Identification of Rice Seed Varieties Based on Near-Infrared Hyperspectral Imaging Technology Combined with Deep Learning

Baichuan Jin, Chu Zhang, Liangquan Jia, Qizhe Tang, Lu Gao, Guangwu Zhao, and Hengnian Qi*

ABSTRACT: Rice is one of the most important food crops in the world, and rice seed varieties are related to the yield and quality of rice. This study used near-infrared (NIR) hyperspectral technology with conventional machine learning methods (support vector machine (SVM), logistic regression (LR), and random forest (RF)) and deep learning methods (LeNet, GoogLeNet, and residual network (ResNet)) to establish variety identification models for five common types of rice seeds. Among the deep learning methods, the classification accuracies of most models were higher than 95%. This study further used the deep learning methods to establish variety identification models for 10 varieties of rice seeds without considering their types. Among them, the ResNet model had the best classification results. The classification accuracy on the test set was 86.08%. This study used the saliency map method to visualize each convolutional neural network (CNN) model to find the band region that contributed the most to the data. The results showed that the bands with the largest data contribution were 1100−1150 nm and secondarily concentrated at approximately 1300−1400 nm. The overall results showed that NIR hyperspectral imaging technology combined with deep learning could effectively distinguish rice seeds of different varieties. This method provided an effective way to identify rice seed varieties in a quick and nondestructive manner.

1. INTRODUCTION

Rice is one of the world’s three major food crops, and China’s rice output has ranked first in the world throughout the years. Due to differences in temperature, humidity, and soil conditions in different regions, rice quality also varies. The quality of rice seeds directly affects the yield and quality of grain. High-quality rice varieties have a higher nutritional and economic value. However, in actual market transactions, shoddy goods are often encountered, which harms the interests of farmers and affects grain production. With the development of hybridization technology and molecular breeding technology, the number of rice varieties continues to increase, and the existing detection technology can no longer meet the needs of rice seed variety detection.

Many types of rice seeds are available. According to the different morphological and physiological characteristics, rice types can be divided into japonica rice and indica rice. Based on whether it is obtained by hybridization or mutation, rice can be divided into conventional rice and hybrid rice. According to whether it is obtained by genetically modified technology, rice can be divided into transgenic rice and nontransgenic rice. Different varieties of rice seeds are available for these different types. At present, most studies on the classification of rice seed varieties are mainly based on direct variety classification, without considering the type of rice seed. Existing seed variety detection methods include morphological methods, fluorescence scanning-based identification methods, chemical identification methods, and electrophoresis identification methods, but these methods have disadvantages such as high time consuming, low precision, and cumbersome operation. Therefore, a rapid and nondestructive detection technology for rice seed varieties is needed. Near-infrared (NIR) hyperspectral imaging technology is a nondestructive testing technology that can obtain the spatial information and spectral information inside the given sample and can be used to obtain the physicochemical characterization and external morphological characteristics of the sample. In recent years, NIR technology has been widely used to test the quality and variety of various seeds, such as corn, wheat, rice, and soybeans.

Each pixel in hyperspectral image data has a spectrum, and each band is a grayscale image, which can provide both spatial and spectral information about the sample. The spectral information contained in samples is very similar, and it is
difficult to complete a quantitative analysis or perform accurate classification by observation. Therefore, it is necessary to use machine learning methods to extract information from the input data that is useful for the target study. Hyperspectral image data processing is usually combined with machine learning methods. Machine learning methods can be used to mine the information contained in hyperspectral images deeply. A suitable machine learning method can effectively process the relevant information in a hyperspectral image. Deep learning is the current research hotspot within machine learning, and it has a good feature of self-learning ability. Deep learning has been widely used for data processing and analysis in different fields. Recently, some scholars have studied combinations of hyperspectral imaging technology and deep learning methods to detect the quality and varieties of seeds. Nie et al.\textsuperscript{15} used the combination of NIR hyperspectral imaging technology and deep convolutional neural network (DCNN) to identify hybrid okra seeds and hybrid loofah seeds. Weng et al.\textsuperscript{16} combined hyperspectral imaging technology and a deep learning-based principal component analysis network to establish a rice variety identification model. Zhang et al.\textsuperscript{17} used NIR hyperspectral technology in

Figure 1. Average spectra of different types of rice seeds: (a) conventional japonica rice: Huaidao 5 and Nanjing 9108, (b) conventional indica rice: Zhongjiazao 17 and Zhongzao 39, (c) hybrid japonica rice: Bayou 8 and Yongyou 10, (d) hybrid indica rice: Chunyou 84 and Yongyou 12, (e) indica–japonica hybrid rice: Y liangyou 2 and Zhongzheyou 8, and (f) all varieties.
combination with deep learning methods to identify coated corn seed varieties and used the CNN, recurrent neural network (RNN), and long short-term memory (LSTM) to establish classification models. The classification accuracy exceeded 90%. The above studies have shown that the combination of hyperspectral imaging technology and deep learning can effectively identify seed varieties. However, although the deep learning methods are effective, they lack an explanatory nature. Therefore, Zhang et al. used the class activation map (CAM) method to visualize the CNN. Yan et al. used the saliency map method to visualize the CNN. Currently, most studies successfully use NIR hyperspectral imaging in combination with deep learning methods to identify the seed varieties of various crops. Among them, the varieties of rice seeds have also been classified, but most of the related studies did not consider the effect of the rice seed type on variety classification. Moreover, deep learning models are poorly interpreted, and most studies have not investigated this aspect.

In this study, we studied 5 common rice types: conventional japonica rice, conventional indica rice, hybrid japonica rice, hybrid indica rice, and indica—japonica hybrid rice. In addition, the saliency map method was used to visualize the CNN. This method was employed to find the band region that contributed the most to the classification of the rice seed varieties in the hyperspectral data. We studied two cases considering varieties and not considering varieties. We used the saliency map to visualize the tested deep learning models, thereby increasing their interpretability. The main purposes of this paper were to (1) study NIR hyperspectral imaging technology in combination with deep learning methods to identify the varieties of different types of rice seeds; (2) use NIR hyperspectral imaging technology with deep learning methods to identify 10 varieties of rice seeds regardless of their type; and (3) use saliency map to visualize CNN models and find the band region where the hyperspectral data contributed the most to the classification of the rice seed varieties.

### 2. RESULTS AND DISCUSSION

#### 2.1. Spectroscopic Analysis

Figure 1 shows the average preprocessed spectra of the different rice seed varieties within each type. The raw spectra and preprocessed spectra of different types of rice seeds are shown in Figure S1 (in the Supporting Information). Differences were observed between the average spectra of different varieties of rice seeds. Among the conventional japonica rice, Huaidao 5 and Nanjing 9108 had large differences in the wavelength range of 1000–1100 nm, but the differences in other wavelengths were small. Among the conventional indica rice, the differences between Zhongjiazao 17 and Zhongdao 39 in all bands were small. Among the hybrid japonica rice, Bayou 8 and Yongyou 10 were different at approximately 1200 nm, but the differences at other wavelengths were small. Among the hybrid indica rice, Chunyou 84 and Yongyou 12 were different in the wavelength range of 1000–1400 nm. Among the indica—japonica hybrid rice, Y lianyaou 2 and Zongzheyou 8 had relatively small differences in all bands. Figure 1(f) shows the average spectral curves of all varieties of rice seeds. Without considering the seed type, differences in the average spectra were observed between some varieties, but the differences between most varieties were not obvious. In general, the differences between the average spectra of different varieties of rice samples were not obvious, and further analysis was needed for the classification of rice seed varieties.

#### 2.2. Classification Results of Rice Seed Varieties Considering Seed Types

##### 2.2.1. Classification Result

The average spectra could not effectively distinguish different rice seed varieties. To obtain better classification results, this study used three conventional machine learning methods (support vector machine (SVM), logistic regression (LR), and random forest (RF)) and the CNN with three network structures (LeNet, GoogLeNet, and residual network (ResNet)) to establish models for identifying rice seeds of the same type but with different varieties. The number of rice seeds of each variety is shown in Table 1, with a total of 1900 grains. We took each type of rice seed (each type contained two varieties) as a whole and divided them into a training set, validation set, and test set in an approximate ratio of 6:1:1. Table S1 shows the data set division for each variety of samples.

Table 2 shows the classification results of different models for each type of rice seed. A model with 90% or greater accuracy on all three sets was defined as good, a model with 80% or greater accuracy on all three sets was defined as fair, and the rest were defined as poor. For the conventional japonica rice models, Huaidao 5 and Nanjing 9108 were assigned values of 0 and 1, respectively. The LR model had the worst classification results, and its classification accuracy was only approximately 70%. The classification accuracies of the other models were above 90%. Overall, the GoogLeNet model had the best classification results. Its accuracy on the training set was 99.33%, and its accuracy on the validation set was 100%.

For conventional indica rice models, the category values of Zhongjiazao 17 and Zhongdao 39 were 0 and 1, respectively. The results of the LR model were still unsatisfactory. The accuracies of the RF model on the training set and validation set were high, but the accuracy on the test set was only 74%. The RF model had a certain degree of overfitting. The overall results of the deep learning models were better than those of conventional machine learning models. The test set accuracy rate of the LeNet model was the highest among all models.

For hybrid japonica rice models, the category values of Bayou 8 and Yongyou 10 were 0 and 1, respectively. The LR model performed the worst. All deep learning models produced good results. Among them, the GoogLeNet model had the best classification results. Its accuracies on the validation set and test set were 100%. For hybrid indica rice models, the category values of Chunyou 84 and Yongyou 12 were 0 and 1, respectively. The

---

**Table 1. Sample Number of Different Varieties of Rice Seeds**

| type                   | variety     | number |
|------------------------|-------------|--------|
| conventional japonica  | Huaidao 5   | 200    |
|                        | Nanjing 9108| 200    |
| conventional indica     | Zhongjiazao 39| 200         |
|                        | Zhongdao 39 | 200    |
| hybrid japonica         | Yongyou 10  | 100    |
|                        | Bayou 8     | 100    |
| hybrid indica           | Zhongzheyou 8| 300         |
|                        | Yliangyou 2 | 300    |
| indica—japonica hybrid  | Chunyou 84  | 100    |
|                        | Yongyou 12  | 200    |
LR and RF models had poor classification results, and the RF model exhibited overfitting. The classification results of the three deep learning models were relatively close.

For indica–japonica hybrid rice models, the category values of Yliangyou 2 and Zhongzheyou 8 were 0 and 1, respectively. All models had good classification results. The classification accuracies of both the deep learning models and the SVM model reached 100%

We further analyzed the model results using the area under the curve (AUC) metric. The AUC values for each model are shown in Table 3. The closer the AUC value is to 1, the more effective the model is. As seen from the table, the AUC results were generally consistent with the results of model accuracy results.

The overall results showed that for each type of rice seed, the classification results of the deep learning methods were better than those of the conventional machine learning methods. Among the conventional machine learning methods, the SVM had the best classification results, and LR had poor classification results. Because the form of the LR model is relatively simple, it is essentially a linear classifier, which makes it difficult to fit the real distribution of the input data. The hyperspectral data are relatively complex, and the LR model could not effectively handle the relationships between different features. RF models are prone to overfitting when noise is contained in the given data, and hyperspectral data inevitably generate noise during the acquisition process. Furthermore, in this study, the sample size for each variety was not sufficiently large, which could have led to the overfitting of the RF model.

To compare the performances of different kinds of models, we conducted a one-way analysis of variance (ANOVA) and multiple comparisons among the accuracies of the different models using the least significant difference (LSD). Significant differences could be found between LR and the deep learning models with \( p < 0.05 \). Deep learning models performed better than LR models. Significant differences could be found between the RF and the deep learning models with \( p < 0.05 \). The deep learning models performed better than the RF model. No significant differences were observed between the SVM models and the deep learning models with \( p > 0.05 \). We further compared the average accuracies of the SVM models and the deep learning models, and all three deep learning models have higher average accuracies than the SVM models. No significant differences were detected among the three deep learning models with \( p > 0.05 \). Among the deep learning

### Table 2. Classification Accuracy of Different Types of Rice Variety Detection Models

| type                               | models     | training | validation | test     | model performance |
|------------------------------------|------------|----------|------------|----------|-------------------|
| conventional japonica rice        | RBF-SVM    | 99.33%   | 90.00%     | 98.00%   | good              |
|                                   | LR         | 74.33%   | 66.00%     | 70.00%   | poor              |
|                                   | RF         | 100.00%  | 94.00%     | 96.00%   | good              |
|                                   | LeNet      | 98.67%   | 100.00%    | 96.00%   | good              |
|                                   | GoogLeNet  | 99.33%   | 100.00%    | 96.00%   | good              |
|                                   | ResNet     | 99.33%   | 94.00%     | 98.00%   | good              |
| conventional indica rice          | RBF-SVM    | 100.00%  | 94.00%     | 90.00%   | good              |
|                                   | LR         | 75.33%   | 88.00%     | 76.00%   | poor              |
|                                   | RF         | 100.00%  | 90.00%     | 74.00%   | poor              |
|                                   | LeNet      | 99.00%   | 100.00%    | 96.00%   | good              |
|                                   | GoogLeNet  | 98.33%   | 100.00%    | 92.00%   | good              |
|                                   | ResNet     | 97.67%   | 98.00%     | 92.00%   | good              |
| hybrid japonica rice              | RBF-SVM    | 95.33%   | 96.00%     | 96.00%   | good              |
|                                   | LR         | 70.00%   | 80.00%     | 72.00%   | poor              |
|                                   | RF         | 100.00%  | 84.00%     | 88.00%   | fair              |
|                                   | LeNet      | 99.33%   | 92.00%     | 100.00%  | good              |
|                                   | GoogLeNet  | 98.67%   | 100.00%    | 100.00%  | good              |
|                                   | ResNet     | 100.00%  | 92.00%     | 96.00%   | good              |
| hybrid indica rice                | RBF-SVM    | 88.22%   | 85.33%     | 90.67%   | fair              |
|                                   | LR         | 74.67%   | 78.67%     | 74.67%   | poor              |
|                                   | RF         | 100.00%  | 77.33%     | 77.33%   | poor              |
|                                   | LeNet      | 94.00%   | 89.33%     | 88.00%   | fair              |
|                                   | GoogLeNet  | 90.22%   | 85.33%     | 82.67%   | fair              |
|                                   | ResNet     | 92.89%   | 84.00%     | 90.67%   | fair              |
| indica–japonica hybrid rice       | RBF-SVM    | 100.00%  | 100.00%    | 100.00%  | good              |
|                                   | LR         | 97.33%   | 100.00%    | 97.30%   | good              |
|                                   | RF         | 100.00%  | 100.00%    | 97.30%   | good              |
|                                   | LeNet      | 100.00%  | 100.00%    | 100.00%  | good              |
|                                   | GoogLeNet  | 100.00%  | 100.00%    | 100.00%  | good              |
|                                   | ResNet     | 100.00%  | 100.00%    | 100.00%  | good              |

### Table 3. AUC of Different Types of Rice Varieties Detection Models (1, conventional japonica rice; 2, conventional indica rice; 3, hybrid japonica rice; 4, hybrid indica rice; 5, indica–japonica hybrid rice)

| SVM     | LR     | RF     | LeNet  | GoogLeNet | ResNet |
|---------|--------|--------|--------|-----------|--------|
| 1       | 0.9839 | 0.7275 | 0.9141 | 0.9576    | 0.9474 | 0.9839 |
| 2       | 0.9074 | 0.7649 | 0.9074 | 0.9630    | 0.9195 | 0.9259 |
| 3       | 0.9375 | 0.7610 | 0.8787 | 1         | 1      | 0.9706 |
| 4       | 0.9109 | 0.7460 | 0.7687 | 0.8787    | 0.8189 | 0.9109 |
| 5       | 1      | 0.9828 | 0.9375 | 1         | 1      | 1      |

4738 https://doi.org/10.1021/acsomega.1c04102
ACS Omega 2022, 7, 4735–4749
methods, the performance of the three methods was relatively close and all models had good classification results.

2.2.2. CNN Visualization. In this study, the saliency map method was used to visualize the CNN models. Figure 2 shows the visualization results of all LeNet models. For conventional japonica rice, the bands at approximately 1300−1400 nm provided the highest contribution. For conventional indica rice, the bands at approximately 1200−1250 nm and 1350−1400 nm contributed the most, followed by the bands at approximately 1050 nm and 1150−1200 nm. For hybrid japonica rice, the bands at approximately 1350−1400 nm contributed the most, followed by the bands at approximately 1150−1250 nm. For hybrid indica rice, the bands at approximately 1350−1400 nm contributed the most, followed by the bands at approximately 1200−1250 nm and 1050 nm. For indica−japonica hybrid rice, the bands at approximately 1300−1400 nm and 1100−1150 nm both provided high contributions.

Figure 3 shows the visualization results of all GoogLeNet models. For conventional japonica rice, the bands with the
largest contribution rate were mainly concentrated at approximately 1350–1400 nm, followed by the bands at approximately 1200–1250 nm. For conventional indica rice, the contribution of the bands near 1350–1550 nm was relatively high. For hybrid japonica rice, the bands at approximately 1100–1150 nm and 1250 nm. For indica–japonica hybrid rice, the bands at approximately 1225–1275 nm and 1150–1175 nm contributed the most, followed by the bands at approximately 1025–1075 nm.

Figure 4 shows the visualization results of all ResNet models. For conventional japonica rice, the bands at approximately 1350–1400 nm contributed the most, followed by the bands at approximately 1200–1250 nm. For conventional indica rice, the bands at approximately 1350–1550 nm provided the highest contributions, followed by the bands at approximately 1500–1550 nm. For hybrid japonica rice, the band at approximately 1350–1400 nm contributed the most, followed by the bands at approximately 1200–1300 nm. For hybrid indica rice, the bands at approximately 1300–1350 nm and 1375–1400 nm contributed the most, followed by the bands at approximately 1100–1150 nm and 1250 nm. For indica–japonica hybrid rice, the bands at approximately 1225–1275 nm and 1150–1175 nm contributed the most, followed by the bands at approximately 1025–1075 nm.

Figure 3. Saliency maps of the GoogLeNet model: (a) conventional japonica rice: Huaidao 5 and Nanjing 9108, (b) conventional indica rice: Zhongjiazao 17 and Zhongzao 39, (c) hybrid japonica rice: Bayou 8 and Yongyou 10, (d) hybrid indica rice: Y liangyou 2 and Zhongzheyou 8, and (e) indica–japonica hybrid rice: Chunyou 84 and Yongyou 12.
approximately 1350–1400 nm contributed the most, followed by the bands at approximately 1050–1250 nm. For hybrid indica rice, the bands at approximately 1050–1250 nm contributed the most, followed by the bands at approximately 1150–1300 nm. For conventional japonica rice, the bands with the largest contribution rate were mainly concentrated at approximately 1300–1400 nm, followed by the bands at approximately 1200–1250 nm. For conventional indica rice, the bands at approximately 1350–1550 nm had the largest contribution rate, followed by the bands at approximately 1050–1200 nm. For hybrid japonica rice, the bands with the largest contribution rate were mainly concentrated at approximately 1350–1400 nm, followed by the bands at approximately 1150–1300 nm. For hybrid indica rice, the bands at approximately 1300–1400 nm provided the highest contribution, followed by the bands at approximately 1050–1250 nm.

Figure 4. Saliency maps of the ResNet model: (a) conventional japonica rice: Huaidao 5 and Nanjing 9108, (b) conventional indica rice: Zhongjiangao 17 and Zhongzao 39, (c) hybrid japonica rice: Bayou 8 and Yongyou 10, (d) hybrid indica rice: Y liangyou 2 and Zhongzheyou 8, and (e) indica–japonica hybrid rice: Chunyou 84 and Yongyou 12.
For the indica–japonica hybrid rice, the bands with the largest contribution rate were mainly concentrated at approximately 1100–1275 nm and 1300–1400 nm. Overall, for all types of rice seeds, the bands with the largest contribution rate were mainly concentrated at approximately 1300–1400 nm, followed by the bands at approximately 1050–1250 nm. Table 4 shows the NIR absorption bands produced by the relevant experiments. The 1050 nm–1200 nm and 1300 nm–1500 nm bands are the main characteristic spectral regions of the 20 amino acids that constitute proteins. The 1050–1200 nm region is mainly composed of the second overtone of C–H, and the 1300–1500 nm region is mainly composed of the combined frequency of C–H, which can reflect the amino acid composition differences among different samples.

### Table 4. NIR Absorption Bands in the Relevant Studies

| Wavelength | Bond vibration                          | Researchers          |
|------------|----------------------------------------|----------------------|
| 1202 nm    | C–H second overtone                    | Miao et al.          |
| 1207 nm    | C–H second overtone                    | Wimonswiri et al.    |
| 1140–1350 nm | C–H second overtone                  | Amanah et al.        |
| 1090–1180 nm | C–H second overtone                  | Westad et al.        |
| 1100–1200 nm | C–H second overtone                  |                      |
| 1150–1260 nm | C–H second overtone                  |                      |
| 1350–1430 nm | C–H combination                        |                      |
| 1360–1420 nm | C–H combination                        |                      |
| 1228 nm    | C–H second overtone                    | Xie et al.           |
| 1191 and 1209 nm | C–H second overtone | Kaeowsorn et al.     |
| 1388 nm    | C–H combination                        |                      |
| 1204 and 1301 nm | C–H second overtone | He et al.            |
| 1204 nm    | C–H stretching and deformation        | Shen et al.          |

Compared with those achieved in the case where the type of seed was considered, the classification results in this scenario were relatively worse. Mutual influences were observed between different types of seeds.

The confusion matrix of the classification results of the three models is shown in Figure 5. The horizontal axis of the confusion matrix denotes the true category of the sample, and the vertical axis represents the sample category predicted by the model. Through the confusion matrix, you can observe the number of correct predictions and the number of incorrect predictions for each category. Figure 5(a) is the confusion matrix for the LeNet models. It can be seen from the figure that the LeNet models had the worst classification results for Bayou 8, and it was most likely to be misjudged as Huaidao 5, Zhongjiazao 17, and Nanjing 9107.

Figure 5(b) is the confusion matrix for the GoogLeNet models. The GoogLeNet models had the worst classification results for Yongyou 10, and it was most likely to be misjudged as Huaidao 5.

Figure 5(c) is the confusion matrix for the ResNet models. The classification results of the ResNet models for Yongyou 10 and Chunyou 84 were relatively poor. Among them, Yongyou 10 was most likely to be misjudged as Huaidao 5 and Zhongzao 39, and Chunyou 84 was most likely to be misjudged as Huaidao 5.

2.3.2. CNN Visualization. In this study, the saliency map method was also used to visualize the three CNN models for evaluating the classification results of ten rice varieties. The visualization results are shown in Figure 6. For the LeNet model, the bands with the largest contribution rate were mainly concentrated at approximately 1350–1500 nm. For the GoogLeNet model, the bands with the largest contribution rate were mainly concentrated at approximately 1050–1250 nm and 1300–1400 nm. For the ResNet model, the bands with the largest contribution rate were mainly concentrated at approximately 1000–1100 nm and 1300–1400 nm. Overall, the bands with the largest contribution rate were mainly concentrated at approximately 1050–1250 nm and 1300–1400 nm. The results were close to the visualization results for the case in which the seed type was considered.

2.4. Discussion. Differences are present in the quality of different varieties of rice. High-quality rice has a higher economic and nutritional value. Therefore, it is important to identify different varieties of rice seeds in a quick and nondestructive manner. In addition to varieties, different types of rice are available, such as indica and japonica, late rice, and early rice. Different varieties of rice may belong to the same type. Different varieties of rice seeds have small grains and similar colors and shapes, which are difficult to distinguish by visual observation, so it is important for us to choose a suitable classification strategy when classifying rice seeds.

In this study, we used NIR hyperspectral imaging combined with deep learning to identify the varieties of different types of rice seeds. We studied two cases considering the rice seed type and not considering the rice seed type. Some studies have also classified rice seed varieties, but they did not consider the type of rice seeds. Wang et al. used hyperspectral imaging combined with the back-propagation neural network (BPNN) to identify rice varieties and quality, where the accuracy of the BPNN model based on data fusion reached 94.45%. The authors studied only three rice varieties. Samson et al. used RGB and hyperspectral imaging to identify rice seed varieties. They studied 90 rice varieties, but they did not consider the effect of
the rice type. Weng et al. used hyperspectral imaging in combination with the principal component analysis network (PCANet) with multifeatured fusion to identify rice seed varieties achieving a maximum accuracy of 98.57%. They studied 10 rice varieties, but they also did not consider the effect of the rice type. In a study by Qiu et al., who also...
identified rice seed varieties, two different rice seed types were contained in their study sample, but the authors did not consider the rice seed types when modeling. From the results of this study, the types of rice seeds influence the classification of rice varieties, so it is meaningful to consider the types of rice seeds when identifying rice seed varieties. In this study, the highest accuracy of 86.08% was obtained for the identification of 10 different varieties of rice seeds without considering the type of rice seeds, and our results were not poor compared to those of other similar studies. In the case when rice seed types were considered, the accuracies of most of our models exceeded 90%, and the overall results of this study were good. In this study, we used deep learning methods. Compared with other similar studies that used deep learning methods, we used saliency maps to visualize the deep learning models to improve the interpretability of the models.

Deep learning is widely used in NIR spectral analysis. Among deep learning approaches, CNNs are the most commonly used deep learning methods. In this study, we further studied the application of CNN in NIR spectral analysis, and we used three CNN models with different network structures to identify rice seed varieties. The performance of the three deep learning methods was very close when considering rice seed types. The ResNet model performed the best when the rice seed types were not considered. Moreover, we used conventional machine learning methods to compare with deep learning methods. The results of SVM and deep learning methods were very close.

In the results of this study, the overall performances of the deep learning models were better than that of the SVM models when considering rice seed types, but the advantage was not very significant. We reviewed the related literature and found that some studies also used CNN models and SVM models for spectral data processing. Zhang et al.17 used NIR hyperspectral imaging to identify the coated maize seed varieties and used the CNN and SVM models in their study. From the results, the CNN model performed slightly better than the SVM model overall, but the difference was not significant. Nie et al.15 used NIR hyperspectral imaging combined with a deep learning approach to classify hybrid seeds of loofah and okra, while the study also used the SVM algorithm. The overall performance of the SVM model and the DCNN model were very close, with the DCNN model performing slightly better. Xiao et al.29 used visible/shortwave NIR and NIR hyperspectral imaging to identify the origin of Astragalus. The CNN and SVM models were also used in this study, and from the results, the two models performed very similarly. Gao et al. used NIR hyperspectral imaging to identify the geographic origin of narrow-leaf olive fruit, where SVM models and CNN models were also used. From the results, it can be seen that the performance of the SVM model was very close to the overall performance of the CNN model, with the CNN model performing slightly better than the SVM.30 Zhu et al. used NIR hyperspectral imaging in combination with a deep learning approach to identify cotton seed varieties and used an SVM model in comparison with a deep learning model, and from the results, it can be seen that some of the deep learning models
performed slightly better than the SVM, but the overall results were close.\textsuperscript{37} Similar results have been obtained in some other related studies.\textsuperscript{32−35} From the results of these studies, both SVM and deep learning models are effective methods for spectral data processing, and in most cases, the CNN performs slightly better than the SVM, but their overall performances are very close. These findings are similar to the results of this study.

SVM and deep learning have been proven effective for data processing in spectral data analyses. However, they work based on different principles. SVM is the widely used method that can deal with both linear and nonlinear problems. In spectral data analysis, SVM with kernel functions is the most commonly used. SVM maps the input data into higher dimensions using a kernel function and then classifies samples. Deep learning methods use multiple layers of nonlinear processing units for feature extraction and transformation, and deep learning has been proven to have a powerful feature learning capability and can effectively extract information from the data.\textsuperscript{36} SVM are suitable for small datasets.\textsuperscript{37} The number of samples in this study was small, as were the sample sizes in the abovementioned studies. The advantage of deep learning for large datasets was not fully revealed. However, the results we obtained in this study and those in the abovementioned studies, deep learning models obtained equivalent or better results than the SVM models, exhibiting great potential for rice seed variety identification. Moreover, this study used one-dimensional spectral rice seed data, and the form of the data was not complex, so the data did not give full play to the advantages of deep learning in dealing with complex features. Therefore, in this study, the results of the deep learning models and the SVM models were very close.

In the future, we will study more varieties and a larger number of samples. We will also study 2D images and 3D hyperspectral data to exploit the information of hyperspectral images more fully and fully reveal the potential of deep learning methods.

3. CONCLUSIONS

In this study, we successfully used NIR hyperspectral imaging technology in combination with conventional machine learning methods and deep learning methods to identify rice seeds of different varieties but with the same type. This study identified two different varieties of rice seeds under the conventional japonica rice, conventional indica rice, hybrid japonica rice, hybrid indica rice, and indica–japonica hybrid rice types. The experimental results showed that among the conventional machine learning methods, the SVM method could effectively detect different varieties of rice seeds, and the effects of LR and the RF were poor. Among the deep learning methods, the LeNet, GoogLeNet, and ResNet models could effectively identify rice seed varieties, the deep learning methods performed significantly better than the conventional machine learning algorithms, and the classification accuracies of most models exceeded 95%. This study further classifies different varieties of rice seeds without considering the seed types. LeNet, GoogLeNet, and ResNet were used to classify ten different varieties of rice seeds. Among them, ResNet had the best classification results, and its classification accuracy was 86.08%. The results showed that ResNet could effectively classify different varieties of rice seeds. After using the saliency map method to visualize each CNN model, the band was located at approximately 1300−1400 nm, followed by the band at approximately 1050−1250 nm. In summary, the employed research method can be used to identify rice seed varieties. The combination of deep learning methods and NIR hyperspectral imaging technology is better than conventional machine learning methods. This approach provides a way to identify the varieties of rice seeds in a quick and nondestructive manner.

4. MATERIALS AND METHODS

4.1. Sample Preparation. In this study, rice seed samples were provided by the College of Agriculture and Food Science, Zhejiang Agriculture and Forestry University, Lin’an, Zhejiang Province, China. All seeds were numbered when they were collected, and the numbers corresponded to the relative seed information, including their variety information.

4.2. NIR Hyperspectral Image Acquisition and Correction. The NIR hyperspectral imaging system in this experiment was mainly composed of an FX17 NIR hyper-spectral camera (Spectral Imaging Ltd.), a light source, a mobile platform, a computer, and control software. Its main structure is shown in Figure 7. The spectral range of the hyperspectral imaging system was 900−1700 nm, and the spectral resolution was 8 nm.

To reduce the influence of dark current noise and external factors, each image needed to be corrected. Before collecting each sample image, a white reference image (W) was first collected. Then, the light source was turned off and the camera lens was covered by a black opaque barrier to collect a black reference image (D). The corrected image (R) was obtained by the following formula (1)

\[
R = \frac{I - D}{W - D}
\]
In formula (1), I is the original image, R is the corrected image, W is the white reference image, and D is the black reference image.

4.3. Spectral Data Extraction and Preprocessing. Before obtaining the spectral data for each sample, a series of preprocessing steps were required for the original image. In this study, we used threshold segmentation based on the intensity to remove the background of the original image. Then, we used the connected domain method to label each seed and treated each rice seed as a region of interest (ROI). Then, the average reflectance among all pixels in the ROI was calculated to obtain the spectral data of each rice seed.

A certain amount of noise was contained in the obtained spectral data. Therefore, the data needed to be preprocessed to reduce the impact of noise. Before preprocessing, the bands at the front and rear ends in the spectral data with severe noise...
were removed, and wavelengths in the range of 1005–1634 nm were retained and used for further analysis. This study used the moving average (MA) and standard normal variables (SNV) to preprocess the spectral data. The MA could filter out the high-frequency noise in the data and retain useful low-frequency trends. SNV could reduce the spectral error caused by particle scattering between the samples. When performing MA-based processing, the segment size was set to 5.

4.4. Data Analysis Methods. 4.4.1. Conventional Machine Learning Methods. SVM is a machine learning algorithm that assigns labels to objects through instance learning. SVM is based on statistical learning theory and can effectively handle classification and regression problems. In linear problems, the principle is to find an optimal hyperplane that satisfies the classification requirements while maximizing the interval. In nonlinear problems, low-dimensional samples are transformed into high-dimensional feature spaces through a kernel function so that the difficult problem of space division is transformed into a high-dimensional linear division problem. This study chose the kernel function of the model from “Linear” and “RBF” (a radial basis function) and then used the grid search method to determine the penalty coefficient (C) and the kernel width parameter (γ). The optimization range of the parameter C was [1, 10, 50, 100]. The optimization range of the parameter γ was $[10^{-4}, 10^4]$.

LR is a linear model commonly used for binary classification problems. The model is simple, and its training speed is fast, so it has a wide range of applications in various fields. LR predicts the probability of an event by fitting a logistic function and generally uses the sigmoid function as a predictive function. In this study, L2 regularization was selected for LR and liblinear was selected for model optimization.

RF is an ensemble learning algorithm proposed by Leo Breiman, which was inspired by the early work of Amit and Geman. It can be used for both classification and regression. An RF has the advantages of a fast training speed and few tuning parameters, and it can be directly applied to high-dimensional data. Its essence is an algorithm that integrates multiple trees, and its basic unit is a decision tree.

4.4.2. CNN. CNNs are feedforward neural networks with deep structures based on convolutional layers. The structure of the CNN is usually composed of an input layer, the convolutional layer, the pooling layer, the fully connected layer, and an output layer. With the continuous development of the CNN, an increasing number of model structures have been proposed. LeNet is a classic CNN proposed by LeCun et al. in 1998. It is composed of a convolutional layer, a pooling layer, and other modules. GoogLeNet is a deep neural network model based on the Inception module proposed by Szegedy et al. in 2014. The Inception module puts multiple convolutions or pooling operations together to form a network module. The advantage of this approach is that it reduces the number of parameters and effectively avoids problems such as overfitting, gradient disappearance, or gradient explosion caused by the increase in the number of network layers. ResNet is a CNN structure proposed by He et al. ResNet solves the problem of degradation caused by the increase in network depth through residual learning. Compared with ordinary networks, ResNet adds a short-circuit mechanism, and its residual modules are connected through short-circuits, alleviating the problem of gradient disappearance in deep neural networks.

In this study, LeNet, GoogLeNet, and ResNet were used to establish rice seed variety identification models. The structure of the LeNet model is shown in Figure 8(a). It contained 3 convolutional layers, the size of each convolution kernel was $1 \times 4$, and the numbers of channels were 8, 16, and 32. A max pooling layer was used to extract features, the kernel size was $1 \times 4$, and the padding was set to 1. Each layer performed batch normalization on the data before utilizing an activation function to improve the learning rate. The rectified linear unit (ReLU) function was selected as the activation function to reduce the effect of the gradient disappearance and increase the calculation speed. The GoogLeNet model structure is shown in Figure 8(b); it contains two convolutional layers and two Inception modules. Each Inception module had four branches. The first branch consisted of three convolutional layers, and the number of channels in each of the three convolutional layers was 16. The convolution kernel sizes of the three convolutional layers were $1 \times 1$, $1 \times 3$, and $1 \times 3$. The second branch consisted of two convolutional layers, the number of channels in each of the two convolutional layers was 16, and the sizes of the convolution kernels were $1 \times 1$ and $1 \times 5$. The third branch contained only one convolutional layer, the number of channels in the convolutional layer was 16, and the size of the convolution kernel was $1 \times 1$. The fourth branch contained an average pooling layer and a convolution layer. The kernel size of the average pooling layer was 3, the number of channels of the convolution layer was 16, and the size of the convolution kernel was $1 \times 1$. The Inception module replaced the human hand to determine the size of the convolution kernel in each convolutional layer and to determine whether a convolutional or pooling layer was needed. The size of the convolution kernels of the two convolution layers was $1 \times 5$, and the numbers of channels were 10 and 20. The 'ReLU' function was selected as the activation function. The Inception module structure is shown in Figure 8(b). The ResNet model structure is shown in Figure 8(c). ResNet used two convolutional layers and two residual modules. The size of the convolution kernel of the two convolution layers was $1 \times 5$, and the numbers of channels were 16 and 32. When training the CNN model, the learning rates of all LeNet models were set to 0.001, and the learning rates of all GoogLeNet and ResNet models were set to 0.0001. The Adam optimizer was used for training to speed up the convergence process.

4.5. Saliency Map. The saliency map is a CNN visualization method. When the CNN correctly predicts the class of a sample, each element in the data has a corresponding contribution value. The sizes of the contribution values can reflect the importance levels of these elements. The saliency map can visualize the contribution value of each element to intuitively see which elements play important roles in the process of CNN-based sample identification. After the hyperspectral data, a saliency map can reflect the importance of each band. After the hyperspectral data $C_0$ of a sample in the test set was classified by the CNN model, we can obtain the score value $S$ for each band. If the category of this sample was correctly predicted, we could use formula 2 to calculate the weight $w$.

$$w = \text{abs} \left( \frac{\partial S}{\partial C} \right) C_0$$

where $w$ is the absolute value of the derivative of the score value $S$ with respect to the data $C_0$. In this study, the contribution value of each band was calculated for all of the correctly predicted samples in the test set.
set, and the average value of the contribution of each band was calculated for each type of sample.

4.6. Model Evaluation and Software. This study used the classification accuracy and AUC metrics to evaluate the performance of the models. The definition of classification accuracy is the ratio of the number of correct predictions to the total number of predictions. The SVM, LR, and RF models were implemented in Python 3.8 with scikit-learn (0.23.2). All CNN models were built using PyTorch (1.7.0), the deep learning framework. The two data preprocessing methods for the MA and SNV in this study were implemented in Unscrambler X 10.1 (CAMO AS, Oslo, Norway). All data analyses were performed on a computer configured with an Intel Core i5-8300H CPU at 2.30 GHz and 16 GB of RAM.

■ ASSOCIATED CONTENT

* Supporting Information
The Supporting Information is available free of charge at https://pubs.acs.org/10.1021/acsomega.1c04102.

Raw spectra and preprocessed spectra of different varieties of rice seeds (huaidao 5, nanjing 9108, zhongjiazaa 17, zhongzao 39, bayou 8, yongyou 10, yiliangyou2, zhongzhuyou 8, chunyou 84, and yongyou 12) and the number of samples in the training set, validation set, and test set for rice seed variety identification with or without considering the types of rice seeds (PDF)

■ AUTHOR INFORMATION

Corresponding Author
Hengnian Qi — School of Information Engineering, Huzhou University, Huzhou 313000, China; orcid.org/0000-0002-1927-7160; Email: qihengnian@foxmail.com

Authors
Baichuan Jin — School of Information Engineering, Huzhou University, Huzhou 313000, China
Chu Zhang — School of Information Engineering, Huzhou University, Huzhou 313000, China
Liangquan Jia — School of Information Engineering, Huzhou University, Huzhou 313000, China
Qizhe Tang — School of Information Engineering, Huzhou University, Huzhou 313000, China
Lu Gao — School of Information Engineering, Huzhou University, Huzhou 313000, China
Guangwu Zhao — College of Agriculture and Food Science, Zhejiang Agriculture and Forestry University, Lin’an 311300, China; orcid.org/0000-0001-5646-9922

Complete contact information is available at: https://pubs.acs.org/10.1021/acsomega.1c04102

Notes
The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS
This study was funded by the Zhejiang Key R&D Plan (2019C02013) and the General Scientific Research Projects of Department of Education of Zhejiang Province (Y201941626).

■ REFERENCES

(1) He, X.; Feng, X.; Sun, D.; Liu, F.; Bao, Y.; He, Y. Rapid and nondestructive measurement of rice seed vitality of different years using near-infrared hyperspectral imaging. *Molecules* 2019, 24, 2227.
(2) Wang, L.; Liu, D.; Pu, H.; Sun, D.-W.; Gao, W.; Xiong, Z. Use of hyperspectral imaging to discriminate the variety and quality of rice. *Food Anal. Methods* 2015, 8, 515–523.
(3) Qiu, Z.-J.; Chen, J.; Zhao, Y.; Zhu, S.; He, Y.; Zhang, C. Variety identification of single rice seed using hyperspectral imaging combined with convolutional neural network. *Appl. Sci. 2018, 8, 212.
(4) Yu, Y.-X.; Yu, H.-Y.; Guo, L.-B.; Li, J.; Chu, Y.-W.; Tang, Y.; Tang, S.-S.; Wang, F. Accuracy and stability improvement in detecting Wuchang rice adulteration by piece-wise multiplicative scatter correction in the hyperspectral imaging system. *Anal. Methods* 2018, 10, 3224–3231.
(5) Qian, S.; Wu, W.-j.; Wang, H.-w.; Wang, K.; An, D. Fast discrimination of varieties of corn based on near infrared spectra and biomimetic pattern recognition. *Spectrosc. Spectral Anal. 2009, 29, 2413–2416.
(6) Feng, L.; Zhu, S.; Liu, F.; He, Y.; Bao, Y.; Zhang, C. Hyperspectral imaging for seed quality and safety inspection: A review. *Plant Methods* 2019, 15, 1–25.
(7) Zhou, Q.; Huang, W.; Fan, S.; Zhao, F.; Liang, D.; Tian, X. Non-destructive discrimination of the variety of sweet maize seeds based on hyperspectral image coupled with wavelength selection algorithm. *Infrared Phys. Technol. 2020, 109, No. 103418.
(8) Wang, Z.; Fan, S.; Wu, J.; Zhang, C.; Xu, F.; Yang, X.; Li, J. Application of long-wave near infrared hyperspectral imaging for determination of moisture content of single maize seed. *Spectrochim. Acta, Part A 2021, 254, No. 119666.
(9) Vermeulen, P.; Suman, M.; Pierna, J. A. F.; Baeten, V. Discrimination between durum and common wheat kernels using near infrared hyperspectral imaging. *J. Cereal Sci. 2018, 84, 74–82.
(10) Hu, N.; Li, W.; Du, C.; Zhang, Z.; Gao, Y.; Sun, Z.; Yang, L.; Yu, K.; Zhang, Y.; Wang, Z. Predicting micronutrients of wheat using hyperspectral imaging. *Food Chem. 2021, 343, No. 128473.
(11) Fabyis, S. D.; Vu, H.; Tachtatzis, C.; Murray, P.; Harle, D.; Daol, T. K.; Andonovic, I.; Ren, J.; Marshall, S. Varietal classification of rice seeds using RGB and hyperspectral images. *IEEE Access 2020, 8, 22493–22505.
(12) Mu, C.; Ren, Z.; Zhang, Z.; Du, J.; Jin, C.; Yin, X. Development of simplified models for nondestructive testing of rice (with husk) protein content using hyperspectral imaging technology. *Vib. Spectros. 2021, 114, No. 103230.
(13) da Silva, C. A., Jr; Teodorro, L. P. R.; Teodorro, P. E.; Baio, F. H. R.; de Andrea Pantaleão, A.; Capristo-Silva, G. F.; Facco, C. U.; de Oliveira-Júnior, J. F.; Shiratsuchi, L. S.; Skripachev, V.; et al. Simulating multispectral MSI bandsets (Sentinel-2) from hyperspectral observations via spectroradiometer for identifying soybean cultivars. *Remote Sens. Appl. Soc. Environ. 2020, 19, No. 100328.
(14) Huang, M.; Wang, Q.; Zhang, M.; Zhu, Q. Prediction of color and moisture content for vegetable soybean during drying using hyperspectral imaging technology. *J. Food Eng. 2014, 128, 24–30.
(15) Nie, P.; Zhang, J.; Feng, X.; Yu, C.; He, Y. Classification of hybrid seeds using near-infrared hyperspectral imaging technology combined with deep learning. *Sens. Actuators, B 2019, 296, No. 126630.
(16) Weng, S.; Tang, P.; Yuan, H.; Guo, B.; Yu, S.; Huang, L.; Xu, C. Hyperspectral imaging for accurate determination of rice variety using a deep learning network with multi-feature fusion. *Spectrochim. Acta, Part A 2020, 234, No. 118237.
(17) Zhang, C.; Zhao, Y.; Yan, T.; Bai, X.; Xiao, Q.; Gao, P.; Li, M.; Huang, W.; Bao, Y.; He, Y.; et al. Application of near-infrared hyperspectral imaging for variety identification of coated maize kernels with deep learning. *Infrared Phys. Technol. 2020, 111, No. 103550.
(18) Zhang, X.; Xu, J.; Yang, J.; Chen, L.; Zhou, H.; Liu, X.; Li, H.; Lin, T.; Ying, Y. Understanding the learning mechanism of...
convolutional neural networks in spectral analysis. *Anal. Chim. Acta* 2020, 1119, 41–51. 
(19) Yan, T.; Xu, W.; Lin, J.; Duan, L.; Gao, P.; Zhang, C.; Lv, X. Combining Multi-Dimensional Convolutional Neural Network (CNN) With Visualization Method for Detection of Aphis gossypii Glover Infection in Cotton Leaves Using Hyperspectral Imaging. *Front. Plant Sci.* 2021, 12, No. 604510. 
(20) Tao, L.; Huang, W.; Yang, X.; Cao, Z.; Deng, J.; Wang, S.; Mei, F.; Zhang, M.; Zhang, X. Correlations between near infrared spectra and molecular structures of 20 standard amino acids. *Spectrosc. Spectral Anal.* 2016, 36, 2766–2773. 
(21) Ciuczek, E. W.; Igne, B.; Workman, J., Jr; Burns, D. A. *Handbook of Near-Infrared Analysis*; CRC press, 2021. 
(22) Miao, X.; Miao, Y.; Tao, S.; Liu, D.; Chen, Z.; Wang, J.; Huang, W.; Yu, Y. Classification of rice based on storage time by using near infrared spectroscopy and chemometric methods. *Microchem. J.* 2021, 171, No. 106841. 
(23) Wimonsiri, L.; Rithiruangdej, P.; Kasemsumran, S.; Therdthai, N.; Chanput, W.; Ozaki, Y. Rapid analysis of chemical composition in intact and milled rice cookies using near infrared spectroscopy. *J. Near Infrared Spectrosc.* 2017, 25, 330–337. 
(24) Amanah, H. Z.; Wakholi, C.; Perez, M.; Faqeerzada, M. A.; Tunny, S. S.; Masithoh, R. E.; Choung, M.-G.; Kim, K.-H.; Lee, W.-H.; Cho, B.-K. Near-Infrared Hyperspectral Imaging (NIR-HSI) for Nondestructive Prediction of Anthocyanins Content in Black Rice Seeds. *Appl. Sci.* 2021, 11, 4841. 
(25) Westad, F.; Schmidt, A.; Kermit, M. Incorporating chemical band-assignment in near infrared spectroscopy regression models. *J. Near Infrared Spectrosc.* 2008, 16, 265–273. 
(26) Xie, L. H.; Tang, S. Q.; Chen, N.; Luo, J.; Jiao, G. A.; Shao, G. N.; Wei, X. J.; Hu, P. Optimisation of near-infrared reflectance model in measuring protein and amylose content of rice flour. *Food Chem.* 2014, 142, 92–100. 
(27) Kaewsorn, K.; Sirisomboon, P. Determination of the gamma-amino butyric acid content of germinated brown rice by near infrared spectroscopy. *J. Near Infrared Spectrosc.* 2014, 22, 45–54. 
(28) Shen, F.; Wu, Q.; Shao, X.; Zhang, Q. Non-destructive and rapid evaluation of aflatoxins in brown rice by using near-infrared and mid-infrared spectroscopic techniques. *J. Food Sci. Technol.* 2018, 55, 1175–1184. 
(29) Rong, D.; Wang, H.; Ying, Y.; Zhang, Z.; Zhang, Y. Peach variety detection using VIS-NIR spectroscopy and deep learning. *Comput. Electron. Agric.* 2020, 175, 105553–105562. 
(30) Pang, L.; Sen, M.; Lei, Y.; Jiang, X. Rapid vitality estimation and prediction of corn seeds based on spectra and images using deep learning and hyperspectral imaging techniques. *IEEE Access* 2020, 8, 123026–123036. 
(31) Gao, P.; Xu, W.; Yan, T.-Y.; Zhang, C.; Lv, X.; He, Y. Application of near-infrared hyperspectral imaging with machine learning methods to identify geographical origins of dry narrow-leaved oleaster (elaeagnus angustifolia) fruits. *Foods* 2019, 8, 620. 
(32) Zhu, S.-S.; Zhou, L.; Gao, P.; Bao, Y.-D.; He, Y.; Feng, L. Near-infrared hyperspectral imaging combined with deep learning to identify cotton seed varieties. *Molecules* 2019, 24, 3268. 
(33) Wu, N.; Zhang, C.; Bai, X.-L.; Du, X.-Y.; He, Y. Discrimination of chrysanthemum varieties using hyperspectral imaging combined with a deep convolutional neural network. *Molecules* 2018, 23, 2831. 
(34) Zhu, H.-Y.; Aoife, G.; Feng, H.-L.; Yu, K.-P.; Xu, J.-L. Deep spectral-spatial features of near infrared hyperspectral images for pixel-wise classification of food products. *Sensors* 2020, 20, 5322. 
(35) Hasan, H.; Helmi, Z. M. S.; Mohammed, H. A comparison between support vector machine (SVM) and convolutional neural network (CNN) models for hyperspectral image classification. *IOP Conf. Ser.: Earth Environ. Sci.* 2019, 357, No. 012035. 
(36) Pramila, P. S.; Seema, S. In A review of machine learning and deep learning applications, 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA); IEEE, 2018. 
(37) Nitin, K. C.; Krishna, S. In A review on conventional machine learning vs deep learning, 2018 International Conference on Computing, Power and Communication Technologies (GUCON); IEEE, 2018; pp 347–352. 
(38) Durgesh, K. S.; Lekha, B. Data classification using support vector machine. *J. Theory Appl. Inf. Tech.* 2010, 12, 1–7. 
(39) LaValley, M. P. Logistic regression. *Circulation* 2008, 117, 2395–2399. 
(40) Breiman, L. Random forests. *Mach. Learn.* 2001, 45, 5–32. 
(41) LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-based learning applied to document recognition. *Proc. IEEE* 1998, 86, 2278–2324. 
(42) Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. In Going deeper with convolutions, Proceedings of the IEEE conference on computer vision and pattern recognition; IEEE, 2015; pp 1–9. 
(43) He, K.; Zhang, X.; Ren, S.; Sun, J. In Deep residual learning for image recognition, Proceedings of the IEEE conference on computer vision and pattern recognition; IEEE, 2016; pp 770–778. 
(44) Hong, S.; You, T.; Kwak, S.; Han, B. In Online tracking by learning discriminative saliency map with convolutional neural network, International conference on machine learning; IEEE, 2015; pp 597–606.