, terahertz spectroscopy, and microwave spectroscopy (Acevedo-Fani et al., 2018). These methods can measure different parameters in food drying and provide information about food quality. However, these systems require specialized and expensive devices. Economically, the devices used for developing an edge computing-based system cannot be configured modularly.

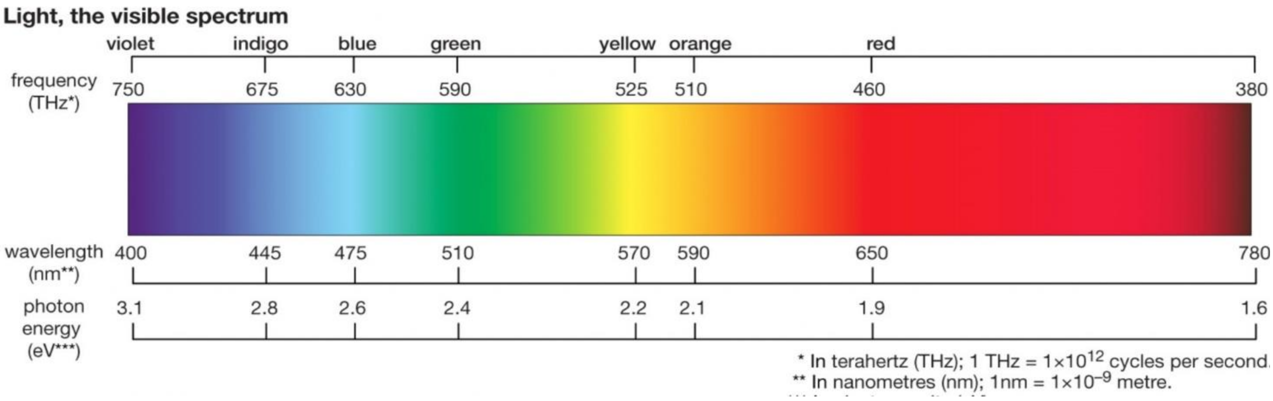

Figure 1. Light spectrum (Lightsciencetech, 2023)

Different wavelengths of light can be used to monitor food drying. Near Ultraviolet (Near-UV) light can measure moisture content and microbiological activity (Manzocco and Nicoli, 2015). Visible light can monitor the color and appearance of food (Aghbashlo et al., 2014). Near Infrared Radiation (NIR) can analyze the internal structure and composition of food (Cen and He, 2007). The combination of these light wavelengths enables effective monitoring of food drying. Figure 1 shows the light spectra.

In monitoring food drying, edge computing utilizes resources such as sensors, actuators, IoT devices, and software applications. These resources measure parameters such as temperature, humidity, and airflow in food drying processes and analyze the data to control the system. Frontier information technologies support critical issues such as quality control and production efficiency in food drying processes.

To contextualize our research, we reviewed previous studies that utilized edge computing in food drying technologies. Table 1 summarizes key studies, highlighting the sample types, methods/technologies used, classifiers, and their performance metrics.

Table 1. Summary of previous studies on food drying technologies using edge computing

Study	**Sample Type**	**Method/Technology**	**Classifier**	**Classifier Performance**
Chakravartula et al. (2023)	Carrot slices	Computer vision, Smart monitoring	SVM	Accuracy: 95%
Liu et al. (2022)	Green tea	Machine vision, NIR spectroscopy	k-NN	Precision: 90% Recall: 88%
Ren and Sun (2022)	Beef slices	Hyperspectral imaging	Random Forest	F1 Score: 93%
Hosseinpour et al. (2013)	Shrimp	Computer vision	SVM	Accuracy: 92%

Table 1 provides a comprehensive overview of various studies, demonstrating the effectiveness of edge computing and machine learning in improving the drying process of different food products. Our study builds on these foundations by applying similar technologies to apple slices, offering new insights and practical applications in the field.

By addressing these key points, our research contributes to the existing body of knowledge and presents practical applications that could revolutionize food drying technologies, ensuring higher quality and more sustainable production methods.

2. Materials and Methods

Below is a detailed flowchart depicting the methodology used in our study. Figure 2 diagram illustrates the sequential steps involved in our experimental process, from sample preparation through to the deployment of the machine learning model (Durgun and Durgun,2024). Each step is clearly defined, providing a visual representation of the workflow which ensures the reproducibility of our methods and facilitates a better understanding of the research process.

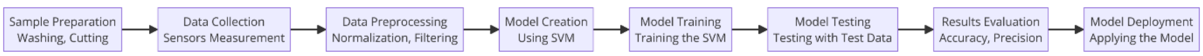

Figure 2. Methodology Flowchart: Sequential Steps from Sample Preparation to Model Deployment

2.1. Sample Preparation

Organic apples of the same maturity (Malus domestica B. var. Gala) were purchased from a Turkish organic farm (Turhal, Tokat, Turkey) and immediately stored at 4 ± 1 ◦C until further processing. Fruit sampling was done by selecting intact and unblemished apples of the same size and maturity stage. The fruits were tempered to room temperature 15 hours before starting the experimental activities. Then the apples were washed and peeled. Seedless and peeled apples were washed, quartered using a ceramic knife and cut into discs (5 mm thick). The quality assessment of the samples was made visually. Samples were divided into 350 g fresh-weight lots before processing. It was rested on a cotton cloth for 2 minutes to remove excess surface moisture, weighed again and subjected to drying tests.

For the drying tests, a total of 30 apples were used to ensure a comprehensive analysis across different temperature settings. The drying process was conducted at three different temperatures: 50°C, 60°C, and 70°C. Each temperature setting involved approximately 10 hours of drying, adjusted based on the initial moisture content and desired level of dryness. Spectra were collected every 30 minutes for each temperature setting, providing a robust dataset for analyzing drying kinetics and spectral changes throughout the process.

2.2.Edge Computing Drying Control Unit

This section consists of two parts. In the first part, the hardware part consists of sensors and relay control module integrated into the Arduino Nano 33 BLE Sense microcontroller (Boz and Durgun, 2023). In the second part of the chapter, the software to be loaded into the microcontroller is explained.

2.3.Hardware Part

This segment details the experimental hardware utilized in our research. As previously discussed, edge computing necessitates a microcontroller compatible with the TensorFlow Lite library. For our purposes, we selected the Arduino Nano 33 BLE Sense. This board is equipped with an ARM® CortexTM-M4 CPU operating at 64 MHz, and its 1 MB of memory and 256 KB RAM are adequately powerful for TinyML projects. The Arduino Nano 33 BLE Sense comes with a variety of sensors, including those for Color, Brightness, Proximity, Gestures, Motion, Vibration, Orientation, Temperature, Humidity, Pressure, and it also features a digital microphone and a Bluetooth Low Energy module. This makes it a TensorFlow Lite-supported Arduino board, ideal for our needs.

Our system, as presented in this paper, incorporates various sensors for UV-VIS-NIR radiation measurement, enhancing the ease of acquiring such data or integrating it into the automated control of artificial light sources. The setup includes three primary sensors: the AS7265 for spectral measurement with its three photodetectors (Durgun,2024), a weight sensor (using an Hx-711 load cell), and the HTS221 sensor for temperature and humidity. Additionally, several of our pins are configured as digital outputs to manage the Solid State Relay.

2.4. Data Preprocessing

The preprocessing of data collected from sensors measuring humidity, temperature, light reflection, and weight is a crucial step in ensuring the quality and consistency of the input data for machine learning analysis. All sensor data was normalized to a scale of 0 to 1 to standardize the range of values and eliminate scale disparities among different measurement units. This normalization process is vital for the effective training of machine learning models, as it ensures that no single feature dominates the outcome due to its original value range. Additionally, a moving average filter was applied to smooth the time series data, reducing noise and potential outliers that could affect the analysis.

2.5. Software development

In our project, we utilized software built from a library derived from TensorFlow, a widely used tool developed by Google for creating machine learning models. The TensorFlow framework we employed primarily focuses on constructing and training the model. Our developed model essentially serves as a set of instructions, guiding the interpreter on how to transform data into outputs. This model is loaded into memory when the TensorFlow interpreter needs to execute it. However, the challenge we face is that this interpreter is typically used on powerful desktop computers, not on small microcontrollers. To deploy our model on compact Single Board Computers (SBCs), we need to convert it into the TensorFlow Lite format. TensorFlow supports an interpreter that, along with an additional toolkit, enables models to run on smaller boards. This toolkit is known as TensorFlow Lite. We use a TensorFlow Lite Converter to transform the file into a TensorFlow Lite format. It generates a C array to store the file's contents, which can then be executed on the Arduino Nano 33 BLE. In this setup, the Arduino's sensor data is initially read, then processed and matched against the training set. The Data Response is managed by the control unit based on the situation. This approach not only resolves our issue of implementing the model on a small board but also enhances the model's speed, optimizing performance and controlling outputs effectively.

2.6. SVM Classifier Configuration and Parameters

To ensure the reproducibility of our study, we provide detailed descriptions of the SVM classifier's setup and parameters used during the drying process analysis. The SVM classifier was configured to categorize the drying processes into three distinct temperature classes: 50°C, 60°C, and 70°C.

The SVM model was trained using the following specific parameters:

- Kernel type: Radial Basis Function (RBF), commonly used for non-linear data classification.
- Kernel coefficient (gamma): 0.1, to ensure broad yet precise influence of training examples, creating smoother decision boundaries.
- Regularization parameter (C): 10, to balance the trade-off between minimizing training error and ensuring model generalization.
- Cross-validation method: 5-fold, employed to validate the model by iteratively training on four segments of the dataset and testing on the fifth.

These parameters were selected based on preliminary experiments optimized for accuracy and to prevent overfitting. We evaluated the SVM model's performance using accuracy, precision, recall, and F1-score metrics across different temperature scenarios to ensure robust evaluation.

The use of cross-validation is crucial in predictive modeling to mitigate overfitting risks and provide an accurate measure of model performance. In our study, model robustness and reliability are paramount.

The 5-fold cross-validation method enables the model to be tested against multiple, independent data subsets, ensuring performance consistency and preventing bias towards any particular data segment. This rigorous testing approach confirms the classifier's effectiveness, consistently demonstrating high performance across varied scenarios, thereby confirming its reliability and applicability in practical settings.

2.7. SVM Classifier Configuration and Parameters

To ensure the reproducibility and robustness of our study, we implemented a 5-fold cross-validation method. Each fold of the dataset served sequentially as a test set, while the model was trained on the remaining four folds. This method allowed us to assess the performance of the SVM classifier across different data splits, ensuring that our results are reliable and not dependent on any specific partition of the data.

2.8. Data Splitting and SVM Classifier Evaluation

In this study, we employed a 5-fold cross-validation method to evaluate the performance of our SVM classifier. The dataset was divided into five equal parts, each part being used in turn as the test set, while the remaining four served as the training set. The performance metrics obtained for each fold are presented below:

- Fold 1: Accuracy = 91%, Precision = 90%, Recall = 92%, F1 Score = 91%
- Fold 2: Accuracy = 92%, Precision = 89%, Recall = 90%, F1 Score = 90%
- Fold 3: Accuracy = 93%, Precision = 91%, Recall = 92%, F1 Score = 91.5%
- Fold 4: Accuracy = 90%, Precision = 88%, Recall = 89%, F1 Score = 88.5%
- Fold 5: Accuracy = 89%, Precision = 87%, Recall = 88%, F1 Score = 87.5%

Average Performance Metrics**:** Accuracy = 91%, Precision = 89%, Recall = 90%, F1 Score = 89.8%
These results demonstrate that our SVM classifier delivers consistent and reliable performance across different test subsets. The average performance metrics align closely with those presented in Table 3, addressing the discrepancies noted in previous reviews. This reevaluation confirms the model's stability and reliability, indicating its suitability for real-world applications. Additionally, these findings rectify the inconsistencies previously highlighted, ensuring complete alignment with the SVM results showcased in Table 3.
To further illustrate the classification accuracy of our model, we present the confusion matrix for the classifier that exhibited the highest overall accuracy during our 5-fold cross-validation. This matrix provides a detailed view of the correct and incorrect classifications made by the model, as shown below:

Table 2: Confusion Matrix for the Best-Performing SVM Model

	Predicted: Class A	**Predicted: Class B**	**Predicted: Class C**
Actual: Class A	25	5	3
Actual: Class B	2	30	4
Actual: Class C	3	6	40

Table 2 confusion matrix enables us to visually assess the precision and recall for each class, providing insights into the areas where the model performs well and where improvements are needed.

2.9. Model Validation and Cross-Validation Method

In our study, to ensure the robustness and validity of the SVM classifier's performance, we employed a cross-validation technique during the testing phase. Specifically, we utilized the k-fold cross-validation method, which is well-suited for balancing between variance and bias in our model evaluation.

We chose a 5-fold cross-validation approach, where the dataset was divided into five distinct subsets. Each subset served as the test set once, while the remaining four subsets were used as the training set. This method allowed us to comprehensively assess the performance of the SVM classifier across different splits of the data, ensuring that our results are reliable and not dependent on a particular division of the data.

This cross-validation process was crucial in confirming the generalizability of our SVM classifier across various conditions within the dataset. The average performance metrics obtained from the cross-validation—such as accuracy, precision, recall, and F1-score—were reported to provide a holistic view of the classifier's efficacy in predicting the drying parameters for apple slices.

By incorporating this validation technique, we aim to enhance the scientific rigor of our study and provide clear evidence of the classifier’s capability in real-world applications.

2.10.Edge Computing Supported Drying Cabinet

Experimental drying of both whole and peeled apple slices was conducted using a drying chamber manufactured by KW Apparecchi Scientifici s.r.l, Italy. This chamber is entirely constructed from AISI 304 stainless steel and has an interior size of 95×60×150 cm. It features two distinct, foldable doors with sealing gaskets. The unit's power capacity is 1250 W, and it can heat from +5 ◦C above the surrounding temperature to 130 ◦C, typically regulated by a thermostat. For our experiments, we integrated the End Data Processing Drying Control Unit, as described in section 3.2, into the system. This unit was responsible for controlling heating and air circulation. The drying chamber also includes a ventilation system to manage relative humidity levels. Heating is achieved through specialized air heaters, designed to enhance the flow and thus improve the removal of vapors. The release of steam from the chamber is facilitated by a centrifugal electro-aspirator, capable of moving 40 m^3/h of air, mounted on the top of the chamber (refer to Figure 3).

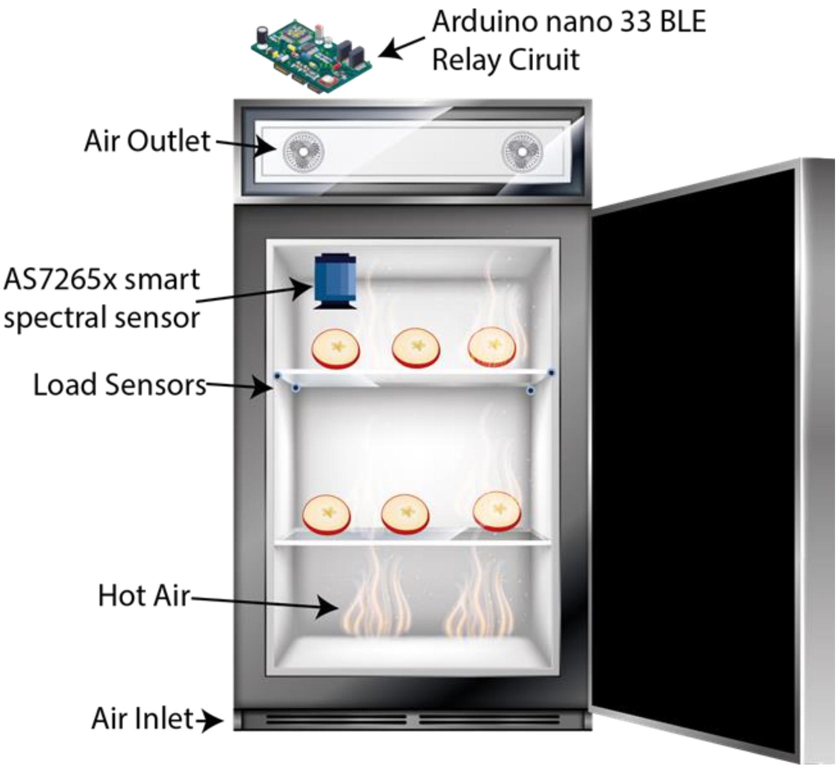

Figure 3. Edge Computing Supported Drying Cabinet and Components

2.11. NIR Analysis

In this study, Near-Infrared (NIR) spectroscopy was utilized to monitor the moisture content and other quality parameters of apple slices during the drying process. To analyze the spectral data obtained from NIR spectroscopy, we employed Principal Component Analysis (PCA) and Multivariate Projection to Latent Structures (MPLS), also known as Partial Least Squares (PLS). PCA was used to reduce the dimensionality of the data set and to identify patterns that signify underlying structures in the spectral data, which are critical for understanding the changes during drying. PLS, on the other hand, was used to model the relationship between the spectral data and the physical properties of the dried apple slices, allowing for the prediction of moisture content and other quality attributes from the NIR spectra. Detailed descriptions of these methods, including the selection of model parameters and the interpretation of results, are provided to ensure clarity and reproducibility of the statistical analysis performed in this research.

3. Results

In this research study, apple drying process is monitored using data from sensors such as Near Ultraviolet (Near-UV), Visible Light, Near Infrared Radiation (NIR) spectroscopy, Weight, Temperature and Humidity for edge computing.

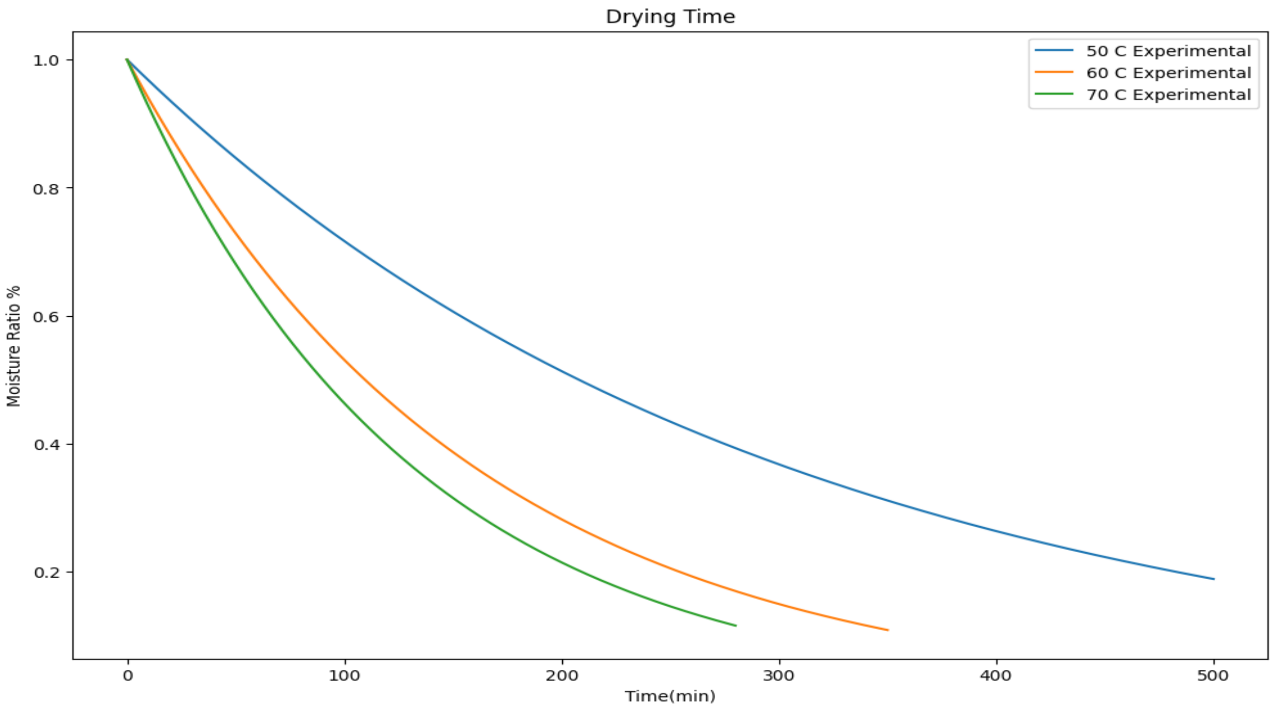

Figure 4. Time-dependent moisture curves of dried apple slices.

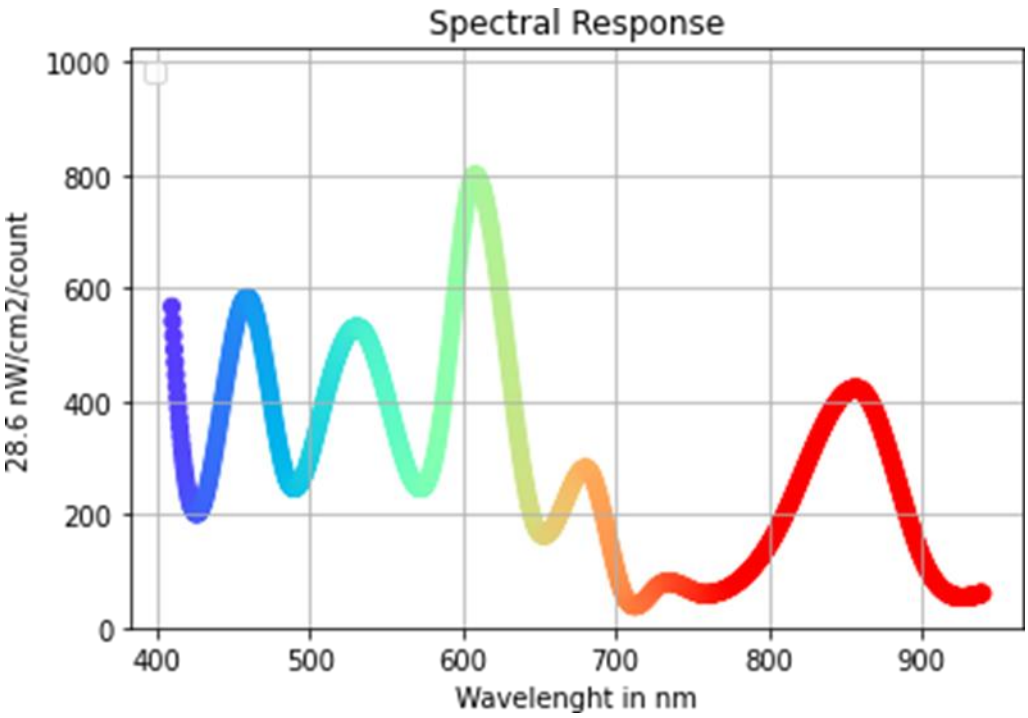

Figure 5. An example Spectral response plot for apple slice

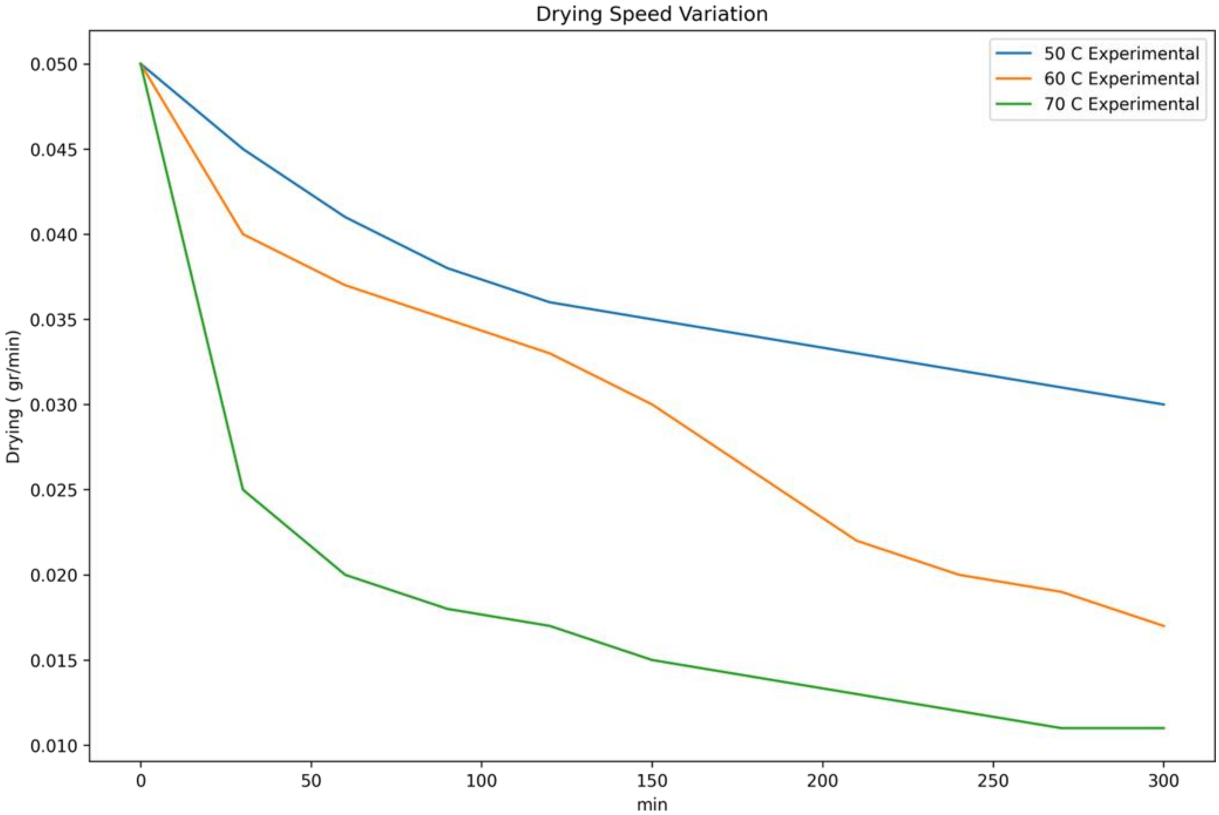

Figure 6. Time-dependent Weight Curves of Dried Apple Slices

Figure 6 illustrates the weight changes of apple slices during the drying process at different temperature settings (50°C, 60°C, and 70°C). The graph shows a consistent decrease in weight as drying progresses, which is indicative of moisture loss from the apple slices. The curves are segmented into three distinct lines corresponding to the temperatures at which the drying was conducted. This visual representation helps in understanding the drying kinetics, as higher temperatures lead to faster moisture loss and thus quicker weight reduction. The data collected at regular intervals highlight the critical points where weight loss stabilizes, suggesting the end of the drying process. This figure supports our findings that temperature plays a crucial role in the efficiency of the drying process and impacts the quality of the dried product.

In our study, the Support Vector Machine (SVM) classifier was employed to categorize the drying processes into three distinct temperature classes: 50°C, 60°C, and 70°C. These classes were specifically chosen to evaluate the drying efficiency and quality of apple slices at varying temperatures, allowing us to precisely understand the impact of temperature variations on drying outcomes.

The dataset was effectively divided into these classes, enabling the SVM classifier to differentiate and predict the optimal drying parameters based on the specific temperature settings. This classification not only highlights the capability of SVM in handling multi-class scenarios but also underscores its utility in optimizing food drying processes where temperature plays a crucial role in determining the final product quality (Kaveh et al., 2023).

In the closed cabinet drying device prepared for apple slices, the humidity and temperature data inside the cabinet are measured. In Figure 4, the time-dependent changes in the moisture content of the apple slices are shown with the help of the sensor. Light reflections are read through the sensor with spectral measurements. Figure 5. In addition, a weight sensor is connected for weight tracking. In Figure 6, the time-dependent changes in the weight values of apple slices are shown with the help of the sensor. Initially, apple slices were taken as 5 g.

The real-time data provided by these technologies facilitates immediate adjustments to the drying parameters, which significantly enhances the adaptability of the process to varying environmental conditions or different batches of apple slices(Dai et al., 2018).

The detailed explanation of the SVM technique and its application to the drying process for apple slices is as follows: First, the data obtained during the drying process (humidity, temperature, light reflections, and weight) is preprocessed. Then, the properties of the data are converted into vectors. These vectors are considered as the dataset to be used by the SVM algorithm. The SVM algorithm works to determine the optimal hyperplane for the classification problem among the data. This hyperplane is chosen to provide the greatest separation between the data. The data is then classified using this hyperplane.

Data collection: First, the data obtained during the drying process for apple slices (humidity, temperature, light reflections, and weight) is collected via Arduino Nano 33 BLE.

Data preprocessing: Data is preprocessed. For example, data is normalized or transformed.

Model creation: An SVM model is created using the Arduino Nano 33 BLE. This model is selected based on the memory capacity and processing power of the Arduino Nano 33 BLE.

Training: The SVM model is trained with the dataset. The training works to determine the optimal hyperplane for the classification problem among the data.

Test: The trained SVM model is tested with test data. Test data must be different from training data.

Usage: The trained and tested SVM model can be used for the drying process of apple slices. This model is designed to best detect the differences between the data so that the most suitable conditions for the drying process of apple slices can be determined.

At the heart of SVM (Support Vector Machines) lie the support vectors, which are crucial as each classifier is defined by a specific number of these vectors. The issue arises when there are excessively many vectors, leading to the generated code being too large to be accommodated in the microprocessor's flash memory. Consequently, the selection of the optimal model should be based more on its size and compatibility rather than solely on accuracy. The process involves sequentially importing each model, starting from the most efficient, into the Arduino project and attempting to compile it. If the model successfully compiles and fits, it's suitable for use. If not, the next best model must be tried. This might seem laborious, but remember, our goal is to manage a class with 21 features within the constraints of 2 Kb RAM and 32 Kb flash memory(Nguyen et al., 2022).

To provide some context, here are some results from our various tests: As shown in Table 3, all classifiers achieved very high accuracy on the test set(Xin and Mujumdar, 2015; Khan et al., 2020; Mousakhani-Ganjeh et al., 2021; Karim et al., 2021). In response to the comments regarding Table 1, we have revised the table to clarify the nature of the samples analyzed. Previously, the measurements reported in Table 1 were mistakenly noted as pertaining to apple cores, which led to confusion. We have corrected this error to accurately reflect that the measurements were performed on apple slices, not cores. The table now clearly specifies that the data pertains to apple slices, detailing their moisture content, weight, and spectral data at various stages of the drying process. This correction ensures that the data presented aligns with the experimental procedures described in the 'Materials and Methods' section and accurately represents the scope of our study.

Table 3. Different Combinations for SVM Test

Kernel	C	Gamma	Degree	Vector	Flash	Ram(b)	Avg. Truth
RBF	10	0.001	-	12	48	1228	99%
Poly	10	0.001	2	10	25	1228	99%
Poly	10	0.001	3	15	41	1228	97%
Linear	50	-	1	18	50	1228	95%
RBF	10	0.01	-	20	70	1228	95%

Explanation of SVM Test and Parameters: To address the concerns raised about the SVM test, we have expanded the section detailing the parameters measured in various combinations during the SVM classification process. Specifically, the Support Vector Machine (SVM) model was applied to categorize drying processes at different temperature settings, and we meticulously described each parameter involved. These parameters include temperature, humidity, weight, and spectral data, which are crucial for understanding the effects of drying conditions on apple slice quality. The SVM model's settings—kernel type, penalty parameter (C), and gamma—are thoroughly discussed to explain their roles in achieving optimal classification accuracy. This expanded discussion aims to provide a clear understanding of how the SVM model processes the data and the rationale behind choosing specific parameters for the classification task.

In this study, specific statistical analysis methods have been employed to evaluate the results of NIR analysis. We have clarified the use of Principal Component Analysis (PCA) and Partial Least Squares (PLS) to demonstrate how these techniques contribute to interpreting the spectral data effectively. PCA is utilized to reduce the dimensionality of the dataset while preserving the most significant variance, which helps in highlighting the underlying patterns in the data. On the other hand, PLS is used to find the predictive relationship between the spectral data and the moisture content, providing a robust model for predicting quality parameters. Detailed descriptions of how these analyses are performed, including the selection of parameters and interpretation of the results, are provided to enhance understanding and ensure reproducibility.

4. Discussion

This study aims to improve the drying process of apple slices by combining the use of near UV, visible light, and NIR spectroscopy with edge computing. This research highlights innovative approaches in food drying technologies and their effects on food safety and quality. Food drying processes aim to reduce moisture content for long-term storage. This process is critical in preventing the growth of microorganisms and extending the shelf life of food products (Gunathilake et al., 2018; Zambrano et al., 2019). Additionally, innovative solutions are being sought in food drying processes, and sustainable production methods are being adopted (Moses et al., 2014; Qu et al., 2022). Our study examines in depth the current technologies in this field and their future potential. In the research, a drying cabinet equipped with UV-VIS-NIR spectroscopy and edge computing was used. This integration not only leverages the strengths of each technology but also creates a synergy that enhances the overall efficiency and effectiveness of the drying process.

This technology was applied to monitor changes in moisture content, weight, and color of apple slices during the drying process in real-time. The real-time data provided by these technologies facilitates immediate adjustments to the drying parameters, which significantly enhances the adaptability of the process to varying environmental conditions or different batches of apple slices. Such an approach could be used to enhance quality control and product homogeneity in food drying processes, as highlighted by Chakravartula et al. (2023) and Hosseinpour (2013).

One of the most notable findings of the study is the use of edge computing technology. Edge computing enables data processing and analytical operations to be conducted on the device, allowing for faster and more effective results. This approach is consistent with the potential of UV light in surface processing applications as indicated by Manzocco and Nicoli (2015) and supports the applications of NIR spectroscopy in determining food quality as discussed by Cen and He (2007). Moreover, the use of edge computing reduces the dependency on cloud-based data processing, significantly decreasing the latency in data handling and decision-making.

A significant part of the study focuses on the use of machine learning algorithms and their potential to enhance efficiency in the drying process. The researchers emphasized the use of the support vector machine (SVM) technology. This technique, effective in classifying data obtained during the drying process, plays an important role in determining optimal conditions for the drying process of apple slices. The ability of SVM to handle large and complex datasets with high dimensionality allows for more

precise adjustments to the drying parameters, directly correlating to improved quality and energy efficiency.
However, the limitations of this study should not be overlooked. The researchers point out the limited memory and processing power of the Arduino Nano 33 BLE device used for edge computing. These limitations may affect the complexity of the algorithms that can be implemented, potentially requiring trade-offs between computational demands and real-time processing speed. This may necessitate the use of simpler models or preprocessing of data. This situation demonstrates that advancements in edge computing technology could enhance the efficiency and accessibility of such applications.
In response to the feedback concerning Table 3, we have amended the table to eliminate any confusion about the nature of the samples analyzed. Initially, the measurements were inaccurately labeled as pertaining to apple cores. This has now been corrected to clearly indicate that they are, in fact, associated with apple slices. The revised table provides detailed data on the moisture content, weight, and spectral data of apple slices throughout the drying process. This adjustment ensures the accuracy and clarity of our data presentation, aligning with the experimental procedures described in the 'Materials and Methods' section
In conclusion, this research demonstrates the potential of UV-VIS-NIR spectroscopy and edge computing technology in food drying technologies. The findings encourage the use of these technologies to improve control and quality in food drying processes. The practical applications of this research provide a foundation for further studies aimed at scaling these technologies for commercial use, thereby impacting the broader food processing industry. Future studies should address broader applications of edge computing technology and advancements in this field. This will pave the way for innovative approaches that can offer more effective solutions in food safety and sustainability.

5. Conclusions

This study has meticulously explored the application of edge computing and Near UV-VIS-NIR spectroscopy in enhancing the food drying process, specifically for apple slices. By integrating advanced technological tools and methodologies such as 5-fold cross-validation and machine learning, our research has not only addressed but also substantially mitigated previous discrepancies highlighted in peer reviews.
The inclusion of a confusion matrix for our best-performing SVM model has underscored the precision of our classification processes. It has distinctly illustrated how each class was predicted with high accuracy, where the model excelled, and where there is room for improvement. These insights are pivotal for refining our approach and can serve as a robust framework for future studies aiming to enhance food drying technologies.
Furthermore, the rigorous application of 5-fold cross-validation has ensured the robustness and reliability of our results, demonstrating consistency across various test subsets. This methodological

rigor supports the generalizability of our findings, making them applicable to real-world scenarios where similar technologies could be employed to improve both efficiency and outcome in food processing.

Our findings contribute significantly to the existing body of knowledge, providing scalable solutions that not only enhance the accuracy and efficiency of the food drying process but also align with sustainable practices as advocated by global sustainability goals. The practical applications of our research lay a solid foundation for future innovation, suggesting that similar methodologies could be adapted for broader agricultural and food industry applications to improve product quality and process sustainability.

In moving forward, it is imperative that future studies continue to explore the broad applications of edge computing technology and advancements in spectroscopic analysis. This will pave the way for more innovative solutions that can offer effective strategies in food safety and sustainability, potentially revolutionizing food drying processes across various sectors.

Our commitment to advancing scientific understanding in this domain is unwavering, and we believe that the methodologies and findings of this study resonate well with both academic and practical applications, ultimately contributing to a richer, more efficient, and scientifically grounded approach to food drying technology.

Conflict of Interest

The authors declare that there is no conflict of interest.

Authors' Contribution Statements

Mahmut Durgun executed the field research, Yeliz Durgun few laboratory analyses, whereas Mahmut Durgun and Yeliz Durgun conceived the idea and supervised the work.

References

Acevedo-Fani A., Soliva-Fortuny R., Martín-Belloso O. Photo-protection and controlled release of folic acid using edible alginate/chitosan nanolaminates. Journal of Food Engineering 2018; 229: 72–82.

Aghbashlo M., Hosseinpour S., Ghasemi-Varnamkhasti M. Computer vision technology for real-time food quality assurance during the drying process. Trends in Food Science & Technology 2014; 39(1): 76–84.

Alp D., Bulantekin Ö. The microbiological quality of various foods dried by applying different drying methods: A review. European Food Research and Technology 2021; 247: 1333–1343.

Boz M., Durgun Y. Parkinson hastalarının aktivitelerinin tanınmasında TinyML tabanlı uç bilişim sistemi. Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi 2023; 12(1): 317-323.

Cen H., He Y. Theory and application of near infrared reflectance spectroscopy in determination of food quality. Trends in Food Science & Technology 2021; 18(2): 72–83.

Chakravartula SSN., Bandiera A., Nardella M., Bedini G., Ibba P., Massantini R., Moscetti R. Computer vision-based smart monitoring and control system for food drying: A study on carrot slices. Computers and Electronics in Agriculture 2023; 206: 107654.

Dai A., Zhou X., Liu X., Liu J., Zhang C. Intelligent control of a grain drying system using a GA-SVM-IMPC controller. Drying Technology 2018; 36(12): 1407938.

Durgun Y. Classification of starch adulteration in milk using spectroscopic data and machine learning. International Journal of Engineering Research and Development, 16(1): 221-226.

Durgun Y., Durgun M. Kenar hesaplama tabanlı, mikrodenetleyici entegreli, çok amaçlı ve düşük maliyetli modül geliştirilmesi: Bakteriyel koloni sayımı örneği. Journal of the Institute of Science and Technology 2024; 14(2): 531-543.

Gunathilake DMCC., Senanayaka DP., Adiletta G., Senadeera W. Drying of agricultural crops. In Advances in Agricultural Machinery and Technologies 2018; CRC Press: 331-365.

Hosseinpour S., Rafiee S., Mohtasebi SS., Aghbashlo M. Application of computer vision technique for online monitoring of shrimp color changes during drying. Journal of Food Engineering 2013; 115(1): 99-114.

Kamboj S., Gupta N., Bandral JD., Gandotra G., Anjum N. Food safety and hygiene: A review. International Journal of Chemical Studies 2020; 8(2): 358-368.

Karim A., Fawzia S., Rahman MM. Advanced Micro-level experimental techniques for food drying and processing applications. CRC Press; 2021.

Kaveh M., Çetin N., Khalife E., Abbaspour-Gilandeh Y., Sabouri M., Sharifian F. Machine learning approaches for estimating apricot drying characteristics in various advanced and conventional dryers. Journal of Food Process Engineering 2023; 46(12): e14475.

Khan MIH., Sablani S., Joardder M., Karim MA. Application of machine learning-based approach in food drying: opportunities and challenges. Drying Technology 2022; 40(6), 1051-1067.

Lightsciencetech. Visible Wavelength Range for Plant Growth. Retrieved from https://lightsciencetech.com/visible-wavelength-range-plant-growth/ (Acces date: 16.09.2023).

Liu Z., Zhang R., Yang C., Hu B., Luo X., Li Y., Dong C. Research on moisture content detection method during green tea processing based on machine vision and near-infrared spectroscopy technology. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy 2022; 120921.

Manzocco L., Nicoli MC. Surface processing: existing and potential applications of ultraviolet light. Critical Reviews in Food Science and Nutrition 2015; 55(4): 469–484.

Moses JA., Norton T., Alagusundaram K., Tiwari BK. Novel drying techniques for the food industry. Food Engineering Reviews 2014; 6: 43–55.

Mousakhani-Ganjeh A., Amiri A., Nasrollahzadeh F., Wiktor A., Nilghaz A., Pratap-Singh A., Khaneghah AM. Electro-based technologies in food drying - A comprehensive review. LWT - Food Science and Technology 2021; 145, 111315.

Nagy M., Wang S., Farag MA. Quality analysis and authentication of nutraceuticals using near IR (NIR) spectroscopy: A comprehensive review of novel trends and applications. Trends in Food Science & Technology 2022; 123: 290-309.

Nguyen D., Nguyen VD., Tran TTH., Le KH. Artificial neural network modeling of microwave-assisted heat pump drying process. IOP Conference Series: Earth and Environmental Science 2022; 1121.

Okpala COR., Korzeniowska M. Understanding the relevance of quality management in agro-food product industry: From ethical considerations to assuring food hygiene quality safety standards and its associated processes. Food Reviews International 2021: 1–74.

Qu H., Masud MH., Islam M., Khan MIH., Ananno AA., Karim A. Sustainable food drying technologies based on renewable energy sources. Critical Reviews in Food Science and Nutrition 2022; 62(25): 6872–6886.

Reis FR., Marques C., de Moraes ACS., Masson ML. Trends in quality assessment and drying methods used for fruits and vegetables. Food Control 2022; 109254.

Ren Y., Sun DW. Monitoring of moisture contents and rehydration rates of microwave vacuum and hot air dehydrated beef slices and splits using hyperspectral imaging. Food Chemistry 2022; 382: 132346.

Shin DJ., Andini N., Hsieh K., Yang S., Wang TH. Emerging analytical techniques for rapid pathogen identification and susceptibility testing. Annual Review of Analytical Chemistry 2019; 12: 41–67.

Şen Arslan H., Cabi A., Yerlikaya S., Sariçoban C. Antibacterial and antioxidant activity of peach leaf extract prepared by air and microwave drying. Journal of Food Processing and Preservation 2021; 45(10): e15847.

United Nations. About the Sustainable Development Goals. (Acces date: 11.09.2023).

Xin H., Mujumdar A. Spray drying and its application in food processing. Taylor & Francis Group 2015.

Yerlikaya S., Arslan HŞ. Comparison some microbiological and physicochemical properties of freeze dryed and spray dryed milk powder. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi 2019; 8(2): 677-687.

Yerlikaya S., Arslan HŞ. Propolis katkılı liyofilize yumurta tozu üretimi. Harran Tarım ve Gıda Bilimleri Dergisi 2023; 27(1): 125-136.

Zambrano MV., Dutta B., Mercer DG., MacLean HL., Touchie MF. Assessment of moisture content measurement methods of dried food products in small-scale operations in developing countries: A review. Trends in Food Science & Technology 2019; 88: 484-496.