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# Determination of Quality Changes of Hard-Boiled Chicken Eggs Due to Slow and Fast Cooling by Electronic Nose and Machine Learning

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ABSTRACT

In this study, the freshness levels of boiled chicken eggs were determined using an electronic nose and machine learning techniques. Eggs were boiled and stored under refrigerator conditions (3±1ºC) from day 0 to day 6. Each storage day, eggs were divided into two groups based on cooling methods: quick-cooled and fast-cooled. Sensor readings were taken using an electronic nose, and image changes from 110 daily image files were processed with a machine learning program. With 85% of the image data used for training and 15% for testing, a classification accuracy of over 98% was achieved. The results showed that egg white solidified in more than 4 minutes and yolk solidified in 11 minutes. Fast-cooled eggs exhibited significantly lower odor levels, indicating superior freshness. This study demonstrates the effectiveness of electronic nose and machine learning systems in accurately determining the freshness of boiled eggs.

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## Introduction

Egg, one of the third most important animal protein sources after meat and milk, contains many elements necessary for nutrition. Although different poultry (turkey, goose, quail, etc.) also have eggs, chicken eggs come to mind when "egg" is mentioned in nutrition terminology because they are produced industrially, are easily accessible, and create unique flavors by increasing the consistency of other foods. The important role of chicken eggs in human nutrition is based on the fact that they are considered to be excellent sources of high-quality protein, vitamins, and minerals. (Elkin & Harvatine, 2023; Hossain et al., 2024). However, eggs, considered a complete source of protein essential for optimal growth and maintenance of body tissues (Hossain et al., 2024), are known to have an important mission to meet the increasing demand for protein worldwide (Ahmed et al., 2023).

Eggs, as a metabolic product, start to show undesirable changes in their quality levels from the moment they are laid by the hen (Jariyapamornkoon et al., 2023), and the increase in storage time, temperature, environmental conditions, and undesirable microbial changes in storage conditions further deteriorate their quality (da Silva Pires et al., 2022; Saleh et al., 2020; Yavuzer et al., 2020; Yavuzer & Kuley, 2020).

Because undesirable water and carbon dioxide will escape from the pores on the surface of the eggshell during storage, undesirable results such as a decrease in humidity and pH increase will cause a decrease in quality(Santos Almeida et al., 2024).As with other foods with high amounts of animal protein, increases in temperature accelerate egg spoilage and reduce shelf life (de Araújo et al., 2023; Samli et al., 2005; Sariyel et al., 2022).

Modern food technology performs sensory, chemical, and microbiological analyses to determine the shelf life of perishable foods such as fish, eggs, and milk (Yavuzer, 2023; Yavuzer & Köse, 2022). However, due to the development of technology, the production of rapid diagnostic kits, and the low time tolerance of the globalized trade system, electronic noses and machine learning have been used to determine the quality level of different foods in recent years (Azadbakht et al., 2024; Deng et al., 2010; Moallem et al., 2017; Wang et al., 2022; Yavuzer, 2018; Zhu et al., 2020).

Eggs are one of the most important animal products in the human diet because of their balanced chemical composition and relatively low price (Drabik et al., 2021). Different studies have been conducted on the quality levels of eggs that have not yet been heat treated. In the present study, the determination of the subsequent consumption of boiled eggs, control of quality levels, the effect of fast or late cooling of the egg on odor changes and the use of electronic noses and machine learning to quickly determine these changes were investigated.

## Materials and Methods

### *Machine Learning, Egg Material, And Imaging Conditions*

In this study, a web-based platform called Teachable Machine (TM) developed by Google was used for machine learning. A total of 40 medium-sized (M) chicken eggs were used in this study. The eggs were obtained from Niğde Ömer Halisdemir University Farm and were approximately 10 days old at the time of the experiment. The eggshell color was white. Egg samples were boiled for 12 min, and one group was rapidly cooled under cold water and the other group was cooled slowly under room conditions. The boiled egg samples were divided into two groups and stored under refrigerator conditions (3±1ºC) and their images were photographed daily with the help of a camera (Nikon P1000) from different angles on a white background.

### *Deep Learning*

Convolutional neural networks (CNN), the best-known deep learning network, were used to determine the daily changes in boiled egg samples (Mathworks, 2022). The ResNet-50 model defined in MATLAB Deep Learning Toolbox was used in the CNN environment to determine the features of 110 images per day, and the support vector machine (SVM) algorithm was used to classify the boiled egg features obtained by CNN.

### *Electronic Nose Environment*

In this study, an electronic nose environment designed with MQ3, MQ4, MQ5, MQ8, MQ9, and MQ135 sensors that are compatible with Arduino previously developed by (Yavuzer, 2021) was used. The electronic nose environment used in the study is shown in Figure 1. In the study, the data of the boiled egg samples with shells intact kept in the electronic nose for 15 min were recorded on a card reader connected to Arduino and read in the computer environment, and averages were taken. The decision to conduct measurements with shell-on eggs was made to simulate real-life storage conditions. One limitation is the potential interference of environmental factors, which could be mitigated by conducting tests in a controlled environment.

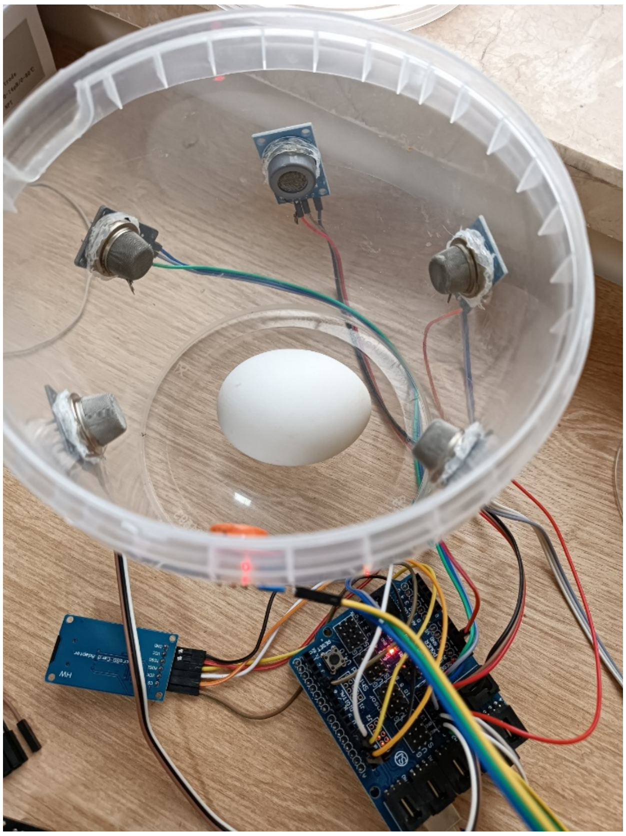

Figure 1. Electronic nose box construction with MQ sensors

### *Microbiological Analysis*

For total viable count (TVC), 10 g of boiled egg samples were taken and mixed in 90 ml Ringer’s solution for 5 min using a stomacher and incubated in PCA (Plate Count Agar) medium at 30°C for 2 days.

### *Statistical Analysis*

All data were presented as mean standard deviation (SD). To assess significant ($p \leq 0.05$) differences among experimental conditions, ANOVA was performed, followed by Tukey's test. Tukey's test was chosen because it is suitable for comparing all possible pairs of means to identify significant differences across experimental conditions. Minitab 18 (Minitab Inc.) was used to perform all statistical analyses. Analyses were repeated 3 times. Principal Component Analysis (PCA) was conducted to identify patterns and relationships among odor data. The PCA analysis was performed using Minitab 18, and the first two principal components (PC1 and PC2) were used to visualize variations among the samples.

## Results and Discussion

The data obtained from the electronic nose during the storage days of the late-cooled egg samples in the study were given in Table 1. In the study, it was determined that the egg white of the randomly selected samples solidified after 4 min and the yolk solidified in 11 min at the time of boiling. These times were recorded by direct visual observation of the coagulation process during boiling. On the first day of storage, the odor values given by the MQ3, MQ4, MQ5, MQ9 and MQ135 sensors were 506, 488, 457, 154 and 193, respectively.

Table 1. Odour changes of late cooled egg samples depending on storage days

| Days | MQ3 x̄±Sd | MQ4 x̄±Sd | MQ5 x̄±Sd | MQ9 x̄±Sd | MQ135 x̄±Sd |
|---|---|---|---|---|---|
| 0 | 506±7.16$^{aA}$ | 488±4.65$^{aB}$ | 457±9.64$^{aC}$ | 154±6.62$^{aE}$ | 193±9.96$^{fD}$ |
| 1 | 221±9.45$^{dB}$ | 247±7.71$^{fA}$ | 243±6.82$^{eA}$ | 99±2.18$^{fD}$ | 164±3.86$^{gC}$ |
| 2 | 224±7.76$^{dB}$ | 270±4.78$^{eA}$ | 221±7.85$^{fB}$ | 110±6.67$^{dD}$ | 201±7.21$^{dC}$ |
| 3 | 222±6.41$^{dB}$ | 251±4.52$^{fA}$ | 205±3.03$^{gC}$ | 106±8.18$^{eE}$ | 197±3.50$^{eD}$ |
| 4 | 227±5.33$^{dC}$ | 283±5.08$^{dA}$ | 253±5.04$^{dB}$ | 116±8.34$^{cE}$ | 218±9.14$^{cD}$ |
| 5 | 233±4.50$^{cD}$ | 341±3.50$^{cA}$ | 282±6.47$^{cB}$ | 144±2.99$^{bE}$ | 262±4.48$^{bC}$ |
| 6 | 270±7.46$^{bD}$ | 346±5.75$^{bA}$ | 289±9.28$^{bC}$ | 154±4.69$^{aE}$ | 319±6.28$^{aB}$ |

Different letters (a − g) in the same column and different letters (A − G) in the same row show significant differences (p ≤ 0.05)

Table 2. Odour changes of rapidly cooled egg samples depending on storage days

| Days | MQ3 x̄±Sd | MQ4 x̄±Sd | MQ5 x̄±Sd | MQ9 x̄±Sd | MQ135 x̄±Sd |
|---|---|---|---|---|---|
| 0 | 211±1.70$^{gB}$ | 217±3.08$^{gA}$ | 210±2.11$^{eB}$ | 108±1.70$^{fD}$ | 184±3.22$^{fC}$ |
| 1 | 224±2.87$^{fB}$ | 232±3.28$^{fA}$ | 231±3.62$^{dA}$ | 112±2.98$^{eD}$ | 207±3.63$^{eC}$ |
| 2 | 238±7.37$^{eA}$ | 238±5.87$^{eA}$ | 233±2.70$^{dA}$ | 116±1.29$^{deB}$ | 235±5.62$^{dA}$ |
| 3 | 247±4.35$^{dB}$ | 262±2.86$^{dA}$ | 250±6.62$^{cB}$ | 119±6.74$^{dC}$ | 251±2.62$^{cB}$ |
| 4 | 256±4.94$^{cC}$ | 250±3.19$^{cD}$ | 260±3.50$^{bB}$ | 113±0.82$^{cE}$ | 263±4.03$^{bA}$ |
| 5 | 267±4.40$^{bB}$ | 256±5.32$^{bC}$ | 273±2.70$^{aA}$ | 140±1.37$^{bD}$ | 264±2.10$^{bB}$ |
| 6 | 263±3.34$^{aD}$ | 283±5.01$^{aB}$ | 276±4.86$^{aC}$ | 182±3.84$^{aE}$ | 299±1.77$^{aA}$ |

Different letters (a − g) in the same column and different letters (A − G) in the same row show significant differences (p ≤ 0.05)

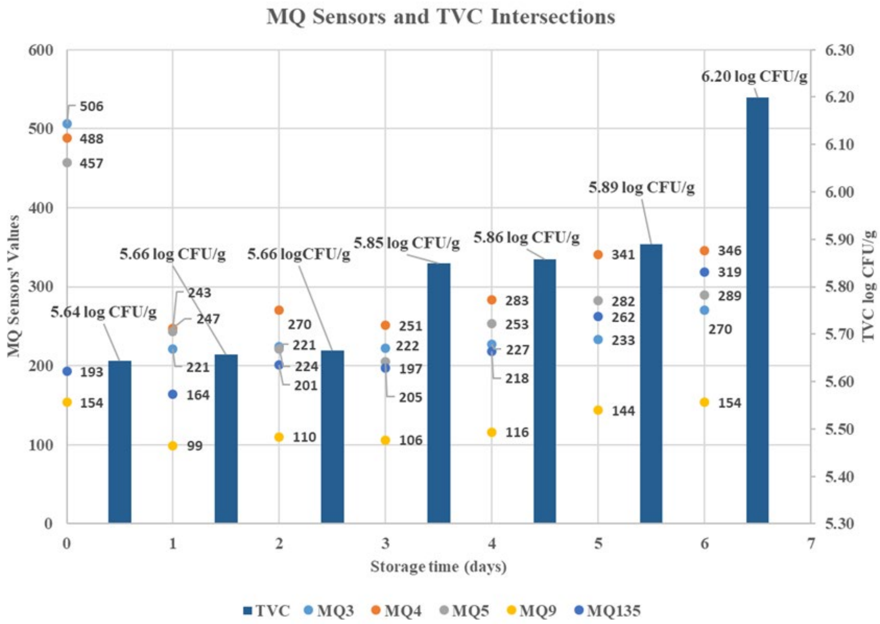


Figure 2. MQ sensors and TVC intersections of slow chilled egg during storage

The data obtained by the MQ4 and MQ5 sensors were recorded at values close to the readings obtained from food with a heavier odor, such as fish, in previous studies (Yavuzer, 2021). It is thought that this high initial reading data is due to the iron sulfide formed by combining the sulfur in the egg white with the iron on the yellow surface with the effect of heat treatment.

In the fast-cooled groups (Table 2), the electronic nose initial values were found to be 211, 217, 210, 108, and 184 for the MQ3, MQ4, MQ5, MQ9, and MQ135 sensors, respectively. The reason why the electronic nose readings of the rapidly cooled groups were significantly (p<0.05) lower than those of the slowly cooled group may be the decrease in gas pressure due to the rapid cooling of the eggshell. The decrease in the level of combination of hydrogen sulfide with the iron coming from the yolk as it approaches the shell and consequently the decrease in the rate of iron-sulfur formation was determined by electronic nose data.

The points of the TVC data intersecting with the electronic nose data of the late-cooled egg samples were shown in Figure 2. The initial TVC level of the egg samples was 5.64 log CFU/g and increased to 6.20 log CFU/g on the 6th day of storage. The microbiological stability of slow-chilled eggs decreases over time, with TVC exceeding the acceptable threshold by day 6. The sensor values (MQ3, MQ4, MQ5, MQ9, MQ135) exhibited variations throughout the storage period. Notably, the values of MQ3, MQ4, and MQ9 showed an increasing trend, suggesting a potential relationship between microbial growth and volatile compounds detected by the sensors. In general, the increase in the values read by the sensors was proportional to the increase in the number of TVCs.

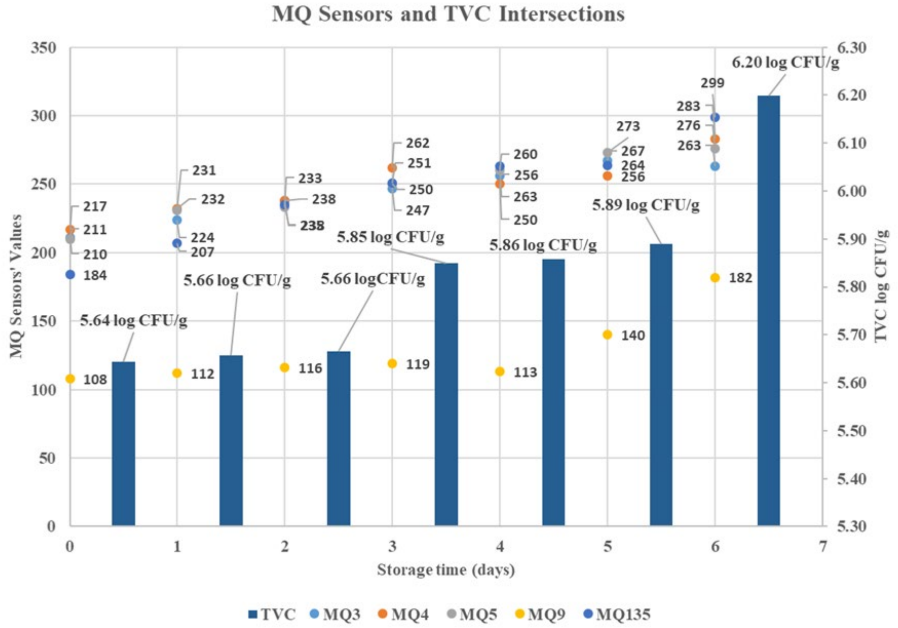

Figure 3. MQ sensors and TVC intersections of quick chilled egg during storage

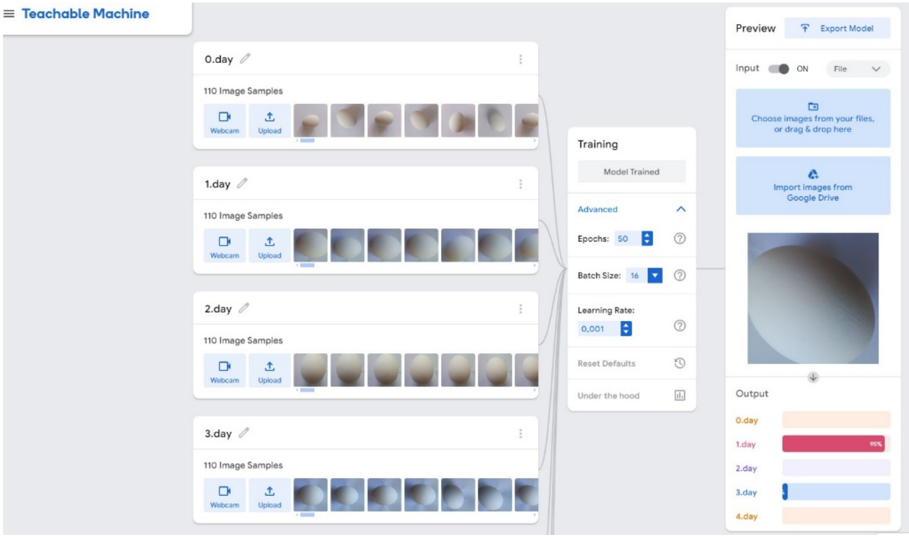

Figure 4. Classification performance of TM for first storage day

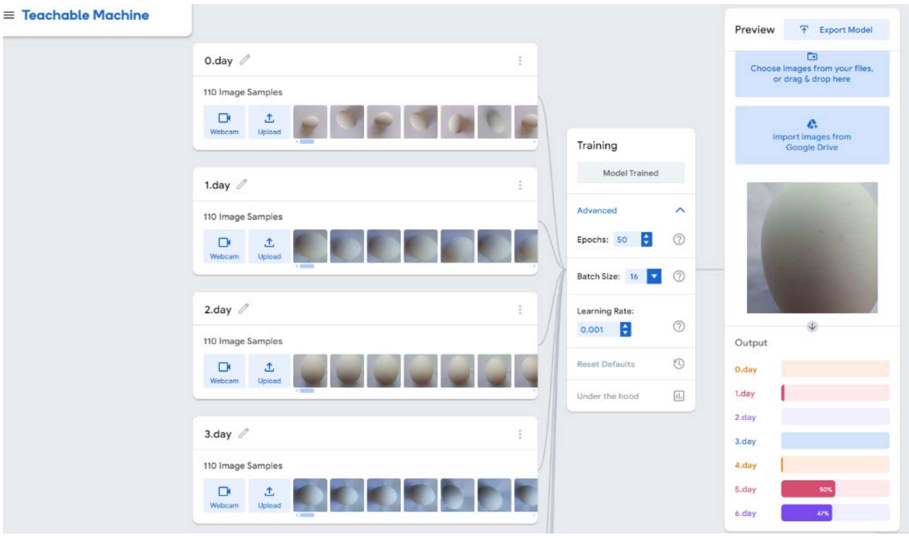

Figure 5. Classification performance of TM for fifth storage day

Table 3. Confusion matrix data for boiled eggs during storage days

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 0.day | 100 | | | | | | |
| 1.day | | 100 | | | | | |
| 2.day | | | 100 | | | | |
| 3.day | | 5.88 | | 94.12 | | | |
| 4.day | | | | | 100 | | |
| 5.day | | | | | | 100 | |
| 6.day | | | | | | | 100 |
| | 0.day | 1.day | 2.day | 3.day | 4.day | 5.day | 6.day |

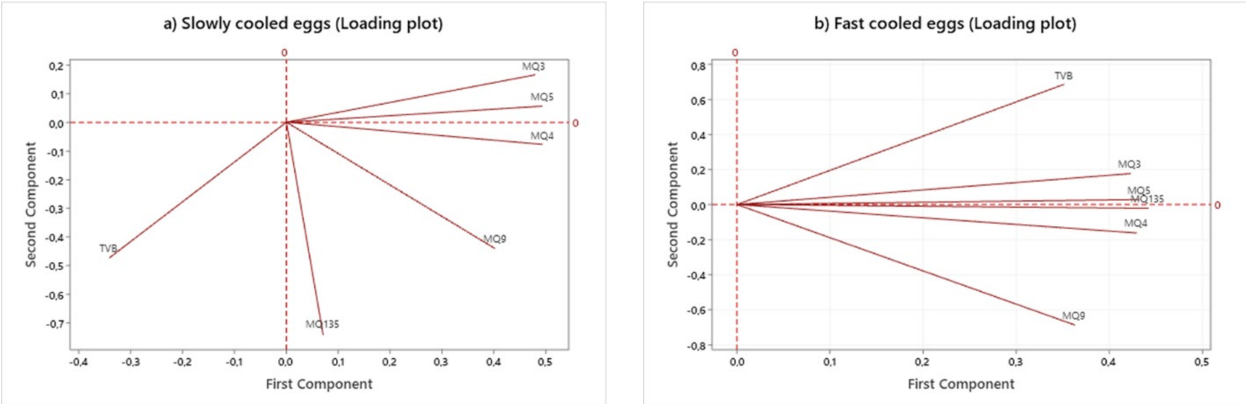


Figure 6. Loading plot of slow (a) and fast (b) cooled eggs

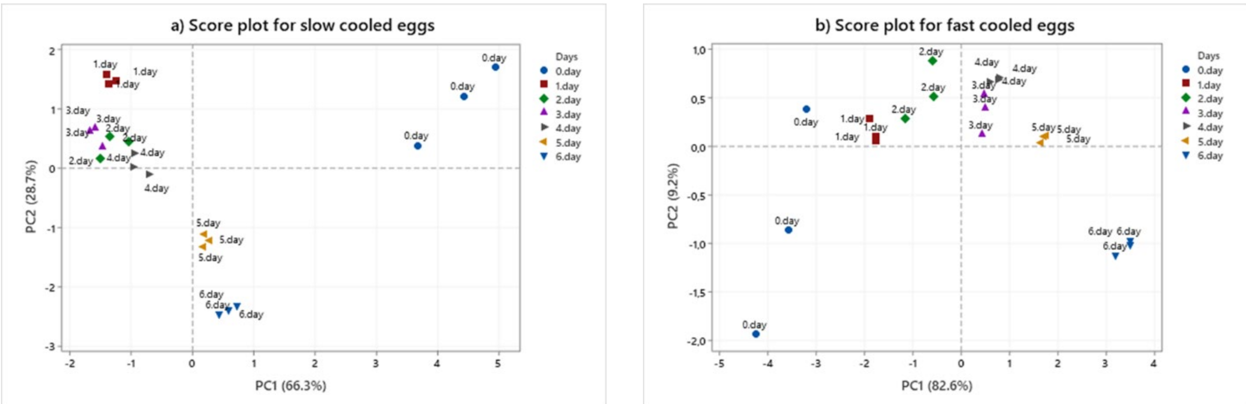


Figure 7. Score Plot of slow (a) and fast (b) cooled eggs

Odor and TVC changes in the rapidly cooled egg group were shown in Figure 3. On the 3rd day of storage, when MQ3, MQ4, MQ5, and MQ135 sensor data reached 250, the TVC number reached 5.85 log CFU/g. Quick-chilled eggs exhibit a steady increase in microbial load during storage, reaching the spoilage threshold by day 6.

TM, a web-based image processing program developed by Google, was used to teach the changes in egg images during storage days. The performance of TM in determining the quality levels of a food without very specific variables such as eggs was found to be very successful. Figure 4 shows the TM data for an egg on day 1 of storage with an accuracy of 92%, and Figure 5 shows the TM prediction performance for an egg on day 5 of storage. The tested egg was most frequently confused with the 4th day of storage (43%. Previous studies (de Araújo et al., 2023; Yavuzer, 2023) have reported that increasing the training data learnt by the machine will increase the success performance. In this study, although 110 images were taken for each storage day, storage days could be determined with high accuracy.

Confusion matrix data from the study were given in Table 3. According to the confusion matrix data, when 85% of the food samples were used in the experiment and 15% in the test, the learned machine was able to predict the boiled eggs correctly for all days except the 3rd day of storage. Only the 3rd day of storage was confused with the 1st day of storage, with an error of 5.88%. In other words, machine learning could successfully predict the day of storage of a shelled egg.

The data obtained because of the analyses performed using Arduino-based MQ sensors were analyzed using principal component analysis (PCA). According to the outlier graph based on PCA, there were no outliers in either group of eggs. All points were below the reference line of 4.134. The first principal components were positively correlated with all variables except the total viable bacteria count in late chilled eggs (Figure 6a), whereas they were positively correlated with all variables except the total viable bacteria count and MQ9 sensor in fast chilled eggs (Figure 6b).

In the study, MQ3, MQ4, MQ5, and MQ9 sensors were the most correlated variables with the first principal component (PC1) in late-cooled eggs, whereas MQ3, MQ4, MQ5, and MQ135 were determined in quick-cooled eggs. These types of sensors were used previous research (Alvarez et al., 2019; Karami et al., 2020).

PC1 was positively correlated with these four variables during storage and had similar scores. In late chilled eggs, the grouping levels of the samples according to the sensors used and total viable bacteria were clustered according to the storage period. Samples at the beginning of the storage period (day 0) were grouped separately on the upper right side of the graph, samples stored on the 2nd, 3rd, and 4th days were grouped on the upper left side of the graph, and samples stored on the 5th and 6th days were grouped on the lower right side of the graph. According to the loading plot, it was determined that the MQ3 and MQ5 sensors characterized day 0 egg samples. The 5- and 6-day-stored egg samples were characterized by MQ4, MQ9, and MQ135 sensors (Figure7a).

In quickly cooled eggs, it was observed that the samples formed clusters according to the sensors used and total viable bacteria. At the beginning of the storage period (day 0), the samples were collected on the left side of the graph, on days 1 and 2 on the upper left side, on days 3, 4, and 5 on the upper right side of the graph, and on day 6 on the lower left side of the graph. When the loading graph (Figure 7b) is examined according to the sensors used, the MQ9 sensor characterized the egg samples on day 6. MQ3, MQ5, and MQ135 sensors characterize the quickly cooled egg samples stored on days 3, 4, and 5.

## Conclusion

In this study, odor and microbial quality changes in egg samples cooled quickly and slowly after boiling were examined using low-cost sensors with fast reading capacity connected to an Arduino microcontroller. According to electronic nose data, it has been determined that unpleasant odors were prevented by rapid cooling of the eggs after boiling. Arduino, which works with the electronic nose sensors used in the study, is an open-source platform. In addition, the Teachable Machine platform developed by Google is a web-based and free image processing platform. The fact that the quality level of an important protein source such as eggs is determined by machine learning can inspire the industry to quickly analyze other functional foods. These findings suggest that the combination of low-cost sensors and machine learning-based classification can be adapted for large-scale applications in the food industry. By integrating such technologies into production lines, real-time quality monitoring of eggs and other perishable foods could be achieved efficiently. The cost-effectiveness and accessibility of open-source platforms like Arduino and Teachable Machine further support the feasibility of industrial implementation, offering a promising approach for quality control and safety assessment in food processing.

## Declarations

### *Author Contributions*

Metehan Denli: Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); writing – original draft (equal). Emre Yavuzer: Conceptualization (equal); funding acquisition (equal), investigation (equal); methodology (equal); supervision (equal); writing – original draft (equal). Hasan Tangüler: Resources (equal); software (equal); validation (equal); writing – review and editing (equal). Memduh Köse: Software (equal); visualization (equal); writing – review and editing (equal). Mehmet Kürşat Yalçın: Conceptualization (equal); data curation (equal). Hasan Macit: Formal analysis (equal). Mehmet Yetişen: Visualization (equal); writing – review and editing (equal).

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### *Ethical Approval*

Ethics approval was not required for this study.

### *Conflict of Interest Statement*

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### *Data Availability Statement*

The data supporting the findings of this study are available in the supplementary material of this article.

## References

Ahmed, M. W., Hossainy, S. J., Khaliduzzaman, A., Emmert, J. L., & Kamruzzaman, M. (2023). Non-destructive optical sensing technologies for advancing the egg industry toward Industry 4.0: A review. *Comprehensive Reviews in Food Science and Food Safety*, *22*(6), 4378–4403. https://doi.org/10.1111/1541-4337.13227

Alvarez, C. S., Sierra-Sosa, D., Garcia-Zapirain, B., Yoder-Himes, D., & Elmaghraby, A. (2019). Detection of Volatile Compounds Emitted by Bacteria in Wounds Using Gas Sensors. *Sensors 2019, Vol. 19, Page 1523*, *19*(7), 1523. https://doi.org/10.3390/S19071523

Azadbakht, M., Shabankareh, S. H., Kiapey, A., Rezaeiasl, A., Mahmoodi, M. J., & Torshizi, M. V. (2024). Assessing kiwifruit quality in storage through machine learning. *Journal of Food Process Engineering*, *47*(7), e14681. https://doi.org/10.1111/JFPE.14681

da Silva Pires, P. G., Bavaresco, C., Wirth, M. L., & Moraes, P. O. (2022). Egg coatings: trends and future opportunities for new coatings development. *World's Poultry Science Journal*, *78*(3), 751–763. https://doi.org/10.1080/00439339.2022.2075298

de Araújo, M. V., Oliveira, G. da S., McManus, C., Vale, I. R. R., Salgado, C. B., Pires, P. G. da S., de Campos, T. A., Gonçalves, L. F., Almeida, A. P. C., Martins, G. dos S., Leal, I. C. R., & dos Santos, V. M. (2023). Preserving the Internal Quality of Quail Eggs Using a Corn Starch-Based Coating Combined with Basil Essential Oil. *Processes 2023, Vol. 11, Page 1612*, *11*(6), 1612. https://doi.org/10.3390/PR11061612

Deng, X., Wang, Q., Chen, H., & Xie, H. (2010). Eggshell crack detection using a wavelet-based support vector machine. *Computers and Electronics in Agriculture*, *70*(1), 135–143. https://doi.org/10.1016/j.compag.2009.09.016

Drabik, K., Próchniak, T., Spustek, D., Wengerska, K., & Batkowska, J. (2021). The Impact of Package Type and Temperature on the Changes in Quality and Fatty Acids Profile of Table Eggs during Their Storage. *Foods 2021, Vol. 10, Page 2047*, *10*(9), 2047. https://doi.org/10.3390/FOODS10092047

Elkin, R. G., & Harvatine, K. J. (2023). A review of recent studies on the enrichment of eggs and poultry meat with omega-3 polyunsaturated fatty acids: novel findings and unanswered questions. *Poultry Science*, *102*(10), 102938. https://doi.org/10.1016/J.PSJ.2023.102938

Hossain, A., Ahmed, M. W., Rabin, M. H., Kaium, A., Razzaque, M. A., & Zamil, S. S. (2024). Heavy metal quantification in chicken meat and egg: An emerging food safety concern. *Journal of Food Composition and Analysis*, *126*, 105876. https://doi.org/10.1016/J.JFCA.2023.105876

Jariyapamornkoon, N., Phongthajitr, C., Sritharet, N., & Sutthitham, W. (2023). Preservation of chicken egg quality using pectin derived from water hyacinth. *Applied Food Research*, *3*(2), 100355. https://doi.org/10.1016/J.AFRES.2023.100355

Karami, H., Rasekh, M., & Mirzaee-Ghaleh, E. (2020). Application of the E-nose machine system to detect adulterations in mixed edible oils using chemometrics methods. *Journal of Food Processing and Preservation*, *44*(9), e14696. https://doi.org/10.1111/JFPP.14696

Moallem, P., Serajoddin, A., & Pourghassem, H. (2017). Computer vision-based apple grading for golden delicious apples based on surface features. *Information Processing in Agriculture*, *4*(1), 33–40. https://doi.org/10.1016/j.inpa.2016.10.003

Saleh, G., El Darra, N., Kharroubi, S., & Farran, M. T. (2020). Influence of storage conditions on quality and safety of eggs collected from Lebanese farms. *Food Control*, *111*, 107058. https://doi.org/10.1016/J.FOODCONT.2019.107058

Samli, H. E., Agma, A., & Senkoylu, N. (2005). Effects of Storage Time and Temperature on Egg Quality in Old Laying Hens. *Journal of Applied Poultry Research*, *14*(3), 548–553. https://doi.org/10.1093/JAPR/14.3.548

Santos Almeida, D. dos, Schneider Bedin, A. F., Miletti, L. C., & Gewehr, C. E. (2024). Internal quality of commercial eggs subjected to different shell treatments and storage times. *Semina: Ciências Agrárias*, *45*(2), 527–536. https://doi.org/10.5433/1679-0359.2024v45n2p527

Sariyel, V., Aygun, A., Coklar, H., Narinc, D., & Akbulut, M. (2022). Effects of Prestorage Application of Gum Arabic Coating on the Quality of Table Eggs During Storage. *Kafkas Üniversitesi Veteriner Fakültesi Dergisi*, *28*(3), 363–370. https://doi.org/10.9775/KVFD.2022.27077

Wang, B., Deng, J., Jiang, H., & Chen, Q. (2022). Electronic nose signals-based deep learning models to realize high-precision monitoring of simultaneous saccharification and fermentation of cassava. *Microchemical Journal*, *182*, 107929. https://doi.org/10.1016/j.microc.2022.107929

Yavuzer, E. (2018). Development of defective fish egg sorting machine with colour sensor for trout facilities. *Aquaculture Research*, *49*(11), 3634–3637. https://doi.org/10.1111/are.13831

Yavuzer, E. (2021). Determination of fish quality parameters with low cost electronic nose. *Food Bioscience*, *41*, 100948. https://doi.org/10.1016/J.FBIO.2021.100948

Yavuzer, E. (2023). Rapid detection of sea bass quality level with machine learning and electronic nose. *International Journal of Food Science & Technology*, *58*(5), 2355–2359. https://doi.org/10.1111/IJFS.16365

Yavuzer, E., & Köse, M. (2022). Prediction of fish quality level with machine learning. *International Journal of Food Science & Technology*, *57*(8), 5250–5255. https://doi.org/10.1111/ijfs.15853

Yavuzer, E., & Kuley, E. (2020). Testing the Antimicrobial Effects of Some Hydrosols on Food Borne-Pathogens and Spoilage Bacteria. *Journal of Limnology and Freshwater Fisheries Research*, 47–51. https://doi.org/10.17216/limnofish.618101

Yavuzer, E., Özogul, F., & Özogul, Y. (2020). Impact of icing with potato, sweet potato, sugar beet, and red beet peel extract on the sensory, chemical, and microbiological changes of rainbow trout (Oncorhynchus mykiss) fillets stored at (3 ± 1 °C). *Aquaculture International*, *28*(1), 187–197. https://doi.org/10.1007/s10499-019-00454-7

Zhu, D., Ren, X., Wei, L., Cao, X., Ge, Y., Liu, H., & Li, J. (2020). Collaborative analysis on difference of apple fruits flavour using electronic nose and electronic tongue. *Scientia Horticulturae*, *260*, 108879. https://doi.org/10.1016/J.SCIENTA.2019.108879