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ORIGINAL PAPER

Determining the quality level of ready to-eat stuffed mussels with Arduino-based electronic nose

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Abstract
In this study, the performance of a pre-designed and low-cost Arduino electronic nose for determining the quality of stuffed mussels was analyzed. In addition, 1000 images were taken on each storage day in order to determine the quality levels of stuffed mussel groups with open and closed shells by machine learning. Freshness limit values of stuffed mussels were determined as 200 for MQ3 and MQ135 sensors and 100 for MQ9 on the 3rd storage day when the total viable count (TVC) value exceeded 3 log CFU/g. In the study, faster neural networks with lower prediction times, such as SqueezeNet and GoogLeNet, were compared with ResNet-50, ResNet-101 and DenseNet-201 neural networks, which have larger prediction times but better accuracy. Study data showed that residual network (ResNet) 50 and Teachable Machine (TM) had high success in determining the quality levels of stuffed mussels.

Keywords Electronic nose · Prediction accuracy · MQ sensor · Mussel quality

Introduction

Mussel (*Mytilus galloprovincialis*) consumption has increased at a high rate in the last 20 years due to the increase in the world population, the need for alternative protein sources and the proof of the essential components found in seafood with the literature. With an annual production volume of nearly 20 million tons [1], mussels are also important as a cheap and sustainable source of long-chain fatty acids. The high protein level [2], the excess of beneficial components, mainly selenium [3], and studies on its aphrodisiac effect [4] have turned mussels into an important fast food product, especially in Mediterranean countries. In addition, today, in terms of gastronomy art in restaurant and hotel kitchens, it is processed with special names such as fried mussels, mussel stew, mussel salad and stuffed mussels. In general, the most important factor that makes mussel different from other fast food products is that it is a food that spoils very quickly. The fact that mussels can harbor harmful pathogens such as *Bacillus cereus*, *Shigella*, *Salmonella* and *Vibrio* [5, 6] poses a risk to food safety. Lack of supervision of street vendors, lack of depuration, contamination elements and lack of control of microorganism activities during the processing of the product also increase this risk.

There are main parameters in the quality determination process of seafood, which have the above-mentioned risks in terms of infection and intoxication [7]. The most accepted ones in the literature are chemical analyses such as Total Volatile Basic Nitrogen (TVB-N), Thiobarbituric acid reactive substances (TBARS), peroxide value (PV) and microbiological analyses such as total aerobic mesophilic count (TAMB) and total aerobic psicrophilic count (TAPB). However, the costly and time-consuming methods of these analyses increase the studies for the development of rapid quality determination methods in food safety. In previous studies, computer and automation technologies have been used in the determination of various limits of foods such as separation of foods by machine learning [8], determination of fish quality levels [9], classification of tomatoes [10] or apples [11, 12], eggs [13, 14] and rice [15]. The literature on the use of electronic sensors and noses in food quality determination has been growing in recent years [16–24]. What is important here is the development of economical solutions where a fast solution can be obtained at low cost

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and the benefit/cost ratio increases. Arduino microcontroller has a structure that can address the needs of many sectors and is easily accessible. The open source code of Arduino and the ease of use of its sensors, which are very economical, allow it to be used in different industries. In this study, it is aimed to quickly identify the quality parameters of mussel, which is a rapidly deteriorating food, in the electronic nose environment obtained with sensors connected to the Arduino microcontroller. In addition, the performance of machine learning and teachable machine (TM), an open source platform, in determining the quality of the stuffed mussels was determined in the study. The data of the low-cost electronic nose and machine learning obtained can be redesigned and reused by producers, consumers and industry with its open source and easy-to-use form.

Materials and methods

Stuffed mussels and storage conditions

In order to store the stuffed mussels from freshest to stale, the data belonging to the groups with the lowest total number of organisms from the groups purchased from local sellers (Kırşehir/Turkey) were taken into consideration and used in the study. Stuffed mussels (100 pieces in total) were stored in polystyrene boxes without opening the shells for 7 days at 3 ± 1 °C without ice and were randomly selected and taken into electronic nose and image processing platforms. The placement of the stuffed mussels in the electronic nose chamber is shown in Fig. 1.

Electronic nose media

In the study, the electronic nose system designed in our previous study [18], that communicates with the Arduino microcontroller, was used. Arduino Uno and Arduino Uno Sensor Shield, which allows multiple sensor connections, were used to create the electronic nose. The odour sensors (MQ sensors) used in the study and their general characteristics are given in Table 1.

Machine learning program

The machine learning platform TM developed by Google was used for part of the machine learning in the study. Epoch: 50, Batch size: 16 and learning rate 0.001 settings were used in the training of the program. 1000 different stuffed mussels appearances were used for fresh and spoiled stuffed mussels entering the system.

Deep learning

Convolutional neural networks (CNN), the best known deep learning network, were used to determine the daily changes of the stuffed mussels samples [25]. The ResNet-50, SqueezeNet, GoogLeNet, ResNet-101 and DenseNet-201 models defined in the MATLAB Deep Learning Toolbox was used for the CNN environment used to determine the attributes of 1000 images per day. A support vector machine (SVM) algorithm was used to classify the features of the stuffed mussels obtained by CNN.

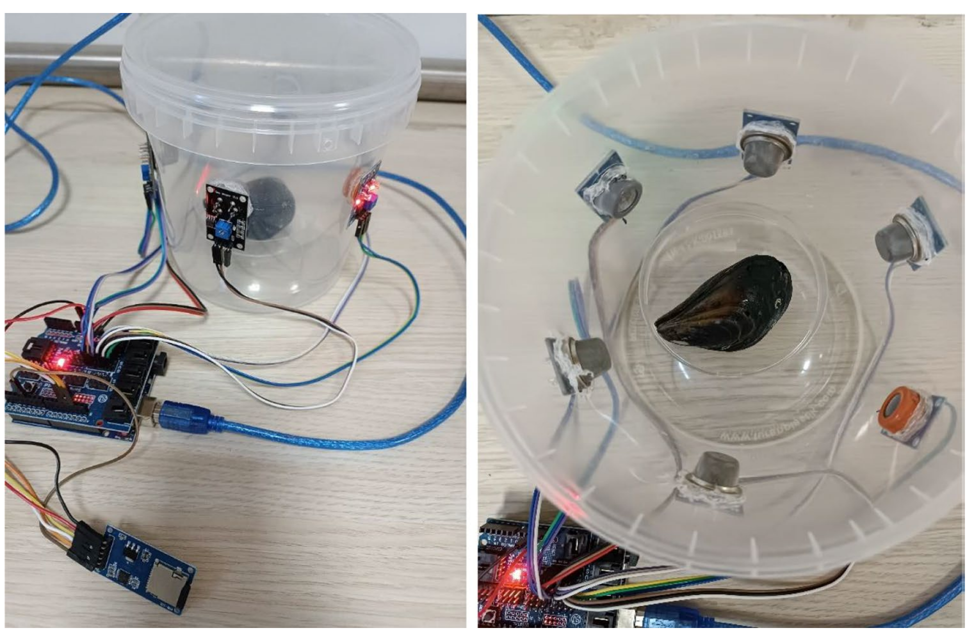


Fig. 1 Electronic nose box used to determine the odor changes of mussels

Table 1 The sensors used in the study and the gases they measure

Sensor	Measurement
MQ3	Detects the presence of alcohol gas at an appropriate range of concentrations between 0.04 mg/L and 4 mg
MQ4	Detects the presence of methane (CNG) natural gas between 300 and 10,000 ppm
MQ5	Detects the presence of isobutane and propane range of concentrations between 300 ppm ve 10.000 ppm
MQ8	High sensitivity to hydrogen but low sensitivity to alcohol vapor. It can measure the concentration range between 10 and 10,000 ppm
MQ9	Detects carbon monoxide (CO) at concentrations from 10 to 1000 ppm and combustible gas from 100 to 10,000 ppm
MQ135	Dedects the amount of ammonia, alcohol vapor, benzene, smoke and carbon dioxide gases. It can measure the concentration range between 10 and 1000 ppm

Acting as a classifier, SVM are utilized to categorize the input features, while CNN serve as feature extractors in the investigation. This article employs various pretrained CNNs as feature extractors for image classification. Each CNN incorporates a fully connected layer comprising 1000 neurons. The feature vector is constructed by amalgamating features derived from these models. Subsequently, a multi-class error correction exit codes (ECOC) model is trained utilizing SVM. This ECOC model comprises linear classification models.

In this methodology, features are extracted through a pretrained CNN, thus streamlining the feature extraction process [25]. The initial layer of the CNN specifies the input dimensions of the images. To accommodate images with varying dimensions, resizing functions can be employed. The subsequent layers, following the input layer, consist of rectified linear units, maximum pooling layers, and interspersed convolution layers [26]. These layers are interconnected with the classification layer for feature classification.

Microbiological analysis

Triplicate samples were taken for total viable count (TVC). Ninety ml of sterile Ringer solution (1/4 strength) was mixed with 10 g of stuffed mussels muscle and then stomached (Masticator Nr S18/420, IUL Instruments, Barcelona, Spain) for 3 min. More decimal dilutions were made, and then 0.1 ml of each dilution was pipetted onto the surface of plate count agar (Fluka 70152, Steinheim, Switzerland) plates in triplicate. After that, plates were incubated for 2 days at 30 °C.

Results and discussion

The sensors used in the study are sensors that can measure approximately 100–10000 ppm. In the electronic nose system, analog reading values of these sensors were used. The data recorded by the electronic nose working with Arduino microprocessor during the storage period are given in Table 2. In addition, the intersection points of TVC values and MQ sensors are given in Fig. 2. The values at the beginning of storage for MQ3, MQ4, MQ5, MQ8, MQ9 and MQ135 sensors were 161, 142, 161, 21, 81 and 160 units, respectively. These values detected by the sensors are considerably lower than the initial values obtained for sea bream, sea bass and trout in our previous study [18]. Considering the initial readings for stuffed mussels, it was determined that MQ3, MQ5 and MQ135 sensors gave close reading ranges to each other and all sensor values except MQ8 increased during storage. It has been determined that the enzymatic and microbial spoilage elements occurring on

Table 2 Changes in the odour values of stuffed mussels given by Arduino during storage

Days	MQ3 $\bar{x} \pm Sd$	MQ4 $\bar{x} \pm Sd$	MQ5 $\bar{x} \pm Sd$	MQ8 $\bar{x} \pm Sd$	MQ9 $\bar{x} \pm Sd$	MQ135 $\bar{x} \pm Sd$
0	161 ± 2.02^{eG}	142 ± 2.30^{bG}	161 ± 2.92^{aG}	21 ± 1.60^{cG}	81 ± 2.22^{dG}	160 ± 1.97^{fG}
1	166 ± 1.70^{eF}	151 ± 2.02^{aF}	166 ± 2.58^{bF}	22 ± 1.65^{dF}	84 ± 2.17^{cF}	172 ± 1.62^{fE}
2	174 ± 2.64^{eE}	153 ± 2.25^{bE}	173 ± 2.22^{aE}	23 ± 1.72^{dE}	92 ± 1.91^{cE}	212 ± 2.99^{fF}
3	204 ± 2.65^{dD}	163 ± 1.66^{cD}	187 ± 2.16^{bD}	22 ± 1.41^{cD}	124 ± 2.72^{aD}	230 ± 1.91^{eD}
4	232 ± 1.95^{eC}	168 ± 2.13^{bC}	202 ± 2.29^{aC}	23 ± 1.50^{dC}	156 ± 3.19^{cC}	253 ± 2.23^{fC}
5	282 ± 2.29^{eB}	182 ± 2.95^{cB}	210 ± 1.31^{aB}	23 ± 1.28^{dB}	184 ± 3.17^{bB}	256 ± 2.27^{fB}
6	306 ± 1.79^{eA}	189 ± 1.66^{dA}	216 ± 2.00^{aA}	23 ± 1.13^{cA}	193 ± 2.60^{bA}	274 ± 2.49^{fA}
7	342 ± 2.13^{eA}	205 ± 2.58^{dA}	226 ± 2.21^{aA}	23 ± 1.47^{cA}	194 ± 1.83^{bA}	288 ± 0.48^{fA}

Different letters (a–f) in the same column and different letters (A–G) in the same row show significant differences ($p < 0.05$)

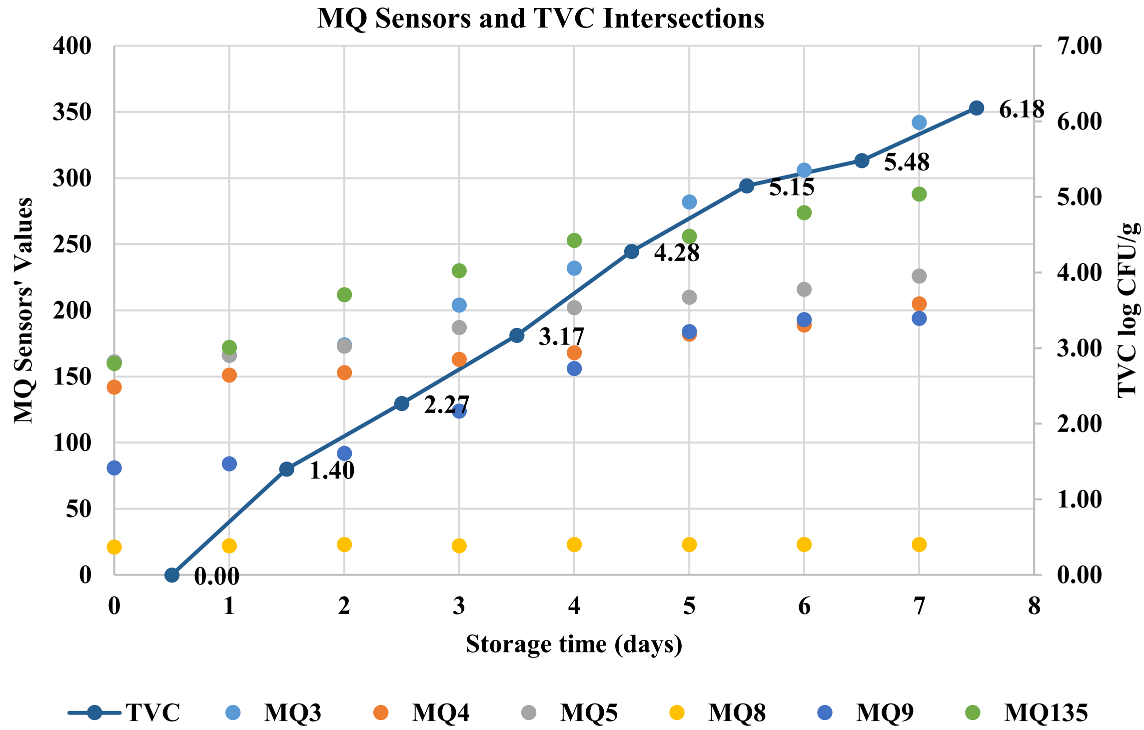


Fig. 2 MQ sensors and TVC intersections during storage

the stuffed mussels cause putrefaction and this is detected by the sensors and increases the analog output values. There are various studies on the use of metal oxide sensors in foods. For example, success was achieved in a study in which 18 different sensors were used and the quality level of grouper fillets was quickly determined [27]. Additionally, there are various studies in which the spoilage limits of chicken, fish and other food products are determined using MQ sensors [18, 20, 22, 28, 29].

There are also some undesirable risks in terms of food safety in the consumption of mussels, which contain functional components. The most important reason for this is that mussels feed by filtering water, so they can absorb undesirable elements found in the region they live in. Exposing mussels to the depuration process before they are put on sale, their high initial freshness level and their processing under hygienic conditions directly affect the product quality. Conversely, in processes carried out, the microbial level increases rapidly, causing putrefaction to begin. Previous studies on stuffed mussels reported that the total number of aerobic mesophilic bacteria was in the range of 2.00–6.44 log CFU/g [30, 31]. In the current study, TVC was found to be between 2.17 and 6.94 CFU/g. When the sensor data were analyzed as a whole, it was determined that the most useful sensors for determining the quality level of stuffed mussels were MQ3, MQ9 and MQ135. The freshness threshold of the mussels was determined as 200 limit in MQ3 and MQ135 sensors and 100 limit in MQ9 when the total viable count (TVC) value exceeded 3 log CFU/g. It is thought that stuffed mussels cannot be fresh after the 3rd day of storage when these values are exceeded.

In order to realize machine learning, the performance of different libraries was examined as a preliminary study and the highest efficiency for stuffed mussels was obtained from Resnet50. The prediction performance of shelled and shell-less stuffed mussel samples given by Resnet 50 is given in Fig. 3. When 15 (1.5%) of the 1000 figures in the study were used in training and 985 (98.5%) were used in testing, the quality levels of shelled and shell-less stuffed mussels were predicted correctly over 87%. When 50 (5%) of the 1000 figures in the study were used in training and 950 (95%) were used in testing, the prediction performance exceeded the 99.9% level.

Figure 4 shows the prediction performance of the TM for stuffed mussels without shells. The correct prediction performance of the TM for shell-less stuffed mussels, which were not used in the study and were not loaded into the TM in any way, was between 75 and 100%. This data range obtained is quite successful in terms of distinguishing foods that are very similar in structure. Additionally, using 1000 image files in the study increased the success rate proportionally.

Figure 5 shows the prediction performance of the TM for stuffed mussel shells. The correct prediction performance of the TM was between 70 and 100% for shelled mussel

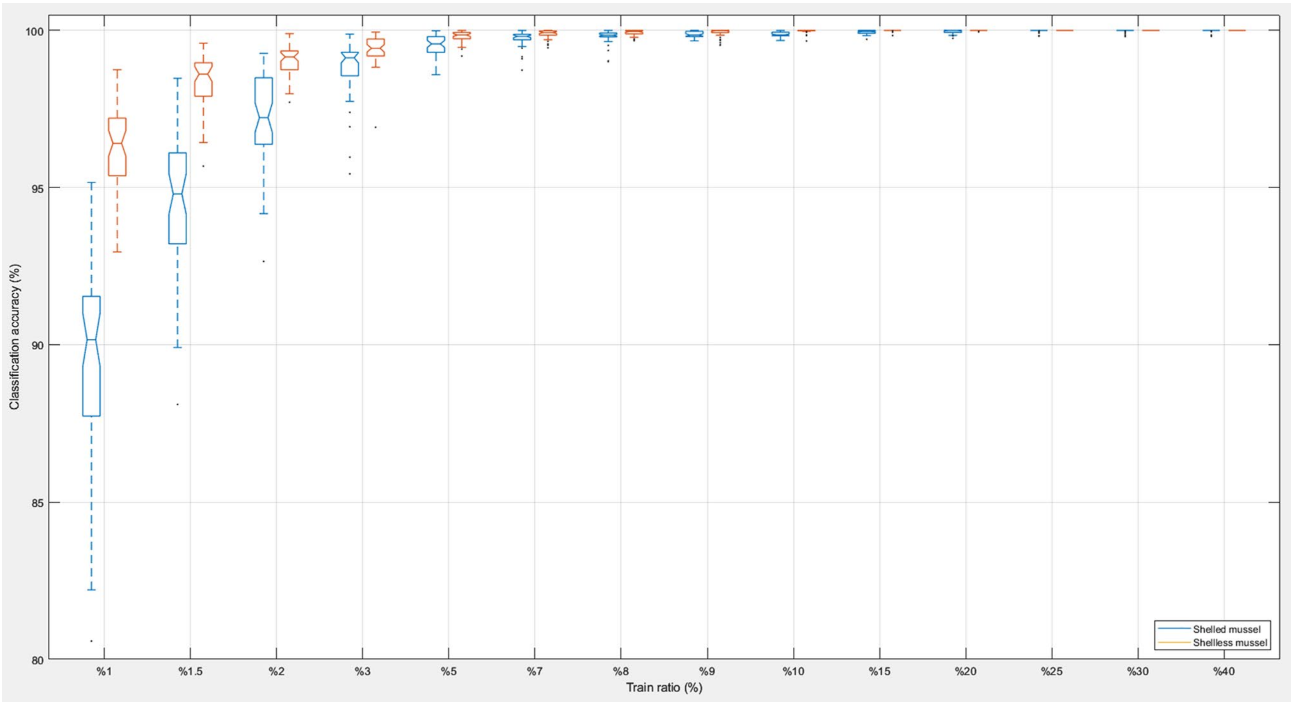


Fig. 3 Prediction performance of Resnet 50 for shelled and shell-less mussel samples

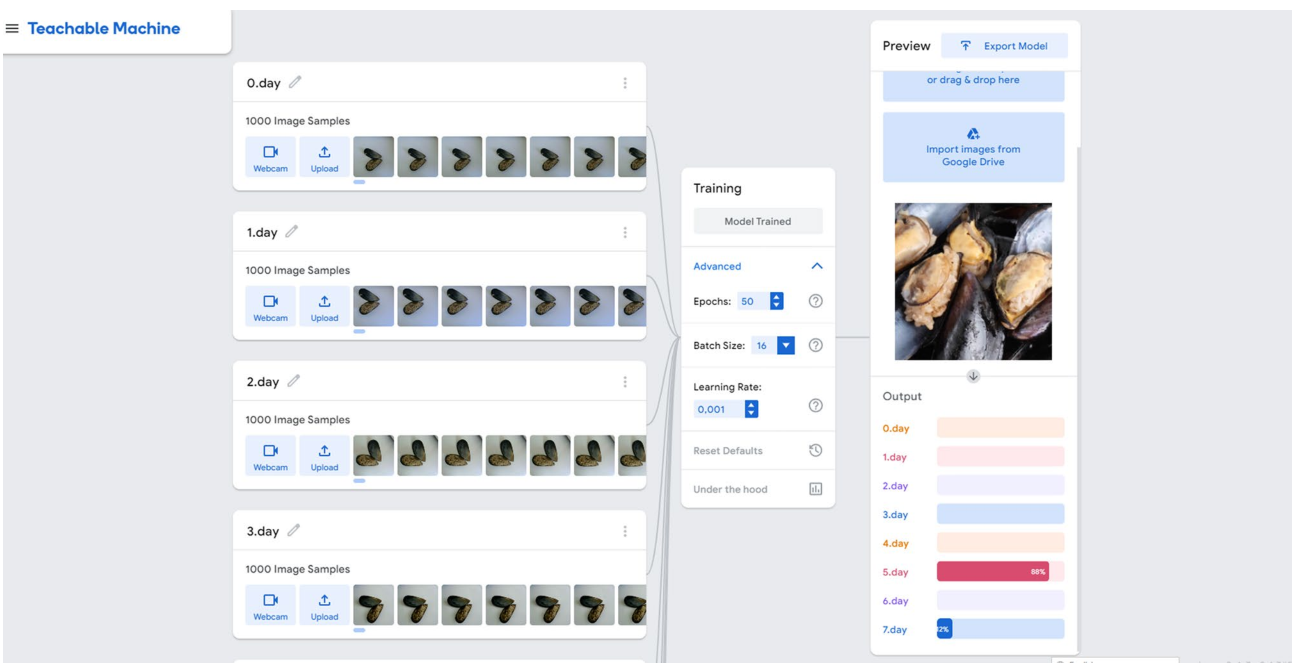


Fig. 4 Estimation example of freshness level of shell-less mussel samples by TM

samples that were not used by the machine in training and testing but whose storage days were known. TM, which is an open source platform, has the potential to be transferred to Android/IOS environment with the tensorflow lite transfer option. This potential allows food quality determination to be made from the mobile phone environment. Therefore, it may be possible to predict fast food from the study data with portable devices in the future.

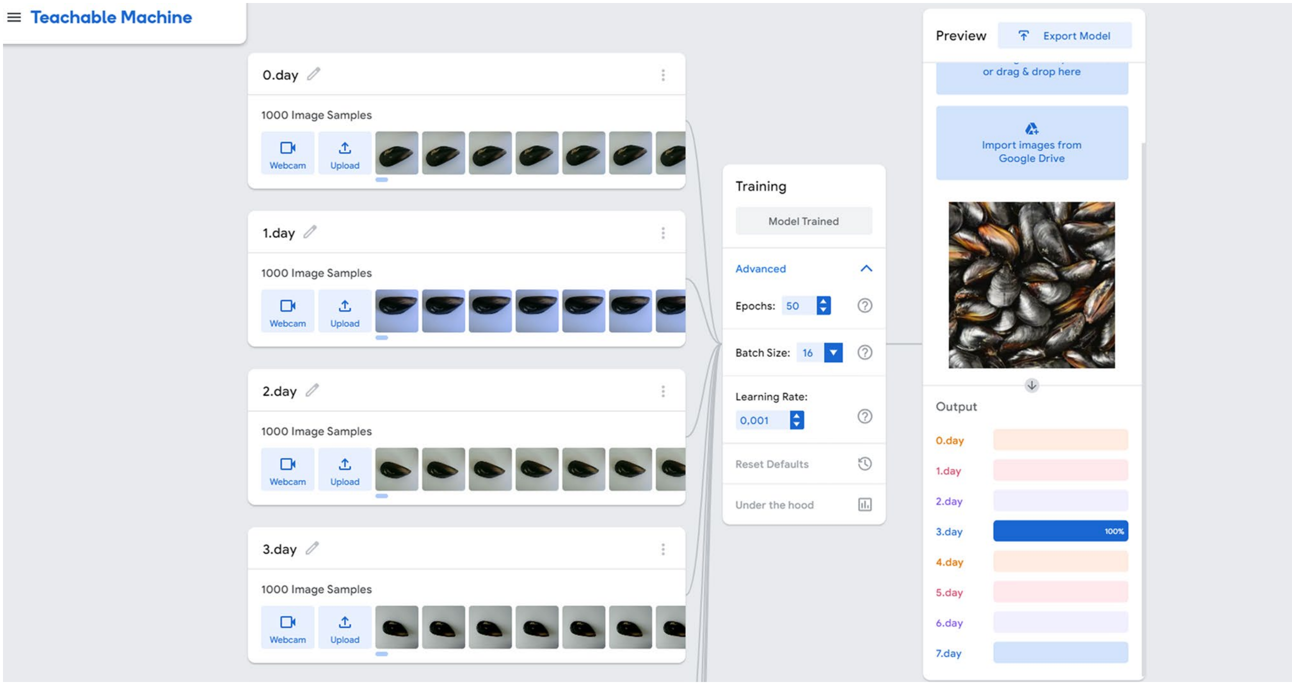


Fig. 5 Estimation example of freshness level of shelled mussel samples by TM

The error matrices resulting from the use of 1.5% (15) of the 1000 daily image files for each storage day for shelled and shell-less stuffed mussels are given in Table 3. The highest prediction success performances for shelled stuffed mussels were 100%, 99.8% and 99.7% on the 3rd, 7th and 1st day of storage, respectively. The lowest prediction performance was realised on the fifth day of storage with 77.7% and the third and fifth storage days were mostly mixed by the machine.

In the study, the lowest prediction performance of shell-less stuffed mussels by the machine was 94.9% on the fifth day of storage and the highest prediction performances were 100% on the 0th and 6th days of storage. The performance of the machine on all storage days was above 96% when 15 of the image files of shell-less stuffed mussels were used in training and the remaining 985 were randomly selected and tested. With this study, it was determined that machine learning can be used to determine the quality level of a food with similar physical properties such as mussels. It was also determined that the success performance increased to 99.9% when the image files used in the training were increased to 5% instead of 1.5%.

The Fig. 6 [32] shows a comparison of the relative speeds of 5 different pre-trained networks. The exact prediction and training iteration times depend on the hardware used and mini-batch size. Here the area of each circular marker is proportional to the size of the neural network in the disk.

When choosing a network suitable for the problem, attention is paid to different important features. The most important of these features are the accuracy, speed and size of the neural network. Faster neural networks with lower prediction times, such as SqueezeNet and GoogLeNet, were compared with ResNet-50, ResNet-101 and DenseNet-201 neural networks, which also have larger prediction times but better accuracy. Classification performance results of four types of trained model networks are given in Fig. 7. After the train ratio was 5%, all networks reached an accuracy rate of 99% for shelled mussels and over 95% for shelled mussels. From these results, it can be seen that pre-trained networks with low prediction times such as SqueezeNet and GoogLeNet can be preferred in systems with low processing power.

Conclusion

In this research, Android-based MQ sensors and an internet-oriented image processing application were employed to swiftly ascertain the freshness metrics of stuffed mussels, recognized as a functional food. The results revealed that discrimination of which storage day the stuffed mussels were on could be established with a high degree of precision using MQ sensor thresholds and applied image processing techniques. Through the data gleaned from this study, it was possible to discern the practical and

Table 3 Confusion matrix for shellled/shellless mussel samples under storage conditions (15 training clusters) 985 test clusters

Confusion matrix (Shell-less mussel)

True Class \ Predicted Class	day0	day1	day2	day3	day4	day5	day6	day7		
day0	985								100.0%	
day1	3	973	9						98.8%	1.2%
day2			984			1			99.9%	0.1%
day3	24	15	2	944					95.8%	4.2%
day4					982			3	99.7%	0.3%
day5	4		1	16	3	935	26		94.9%	5.1%
day6							985		100.0%	
day7			1		23			961	97.6%	2.4%

Confusion matrix (Shelled mussel)

True Class \ Predicted Class	day0	day1	day2	day3	day4	day5	day6	day7		
day0	926		22		17		20		94.0%	6.0%
day1		982					3		99.7%	0.3%
day2		2	900	76			7		91.4%	8.6%
day3				985					100.0%	
day4		3		52	857	1	72		87.0%	13.0%
day5	21	6		132	27	765	34		77.7%	22.3%
day6	23					7	955		97.0%	3.0%
day7					2			983	99.8%	0.2%

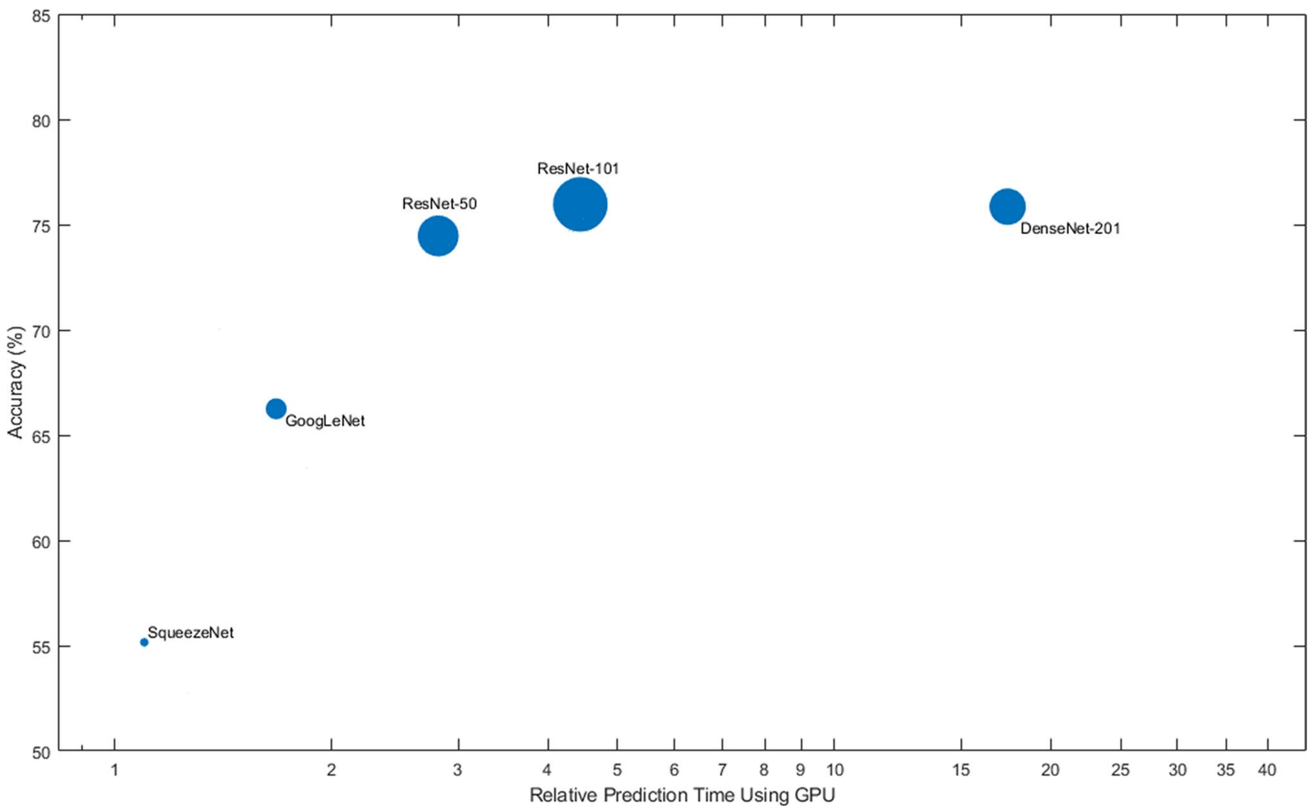
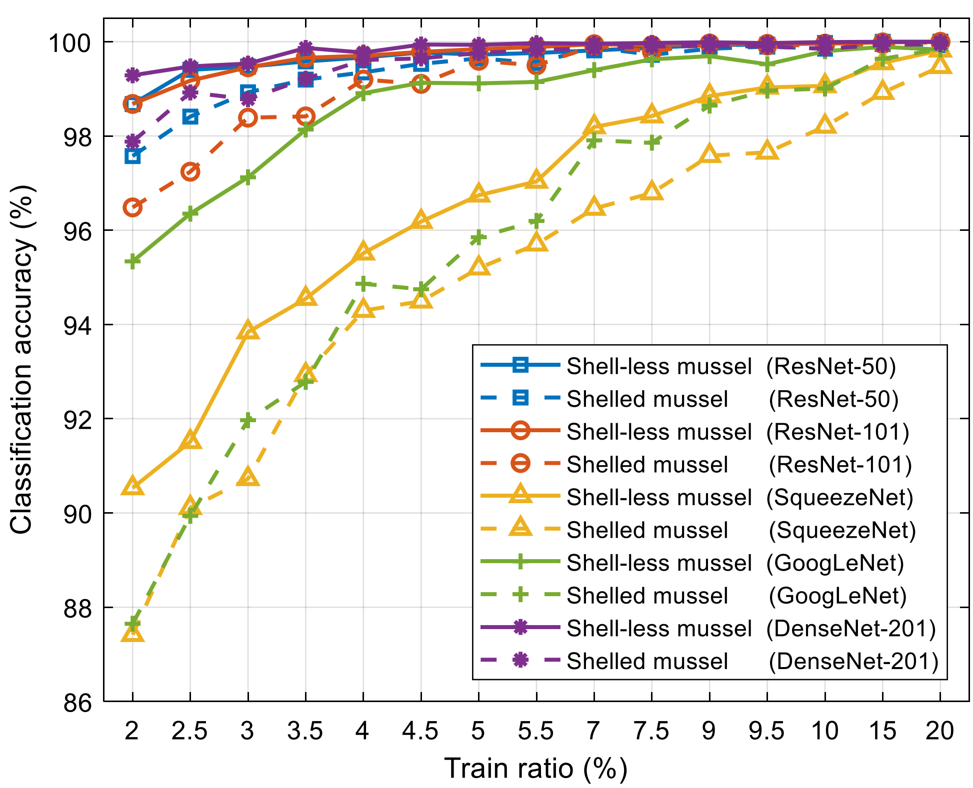


Fig. 6 Illustration of the relative speeds of 5 different pre-trained networks compared

Fig. 7 Prediction performance of five type pre-trained networks for shelled and shell-less mussel samples



expeditious learning framework of TM, alongside validating the proficiency of the cost-effective sensors integrated within the Arduino microprocessor. The adaptability of TM to mobile devices and the ergonomic attributes inherent in Arduino sensors will be able to stimulate numerous forthcoming investigations focused on enhancing methodologies for overseeing food quality.

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Data availability The data that support the findings of this study are available from the corresponding author, [author initials], upon reasonable request.

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