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ORIGINAL PAPER

Deep learning detection of shrimp freshness via smartphone pictures

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Abstract
Shrimp is a type of aquatic product that is easy to deteriorate and the freshness has an essential influence on both its taste and nutritional value. Scientists have developed various approaches to measure shrimp freshness; however, the existing methods are usually destructive, complicated and costly. To develop a fast, non-destructive and low-cost alternative, we utilized deep learning models to identify the freshness of shrimp based on photos taken by smartphones. The models were trained on photographs of 306 shrimp along with their total volatile basic nitrogen values as freshness indicators. Our models achieved an area under receiver operating characteristic above 0.90 for freshness classification and root mean square error of prediction no more than 4.67 mg/100 g on fresh samples during the independent tests. Furthermore, the model performance was evaluated on datasets of shrimp photographed for 7 consecutive days and shrimp placed on different backgrounds and light settings. Our study suggested deep learning as an accurate, easy and low-cost method to detect shrimp freshness, which may have broader applications in food safety.

Keywords Deep learning · Freshness detection · Non-destructive detection · Shrimp · Smartphone

Introduction

Shrimp is one of the most popular aquatic products and nutritious food sources. With the development of cold chain transportation, it becomes convenient to transport shrimp to the consumer markets across the world. According to a recent report in China [1], the consumption of shrimp and crab products has quickly increased from 2,101,700 tons in 2008 to 3,696,700 tons in 2018. However, shrimp products are highly prone to spoilage during storage and transportation. Therefore, it is very important to monitor and detect the freshness quickly and easily.

Ammonia, amines, dimethylamine and trimethylamine oxide are major volatile products of microbial degradation during food spoilage [2–4]. Total volatile bases nitrogen (TVB-N), calculated from the concentrations of the volatile amines, is a commonly used indicator for food freshness. In addition to TVB-N, thiobarbituric acid [5, 6] and hypoxanthin [7, 8] can also be used to measure freshness. Traditionally, destructive methods were utilized to identify these chemicals, which may take time and effort. In recent years, nondestructive detection methods, such as test strips or certain materials to detect volatile gas, are gaining more popularity. For example, cellulose-based fluorescent materials [9] and food-derived edible sensors [10] were developed to monitor changes in biological amines with good responsiveness. Although these methods provide non-destructive solutions for freshness detection, the air fluidity in the environment may impact the measurement accuracy, and the evaluation standards may change depending on the food volume. These limit the applicability of the chemical-based freshness detection methods. In addition, complex, specialized operating conditions mean that high-throughput detection cannot be achieved.

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In addition to the above methods, scientists also developed various spectral technologies for freshness detection [11–13]. Hyperspectral imaging (HSI) integrates the spectra and spatial information into one picture, where the features of structural characteristics and chemical compositions of the samples can be revealed pixel by pixel. Combined with machine learning methods, HSI can be fast, accurate and efficient for chemical component evaluation [14]. Yu et al. further applied deep learning to visible/near-infrared hyperspectral images for detecting shrimp freshness [13]. However, hyperspectral imaging requires professional equipment, which cannot be easily carried around for measurements. In contrast, RGB images are much easier to obtain, and existing studies have shown that the appearance of the head, body, tail, leg and other parts of a prawn changes continuously during the deterioration process [15, 16]. Thus, it is possible to detect deterioration from RGB images.

With the development of deep learning technology, computer vision has been widely used in facial recognition and medical applications [17–19]. They can also help to detect food grading and safety, including the freshness and quality of fruits, vegetables and meat [20–25]. Inspired from the previous studies, we believe it is possible to detect shrimp freshness using computer vision technologies. Convolution neural networks (CNN) are one type of neural networks that can extract spatial features for image recognition [26, 27]. In a typical CNN model, the convolutional layers extract higher-level features in the image via different filters; maximum/average pooling layers reduce the dimension of the feature parameters and prevent overfitting [28, 29]; global average pooling layers transform the output tensor to a one-dimension tensor; batch normalization layers normalize each scalar feature independently and effectively make the training process faster [30]; and dropout layers sample the weight parameters according to a certain probability and effectively prevent overfitting [31].

The Visual Geometry Group (VGG) network was proposed by the Visual Geometry Group of Oxford University, and it is a deep CNN network which has 13 convolution layers stacked together and was designed for image classification [32]. Instead of developing a model from scratch, transfer learning was leveraged to adopt a neural network trained from a large image dataset, VGG-16 [33], and refine it on our specific task with smaller training samples in this study [34, 35]. This model was trained on the ImageNet dataset and obtained 92.3% accuracy on the top-5 classification task. It was used to retrain based on pictures taken directly from smartphones to identify shrimp freshness. When making a prediction, this method only requires shrimp photos and is easy to use and non-destructive.

Materials and methods

Shrimp preparation and freshness detection

392 live white-leg shrimp samples (*Litopenaeus vannamei*) were purchased in five batches from Fuzhou Yonghui supermarket Co., Ltd. in China. In first four batches, 320 live shrimp were killed through suffocation using crushed ice and stored in a refrigerator (4–6 ℃) in batches for up to 10 days. In each day, eight shrimp were randomly chosen for photograph and TVB-N detection. 14 soft-shell shrimp samples were removed due to quality issues, leaving 306 shrimp samples in our dataset. Three types of smartphones were used to take photos of all shrimp on a fixed light platform, which has a light intensity of 450 lx and a color temperature of 5850 K. The platform used a white cutting board as background with crushed ice placed underneath, and the light source was positioned 45° to the platform. We placed the phones about 21 cm away from the platform with 2 cm movement range in each dimension (Fig. 1). Each shrimp in a fixed position had five photos taken by manually adjusting the shooting distance and angle. Then the shrimp was rotated by 90 degrees each time to repeat the above shooting process until a circle was completed. Both sides of the shrimp were photographed in the same manner (Fig. S1). After all, for each smartphone, about 40 photos were taken for each shrimp. Note that some shrimp were shot by only one or two smartphones in the early stage of the experiments. The photos were processed so that each image has the same height and length. In the last batch, 72 live shrimp were killed through suffocation using crushed ice and stored in a refrigerator (4–6 ℃) for up to 8 days. Two different light conditions (800 lx/6080 K and 450 lx/6030 K) and four different backgrounds (crushed ice, wood cutting board, green cutting board and purple cutting boar) were used to capture the pictures for each shrimp (Fig. S2). Eight photos were

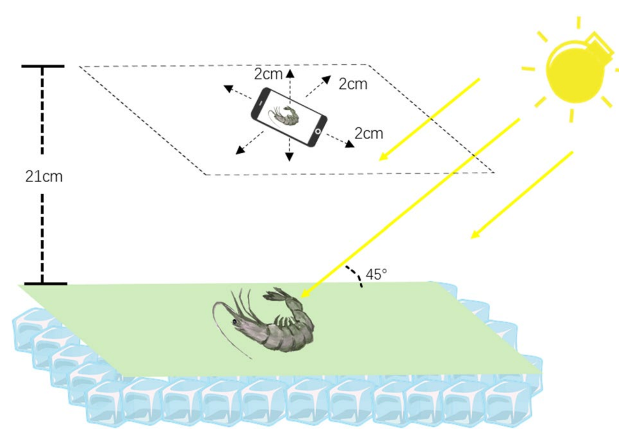

Fig. 1 Demonstration of shrimp image acquisition

acquired under each light condition and background, making up 80 images in total for each shrimp. For all batches of shrimp, the TVB-N values were determined referring to the semi-micro nitrogen determination protocol in the China's Food Safety Standards (GB5009.228-2016). Each shrimp was sampled and tested twice for the TVB-N value by two lab technicians, each lab technician measured TVB-N levels three times, and the average value was used.

Additionally, 6 live shrimp were prepared, rinsed in reverse osmosis water, killed by suffocation using crushed ice and stored in a refrigerator at 4–6 ℃. Pictures of each shrimp were taken every 24 h using the photograph method of the first four batches for seven consecutive days. This dataset was labeled as a "7-day dataset" and used to observe the spoilage process over time.

Data processing

Dataset preparation

According to China's National Food Safety Standard—Fresh/Frozen Aquatic Products of Animal Origin (GB 2733-2015), TVB-N > 20 mg/100 g indicates the spoilage for shrimp, and a two-category dataset was created using this cutoff to divide the 306 shrimp samples as fresh vs spoiled. Furthermore, a three-category dataset was also created, including fresh samples (TVB-N values < 15 mg /100 g), intermediate samples (15 mg/100 g ≤ TVB-N values < 20 mg /100 g) and spoiled samples (TVB-N Values ≥ 20 mg/100 g).

For first four batches, three different smartphones were used to take the pictures of shrimp and the statistics were shown in Table 1. Our data were divided into four datasets: the training set, the validation set, the independent test set 1 and the independent test set 2. While each shrimp may have different photos distributed across different datasets, in order to develop and test the model's generalization capability, "unseen" shrimp samples were included in a part of the validation set and the whole independent test set 2. For these "unseen" samples, no photo of the same shrimp was distributed in any other dataset so that they were completely unseen to the model. From all the 306 shrimp in the first four batches, 6 and 30 shrimp were held out for the validation set and the independent test set 2, respectively. The pictures of the remaining 270 shrimp were randomly divided into the training set, the validation set and the independent test set 1 using the ratio of 8:1:1. The shrimp in the last batch were photographed under different light conditions and backgrounds and were named as the "various condition" dataset. Since all shrimp in the independent test set 2, "7-day" dataset and "various condition" dataset are completely unseen from the training or validation set, they can be used to test the generalizability for the model.

Image processing and augmentation

To keep a consistent input size, all the images were reshaped to the size of 448 pixels by 448 pixels using OpenCV library. Since data augmentation can create additional training samples and prevent model over-fitting [36], the training set images were randomly flipped vertically or horizontally or rotated a random direction within 5 degrees using Keras Image Processing library and OpenCV library to create additional training samples.

Model development and evaluation

As an approach of transfer learning, the VGG-16 model with pre-trained weights was adopted as the scaffold of our model using the Keras library. The model architecture was shown in Fig. 2. The final layers of the VGG-16 model were replaced by an average pooling layer, a maximum pooling layer, a global average pooling layer, two dropout layers and two dense layers (including the final layer). The maximum and average pooling layers reduced the number of features, so that the output dimensions were reduced. Since too many training parameters may increase the risk of overfitting, the two dropout layers were set to large rates (0.5 and 0.7, respectively) to prevent overfitting. Batch normalization layers were inserted after every layer [37]. For the two-category dataset, the three-category dataset and the original TVB-N

Table 1 Distribution of training, validation and test sets for shrimp photos along with camera specifications of the smartphones

Dataset	Training set	Validation set		Independent test set 1	Independent test set 2	Total	Camera specifications		
Shrimp seen in others?	Seen	Seen	Unseen	Seen	Unseen		Aperture	Exposure time (s)	ISO
Phone 1	6230	759	99	755	806	8649	f/1.8	1/30	25
Phone 2	4467	568	132	592	501	6260	f/1.7	1/50	274
Phone 3	4710	599	158	579	870	6916	f/1.8	1/100	80
Total	15407	1926	389	1926	2177	21825			

Each shrimp may have different photos distributed across different datasets unless the dataset is marked as "unseen"

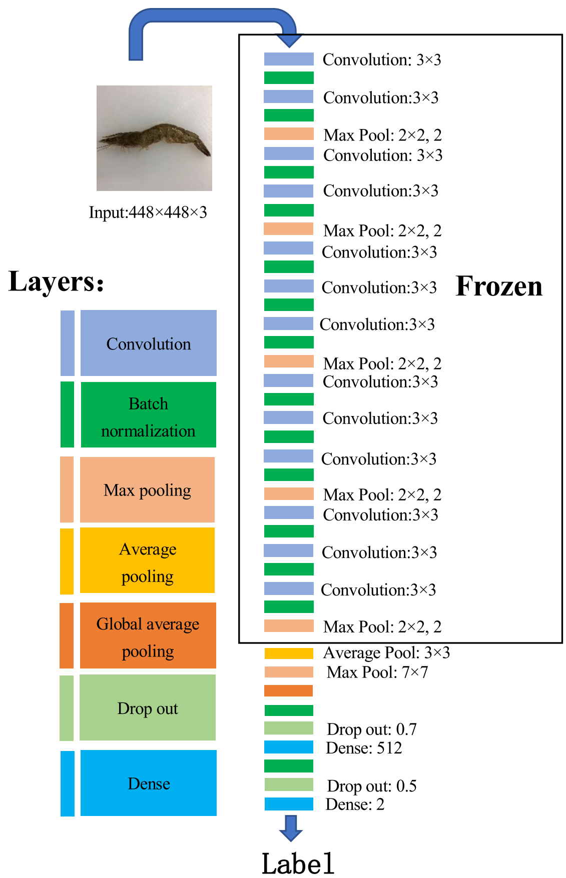

Fig. 2 Architecture of the deep learning model using binary classification as an example. Only the final layer was changed in the three-category classification model and the regression model

values, models for binary classification, three-category classification and regression were developed respectively by changing the output dimensions and the activation of the final dense layer.

During training, the base layers of the VGG-16 model were always frozen and only the added customized layers were trained. Validation loss was monitored during the training process, and the final model was selected when there is no decrease of the loss for 5 epochs. The classification models were evaluated using the receiver operating characteristic (ROC) curves [37] and the regression models were assessed using root mean square error of prediction (RMSEP) and R^2. Additionally, Grad-CAM was used to identify which part of the image that the model paid attention to for model visualization and explanation [38].

Since the fresh shrimp have a narrative TVB-N range of 0 mg/100 g–20 mg/100 g while spoiled shrimp may have a TVB-N value as large as 120 mg/100 g, in addition to the original regression model as a "one-step" approach, a "two-step" approach for TVB-N value prediction was further developed. Two regression models were trained using only the fresh and spoiled shrimp datasets, respectively. For a given photo, the trained binary classification model was first used to predict whether the shrimp is fresh or spoiled, then the corresponding regression model for fresh or spoiled shrimp samples were utilized to predict the TVB-N value (Fig. S3).

To compare our model performance with traditional machine learning models, logistic regression and random forest models were developed for classification and linear regression models for regression using the Scikit-learn library in Python 3.6. These models were trained and tested on the same datasets and evaluated using the same metrics as the deep learning models.

Image processing for shrimp with diverse backgrounds

Since the "various condition" dataset contains images with different backgrounds, to improve the model performance, a background mask model was developed. 200 images from the dataset was manually segmented and labeled using the labelme library [39]. Two architecture of convolution neural networks, Pyramid Scene Parsing Network (PSPNet) [40] and MobileNet [41] were trained on the 200 labelled images to build an image segmentation model (Fig. S4). The rest images were segmented by the trained model and the image backgrounds were removed (Fig. S5).

Results and discussion

Dataset

Instead of using storage time to label the freshness level, TVB-N values were chosen as a more accurate indicator recognized by most researchers [42]. The distribution of TVB-N values from all 378 shrimp were shown in Fig. 3. From the figure we found that more than half of the samples had TVB-N values between 10 mg/100 g and 30 mg/100 g, which are around the freshness cutoff of 20 mg/100 g. While this may make it challenging for the model to distinguish fresh vs spoiled samples, it indicated the fact that a significant proportion of shrimp may be at a critical point of turning spoiled and such data are important to train the model to distinguish them.

Model performance

Binary classification

For binary classification of fresh vs spoiled shrimp, the receiver operating characteristic (ROC) curves of our deep learning model, in comparison with random forest and

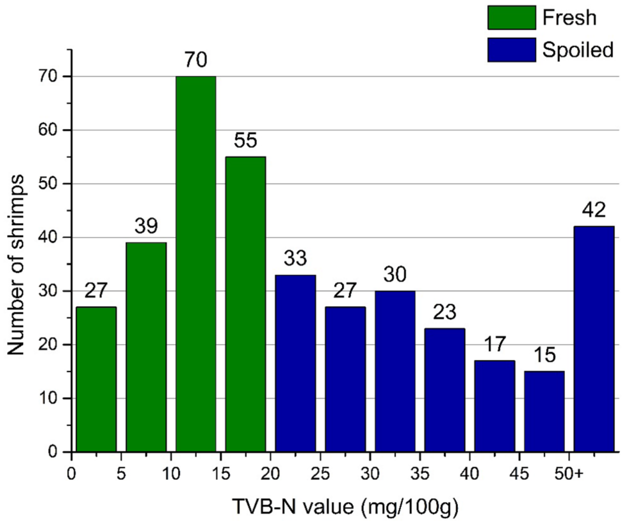

Fig. 3 Distribution of TVB-N values across all shrimp

logistics regression, were shown in Fig. 4. The area under the curve (AUC) of the deep learning model achieved 0.99 on independent test set 1 (seen shrimp) and 0.98 on independent test set 2 (unseen shrimp), indicating our deep learning model performed well for both seen and unseen shrimp samples. The performance also surpassed both random forest (AUC = 0.91–0.92) and logistic regression (AUC = 0.70). The confusion matrices of the deep learning model are also shown in Fig. S6. The better performance of the deep learning model compared to random forest and logistic regression indicated the features extraction by convolutional neural networks may be more powerful than simpler models.

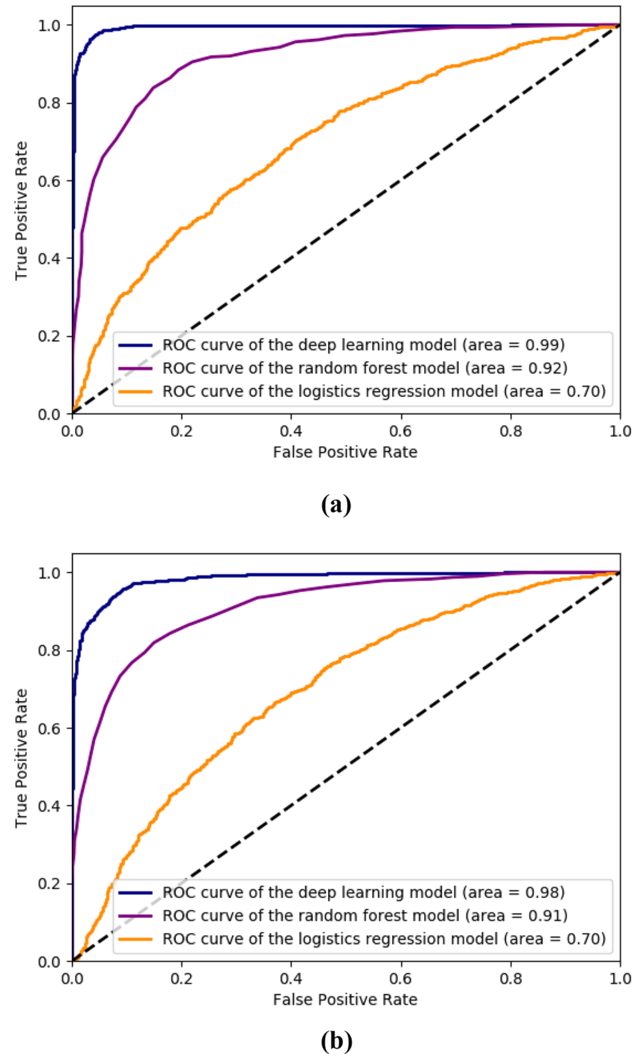

Fig. 4 ROC curves of binary classification models on **a** the independent test set 1 and **b** the independent test set 2

Three-category classification

For three-category classification of the shrimp freshness, micro-averaging ROC curves of our deep learning model in comparison with random forest and logistic regression were shown in Fig. 5. Since the three-category classification required the model to classify one more category around the freshness cutoff, the performance of all models has decreased slightly compared to binary classification. The AUC of our deep learning model on independent test set 1 and 2 are 0.98 and 0.94, respectively, which are better than random forest (AUC = 0.83–0.90) and logistic regression (AUC = 0.70–0.77). The confusion matrices of our model on both independent tests are shown in Fig. S7. From the confusion matrices, we observed that the accurate classification of the "intermediate" vs "fresh" categories is most challenging, especially on the unseen shrimp.

Regression

The RMSEP and R^2 values of different regression models are shown in Table 2. The two-step deep learning model combined the binary classification model along with two separate regression models for TVB-N prediction, while the one-step deep learning model and the linear regression models are just single models. For combined shrimp samples (both fresh and spoiled), the RMSEP values for the two-step regression model are 7.14 mg/100 g and 7.67 mg/100 g for two independent test sets, respectively, which are similar to the performance of one-step regression model (RMSEP = 7.04–7.54 mg/100 g) but much better than the linear regression model (RMSEP = 16.58–20.17 mg/100 g). Since the maximal TVB-N value of spoiled samples is about 6 times of the maximal TVB-N values of fresh samples, and one may want to pay more attention to fresh shrimp

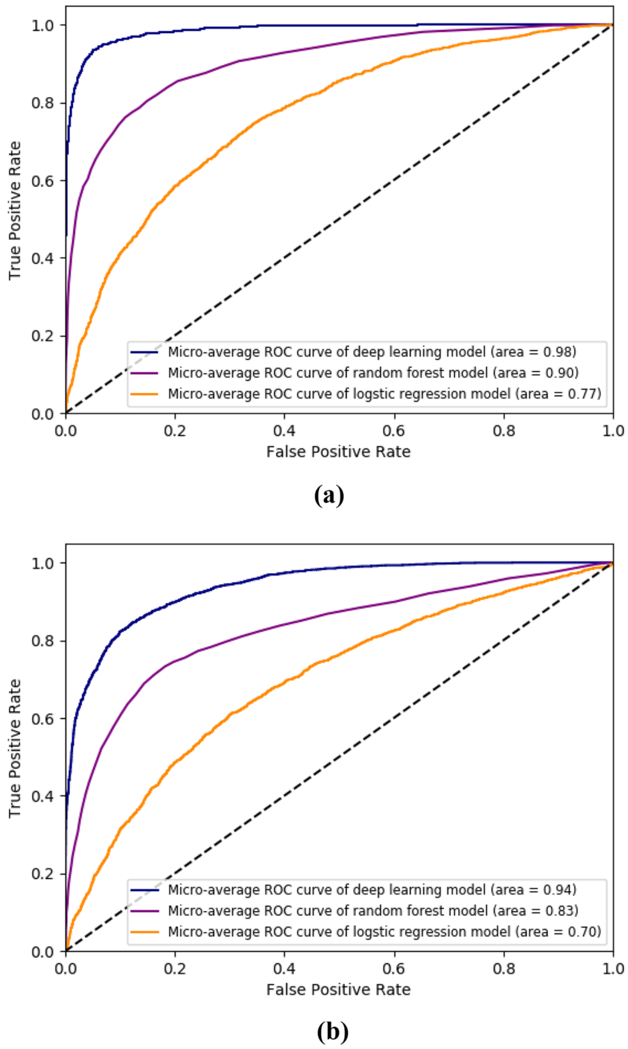

Fig. 5 Micro-averaging ROC curves of three-category classification models on **a** the independent test set 1 and **b** independent test set 2

Table 2 Performance of different regression models on the shrimp separated versus combined by freshness

Condition group	Independent test set 1		Independent test set 2	
	RMSEP (mg/100 g)	R^2	RMSEP(mg/100 g)	R^2
Two-step deep learning regression				
Fresh	3.34	0.70	4.09	0.55
Spoiled	9.47	0.75	10.17	0.22
Combined	7.14	0.87	7.67	0.69
One-step deep learning regression				
Fresh	4.67	0.21	4.39	0.21
Spoiled	9.46	0.74	9.10	0.30
Combined	7.54	0.86	7.04	0.73
Linear regression				
Combined	20.17	– 0.01	16.58	– 0.465

that are getting close to become spoiled, it is reasonable to evaluate RMSEP values of the spoiled and fresh samples separately. The two-step regression model obtained RMSEP = 3.34 mg/100 g and 4.09 mg/100 g on independent test set 1 and 2 for fresh samples, respectively, which are better than the performance of one-step regression model on fresh samples (RMSEP = 4.39–4.67 mg/100 g). The scatterplots between predicted values and actual values for the two models on both independent test sets were shown in Fig. S8. Given the fact that spoiled samples have larger variance of TVB-N values, it is beneficial to use the two-step approach for TVB-N prediction since it does not compromise the performance on fresh samples.

Prediction on the 7-day dataset

Our binary classification model, two-step regression model and one-step regression model were tested on the 7-day dataset and the results were shown in Fig. 6. For this dataset, although the six shrimp were photographed for 7 consecutive days and could not be destroyed in the middle for TVB-N measurement, the overall trends of the prediction results in all models reflected the reality. As the storage time increased, the predicted spoiled probability or TVB-N values all went up over time. It is observed that the one-step model predicted generally higher values in early days compared to the two-step model, and some of the shrimp even had higher predicted TVB-N values in Day 0 compared to Day 1 for the one-step model. This may indicate that the two-step model is more accurate for predicting TVB-N values especially for fresh samples as mentioned above.

Model performance for shrimp under various photograph conditions

Table 3 shows the binary classification performance of different models, including the logistic regression (LR), random forest (RF) and deep learning (DL) models, for shrimp in the "various condition" dataset. All the models were trained on the training set of the first four batches of shrimp photographed under the white background. The trained image segmentation model was utilized to remove the complex backgrounds and the model prediction performance was evaluated before and after the background removal.

The results indicated that the deep learning model overall outperformed the logistic regression and random forest models similar to previous sections. The two light intensity conditions had very minor effects to all the models. When the background condition changed and no segmentation was used, the logistic regression and random forest models had dropped performance, while the deep learning model had more stable performance and better adaptability. Among all the backgrounds, the wood background was the most

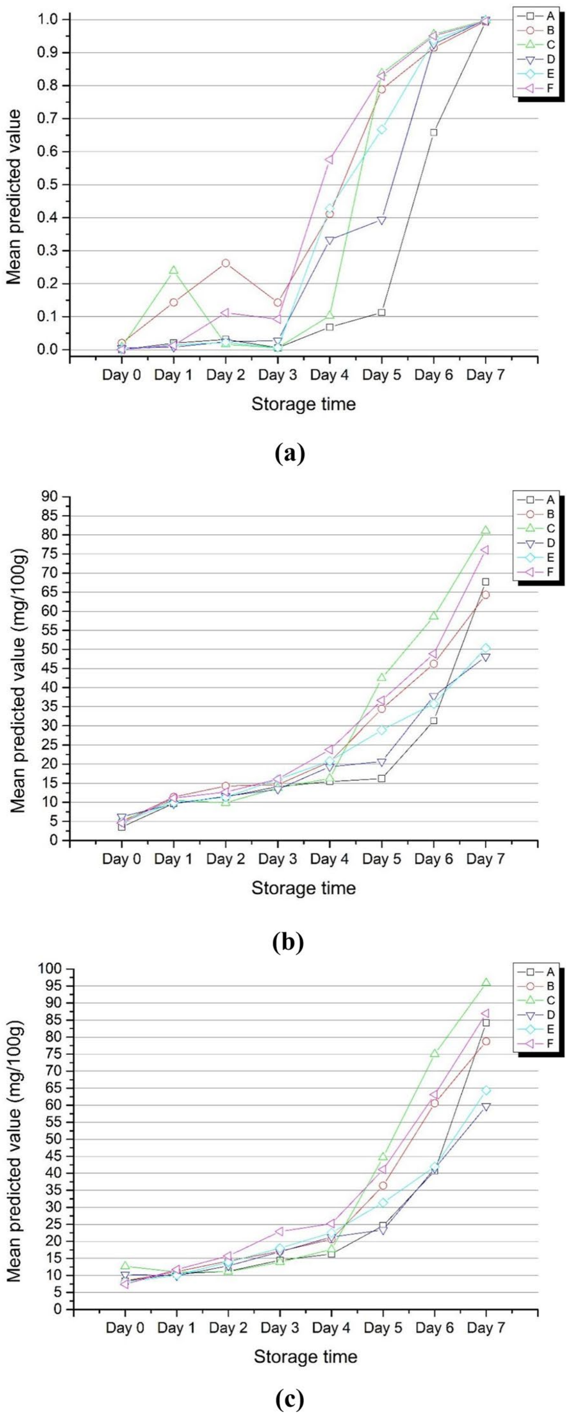

Fig. 6 Mean predicted values of **a** the binary-classification model for deterioration probability, **b** the two-step regression model for TVB-N and **c** the one-step regression model for TVB-N on the 7-day dataset

challenging one for all models probably due to the complex textual. The image segmentation process generally improved the results for all models. After image segmentation, the deep learning model generally archived AUROC values larger than 0.85 for all light conditions and backgrounds, indicating good performance and applicability (Table 3). Since this dataset reflects more practical use of smartphones to detect shrimp freshness in real-life complex environment, it is potential to combine the image segmentation model and the deep learning classification model for such application.

Model interpretation

To interpret the model prediction, the Grad-CAM visualization of some predicted photos were shown in Fig. 7. From the highlights it is observed that the model paid attention to the heads and forelimbs of the shrimp regardless of the shooting distances or shrimp locations in the photos. It indicated that the heads and forelimbs of shrimp may be signs of the shrimp deterioration. The Grad-CAM visualization may help to verify the image recognition accuracy of the deep learning model, and also provide clues for consumers and researchers to visually identify the freshness of shrimp.

Discussion

Our method is a potential easy and quick solution to evaluate the freshness of shrimp without the need of professional equipment. The system has potential to be integrated into a mobile app that can take a picture of shrimp as input and output the freshness prediction along with interpretation in real time. Our experiment was designed to improve model applicability and reduce overfitting by randomly placing shrimp in different positions in contrast to a fixed photograph pattern in a previous study [43]. Additionally, independent test sets of both seen and unseen shrimp were used to test the model performance. Different backgrounds and different light intensities were adopted to mimic the complex conditions of shrimp photographed in real life. It is observed that combining a segmentation model with deep learning image classification may better cope with the challenges of complicated environments and improve practicability. Therefore, this study provided a proof-of-concept of detecting shrimp freshness using smartphone cameras via the deep learning technology, which may potentially have broad applications for food safety. Nonetheless, our future work will continue to expand our sample size, and to adapt more complex backgrounds, photograph conditions and devices.

Conclusion

In this study, pictures of about 400 shrimp were taken via smartphones and their freshness were measured using TVB-N values. Deep learning models were developed to identify the freshness of shrimp with good performance based on the pictures, regardless of shrimp positions, shooting angles or distances. For classification tasks, our model

Table 3 AUROC values of different models on the "various condition" dataset

Light intensity	Shrimp segmented from background	Ice background			Wood background			Purple background			Green background		
		LR	RF	DL	LR	RF	DL	LR	RF	DL	LR	RF	DL
800 lx	No	0.55	0.62	0.93	0.49	0.56	0.79	0.51	0.60	0.91	0.66	0.60	0.87
	Yes	0.57	0.47	0.95	0.68	0.42	0.85	0.72	0.43	0.92	0.67	0.44	0.87
450 lx	No	0.55	0.62	0.95	0.56	0.53	0.83	0.64	0.59	0.93	0.67	0.66	0.91
	Yes	0.64	0.45	0.96	0.67	0.46	0.87	0.72	0.39	0.94	0.68	0.44	0.91

LR logistic regression model, *RF* random forest model, *DL* deep learning model

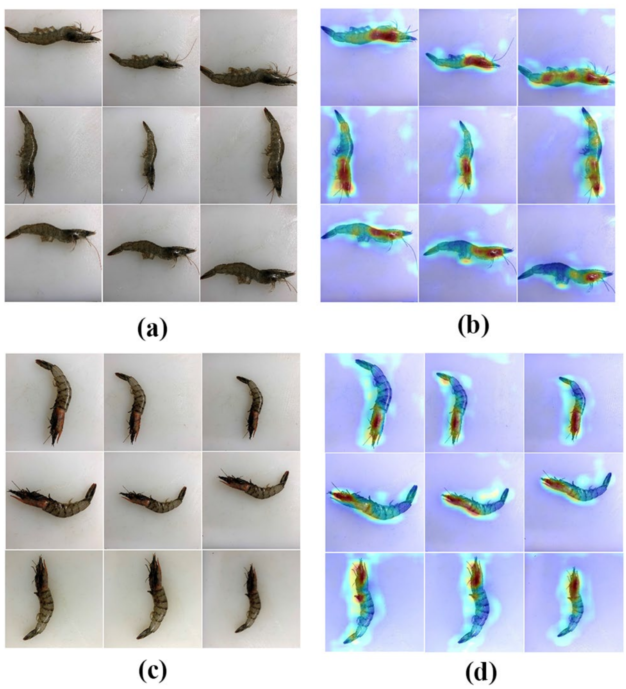

Fig. 7 Shrimp photos and corresponding Grad-CAM visualization. **a** and **b** are fresh shrimp. **c** and **d** are stale shrimp

achieved an AUC close or larger than 0.9 during independent tests. For regression, the RMSEP was 3.34 mg/100 g to 4.67 mg/100 g for fresh samples, and 7.04 mg/100 g to 7.67 mg/100 g for all samples during independent tests. Even under conditions of different light intensities and different backgrounds (some of which have complex textures), the AUC value of our model can reach more than 0.85 for the binary classification tasks in combination of image segmentation. We believe our method is an easy, low-cost and quick approach to detect shrimp freshness, which may have a wider implication for deep learning in food safety.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest 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.

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