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Sensing Feature Fusion with ReliefF Algorithm and Canonical Correlation Analysis in Counterfeit Label Classifications

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In this study, we investigate the application of the sensory fusion method to counterfeit label classification. Image sensing data were collected using a smartphone and processed through multilayer structural operations in various convolutional neural networks (CNNs) to extract features from different types of counterfeit label. The ReliefF algorithm filters out the top 10 important features of each CNN model. Canonical correlation analysis reorganizes the feature data into a small group of feature datasets. Finally, an efficient naive Bayes classifier and support vector machine methods were proposed to complete the classification of feature images. After experimental validation, the sensing feature fusion method proposed in this study demonstrated strong performance in counterfeit label recognition, achieving a maximum accuracy of 99.5238% per group. In addition, the fused feature dataset successfully achieved a high accuracy of 99.0496% under a high compression ratio of 1/50. In the case of wine counterfeit labels, the results showed that we can effectively fuse sensory features to enhance the processing speed while maintaining recognition accuracy.

1. Introduction

In recent years, counterfeit label classification technology has become increasingly important in the food and wine sectors. The labeling technology used in wine bottle caps, as part of the wine packaging, must have counterfeit label features to ensure the authenticity and safety of the product. Sensing-enabled information is collected from wine bottle caps to support a convolutional neural network (CNN)-based system for identifying counterfeits. For example, an infrared sensor can detect the thermal radiation of an object, such as the temperature of a wine bottle cap.(1) CNNs can learn patterns in the infrared information of counterfeit wine bottle caps. Optical sensors can detect the intensity, color, and reflectivity of light. CCNs can analyze the optical images to identify specific textures or markings on wine bottle caps.(2) In addition, a pressure sensor combined with a CNN can learn the pattern of pressure distribution to detect

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pressure changes that occur in a wine bottle cap that has been illegally opened or replaced.[3] The identification of wine labels in daily life has become an important topic, with academic research being carried out on areas such as authenticity verification, product traceability, smart packaging, and consumer behavior analysis. In this study, we focus on anticounterfeiting identification technologies for verifying label authenticity. Sensory image data are progressively collected using smartphones and integrated with data fusion and the development of machine learning models to enhance recognition accuracy and efficiency in real-world, noise-prone environments, thereby increasing the future practical value of this research.

In the modern era of big data, we are faced with diverse, multisource, and heterogeneous datasets that are constantly growing in number and size. This challenge is exacerbated by the continuous advances in information technology and human intelligence, which further increase the size and complexity of data. Feature selection (FS) is a key step in data preprocessing and is crucial for building effective machine learning models. The goal of FS is to identify the most informative and predictive subset of features from the original set in order to reduce the feature dimensions, eliminate redundant information, and improve the accuracy and interpretability of classification or regression models.[4] The Relief algorithm assigns different weights to the features in accordance with the relevance of each feature to the category, and features with weights less than a certain threshold are rejected. ReliefF is an improved version of the original Relief algorithm and is designed to handle multiclass problems. The main purpose of ReliefF is to improve the classification accuracy, especially on high-dimensional data. It can also handle incomplete and interference features.[5] Thus, we intend to utilize the ReliefF algorithm FS to filter out irrelevant or redundant features from the original dataset and retain the valid ones in order to retrieve the sensing information of CNN image features.

The real world comprises a huge amount of information in the wine identification system, and the importance of this type of information is growing expeditiously. Thus, information fusion is becoming a significant research topic in pattern recognition, deep learning, and labeled identification.[6,7] Fusion methods such as serial feature fusion, parallel feature fusion, and canonical correlation analysis (CCA) do not contain any class information. That is, they are unsupervised fusion methods.[8] Information fusion techniques can be broadly classified into supervised and unsupervised fusion techniques. The information collected from multiple sources is then processed using advanced data fusion techniques to produce reliable and consistent information, resulting in more accurate outcomes.

Among the feature fusion methods, CCA is commonly used to approach light but efficient data.[9,10] CCA is a tool that helps unravel the complex relationships between many variables in a large dataset. The main advantage of CCA is that it can evaluate two different sets of variables at the same time without assuming any particular form of precedence or directionality. In other words, CCA identifies the common source of variation in two sets of high-dimensional variables.[11] To use multilayer features in a unified way, feature fusion is an effective step to gain the benefits of transfer learning features in scene comprehension. We utilize the CCA advantage to evaluate and regulate two different feature matrices to enhance the counterfeit label classification performance.

The sensing feature fusion structure is explained in Sect. 2, the basic classification method in Sect. 3, and the experimental results and analyses in Sect. 4. Finally, conclusions are discussed in Sect. 5.

2. Sensing Feature Selection and Fusion Method

In this paper, we focus on the image classification of wine sensing labels and use the commonly used and well-known convolutional neural network models for image classification, namely, AlexNet, GoogleNet, ResNet18, and MobileNet, to extract the labeled image data. First, the labeled image data features are extracted, and then the ReliefF algorithm selects the most important feature subsets while attempting to preserve the main structure and characteristics of the original feature matrix, ensuring that the reduced feature set remains suitable for accurate recognition. The operation flow of this method is shown in Fig. 1. The concept of transfer learning is mainly utilized, and the first feature extraction of the input image from the pretrained

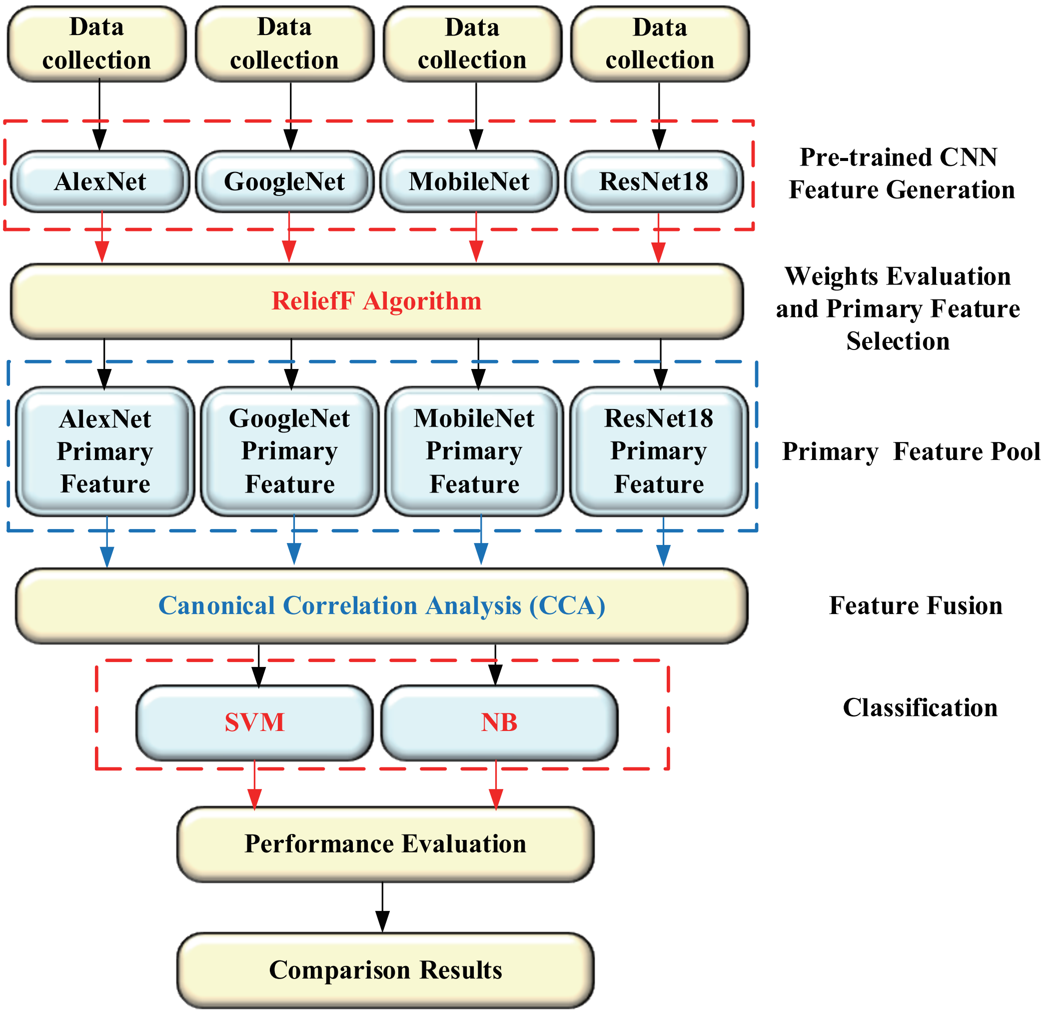


Fig. 1. (Color online) Flow chart of sensing feature fusion system structure.

model is completed using some famous training models such as AlexNet, GoogleNet, ResNet18, and MobileNet, and the extraction of the feature vectors of the input training image is completed through this model. The feature data selection layer is used to extract the values of the features, currently, from the set of feature vectors output from the pretraining model. Then, Relief is used to select the important features on the basis of each feature weight for forming a critical feature layer. CCA, which is known to be a fusion technique of feature layers, is mainly focused on establishing the correlation criterion function between two sets of feature vectors and extracting their typical correlation features. In Fig. 1, it is shown that the most important and critical features are selected using different CNN structures and input into CCA to concatenate and fuse the most suitable set of features and then classify the sensory images of wine labels by NB and SVM classification algorithms.

The preprocessing mechanism for CNNs will generate the multivariate feature generation layers. AlexNet has the fewest layers and uses dropout and data augmentation at layers 6 and 7 to reduce overfitting. The main concept of GoogleNet is to connect nine inception modules, which have a breadth structure and a classifier helper, to form a network structure with both breadth and depth. The ResNet18 network uses the concept of residual learning, which makes it easier for deep networks to achieve convergence after the training cycle. In this paper, MobileNet is a small, low-latency, low-power exponential model. In this multifaceted feature layer domain, owing to the different structures of neural networks, more diverse feature data will be generated, and the data diversity will be selected and fused to create a more stable and efficient sensing pool of labels, which can be categorized to produce better results.

The use of ReliefF is proposed to select the best features in this article.(12) The ReliefF algorithm provides an efficient feature selection method as described below.

The total number of feature datasets is taken to be M. We first set the number of class sets C and select K feature datasets H_i from the M feature datasets that are the most similar to the output target. Then, we select M_j from the K different class datasets and use the different weights to deduce the weights of the different features.

For the class labeling data of the sensed images in this paper, there will be a total of L data classes c = [c1, c2, ..., cL]. ReliefF first randomly selects an M_i sample from the training set and finds K approximations of Hi from the same class using H_j (j = 1, 2, ..., K). Then, K approximate samples of Hi are taken from different categories, denoted by $M_j(C)$ (j = 1, 2, ..., K). Repeat the above steps in each feature dimension and obtain the weight W of each feature as

$$W(A)=W(A)-\sum_{j=1}^{k}\frac{\mathrm{var}\left(A,M_i,H_j\right)}{d^*k}+\sum_{C\neq class(R_i)}\left[\frac{P(C)}{1-P\left(class\left(R_i\right)\right)}\times\sum_{j=1}^{k}\frac{\mathrm{var}\left(A,M_i,H_j\left(C\right)\right)}{d^*k}\right]. \tag{1}$$

In Eq. (1), d is the number of iterations. $P(C)$ is the probability that the category is C. var(A, S_1, S_2) represents the differential evaluation of samples S_1 and S_2 with respect to the set of features A and is calculated as

$$\operatorname{var}\left(A,S_1,S_2\right)=\begin{cases}\dfrac{S_1[A]-S_2[A]}{\max(A)-\min(A)}, & \text{IF } A \text{ is continuous}\\ 0, & \text{IF}\left(A \text{ is discrete}\right)\text{AND}\left(S_1[A]=S_2[A]\right)\\ 1. & \text{IF}\left(A \text{ is discrete}\right)\text{AND}\left(S_1[A]\neq S_2[A]\right)\end{cases} \tag{2}$$

In this work, different CNN feature extraction methods are individually selected by the ReliefF algorithm to generate important features, which are output as feature matrices. CCA will be used to complete the fusion of the output feature of two CNN models.(13) This is explained in the following analysis steps.

Let $\{x_i\}_{i=1}^{m} \in R^p$ and $\{y_i\}_{i=1}^{m} \in R^q$. This is the feature matrix generated by the two-by-two CNN model, composed of zero-mean vectors. The primary operation of CCA is to search two projection directions u_x and u_y. Therefore, the correlation between canonical variables $u_x^T x$ and $u_y^T y$ is maximized by

$$\rho\left(u_x,u_y\right)=\frac{\operatorname{cov}\left(u_x^T x,u_y^T y\right)}{\sqrt{\operatorname{var}\left(u_x^T x\right)\cdot \operatorname{var}\left(u_y^T y\right)}}=\frac{u_x^T\Sigma_{xy}u_y}{\sqrt{u_x^T\Sigma_{xx}u_x\cdot u_b^T\Sigma_{yy}u_y}}. \tag{3}$$

Here, Σ_{xx} and Σ_{yy} are internal-view covariance matrices and Σ_{xy} is the sight distance covariance matrix. The symbol T denotes a transpose operation. Since the correlation coefficient ρ is invariant to the scale of vectors u_x and u_y, the optimization model for CCA can be expressed as

$$\max u_x^T\Sigma_{xy}u_y,\ \text{s.t. } u_x^T\Sigma_{xx}u_x=1,\ u_y^T\Sigma_{yy}u_y=1. \tag{4}$$

The Lagrange multipliers are imported into Eq. (4) and the above problem is converted into a generalized eigenvalue problem (GEP) as

$$\begin{bmatrix}0 & \Sigma_{xy}\\ \Sigma_{xy}^T & 0\end{bmatrix}\begin{bmatrix}u_x\\ u_y\end{bmatrix}=\begin{bmatrix}\Sigma_{xx}^r & 0\\ 0 & \Sigma_{yy}^r\end{bmatrix}\begin{bmatrix}u_x\\ u_y\end{bmatrix}. \tag{5}$$

By solving this GEP using Eq. (5), we can obtain the projection vectors u_x and u_y.

3. Counterfeit Label Classification Methodology

3.1 Naive Bayes (NB) classifier

The classification layer in this study uses the Bayesian classifier, which is a machine learning model based on the chance model.(14) It is first assumed that each feature is independent of each other, and after computation, it can be inferred that the target exhibits the highest likelihood of occurrence under the specified conditions. The basic formula of the Bayesian theorem is

$$P(\text{class}|\text{data}) = \frac{P(\text{data}|\text{class})\,P(\text{class})}{P(\text{data})}. \tag{6}$$

We design a single NB classifier. For a particular feature, the target with the highest probability of event occurrence is set as $P(y_i|X_i)$, where $X_i = x_1, x_2, ..., x_n$, representing the individual features, and yi is one of the categories. y_i in $P(y_i|X_i)$ with the highest probability of occurrence is represented by y^*, which refers to the category that will ultimately be predicted, known as the maximum a posteriori probability (MAP). The formula for MAP is

$$y^* = \arg\max_{y_i \in y} P(y_i \mid x_1, x_2, ..., x_n). \tag{7}$$

Equation (7) can also be rewritten as

$$\begin{aligned} y^* &= \arg\max_{y_i \in y} \frac{P(x_1, x_2, ..., x_n \mid y_i)P(y_i)}{P(x_1, x_2, ..., x_n)} \\ &= \arg\max_{y_i \in y} P(x_1, x_2, ..., x_n \mid y_i)P(y_i). \end{aligned} \tag{8}$$

3.2 Support vector machine (SVM)

In this study, SVM is used as one of the final classification layers to perfectly partition two sets of data using a hyperplane,(14) whose mathematical equation is usually expressed as $w^T x + b = 0$. The goal is to find the optimal separation hyperplane (OSH) by calculating the parameters (w and b in the mathematical equation $w^T x + b = 0$). Therefore, SVM using the mathematical equation needs to satisfy

$$y_i\left(w^T x_i - b\right) \geq 1,\ \forall i = 1, \ldots, n. \tag{9}$$

SVM can be regarded as a solution to the optimization problem. To find the optimal hyperplane, it is necessary to find an extremely large value of the boundary $2/\|w\|$ separating the two classes, which is equivalent to minimizing the L_2 range of the weight vector *w*, as shown below.

$$\max_{w}\left\{2/\|w\|\right\} \rightarrow \min_{w}\frac{1}{2}w^{T}w,\ \text{subject to}\ y_i\left(w^{T}x_i+b\right)\geq 1,\quad \forall\ i=1,\ldots,n \tag{10}$$

The above Eq. (10) is the optimal solution for the hyperplane. The Lagrangian method is used to transform Eq. (10) to reduce the complexity of the high-dimensional solution process as

$$L_q\left(w,b,a\right)=\frac{1}{2}\|w\|^2-\sum_{i=1}^{N}a_i\left[y_i\left(w^{T}x_i-b\right)-1\right]. \tag{11}$$

The performance analysis after completing the categorization will be explained next.

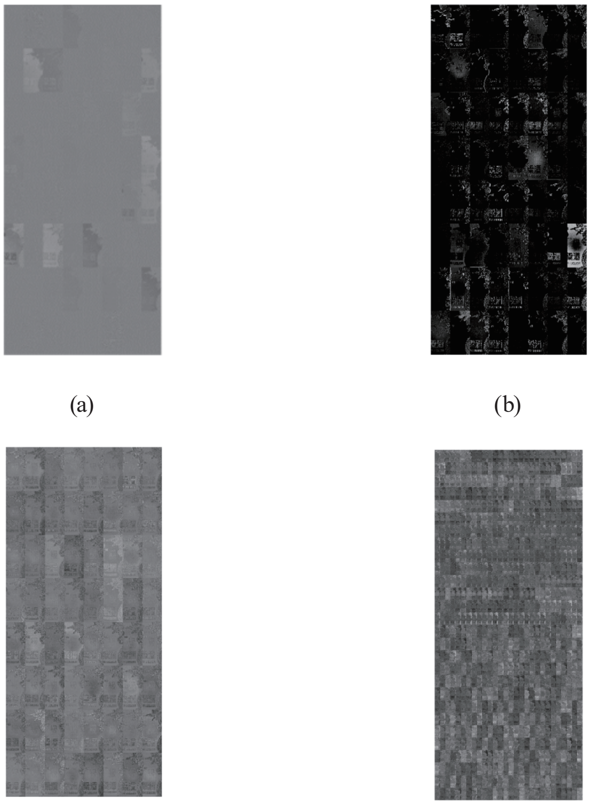
4. Label Recognition Model Testing and Performance Analysis

To verify the effectiveness and robustness of the proposed method, we adopt four CNN architectures, namely, ResNet18, AlexNet, GoogleNet, and MobileNet, to pretrain the model and extract visual features from the middle layer of the network. The comparative analysis of these feature combinations is also carried out. The computer platform used is Intel Corei7-10610U CPU @ 1.80 GHz and 16 GB of main memory. First, images of seven types of wine label are collected and the CNN model is used to extract the features.

In this study, representative images of wine labels from seven brands were captured using a smartphone. There are at least 150 image sensing samples for each brand; some examples are shown in Fig. 2. To enhance the accuracy during model training, the imageDataAugmenter() function in MATLAB was used for data augmentation. Specifically, the RandXReflection parameter randomly flipped images horizontally, the RandXTranslation parameter performed random horizontal translation, and the RandYTranslation parameter performed random vertical translation, thereby improving the overall robustness of the dataset.

A dynamic feature visualization experiment was conducted by selecting a single sensing image from the rightmost class in Fig. 2. This image was passed through multiple convolutional layers of AlexNet, and the corresponding feature maps are shown in Fig. 3, including (a) Conv1, (b) Pool2, (c) Conv5, and (d) Fc8 feature extraction results. The results clearly demonstrate that,

Fig. 2. (Color online) Collected sensing image dataset.



(a) (b)

(c) (d)

Fig. 3. (Color online) Results of dynamic feature visualization experiment of AlexNet. (a) Conv1 feature extraction. (b) Pool2 feature extraction. (c) Conv5 feature extraction. (d) Fc8 feature extraction.

as the network deepens, the features of the sensing image become increasingly segmented into a larger number of smaller pattern sets. Additionally, Fig. 4(c) illustrates the pixel value distribution of the features output by the Fc8 layer.

Similarly, the pixel value distributions produced by other CNN models are shown in Fig. 4: (a) ResNet18, (b) GoogleNet, (c) AlexNet, and (d) MobileNet. These correspond to the output values of the fc1000 layer in ResNet18, the loss3-classifier layer in GoogleNet, the fc8 in AlexNet and the Logits layer in MobileNet, respectively.

4.1 First experiment

Figure 4 presents the pixel value distributions for (a) ResNet18, (b) GoogleNet, (c) AlexNet, and (d) MobileNet, with each network model generating 1000 extracted features.

4.2 Second experiment

In the second experiment, the ReliefF algorithm was used to select 10 eigenvalues, and their distributions are plotted in Fig. 5 for (a) ResNet18, (b) GoogleNet, (c) AlexNet, and (d) MobileNet.

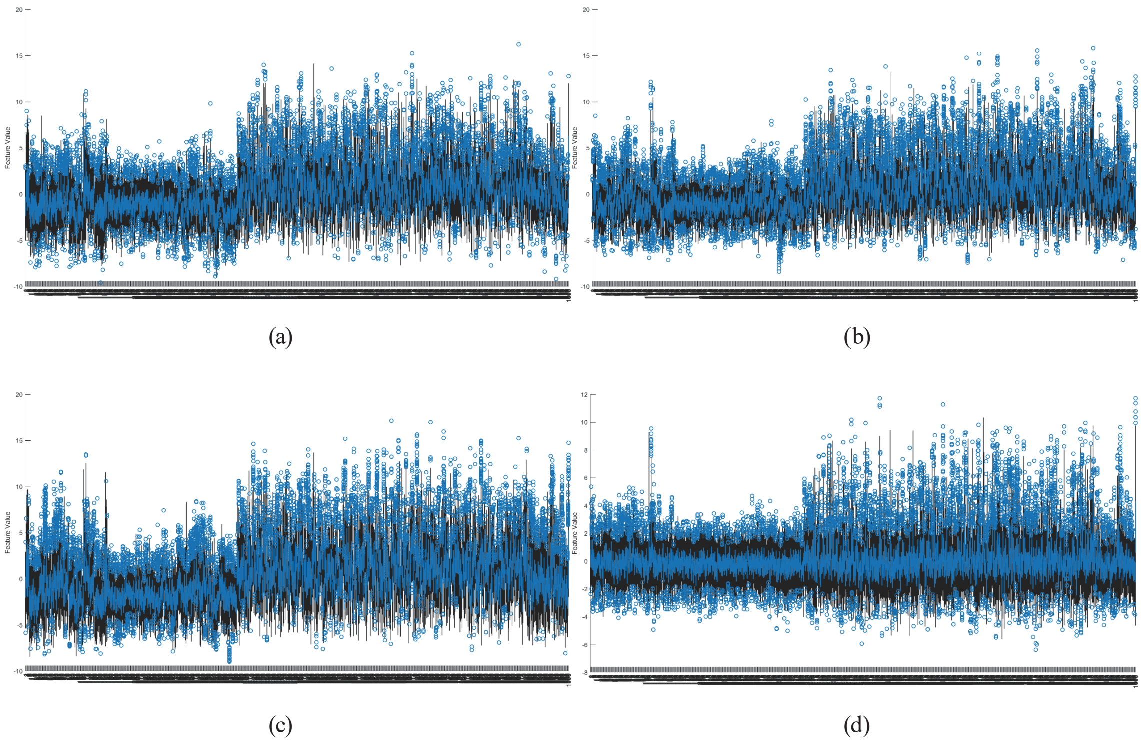


Fig. 4. (Color online) Distributions of eigenvalues captured by various CNN architectures. (a) Distribution of ResNet18 features. (b) Distribution of GoogleNet features. (c) Distribution of AlexNet features. (d) Distribution of MobileNet features.

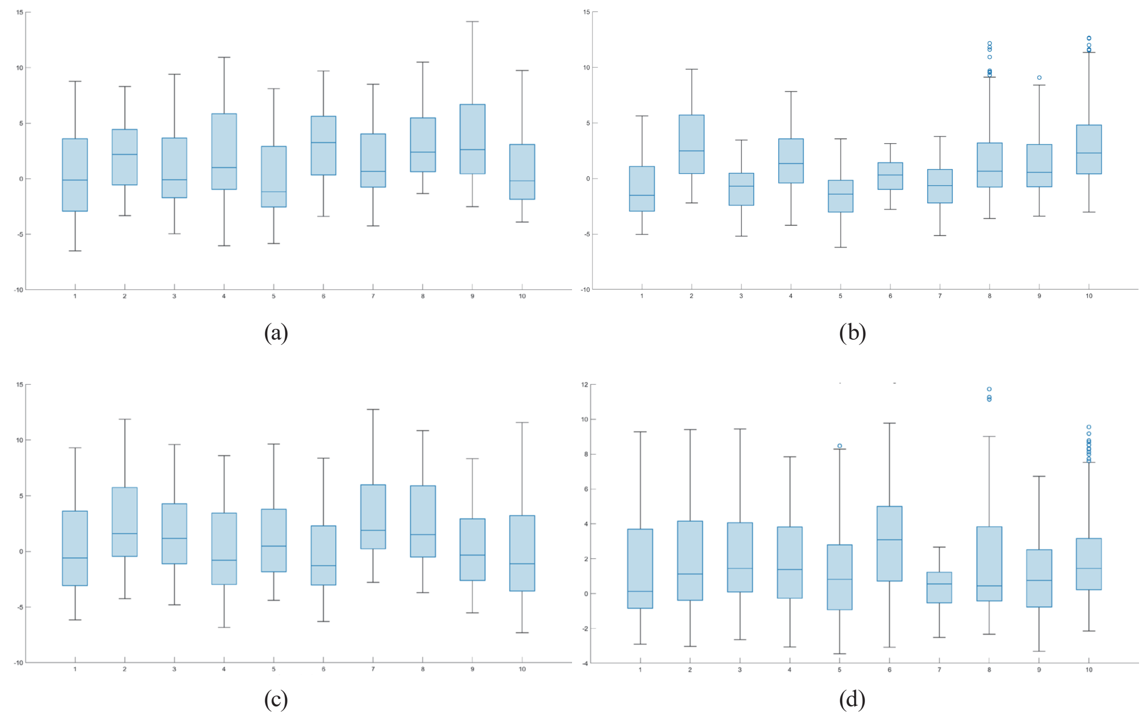


Fig. 5. (Color online) Distribution of the 10 features selected by each CNN architecture using ReliefF. (a) Distribution of ResNet18 features. (b) Distribution of GoogleNet features. (c) Distribution of AlexNet features. (d) Distribution of MobileNet features.

4.3 Third experiment

In the third experiment, CCA was used to fuse the above two models and add SVM or NB image classification. The final eigenvalues and the performances of the six groups—(1) RestNet18+GoogleNet+SVM, (2) RestNet18+GoogleNet+NB, (3) AlexNet+MobileNet+SVM, (4) AlexNet+MobileNet+NB, (5) AlexNet+GoogleNet+NB, and (6) AlexNet+GoogleNet+SVM—are shown in Fig. 6 and Table 1.

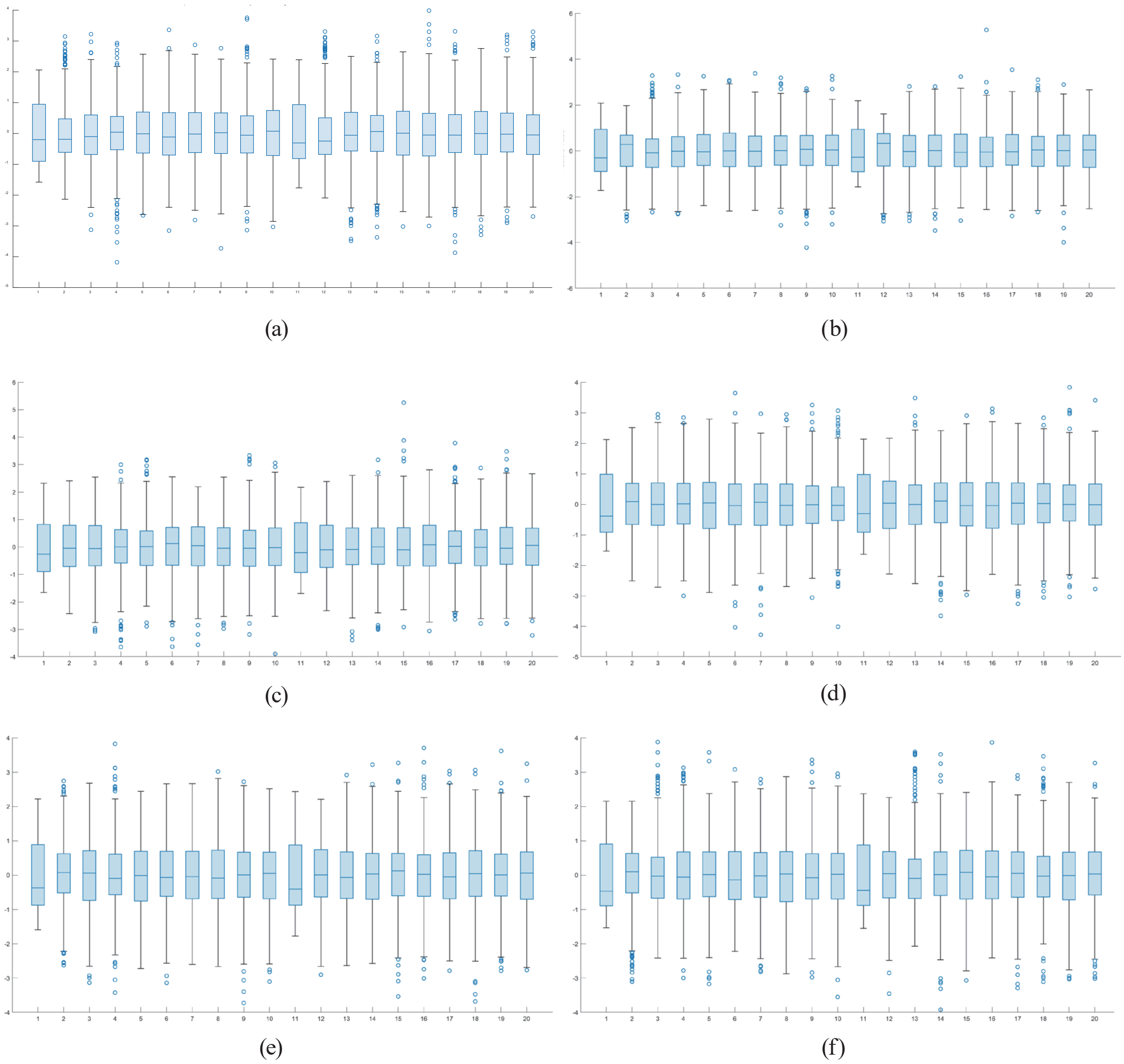


Fig. 6. (Color online) Distributions of eigenvalues of various CNN architectures fused by CCA. (a) Distribution of eigenvalues of RestNet18+GoogleNet+SVM through CCA fusion. (b) Distribution of eigenvalues of RestNet18+GoogleNet+NB through CCA fusion. (c) Distribution of eigenvalues of AlexNet+MobileNet+SVM through CCA fusion. (d) Distribution of eigenvalues of AlexNet+MobileNet+NB through CCA fusion. (e) Distribution of eigenvalues of AlexNet+GoogleNet+NB through CCA fusion. (f) Distribution of eigenvalues of AlexNet+GoogleNet+SVM through CCA fusion.

Table 1
SVM and NB classifier performance analyses of different CNN structures (N = Not used; Y = Used).

No.	CNN1	CNN2	Selection 1 ReliefF algorithm	Selection 2 ReliefF algorithm	CCA	Classification	No. of features	Accuracy
GA1	ResNet18		N		N	SVM	1000	99.5238
GA2		GoogleNet		N	N	SVM	1000	99.0476
GA3		GoogleNet		Y	N	SVM	10	88.0952
GA4	ResNet18		Y		N	SVM	10	90.4762
GA5	ResNet18	GoogleNet	Y	Y	Y	SVM	20	96.1905
GB1	ResNet18		N		N	NB	1000	96.1905
GB2		GoogleNet		N	N	NB	1000	95.2381
GB3		GoogleNet		Y	N	NB	10	84.2857
GB4	ResNet18		Y		N	NB	10	92.8571
GB5	ResNet18	GoogleNet	Y	Y	Y	NB	20	93.8095
GC1	Alex		N		N	NB	1000	97.1429
GC2		MobileNet		N	N	NB	1000	98.5714
GC3		MobileNet		Y	N	NB	10	84.7619
GC4	AlexNet		Y		N	NB	10	83.8095
GC5	AlexNet	MobileNet	Y	Y	Y	NB	20	91.0000
GD1	AlexNet		N		N	SVM	1000	99.5238
GD2		MobileNet		N	N	SVM	1000	99.0476
GD3		MobileNet		Y	N	SVM	10	89.0476
GD4	AlexNet		Y		N	SVM	10	90.4762
GD5	AlexNet	MobileNet	Y	Y	Y	SVM	20	94.7619
GE1	AlexNet		N		N	NB	1000	98.0952
GE2		GoogleNet		N	N	NB	1000	96.1905
GE3		GoogleNet		Y	N	NB	10	86.6667
GE4	AlexNet		Y		N	NB	10	85.7143
GE5	AlexNet	GoogleNet	Y	Y	Y	NB	20	93.3333
GF1	AlexNet		N		N	SVM	1000	99.5238
GF2		GoogleNet		N	N	SVM	1000	99.5238
GF3		GoogleNet		Y	N	SVM	10	89.0476
GF4	AlexNet					SVM	10	94.7619
GF5	AlexNet	GoogleNet	Y	Y	Y	SVM	20	99.0476

The experimental results show that the SVM classifier achieves better classification performance under consistent conditions. In terms of model combinations, the features extracted from AlexNet and GoogleNet were first reduced to the top 10 using the ReliefF algorithm. These selected features were then fused into 20 groups using CCA. The classification accuracy improved from 89.0476% for GoogleNet and 94.7619% for AlexNet (based on their respective original 10 feature groups) to 99.0476% after fusion. The highest performance (99.7619%) was achieved using 1000 feature groups.

Furthermore, by selecting and integrating 10 feature groups from each of GoogleNet and AlexNet, a classification accuracy of 99.0476% was achieved, which is very close to the best performance obtained using 1000 features (99.5238%). This demonstrates that the proposed feature selection and fusion approach can reduce the computational load to just 1/50 of the original, while maintaining nearly the same classification accuracy.

5. Conclusions and Future Work

In this study, the experimental analysis of fusion classification of wine label sensors was completed. The analysis results showed that the proposed AlexNet+GoogleNet+SVM plus ReliefF algorithm with the fusion of CCA reduced the original amount of feature data to 2%, but still achieved an accuracy as high as 99.0476%. In the case of the AlexNet+MobileNet+SVM plus ReliefF algorithm with CCA fusion, even though the AlexNet+MobileNet model alone was the worst SVM classifier, an accuracy of 94.7619% was obtained. Compared with the NB classifier, RestNt18+GoogleNet showed an accuracy of 93.8095%, and AlexNet+MobileNet model was less accurate at 91%. Overall, through the data selection and fusion procedures, high-accuracy classification results of more than 90% can be achieved. In response to the potential noise and blurred image features in smartphone-sensed images, exploring more robust data filtering, important feature selection, and data fusion techniques remains a potential research topic for us in the future.

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