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An innovative approach to detecting the freshness of fruits and vegetables through the integration of convolutional neural networks and bidirectional long short-term memory network

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ABSTRACT

Fruit and vegetable freshness testing can improve the efficiency of agricultural product management, reduce resource waste and economic losses, and plays a vital role in increasing the added value of fruit and vegetable agricultural products. At present, the detection of fruit and vegetable freshness mainly relies on manual feature extraction combined with machine learning. However, manual extraction of features has the problem of poor adaptability, resulting in low efficiency in fruit and vegetable freshness detection. Although exist some studies that have introduced deep learning methods to automatically learn deep features that characterize the freshness of fruits and vegetables to cope with the diversity and variability in complex scenes. However, the performance of these studies on fruit and vegetable freshness detection needs to be further improved. Based on this, this paper proposes a novel method that fusion of different deep learning models to extract the features of fruit and vegetable images and the correlation between various areas in the image, so as to detect the freshness of fruits and vegetables more objectively and accurately. First, the image size in the dataset is resized to meet the input requirements of the deep learning model. Then, deep features characterizing the freshness of fruits and vegetables are extracted by the fused deep learning model. Finally, the parameters of the fusion model were optimized based on the detection performance of the fused deep learning model, and the performance of fruit and vegetable freshness detection was evaluated. Experimental results show that the CNN_BiLSTM deep learning model, which fusion convolutional neural network (CNN) and bidirectional long-short term memory neural network (BiLSTM), is combined with parameter optimization processing to achieve an accuracy of 97.76% in detecting the freshness of fruits and vegetables. The research results show that this method is promising to improve the performance of fruit and vegetable freshness detection.

1. Introduction

Fruits and vegetables are rich in fiber, vitamins and other nutrients and are low in calories, which are of great benefit in reducing the risk of chronic diseases, controlling weight and improving intestinal health (Mahata et al., 2023; Öztürk and Yaman, 2022). Because of this, more and more people regard fruits and vegetables as the first choice for healthy diet (Jaeger et al., 2023). However, this boom has also been accompanied by huge fruit and vegetable production, resulting in labor-intensive work, in which labor costs account for 20%–30% of the entire fruit and vegetable production costs (Livingstone et al., 2020). In addition to labor cost issues, the fruit and vegetable industry's backward technology in post-harvest processing has also led to fruits and vegetables piling up and rotting, causing heavy losses to farmers, fruit and vegetable product wholesalers and retailers (Rodriguez-Aguilera and Oliveira, 2009). Relevant research shows that the main reason for this situation is the lack of efficient fruit and vegetable freshness detection technology.

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Freshness testing of fruits and vegetables not only helps reduce waste in picking, sorting, and transporting fruits and vegetables to sales, but also effectively reduces production costs and sales prices, providing consumers with higher-quality, more affordable fruit and vegetable products (Wang et al., 2018). At the same time, the application of fruit and vegetable freshness detection technology in the Internet of Things, smart homes, unmanned vending and other fields can help users effectively manage and utilize food and improve the quality of life. (Kojic et al., 2022; Pu et al., 2023). The vegetable freshness detection technology allows retailers to quickly identify products that do not meet quality standards and remove them from the shelves in a timely manner, ensuring that the food purchased by consumers is safe and reliable (Gunden and Thomas, 2012). It also improves the circulation efficiency of fruits, vegetables and agricultural products, reducing resource waste and economic losses (Makino and Amino, 2020). In addition, fruit and vegetable freshness detection technology also has positive significance in increasing the added value of fruit and vegetable agricultural products (Xu et al., 2023). Therefore, there is an urgent need for a fast and effective testing method for freshness of fruits and vegetables to reduce postharvest losses of fruits and vegetables and reduce economic losses.

The traditional method for detecting the freshness of fruits and vegetables is sensory testing, which specifically relies on human senses to perceive the shape, weight, hardness, color and other physical properties of vegetables that reflect physiological changes within the tissue, so as to make evaluation and analysis (Gopal et al., 2016). The sensory detecting of fruit and vegetable freshness mainly uses color, smell, taste and shape as detecting indicators. Inspectors need to rely on their eyes, nose, tongue and other sense organs to evaluate the detecting indicators (Saba et al., 2018). Although the sensory detecting method for the freshness of fruits and vegetables is simple and practical and is not subject to geographical restrictions, the accuracy of the detecting results is closely related to the acuity of the detector's sensory organs and actual experience, and is affected by the subjective emotions of the detector and the detecting environment (Luo et al., 2021). Different inspectors may have different standards for the freshness of fruits and vegetables, resulting in inconsistent detect results. Sensory detecting methods for the freshness of fruits and vegetables require a lot of time and human resources, especially in large-scale production and distribution, sensory testing of fruit and vegetable freshness cannot detect and process fruit and vegetable products that do not meet quality standards in a timely manner, resulting in delays and waste (Huang et al., 2019).

In order to reduce labor costs and improve the efficiency of fruit and vegetable freshness detection, some scholars have used manual feature extraction combined with machine learning to achieve automatic detection of fruit and vegetable freshness (Sarkar et al., 2021; Zhang et al., 2021a). Existing research shows that the core work of this fruit and vegetable freshness detection method is concentrated in the manual feature extraction stage, and constructing a set of feature vectors that can accurately represent the freshness of fruits and vegetables has become the focus of research (Koyama et al., 2021). Manually extracted features mainly include features such as texture, shape, and color that characterize the freshness of fruits and vegetables. However, in actual application scenarios, there are often external interference factors such as uneven lighting, complex backgrounds, blur, and collection angles (Bhargava et al., 2022). These interference factors will increase the difficulty of feature extraction, resulting in a decrease in the performance of fruit and vegetable freshness detection. This may lead to errors in the expression of texture, contour, and color, thereby limiting the performance of machine learning in fruit and vegetable freshness detection (Ukwuoma et al., 2022). In order to overcome these challenges, some scholars have introduced deep learning methods to automatically learn more abstract and robust feature representations to cope with the diversity and variability in complex scenes, and improve the robustness and accuracy of fruit and vegetable freshness detection (Mukhiddinov et al., 2022; Saleem et al., 2021; Hussain et al., 2022). Existing research shows that although the fruit and vegetable freshness detection method based on deep learning has attracted the attention of many scholars, in this field, the application of deep learning to fruit and vegetable freshness detection is still in its infancy (Chen et al., 2023). Currently, there is relatively limited research on updating and improving deep learning models to improve the performance of fruit and vegetable freshness detection.

The rest of this paper is structured as follows. Section 2 presents the related work. Section 3 is the materials and methods. Section 4 is the experimental results. Section 5 presents the analysis and discussion. Section 6 is the conclusions.

2. Related work

From the literature survey, it can be found that many methods that combine manual extraction of features with machine learning can automatically detect the freshness of fruits and vegetables (Koyama et al., 2021). Koyama et al. (2021) removed spinach images from the background and then converted to grayscale and CIELab color space and Hue, Saturation and Value. The mean value, minimum value and standard deviation of each color component in spinach leaves were extracted as color features. Local features were extracted using the bag-of-words of key points from oriented features from accelerated segment test and rotated binary robust independent elementary features. Feature combinations were then selected from the spinach images and used to train a machine learning model to identify freshness. The experimental results show that the overall accuracy rate of four-category classification is 70%, the overall accuracy rate of three-category classification is 77%, and the overall accuracy rate of two-category classification is 84%. Bhargava et al. (2022) proposed an automatic machine learning-based algorithm for detecting the type and quality grading of five different vegetables and four different fruits. First, perform Gaussian filter preprocessing on the image to enhance image quality and remove noise; Secondly, fuzzy c-means clustering and grab cutting are used to segment the image; Then, various features, namely statistics, color, texture, geometry, texture energy of laws, gradient histogram and discrete wavelet transform, are extracted and selected from the feature vectors via principal components analysis. Detection of vegetable and fruit types is done through color and geometric features, while all other features are considered for grading. Finally, the fruits are detected and classified into healthy and defective using logistic regression, sparse representative classifier, artificial neural network and support vector machine (SVM) classifiers. The detection report of vegetables and fruits shows that the system has the highest SVM classification recognition rate, reaching 97.63%. Ghazal et al. (2021) proposed a fruit classification method that combines Hue, Color-SIFT, discrete wavelet transform, and Haralick features, which outperformed other hand-crafted visual features. This feature combination is not affected by rotation and illumination, handles intra-class variations well, provides good results for identifying subcategories of fruits, and achieves high classification accuracy for visually similar fruit categories. Their research found that the color SIFT feature performed very well on the fruit classification problem, outperforming other single hand-crafted features. Huynh et al. (2022) proposed a two-stage model for fruit recognition using camera images. In the first module, they used Densnet121 to obtain features from the fruit dataset. In the second stage, they utilized adaptive particle-gray wolf optimization feature subset selection method to select the most important features from fruit images for fruit recognition. Although the above studies show that manual feature extraction combined with machine learning can successfully detect the freshness of fruits and vegetables. However, manual feature extraction combined with machine learning has limitations in the task of freshness detection of fruits and vegetables. Manual feature extraction will be affected by subjective factors, and different experts will select different features, which leads to instability in model performance and reduced generalization ability. In addition, manually extracted features cannot capture comprehensive information of the data, causing the model to be unable to fully utilize the available data, which will limit the performance and applicability of the model. For models based on manually extracted features, updating the model requires re-implementation of feature engineering and model training, which will increase the cost and risk of model updates.

In view of these limitations of artificial feature extraction combined with machine learning in the freshness detection task of fruits and vegetables, some scholars have considered using end-to-end deep learning methods (Fahad et al., 2022). These deep learning methods can learn feature representations directly from raw data, thereby reducing reliance on manual feature engineering to achieve better performance and generalization capabilities (Mukhiddinov et al., 2022). Fahad et al. (2022) proposed two deep learning models, VGG-16 and YOLO, to automatically identify and classify fruits and vegetables. The method first identifies the category of the object in the image and then classifies the fruit or vegetable into one of three categories: fresh, medium fresh and rotten. VGG-16 classifies fruits and vegetables and classifies their freshness, while YOLO in addition to classifying and categorizing, also localizes objects within the image. Their methods achieved 82% and 84% accuracy on the FruitVeg Freshness dataset respectively. Mukhiddinov et al. (2022) proposed a multi-class fruit and vegetable classification deep learning system based on the improved YOLOv4 model. The system first identifies the object type in the image and then classifies it into two categories: fresh or rotten. Ni et al. (2020) used transfer learning to analyze the change process of banana freshness and established the relationship between banana freshness and storage date. They used the GoogLeNet model to automatically extract features of banana images and then classified them through the classifier module. The results show that the model is able to detect the freshness of bananas with an accuracy higher than human detection level. Although the above studies have solved the limitations of feature engineering combined with machine learning for freshness detection of fruits and vegetables, their detection performance needs to be further improved. Further analysis of the above-mentioned research on fruit and vegetable freshness detection based on deep learning found that these studies all used convolutional neural network (CNN) to extract spatial features that represent the freshness of fruits and vegetables in images, and did not take into account the contextual and temporal relationships between the spatial features extracted by CNN. Based on this, this study proposes a novel fruit and vegetable freshness detection model that can not only automatically extract spatial features that characterize the freshness of fruits and vegetables, but also automatically handle the contextual and temporal relationships between the extracted spatial features. It is expected that this novel fruit and vegetable freshness detection model will enhance the understanding and representation capabilities of spatial features in fruit and vegetable images, so as to better capture the correlation between different parts of the fruit and vegetable images and improve the performance of fruit and vegetable freshness detection.

Based on the above analysis, this paper proposes a new deep learning method to detect the freshness of vegetables and fruits. In this method, pictures of vegetables and fruits are input into the deep learning model, spatial features characterizing the freshness of fruits and vegetables are automatically extracted, and the contextual and temporal relationships between the extracted spatial features are processed to detect the freshness of fruits and vegetables. The contributions of this study are as follows.

- Deep learning models are used to extract features, overcoming the shortcomings of manual feature extraction that are time-consuming and have poor adaptability
- Evaluating the performance of different deep learning models and their combinations for detecting the freshness of fruits and vegetables
- Evaluating the performance of different deep learning model parameters for fruit and vegetable freshness detection

3. Materials and methods

3.1. The dataset

This dataset contains images of six fruits and vegetables: apple, banana, bitter gourd, capsicum, orange, and tomato. The images of each fruit or vegetable are grouped into two categories: fresh and stale. Examples of images of fruits and vegetables in the dataset are shown in Fig. 1. The dataset used in this study is available at the following URL https://www.kaggle.com/datasets/raghavrpotdar/fresh-and-stale-images-of-fruits-and-vegetables. For collecting the images to create the dataset, images of the fruits and vegetables were captured daily using a mobile phone camera. Depending on the visual properties of the fruit or vegetable in each image and on the day when the image was captured, each image was labelled as fresh or stale. In addition, the authors of the dataset also took videos of fruits and vegetables and extracted the frames of these videos, conveniently collecting a large number of images. For more details, please refer to the acquisition URL of the data set.

3.2. Deep learning models

Deep learning is a branch of artificial neural networks and a promising image processing technology that has emerged in recent years (Kazi and Panda, 2022; Wang et al., 2022a; Moon et al., 2021; Phan et al., 2023). The most efficient deep learning models include CNN and bidirectional long-short term memory neural network (BiLSTM) (Naranjo-Torres et al., 2020; Wang et al., 2022b; Yang et al., 2020; Gill et al., 2022). In the research on fruit and vegetable freshness detection, most scholars use CNN to extract the spatial features representing the freshness of fruits and vegetables in images to detect the freshness of fruits and vegetables (Ni et al., 2020). Regarding the contextual relationship and temporal relationship between the spatial features extracted by CNN, no scholars have conducted research on this to further improve the performance of freshness detection of fruits and vegetables. In addition, research shows that BiLSTM, which is a further extension and improvement of recurrent neural network, has advantages in tasks of processing contextual relationships and temporal relationships of data (Zhang et al., 2021b). So, inspired by this, this study proposes a model that can automatically extract spatial features that characterize the freshness of fruits and vegetables, and can also automatically process the contextual and temporal relationships between the extracted spatial features, that is, a hybrid model that combines two deep learning models, CNN and BiLSTM, used to detect the freshness of fruits and vegetables. In addition, existing research shows that the fusion method of CNN and BiLSTM has not yet been applied in the task of fruit and vegetable freshness detection. The deep learning hybrid model proposed in this study is CNN_BiLSTM, and its structural block diagram for detecting the freshness of fruits and vegetables is shown in Fig. 2.

As can be seen from Fig. 2, the CNN_BiLSTM deep learning model includes three batch normalization layers, two convolutional layers, two max pooling layers, two BiLSTM layers and four fully connected layers. Since the image sizes of fruits and vegetables in the original data set are inconsistent, it cannot be input to the CNN_BiLSTM deep learning model to detect the freshness of fruits and vegetables. Therefore, before inputting the images of fruits and vegetables in the original dataset to the CNN_BiLSTM deep learning model, the image sizes of the fruits and vegetables need to be reconstructed to meet the input requirements of the CNN_BiLSTM deep learning model. In this study, the image size of fruits and vegetables was reconstructed to $227 \times 227 \times 3$, and then input into the CNN_BiLSTM deep learning model to automatically extract features representing the freshness of fruits and vegetables to detect the freshness of fruits and vegetables. The CNN_BiLSTM deep learning model first normalizes the input image so that the data can be distributed in the area where the input value of the activation function falls in the area where the activation function is sensitive to the input. Then a convolution operation with 16 convolution kernels of 3×3 is used to

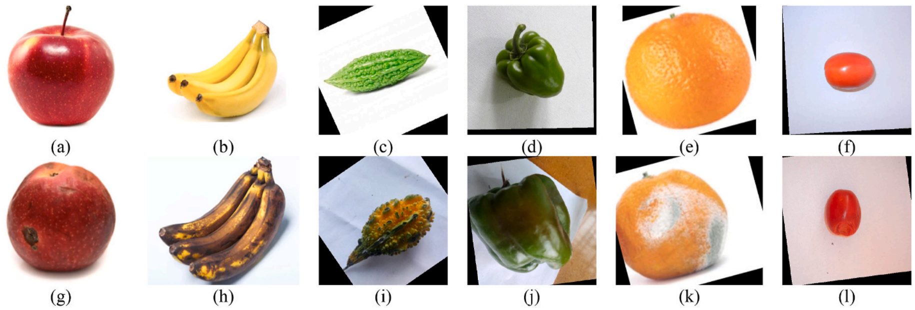

Fig. 1. The examples of images of fruits and vegetables in the dataset. (a) Fresh apple, (b) Fresh banana, (c) Fresh bitter gourd, (d) Fresh capsicum, (e) Fresh orange, (f) Fresh tomato, (g) Stale apple, (h) Stale banana, (i) Stale bitter gourd, (j) Stale capsicum, (k) Stale orange, (l) Stale tomato.

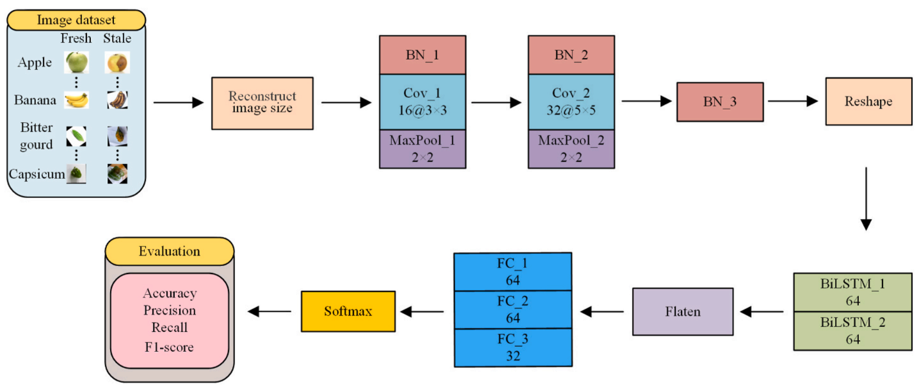

Fig. 2. The structural block diagram of the method proposed in this study to detect the freshness of fruits and vegetables.

extract the features of the image representing the freshness of fruits and vegetables. Subsequently, a max pooling layer is used to retain the most significant features in the 2 × 2 region, which while reducing the spatial dimension of the data allows the network to focus on the most important features, thereby improving the discriminative ability of the model. The same processing method as above is used to further process the data. The difference is that the convolution layer uses 32 convolution kernels for a 5 × 5 convolution operation to extract features representing the freshness of fruits and vegetables in the data. The number of convolution operation kernels in the CNN_BiLSTM deep learning model has been increased from 16 to 32. The increase in the number of convolution operation kernels can greatly enhance the learning ability of the network. Since the features representing the freshness of fruits and vegetables extracted by the CNN deep learning model are not comprehensive enough, this study uses the BiLSTM deep learning model to further extract the information representing the freshness of fruits and vegetables in the data. Before the BiLSTM deep learning model extracts feature information, the features extracted by the CNN deep learning model are dimensionally transformed to meet the input requirements of the BiLSTM deep learning model. This study uses two BiLSTM layers with 64 hidden nodes each to extract feature information representing the freshness of fruits and vegetables in the data. The extracted data is flattened after the BiLSTM deep learning model, and then four fully connected layers are added. The last fully connected layer uses the softmax activation function to output labels that predict the freshness of fruits and vegetables. In addition, the activation functions of the CNN_BiLSTM deep learning model is RelU. The above are all the design ideas of the CNN_BiLSTM deep learning model.

In addition, this study also designed and verified ablation experiments to deeply evaluate the contribution of each part of the model, that is, by gradually eliminating some components of the model to understand the impact of this component on the model performance, and then verify whether the design of the model is consistent with the theoretical research basis (Sun et al., 2023; Hu et al., 2023a; Wei and Zhan, 2024). The ablation experiment comparison models also designed in this study include CNN, BiLSTM and CNN_LSTM deep learning models. The CNN deep learning model is the part after removing the BiLSTM module in the CNN_BiLSTM deep learning model. The BiLSTM deep learning model is the part after removing the CNN module in the CNN_BiLSTM deep learning model. In addition, this study replaced the BiLSTM layer in the CNN_BiLSTM deep learning model with the long-short term memory neural network (LSTM) layer to form the CNN_LSTM deep learning model to further compare and analyze the performance of the CNN_BiLSTM deep learning model in detecting the freshness of fruits and vegetables.

3.3. Performance evaluation

In this study, accuracy (Acc), precision (Pre), recall (Rec) and F1-score (F1) evaluation indicators were used to evaluate the performance of the proposed fruit and vegetable freshness detection model (Tapia-Mendez et al., 2023; Jin et al., 2022; Hu et al., 2023b; Gulzar, 2023; Sekharamantry et al., 2023). Acc is the ratio of the number of samples correctly detected by the model to the total number of samples, which can intuitively reflect the overall performance of the model. Acc refers to the proportion of samples that are actually positive among the samples detected as positive by the model. Pre measures how many of a model's detections are true positives, and is particularly important for tasks that cannot tolerate false positives. Rec rate refers to the ratio of the number of positive samples correctly detected by the model to the actual number of all positive samples. Rec measures the model's ability to detect positive examples, and is especially useful for tasks that cannot tolerate false negatives. The F1 is the harmonic average of precision and recall, which takes both into consideration and is more convincing for imbalanced problems in different categories. Based on better evaluating the performance of the fruit and vegetable freshness detection model, this study selected the above evaluation indicators. These indicators are calculated as follows:

$$\mathrm{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\mathrm{Pre} = \frac{TP}{TP + FP} \quad (2)$$

$$\mathrm{Rec} = \frac{TP}{TP + FN} \quad (3)$$

$$\mathrm{F1} = \frac{2 * \mathrm{Pre} * \mathrm{Rec}}{\mathrm{Pre} + \mathrm{Rec}} \quad (4)$$

Where, *TP*, *FP*, *TN* and *FN* correspond to true positive, false positive, true negative, and false negative, respectively.

4. Result

4.1. Parameter optimization

Differences in deep learning model training parameters will directly affect the performance and generalization ability of the deep learning model. Based on this, this study optimizes the initial learning rate and batch size parameters that affect the generalization ability and training stability of the CNN_BiLSTM deep learning model to find the initial learning rate and batch size that are most suitable for the CNN_BiLSTM deep learning model, so that the model can better adapt to the data, improve efficiency, reduce resource consumption and improve the performance of the model's fruit and vegetable freshness detection. In addition, the dropout layer is used in the CNN_BiLSTM deep learning model. The random dropout rate parameter in this layer will affect the generalization ability and robustness of the model. Therefore, this study also optimizes the parameters of the random dropout rate of the dropout layer to improve the generalization ability of the CNN_BiLSTM deep learning model, reduce over-fitting problems, increase robustness, and make the model easier to optimize and train. This study evaluates the results of parameter optimization of the CNN_BiLSTM deep learning model based on the accuracy rate that reflects the overall performance of fruit and vegetable freshness detection to determine the parameter combination with the best fruit and vegetable freshness detection performance.

The parameter optimization method used in this study for the CNN_BiLSTM deep learning model is shown in Table 1. The initial learning rate of the models M1 and M2 is set to 0.0002, the initial learning rate of the models M3 to M5 is set to 0.002, and the initial learning rate of the model M6 is set to 0.02. The batch size of the M1, M2, and M4 models is set to 32, and the batch size of the M3, M5, and M6 models is set to 64. Random deactivation techniques are used in the models of M1, M2, M4, M5 and M6, where the random dropout rate of the M1 model is set to 0.5, and the random dropout rate of the M2 model is set to 0.2. The M4, M5 and M6 models set the random dropout rate to 0.3 during the training phase, while the M3 model does not use random dropout techniques.

The CNN_BiLSTM deep learning model's fruit and vegetable freshness detection accuracy based on different training parameter combinations is shown in Fig. 3. As can be seen from Fig. 3, the CNN_BiLSTM deep learning model ranks the fruit and vegetable freshness detection performance in the order of M4>M2>M5>M1>M3>M6. The M4 model has the highest fruit and vegetable freshness detection accuracy of 97.76%, and the M6 model has the lowest fruit and vegetable freshness detection accuracy of 92.61%. When the initial learning rate of the CNN_BiLSTM deep learning model training was increased from 0.002 to 0.02, the fruit and vegetable freshness detection accuracy of the M5 model was reduced from 95.53% to 92.61% compared to the M6 model. When the batch size trained by the CNN_BiLSTM deep learning model was increased from 32 to 64, the fruit and vegetable freshness detection accuracy of the M4 model was reduced from 97.76% to 95.53% compared to the M5 model.The random dropout rate also affects the fruit and vegetable freshness detection accuracy of the CNN_BiLSTM deep learning model. Compared with the M1 model's random dropout rate of 0.5, the M2 model's random dropout rate of 0.2 performs better, and its fruit and vegetable freshness detection accuracy increased to 95.53%. However, compared with the M5 model's random dropout rate of 0.3, the model M3 that does not use random deactivation performs worse, and its fruit and vegetable freshness detection accuracy increased to 94.29%.

Table 1
Parameter settings for the CNN_BiLSTM deep learning model optimization.

Model	Initial learning rate	Batch size	Random dropout rate
M1	0.0002	32	0.5
M2	0.0002	32	0.2
M3	0.002	64	–
M4	0.002	32	0.3
M5	0.002	64	0.3
M6	0.02	64	0.3

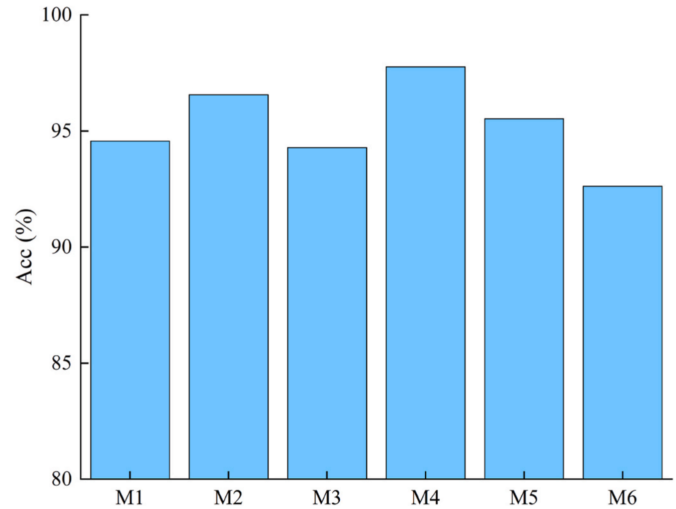

Fig. 3. The CNN_BiLSTM deep learning model's fruit and vegetable freshness detection accuracy based on different parameter combinations.

In addition, for other training parameters of the CNN_BiLSTM deep learning model, this study selected the Adam optimizer that combines the momentum method and adaptive learning rate to optimize the CNN_BiLSTM deep learning model and the cross-entropy loss function with the advantages of high efficiency and stability is used as the loss function. Set the training epoch of the CNN_BiLSTM deep learning model to 300, and randomly shuffle the data before each epoch to improve the training efficiency of the CNN_BiLSTM deep learning model. These parameter settings are also applicable to other ablation experimental comparison models.

4.2. The model performance comparison

This study conducted ablation experiments on the CNN_BiLSTM deep learning model and obtained the Acc, Pre, Rec and F1 of fruit and vegetable freshness detection of all comparison models as shown in

Table 2
The comparison of model performance in fruit and vegetable freshness detection.

Model	Acc	Pre	Rec	F1
CNN	96.07%	92.16%	95.62%	0.94
BiLSTM	94.62%	92.49%	93.27%	0.92
CNN_LSTM	97.13%	94.86%	96.13%	0.96
CNN_BiLSTM	97.76%	95.63%	97.17%	0.97

Table 2. As can be seen from Table 2, the CNN_BiLSTM deep learning model proposed in this study has the highest fruit and vegetable freshness detection Acc, Pre, Rec and F1, which are 97.76%, 95.63%, 97.17% and 0.97 respectively. Among the comparison models, the BiLSTM deep learning model has the worst Acc, Rec and F1 for fruit and vegetable freshness detection, which are 94.62%, 93.27% and 0.92 respectively. The CNN deep learning model has the worst Pre for fruit and vegetable freshness detection, which is 92.16%. In addition, the performance of CNN_LSTM and CNN_BiLSTM, which combine two deep learning models, for fruit and vegetable freshness detection is better than the performance of a single deep model CNN and BiLSTM for fruit and vegetable freshness detection.

4.3. Analysis of detection performance

In this study, Acc, Pre, Rec and F1 were used to further evaluate the performance of the CNN_BiLSTM deep learning model in fruit and vegetable freshness detection. As shown in Table 3, the CNN_BiLSTM deep learning model performs better in detecting fresh banana and fresh capsicum. The Acc, Pre, Rec and F1 detected for fresh capsicum were 98.46%, 96.51%, 98.81% and 0.98 respectively, and the Acc, Pre, Rec and F1 detected for fresh banana were 98.25%, 96.28%, 98.59% and 0.98 respectively. In comparison, the CNN_BiLSTM deep learning model performs poorly on the detection of stale capsicum and stale tomato. The Acc, Pre, Rec and F1 detected for stale tomato were 97.13%, 94.91%, 93.39% and 0.944 respectively, and the Acc, Pre, Rec and F1 detected for stale capsicum were 97.22%, 93.37%, 95.46% and 0.95 respectively. Comprehensive comparison results show that the CNN_BiLSTM deep learning model has advantages in detecting fresh banana and fresh capsicum, but has deficiencies in the performance of stale capsicum and stale tomato.

5. Discussion

This study proposes a novel method that fusion of different deep learning model to extract the features of fruit and vegetable images and the correlation between various areas in the image, so as to detect the freshness of fruits and vegetables more accurately and efficiently. In order to future improve the performance and generalization ability of the CNN_BiLSTM deep learning model for fruit and vegetable freshness detection, this study optimized the training parameters of the CNN_BiLSTM deep learning model. As shown in Fig. 3, the M5 model has better accuracy in detecting the freshness of fruits and vegetables than the M6 model. Combined with the parameter analysis of each model in Table 1, this may be due to the larger initial learning rate causing the model to fail to reach the optimal solution or fall into a local optimal solution. In terms of batch size, the M4 model has better accuracy in detecting the freshness of fruits and vegetables than the M5 model. This may be attributed to the fact that the larger batch size may cause the model to converge to a rougher local optimal solution during the training process while a smaller batch size helps the model better explore the local details of the loss function, which may make it easier to converge to a better solution. Regarding the impact of random dropout rate on the fruit and vegetable freshness detection of the CNN_BiLSTM deep learning mode, the M2 model has a better accuracy in fruit and vegetable freshness detection than the M1 model. This may be explained by the excessive random dropout rate causing too much feature information to be lost in the CNN_BiLSTM deep learning model, which in turn leads to a decrease in the accuracy of fruit and vegetable freshness detection. Surprisingly, the M5 model has better accuracy in detecting the freshness of fruits and vegetables than the M3 model. This may be because the M3 model does not use random dropout techniques, resulting in redundancy in the feature information extracted by the CNN_BiLSTM deep learning model, which in turn affects the accuracy of fruit and vegetable freshness detection. This also shows that the random deactivation technique reduces the interdependence between network nodes of the CNN_BiLSTM deep learning model, reduces complex synergistic effects, and helps avoid overfitting of the CNN_BiLSTM deep learning model, improve the generalization ability of the model.

This study conducts ablation experiments on the proposed CNN_BiLSTM deep learning model to analyze the contribution of each component of the model to fruit and vegetable freshness detection and to verify whether the model design is in line with the basis of empirical research. As can be seen from Table 2, for a single deep learning model, the comprehensive performance of the CNN deep learning model for fruit and vegetable freshness detection is better than the BiLSTM deep learning model. This can be explained by the fact that CNN deep learning model can effectively extract feature information such as texture, color and shape when processing image data, and the CNN deep learning model can detect the same features no matter where the object in the image appears. For the combined deep learning model, the CNN_BiLSTM deep learning model has better comprehensive performance than the CNN_LSTM deep learning model for fruit and vegetable freshness detection. This is due to the fact that the BiLSTM deep learning model can better adapt to diverse data features in the fruit and vegetable freshness detection task compared to the LSTM deep learning model, and can learn the characteristics and changing patterns of fruit and vegetable freshness during the training process. These advantages make the CNN_BiLSTM deep learning model potentially perform better in the vegetable freshness detection task. In addition, the comprehensive performance of the CNN_BiLSTM deep learning model for fruit and vegetable freshness detection is significantly better than the CNN deep learning model and the BiLSTM deep learning model. This situation occurs because each single model only detects the freshness of fruits and vegetables from a single perspective, that is, the CNN deep learning model only extracts spatial features to detect the freshness of fruits and vegetables, the BiLSTM deep learning model only processes contextual relationships and temporal relationships to detect the freshness of fruits and vegetables, the CNN_BiLSTM deep learning model combines the characteristics of the CNN deep learning model and the BiLSTM deep learning model to achieve high performance in fruit and vegetable freshness detection. Compared with the CNN deep learning model and the BiLSTM deep learning model, the accuracy of the CNN_BiLSTM deep learning model for fruit and vegetable freshness detection has increased by 1.69% and 3.14% respectively. This may be attributed to the fact that after the CNN deep learning model extracts the spatial features of the image, the BiLSTM deep learning model can further process the contextual and temporal relationships of the extracted spatial features based on these features, allowing the CNN_BiLSTM deep learning model to more comprehensively understand fruit and vegetable images, thereby achieving high performance in fruit and vegetable freshness detection.

In order to further evaluate the effectiveness and superiority of the proposed method for fruit and vegetable freshness detection, this study compares the performance of the CNN_BiLSTM method with some existing advanced research methods for fruit and vegetable freshness

Table 3
Fruit and vegetable freshness detection performance of CNN_BiLSTM deep learning model.

	Acc	Pre	Rec	F1
Fresh apple	97.41%	95.88%	97.91%	0.97
Fresh banana	98.25%	96.28%	98.59%	0.98
Fresh bitter gourd	97.88%	95.43%	97.28%	0.97
Fresh capsicum	98.46%	96.51%	98.81%	0.98
Fresh orange	98.10%	96.32%	98.12%	0.98
Fresh tomato	97.35%	96.10%	95.85%	0.96
Stale apple	97.71%	95.66%	96.99%	0.97
Stale banana	97.90%	94.92%	98.03%	0.95
Stale bitter gourd	97.63%	96.03%	97.43%	0.96
Stale capsicum	97.22%	93.37%	95.46 %	0.95
Stale orange	98.05%	96.12%	98.21%	0.98
Stale tomato	97.13%	94.91%	93.39%	0.94

detection. As shown in Table 4, among all compared models, the CNN_BiLSTM method proposed in this study has the best performance in detecting the freshness of fruits and vegetables and also has the advantage of not requiring manual feature extraction, which also strongly confirms the effectiveness and superiority of the CNN_BiLSTM method in detecting the freshness of fruits and vegetables.

The CNN_BiLSTM method for fruit and vegetable freshness detection can be used to monitor and ensure product quality and freshness in agricultural production and retail. During the production process of agricultural products, image data of fruits and vegetables are captured by installing cameras or sensors in the planting area, harvest stage, packaging process and transportation vehicles. These image data are transmitted to the data processing system for preprocessing, and then input into the trained CNN_BiLSTM model for analysis to detect the freshness of fruits and vegetables. The system performs freshness evaluation based on the output results of the CNN_BiLSTM model. If the freshness of fruits and vegetables falls below a preset threshold or an abnormality occurs, the system will sound an alarm and take corresponding measures, such as removing the fruits and vegetables from the production line, adjusting storage conditions, or selling them immediately. The fruit and vegetable freshness detection system records the results of each freshness assessment and provides feedback to relevant production personnel or managers. This helps analyze trends in changes in the freshness of fruits and vegetables, thereby optimizing and improving the production process of agricultural products. Similarly, in the fruit and vegetable retail industry, cameras or sensors can be installed at points of sale or agricultural product display areas to obtain image data of fruits and vegetables. The data processing system then performs preprocessing and inputs the trained CNN_BiLSTM model for analysis to detect the freshness of fruits and vegetables. If the freshness of fruits and vegetables output by the CNN_BiLSTM model is lower than the preset threshold or abnormal, the system will issue an alarm and remove the stale fruits and vegetables, adjust the display position, or conduct discount sales, etc. In addition, the fruit and vegetable freshness detection system also records the results of each freshness assessment and provides feedback to relevant retail clerks or managers to analyze trends in fruit and vegetable freshness changes and help retail stores optimize shelf display and inventory management. This automated technology for detecting the freshness of vegetables and fruits is expected to attract the attention of the agricultural and retail industries and win the recognition of manufacturers and retailers. Taking these factors into account, widespread application of this technology in the agricultural and retail industries is feasible and will bring significant benefits, including improved product quality, lower costs, and reduced waste.

In order to further analyze the generalization performance of the proposed CNN_BiLSTM deep learning model, this study uses this model to detect the freshness of fruits and vegetables in different data sets. The data sets used in the generalization performance analysis are the noise data set, the rotated data set and the flipped data set formed by adding noise, random rotation and random flipping to the original data set respectively. The noise data set is obtained by adding Gaussian noise with a mean of 0 and a variance of 0.01 to the original fruit and vegetable images. The rotation data set is formed by randomly rotating the original fruit and vegetable images within a range of plus or minus 30°. The flipped data set is obtained by randomly flipping the original fruit and vegetable images up and down. Subsequently, this study used the CNN_BiLSTM deep learning model on these three data sets to detect the freshness of fruits and vegetables. Experimental results show that on the noisy data set, the CNN_BiLSTM deep learning model achieved a fruit and vegetable freshness detection accuracy of 95.62%. On the rotated dataset, the accuracy reached 96.57%, while on the flipped dataset it was 95.19%. The accuracy of the CNN_BiLSTM deep learning model in detecting the freshness of fruits and vegetables on these three data sets is above 95%. This fully verifies that the CNN_BiLSTM deep learning model proposed in this study has good generalization performance and can achieve better fruit and vegetable freshness detection performance even when applied to other data sets.

Table 4
Comparison between the proposed method and existing advanced research methods.

References	Method	Acc
Bhargava et al. (Bhargava et al., 2022)	Feature extract (statistical, color, textural, geometrical, Laws' texture energy, HOG and DWT), PCA and SVM	96.59%
Hussain et al. (Hussain et al., 2022)	Deep CNN	96%
Fahad et al. (Fahad et al., 2022)	VGG-16	82.2%
Ni et al. (Ni et al., 2020)	GoogLeNet	94.62%
Phan et al. (Phan et al., 2023)	Yolo5m and EfficientNet-B0	94%
Proposed method	CNN_BiLSTM	97.76%

6. Conclusion

This paper proposes a novel method that fusion of different deep learning model to extract the features of fruit and vegetable images and the correlation between various areas in the image, so as to detect the freshness of fruits and vegetables more accurately and efficiently. In the proposed method, the image size in the dataset is reset, and the deep features characterizing the freshness of fruits and vegetables are extracted by the fused deep learning model, the training parameters of the fusion model are optimized based on the performance of fruit and vegetable freshness, and the performance of fruit and vegetable freshness detection was evaluated by evaluation indicators. Experimental results show that the CNN_BiLSTM deep learning model, which fusion CNN and BiLSTM, is combined with parameter optimization processing to achieve a maximum accuracy of 97.76% in detecting the freshness of fruits and vegetables. Research results show that this method can automatically extract deep features that characterize the freshness of fruits and vegetables, and is suitable for the freshness detection of vegetables and fruits.

CRediT authorship contribution statement

Yue Yuan: Methodology, Validation, Formal analysis, Investigation, Writing – original draft. **Jichi Chen:** Writing – original draft, Writing – review & editing. **Kemal Polat:** Writing – review & editing, Supervision. **Adi Alhudhaif:** Validation, Writing – review & editing.

Declaration of competing 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.

Data availability

Data will be made available on request.

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