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Review of Tobacco Leaf Maturity Discrimination Algorithms Using Machine Vision

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Abstract

As a key factor influencing the quality of tobacco production and a crucial indicator for assessing tobacco leaf quality, the recognition of tobacco leaf maturity has garnered significant attention from scholars. Integrating and advancing machine vision technologies in the discrimination of tobacco leaf maturity have made it feasible to apply machine vision in fully automated tobacco leaf harvesting processes. In this review, a comprehensive survey of the latest advancements on machine vision based algorithms for tobacco leaf maturity discrimination was presented, with a particular focus on feature engineering and classification algorithms. In terms of feature engineering, various image feature extraction techniques, analytical methods, and multi-feature fusion strategies for assessing tobacco leaf maturity were explored. These strategies included color and texture analysis, multispectral feature utilization, and advanced methods such as principal component analysis and information fusion. And a detailed discussion of the classification algorithms, spanning statistical recognition, machine learning and deep learning approaches was provided. By analyzing and comparing these existing methods, the study offered valuable insights into the advantages and limitations of various tobacco leaf maturity discrimination techniques. Results show that the accuracy of tobacco leaf maturity recognition using machine vision has reached an impressive 99.9%, establishing a significant milestone with clear practical application potential. Among the technologies applied, deep learning methods exhibit an absolute advantage, significantly outperforming traditional approaches in both feature engineering and classification methodologies. This comprehensive analysis summarizes current knowledge and points the way for future technological improvements and innovations.

Keywords: Precision agriculture, Recognition of tobacco leaf maturity, Machine vision, Image classification, Deep learning

1. Introduction

With the high economic value of tobacco products such as cigarettes, cigars, and pipes, the tobacco industry serves as a significant economic pillar in more than a dozen countries, including China, the United States, India, Indonesia, and Russia [1-4]. Tobacco leaves are the primary raw material of tobacco commodities and have a decisive impact on their economic value. The taste, aroma, and combustion performance of tobacco products depend on the quality of the tobacco leaves [5]. Generally, tobacco quality is determined by the appearance and physicochemical properties of tobacco leaves.

Among all production factors, the maturity status of tobacco leaves at harvest significantly affects their appearance, internal chemical composition, and sensory smoking qualities. Low total nitrogen and sugar content in tobacco leaves can lead to a lack of smoke and aroma, while high total nitrogen and sugar content can cause a burnt taste and a significant increase in tar content [6]. The chemical content of tobacco leaves is closely related to their maturity at harvest, as shown in Table 1 [7-8]. Mature tobacco leaves have a balanced chemical composition, including moderate levels of total nitrogen, nicotine, and sugar, allowing them to release smoke and aromatic compounds with appropriate physiological intensity and concentration during combustion. In contrast, immature tobacco leaves have lower total nitrogen and sugar content, resulting in insufficient smoke and aroma. Meanwhile, overripe tobacco leaves have excessively high total nitrogen and sugar content, leading to a burnt taste and a significant increase in tar content during combustion. Therefore, the accurate discrimination of the tobacco leaf maturity is considered one of the key methods to improve the quality of tobacco production.

Table 1. Chemical composition of tobacco leaves with various maturity

Maturity	Total nitro.	Prot. nitro.	Ammonia	Nicotine	Sugar	Starch
Immature	2.68	1.10	0.176	2.60	20.8	2.77
Mature	2.49	1.04	0.144	2.75	20.4	2.58
Overripe	2.44	0.98	0.124	2.95	18.5	2.54

Early studies primarily focused on mimicking the concept of manual judgment by extracting the appearance features of tobacco leaves and classifying them on the basis of these features. Findings show that mature tobacco leaves not only exhibit distinct color and texture characteristics in their appearance [9-10] but also undergo changes in their internal pigments, such as chlorophyll, lutein, and carotenoids, which can serve as indicators of their maturity [11]. These findings led to the development of maturity recognition methods based on infrared spectroscopy. With the advancement of machine learning technologies, algorithms such as the backpropagation neural network (BPNN) [12], support vector machine (SVM) [13], and random forest (RF) [14] were widely applied to the task of tobacco leaf maturity assessment. The adoption of these

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methods significantly enhanced the accuracy and efficiency of tobacco leaf maturity classification.

In recent years, deep learning models have achieved notable progress in the field of tobacco leaf maturity discrimination. Deep learning approaches, exemplified by convolutional neural networks (CNNs) [15], the MobileNet model [16], and object detection models [17-18], construct adaptive feature learning networks by leveraging large-scale data samples. Through high-performance computing units, these models can capture subtle features that are challenging for traditional machine learning techniques to recognize, thereby significantly improving discriminative performance.

The CiteSpace literature analysis tool [19] was used in this review to provide a more intuitive presentation of research progress in the field of tobacco leaf maturity discrimination. Searches were conducted in the core databases of China National Knowledge Infrastructure (CNKI) and Web of Science (WoS), where relevant research literature is relatively concentrated. The search time frame was from January 1, 1990, to November 30, 2024, using keywords such as "maturity tobacco classification," "maturity tobacco discrimination," "maturity tobacco identification," "maturity tobacco detection," and "maturity tobacco evaluation." Fig. 1 depicts the curve of the number of Chinese and English literature publications within this statistical search period. As shown in Fig. 1, the first Chinese literature in the field of tobacco leaf maturity discrimination was published in 2007, while the first English literature appeared in 2011. In 2013, the number of Chinese literature publications reached its first peak. Despite fluctuations in the number of articles published in both Chinese and English, the overall trend is upward. Since 2020, the publication volume of Chinese and English literature has increased considerably, indicating that studies on tobacco leaf maturity discrimination have garnered growing attention with the development of machine vision technology.

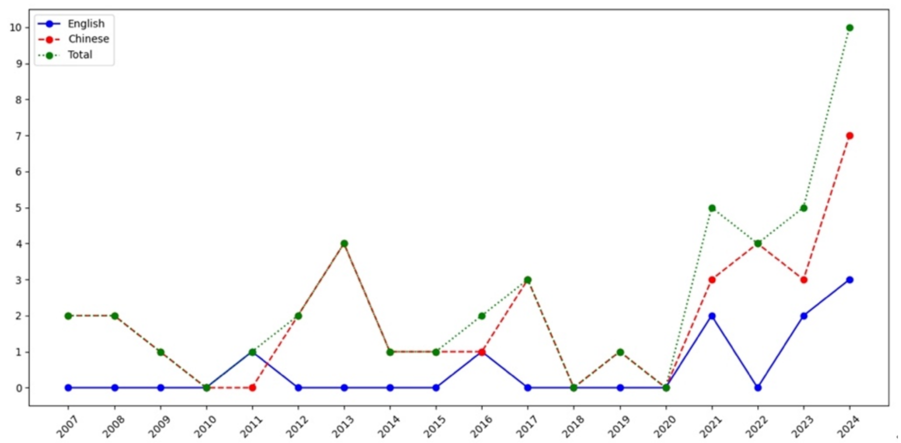
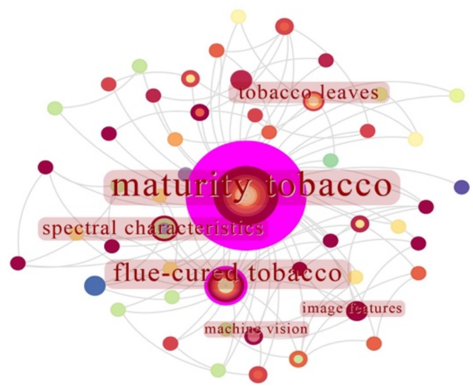


Fig. 1. Statistics of the number of Chinese and English publications



(a) The co-occurrence graph in CNKI.

(b) The co-occurrence graph in WoS.

Fig. 2. The co-occurrence graph of the keywords in the databases.

The co-occurrence graph of CNKI literature keywords comprises 54 nodes and 123 lines, as shown in Fig. 2a. The keyword "maturity tobacco" was the first keyword that was introduced and has the highest centrality, connected to 34 nodes. It is followed by "flue-cured tobacco" and "tobacco leaves," with frequencies of 12 and 7, respectively. The co-occurrence graph of WoS literature keywords consists of 44 nodes and 99 lines, as shown in Fig. 2b. Among the keywords, the term "deep learning" has the highest frequency of occurrence, suggesting that foreign studies on tobacco leaf maturity discrimination are primarily based on deep learning methods.

Given the absence of a comprehensive and detailed discussion on tobacco leaf maturity discrimination technology, this review systematically summarizes the major literature in the field of machine vision-based tobacco leaf maturity discrimination. Additionally, it examines pertinent research efforts within this domain. The review commences with an overview that encompasses two primary facets: feature engineering and classification methodologies. Then, it compares and analyzes existing studies, thereby summarizing the strengths and weaknesses of various approaches. Lastly, it prognosticates and deliberates upon forthcoming trends in the field of machine vision-based tobacco leaf maturity discrimination techniques.

2. Criteria and methods for judging the maturity of tobacco leaves

Tobacco leaf maturity discrimination is the process of evaluating the maturity status of tobacco leaves using various techniques, which subsequently categorizes the maturity levels. Traditionally, the determination of tobacco leaf maturity has largely relied on artificial experience, which is primarily based on the visual characteristics of the leaves. The process involves assessing the maturity status by considering several factors, including the length of time the leaves have been growing in various sections, the degree of yellowing on the leaves, the amount of curling at the leaf edges, changes in the main branches, the loss of leaf fuzz, and the conditions of the cross-sections during the harvesting phase [20]. The primary criteria for this assessment are outlined in Table 2.

Table 2. Maturity criteria for tobacco leaves

Maturity levels	Appearance characteristics of tobacco leaves
Green	The leaves are dark green to green, with no yellowing, the main veins are entirely green, and the hairs are still intact.
Immature	The leaves are green to light green, showing initial signs of yellowing. The main veins turn white from one-third to two-thirds, while the branch veins remain green, and there is minimal shedding of fuzz.
Still ripening	The leaves are transitioning from light green to yellow-green, with two-thirds of the main veins turning white to entirely white, and one-third to two-thirds of the branch veins turning white. Some fuzz has shed, and the leaf tips are starting to curl downward slightly.
Mature	The leaves are predominantly yellow-green, featuring less green and more yellow, appearing yellow to translucent white. The main veins are entirely white, adorned with bright white hair, and two-thirds or more of the branch veins turn white. Most of the fuzz has been shed, and the leaf surface is covered in yellow spots. The leaf tips and edges turn white, showing slight wilting, pointedness, and charring. The leaf tips are curled downward.
Overripe	Both the main and branch veins are completely white, adorned with bright white hair. The leaves exhibit yellow and transparent white bubbles, and most of the fuzz has fallen off. The leaves and ears are all yellow, and numerous patches resembling red star disease are present, with withered and sharp edges.

The criteria for human experience-based judgment are straightforward and easily comprehensible, featuring strong operational applicability and widespread implementation. The primary concept of machine vision-based tobacco leaf maturity discrimination aligns with manual evaluation, with its core discriminative process involving two essential steps: feature engineering and feature classification [21-22]. During the feature engineering phase, critical attributes that reflect tobacco leaf maturity are extracted through image analysis, encompassing color [23], texture [24], size [25], and internal pigment alterations [11]. The efficacy of feature engineering directly impacts the precision of subsequent maturity classification. In the feature classification stage, the leaves are categorized into corresponding maturity levels by utilizing machine learning or deep learning models. The synergistic integration of these two stages forms the cornerstone for ensuring the algorithm's efficiency and accuracy in maturity discrimination.

3. Feature engineering

The basic characteristics of tobacco leaves at the visual level mainly include color, texture, size, and internal pigment features. By utilizing a variety of feature analysis and extraction techniques, the external and internal characteristics of tobacco leaves can be effectively captured.

3.1 Feature analysis methods

Feature analysis serves as a supplementary approach to enhance the quality of feature extraction. By employing feature analysis, it is possible to select the most representative features of tobacco maturity from the available features. The commonly used feature analysis methods include principal component analysis (PCA) [26], variable clustering [27], correlation analysis [28], and function fitting.

3.1.1 PCA

PCA is used for feature dimensionality reduction, which transforms original data into a novel set of variables (termed principal components) via linear transformation. Its objective is to maintain the majority of the data's variance while minimizing its dimensionality. PCA is frequently employed to evaluate the strength and directionality of linear correlations between variables to pinpoint the most influential features on the basis of their contribution.

3.1.2 Variable clustering

Variable clustering is the process of grouping variables with similar characteristics or behaviors together. The method is instrumental in diminishing the dimensionality of variables while preserving their principal disparities, making it particularly advantageous for handling high-dimensional datasets. Common clustering algorithms include K-means and hierarchical clustering.

3.1.3 Correlation analysis

Correlation analysis gauges the magnitude and orientation of the linear association between two variables. By identifying and eliminating highly correlated features, this analytical approach not only curtails model complexity but also mitigates the risk of overfitting. Additionally, it facilitates a deeper comprehension of the linear interplays among variables. The Pearson correlation coefficient is the most frequently utilized metric among the various correlation measures.

3.1.4 Function fitting

The function fitting method is employed to select optimal parameter values within a function, ensuring the most accurate representation of a given dataset. This is achieved by assessing the correlation and contribution of features through mathematical modeling techniques. Commonly used function fitting methods include Gaussian fitting curves [29].

3.2 Color characteristics

Color is a crucial independent attribute in determining the maturity level of tobacco leaves. The color characteristics of tobacco leaves can be quantified using color space models. This model, which is essentially a mathematical framework, depicts color traits, defines their representation, and clarifies the interplay among various hues. By closely observing and analyzing this model, scholars can discern the connection between task objectives and specific colors, thereby enabling the extraction of pertinent color features. Commonly employed color space models in academic studies comprise the RGB color space; hue, saturation, intensity/hue, saturation, value (HSI/HSV) color space [30]; and CIELAB (Lab) color space [31].

3.2.1 RGB color space
The RGB color space is represented by three components: R, G, and B, with each component typically ranging from 0 to 255. The RGB color space has good linear properties, making the calculation of color mixing and transformation relatively simple. Liu Jianjun et al. [32] qualitatively analyzed the RGB variables related to maturity in tobacco images through Gaussian fitting curves of maturity distribution. They analyzed the red R, green G, blue B, R+G, R+B, G+B, R+G+B, and 'RGB color values' C=(65536 × Red)+(256 × Green)+(Blue) eight color features and found that the red R component had the best effect in processing the given eight maturity values.

3.2.2 HSI/HSV color space
The HSI and HSV color spaces are represented by four components: H, S, V, and I. For lighting changes, the hue and saturation in the HSI color space are relatively stable, which is useful in tobacco image processing tasks. Xie Binyao et al. [33] first analyzed the normal parameter features of 10 colors on the basis of RGB color space combined with image processing algorithms, namely, R+G+B, R+B, R+G, B+G, R-B, R-G, G-B, G-R, B-R, and B-G. The R, G, B, H, S, and V values of all sample images are calculated on the basis of the HSV color model. Except for B, all other color features can reflect the color changes of tobacco leaves during the maturation process. Shi Longfei et al. [34] used PCA to analyze H, S, and V values and found that the brightness I and saturation S of images with different maturity levels did not change significantly, indicating that the color tone H plays a dominant role in the maturity of tobacco leaves.

3.2.3 CIELAB (Lab) color space
The CIELAB (Lab) color space is a color space model based on human visual perception, which performs well in color perception and color management. S. Guru and P B. Mallikarjuna [35-36] used the CIELAB color space model to estimate the density and greenness of mature spots on leaves. Lu Xiaochong et al. [37] conducted maturity discrimination classification on the basis of the five color components of L, a, b and H, S in CIELAB (Lab) and HSI/HSV color space. Liu Hao et al. [38] used correlation analysis to analyze the color mean and several combination features 2G-R-B, R/G, G-R based on R, G, and B color matrices, as well as a */b * 10 features based on l * a * b * color matrices, on the basis of RGB and l * a * b * color spaces. The maturity of tobacco leaves can be determined by color characteristics R, a */b *, and l *. Shen Ping et al. [39] used Pearson correlation coefficient to analyze 21 color features, including mean, mode, median, kurtosis, and skewness of R, G, and B channel color levels, Lab color model parameters, and HSV color model parameters. They determined that R mean and B skewness had the highest participation in the tobacco leaf maturity correlation model. Lin Tianran et al. [40] added the mean, mode, median, kurtosis, and skewness features of grayscale images on the basis of Shen Ping's work and used Pearson correlation coefficient to determine the reliability of the features.

3.3 Texture features
The veins of tobacco leave exhibit unique texture characteristics at different maturity levels. Texture features are typically represented by texture matrices such as gray level co-occurrence matrix (GLCM) [41] and gray level run length matrix [42]. GLCM is one of the most commonly used methods in image texture analysis and is widely used to describe the distribution characteristics of grayscale pixel pairs in images.

GLCM describes texture features by calculating the co-occurrence frequency of grayscale values and grayscale values in a specific direction and distance in an image. The calculation formula is as Eqs. (1):

$$P(i,j)=\frac{GLCM(i,j)}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}GLCM(i,j)} \tag{1}$$

where N is the grayscale level of the image, $GLCM(\mathrm{i},j)$ is the number of occurrences of each grayscale value pair (i,j), and $P(i,j)$ is the probability of the occurrence of grayscale values pair (i,j).

GLCM can be used to capture spatial relationships in images and provide rich texture information. Multiple texture features can be extracted from normalized GLCM.

3.3.1 Contrast
Contrast reflects the intensity of local changes in an image, that is, the degree of unevenness in the grayscale values of the image. A high contrast value corresponds to high intensity of grayscale changes in the image. The calculation formula is:

$$Contrast=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2\cdot P(i,j) \tag{2}$$

3.3.2 Correlation
Correlation reflects the spatial correlation of grayscale values in an image, representing the linear dependence between adjacent pixels. It is calculated as follows:

$$Correlation=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)\cdot P(i,j)}{\sigma_i\sigma_j} \tag{3}$$

where μ_i and μ_j are the mean values of the rows and columns of the matrix, respectively, σ_i and σ_{j} are the standard deviations of the rows and columns of the matrix. The closer the correlation value is to 1 or −1, the stronger the spatial correlation of the grayscale values.

3.3.3 Energy
Energy, which is known as angular second moment, reflects the uniformity of an image, that is, the degree of concentration of the grayscale value distribution in the image. A high energy value corresponds to increased uniformity of the texture of the image. The calculation formula is:

$$Energy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j)^2 \tag{4}$$

3.3.4 Entropy
Entropy reflects the complexity of an image, that is, the uncertainty of the distribution of grayscale values in the image. A high entropy value corresponds to increased complexity of the texture of the image. The calculation formula is:

$$Entropy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j)\cdot \log(P(i,j)) \tag{5}$$

3.3.5 Homogeneity
Homogeneity, also known as inverse difference moment, reflects the degree of similarity in grayscale values in an image. A high homogeneity value corresponds to high similarity of the grayscale values in the image. The calculation formula is:

$$Homogeneity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P(i,j)}{1+|i-j|} \tag{6}$$

Shi Longfei et al. [34] analyzed five texture features(diagonal second moment, entropy, correlation, contrast, and offset) and found that these features can effectively describe the texture information of tobacco leaves at different maturity levels from different perspectives and better reflect the image texture changes of tobacco leaves during the maturation process. On this basis, Shen Ping et al. [39] and Xie Binyao et al. [33] introduced the inertia moment feature and reached similar conclusions. Lin Tianran et al. [40] conducted the same texture feature experiment on the basis of the work of Shen Ping et al. and obtained similar results. Liu Hao et al. [38] added a total of 10 texture features, including grayscale average, gradient average, grayscale non-uniformity, gradient non-uniformity, energy, grayscale entropy, and gradient entropy. Through cluster analysis, they found that the characterization effect of inertia moment and gradient non-uniformity on tobacco maturity is not significant.

3.4 Dimensional features
The size characteristics of tobacco leaves are closely related to their maturity and serves as crucial indicators for evaluating the maturity status of tobacco leaves. The size characteristics can be determined by the minimum bounding rectangle (MBR) [43]. MBR is a rectangle determined by the maximum horizontal axis, minimum horizontal axis, maximum vertical axis, and minimum vertical axis as boundary points. Lin Tianran et al. [40] used the long side of MBR to approximate leaf length (LL) and the short side of MBR to approximate leaf width (LW) and calculated the MBR area (S), target leaf width-to-length ratio (WL), and target leaf area ratio (SS). Correlation analysis found that the above size characteristics are significantly negatively correlated with maturity.

3.5 Internal pigment characteristics
The pigment content of the leaves is an important chemical criterion for evaluating the maturity of tobacco leaves [44-45]. Common methods for measuring internal pigment content include spectrophotometry [46], ratio vegetation index (RVI) [47], soil and plant analyzer development (SPAD) [48-49], and spectral curves [50].

3.5.1 Spectrophotometric method
The spectrophotometric method is an analytical technique that determines the concentration of a substance on the basis of its absorption of specific wavelengths of light. The principle is the Beer– Lambert law, which states that when a beam of monochromatic light passes through a solution, its absorbance is proportional to the concentration of the absorbing substance in the solution and the thickness of the liquid layer:

$$A = Ú \times c \times l \tag{7}$$

where A is the absorbance, c is the concentration of light-absorbing substances, U is the molar absorptivity, and l is the thickness of the liquid layer.

The concentration of the substance to be tested can be calculated by measuring the absorbance of the solution.

3.5.2 RVI
RVI is a remote sensing indicator used to estimate vegetation coverage and crop health status, which can be calculated by the reflectance ratio of near-infrared and red light bands:

$$RVI = \frac{Red}{NIR} \tag{8}$$

where NIR represents the reflectance in the near-infrared band, and Red represents the reflectance of the red light band.

3.5.3 SPAD
SPAD infers the chlorophyll content in leaves by measuring their light absorption capacity at specific wavelengths. Usually, SPAD instruments measure the absorption of light at wavelengths of 650 and 940 nm and calculate the SPAD value on the basis of these data.

Yu Zhihong et al. [47] used a spectrophotometer to measure the chlorophyll and carotenoid content of leaves and calculated the changes in all RVI analysis pigments composed of visible light and near-infrared bands. Gao Xianhui et al. [46] used spectrophotometry to determine the content of carotenoids and chlorophyll and then analyzed the pigment content through variance analysis and correlation analysis.

3.5.4 Spectral characteristics
The pigments inside the leaves exhibit different absorption, reflection and projection characteristics toward specific wavelengths of light. The content of pigments can be estimated by analyzing the spectral curve, thereby obtaining the maturity of tobacco leaves. According to different bands, spectral characteristics can be divided into visible light spectral characteristics, near-infrared spectral characteristics, and full band spectral characteristics.

1) Visible light spectral characteristics

The range of visible light is between 380–750 nm. Liang Yin et al. [51] extracted four spectral features from visible light reflection spectra and normalized visible light absorption spectra of tobacco leaves and measured the separability of the four spectral features and their pairwise combinations using J-M distance. They determined that the left half area of the chlorophyll absorption peak and the red edge position parameter were the two combinations with good separability. Diao Hang et al. [52] collected spectra of each selected leaf sample in the 350–780 nm wavelength range, selecting two points in the middle of the leaf surface and two points on both sides of the midrib, and repeating the collection three times for each point. The average of 12 spectra collected from four points of each tobacco leaf sample was taken as the reflectance spectrum of the tobacco leaf sample. A total of 431 points, visible light characteristic bands, and eight visible light spectral features (green peak amplitude, green peak position, red edge amplitude, blue edge amplitude, red edge area, blue edge area, red edge position, and blue edge position) were selected from the continuous spectrum of visible light as the final spectral features.

2) Near-infrared spectral characteristics

Light with a wavelength range between 750–1400 nm is near-infrared light. Fang Zhiwen et al. [53] collected near-infrared spectral data of 56 sets of tobacco leaf samples in the 2630–1000 nm wavelength range. Wang Chengwei et al. [54] collected 45 sample points in the 900–1700 nm wavelength range. Each sample avoids the main vein within the line of sight and takes six points on each side. Each point is measured three times, and the average is taken. The average of all points is taken as the representative spectrum of the tobacco leaf.

3) Full-band spectral characteristics

Li Xin et al. [55] extracted 448 spectral data in the 400–1000 nm wavelength range, divided them into 45 intervals, and then used genetic algorithm to select 19 intervals as the final spectral features. Lu et al. [56] used PCA to extract 22 sets of full-band spectral features in the 400–1000 nm wavelength range. Deng Jianqiang et al. [57] used the average spectral reflectance of all pixels in the region of interest region of a multispectral image as the spectral reflectance feature point of tobacco leaves.

In the visual images of tobacco leaves, features such as color, texture, size, and leaf pigments provide a unique and high-resolution basis for classification, as shown in Table 3. Specifically, scholars commonly use three types of features to characterize maturity: color, texture, and spectral features.

Table 3. Comparison of feature extraction methods

Features	Feature extraction methods	Description of the leaf
Color	Characteristics color space models	Color distribution
Texture	GLCM	Image structure
Size	MBR	Size of the leaf
Internal features	Spectral characteristics	Concentration of internal pigments in tobacco leaves

By comparison, features such as color and texture are susceptible to human factors and external environmental interference. In contrast, discrimination based on internal pigment features shows robustness against external environmental influences and improves discrimination accuracy to a certain extent. However, acquiring spectral characteristics requires expensive specialized equipment, which significantly hinders their practical application.

3.6 Multi-source feature fusion

Fusing these features can obtain stronger maturity representations because of the commonality of color, texture, and spectral features. Wang Qiang et al. [58] extracted the HSV values of tobacco leaves and established an HSV chlorophyll PAD relationship model. A tobacco maturity discrimination model was briefly established by using this model. Pei Wencan et al. [59] first constructed a fresh tobacco leaf SPAD value prediction model based on 19 dimensions of color feature data, including third-order color moments and yellowing rates of each component in the RGB and HSV color spaces, as well as texture feature data in four dimensions, namely, ENE, CON, CORR, and HOM, for a total of 23 color and texture features. Then, a maturity recognition model was constructed on the basis of SPAD values, and the accuracy of maturity recognition was improved by adding SPAD values. Yang Rui et al. [60] used PCA to analyze a total of 30 fused features, including the mean, standard deviation, ENE, ENT, MOI, COR, and 20 color and texture features of H, S, and V, as well as the full band parameters of near-infrared spectra (920–2400 nm).

For tobacco images, feature extraction based on visual level can significantly enhance the ability to represent the maturity level. Visual perception has always been an important basis for early manual judgment of tobacco maturity. With the development of machine vision technology, existing methods quantify the appearance characteristics of tobacco leaves on the basis of artificial sensory perception. These features come from visible light images and hyperspectral images, both of which can clearly display the characteristics of maturity. Studies have shown that the accuracy of tobacco leaf maturity recognition can be significantly improved through multi-source feature fusion.

4. Classification methods

The determination of tobacco maturity belongs to the task of image classification. The methods used can be classified into three categories: statistical recognition, machine learning, and deep learning methods.

4.1 Statistical recognition methods

Statistical recognition methods refer to a set of image classification techniques based on statistical principles, which classify data samples by analyzing their statistical characteristics. The methods are based on probability theory and statistical inference. Mathematical models such as partial least squares analysis [61] and Fisher's linear discriminant [62] are used to make objective classification decisions.

Liu Jianjun et al. [32] converted the obtained tobacco leaf characteristics into maturity values between 0–10 on the basis of artificial sensory judgment criteria and used the TRIMMEAN function to perform extremum removal and mean processing to obtain the maturity level of the entire fresh tobacco leaf. D. S. Guru and P B. Mallikarjuna [35-36] judged the maturity of tobacco leaves by the density of mature spots on the leaves and the greenness of the leaves. Wang Qiang et al. [58] established a TMDHSV tobacco maturity discrimination function relationship model by using the relationship between maturity and SPAD values. Lu et al. [56] established a least squares discriminant analysis model for 22 full-band spectral characteristic bands, with accuracies of 99.32% and 98.46% on the correction and prediction sets, respectively. Gao Xianhui et al. [46] constructed a maturity level function using Fisher's linear discriminant analysis. They substituted three color value indicators of unknown maturity levels into each discriminant function and calculated the function values. The function value with the highest value indicates which maturity level the fresh tobacco belongs to. Yu Zhihong et al. [47] constructed a tobacco leaf maturity classification model based on the relationship between the RVI and chlorophyll content, and the correlation coefficient of the model was as high as 0.9029.

Statistical identification methods can utilize various statistical analysis tools and techniques for data processing and classification, as well as establish mathematical models for objective classification, adapting to different scenarios and needs, with strong interpretability.

4.2 Machine learning methods

Machine learning is a branch of artificial intelligence that learns patterns and relationships from data through algorithms, enabling computers to make decisions or predictions without explicit programming. Machine learning methods have a wide range of applications in various fields, including but not limited to natural language processing, computer vision, and medical diagnosis.

In the task of tobacco maturity discrimination, BPNN [12], SVM [13], RF [14], clustering analysis [63], extreme learning machine (ELM) [64], and XGBoost [65] are the most commonly used classification methods. BPNN is widely used for classifying the color, texture, and size features of tobacco leaves, while SVM is more commonly used for classifying internal pigment features.

4.2.1 BP neural network

BPNN is a multilayer feedforward neural network that consists of an input layer, one or more hidden layers, and an output layer, which has strong nonlinear mapping ability. The input layer is the starting point of the BPNN, responsible for receiving external data. Each neuron corresponds to a feature value, and data enter the network through these neurons. The input layer has no computing function and only serves as a channel for data transmission. The hidden layer is the core of the BPNN, responsible for extracting features from input data and performing nonlinear transformations. Each hidden layer is composed of multiple neurons, each of which computes a weighted sum of the outputs from the previous layer and transforms them through an activation function. The choice of activation function has a significant effect on network performance. The output layer is the endpoint of the BPNN, responsible for generating the final prediction results. For classification problems, the output layer typically uses the softmax activation function. The network structure is shown in Fig. 3.

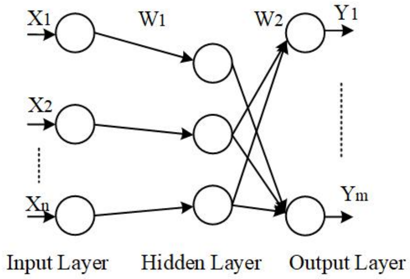


Fig. 3. BPNN structure diagram

Color, texture, and size features typically contain many nonlinear relationships. A BPNN can handle such complex data relationships well because of its powerful nonlinear mapping ability. Through the learning of multiple layers of neurons, it captures complex patterns in the data. In addition, when a network has many layers or a large amount of data, the training cost of BPNN is large. However, for the classification of color, texture, and size features, this computational cost is acceptable because of the richness of image data. In Literatures [34], [37], [39], and [40] BPNNs were used to classify tobacco leaf maturity with an accuracy of more than 90%.

4.2.2 Support vector machine

SVM is a supervised learning model that is primarily used for classification and regression analysis. For linearly separable binary classification problems, the dataset consists of feature vectors and labels. The goal of SVM is to find a hyperplane that correctly classifies data points of different categories and maximizes the classification interval. For a sample, its distance to the hyperplane is:

$$\frac{|w \cdot xi + b|}{\|w\|} \tag{9}$$

The distance needs to be minimized to maximize the classification accuracy. Therefore, the optimization problem can be expressed as:

$$\min_{w,b} \frac{1}{2}\|w\|^2 = subject\,to\; y_i(w \cdot x_i + b) \geq 1, \forall i \tag{10}$$

where w is a vector that represents the normal vector of the hyperplane, and b is a bias term that determines the position of the hyperplane.

Spectral features are the most important characteristic of internal pigment features. SVM is often used in tobacco leaf maturity discrimination tasks based on spectral features because of the strong linear separability between spectral features. In addition, SVM selects the optimal hyperplane by maximizing the classification margin, which enables it to achieve good performance even in small sample situations, which is particularly important for spectral data classification. In Literatures [51], [52], [55], [56], and [57], SVM was employed to classify features, achieving a classification accuracy of more than 90%. Liu Hao et al. and Xie Binyao et al. conducted comparative experiments using BPNN and SVM, respectively, and found that SVM had better discrimination performance, with discrimination accuracies of 92.00% and 97.53%, respectively.

4.2.3 Random forest

RF is an ensemble learning method that constructs multiple decision trees and makes final decisions through voting or averaging. It can improve the accuracy and robustness of the model.

Yang Rui et al. [60] used RF to construct a discriminative model for multi-source feature data reduced by PCA. For each bootstrap sample, an unmodified classification tree was constructed and optimized. Randomly selecting the number of variables at each node and obtaining the optimal separation ratio ensure that the construction of each tree has the characteristics of training samples and random selection. Wang Chengwei et al. [54] conducted detection based on SVM and RF and found that RF had the best discrimination effect, with a high prediction accuracy of more than 90% for upper, middle, and lower leaves.

4.2.4 Cluster analysis
Cluster analysis is an unsupervised learning method used to group data points in a dataset into several clusters, such that data points within the same cluster have high similarity, while data points between different clusters have low similarity. In the case of a large amount of data, cluster analysis can improve the efficiency of data classification. Fang Zhiwen et al. [53] used systematic clustering analysis to perform binary classification on tobacco samples of different maturity levels, achieving an accuracy rate of 92.86%.

4.2.5 Extreme learning machine
ELM is a simple and fast feedforward neural network learning algorithm that not only has extremely fast computation speed but also does not fall into local optima. The parameter selection of ELM is simple. Selecting only appropriate hidden layer nodes can achieve good performance. Traditional gradient descent algorithms such as BP networks require selecting appropriate learning rates and training steps, yet improper selection can affect the generalization of the network. Wang Jie et al. [66] used ELM to discriminate 60 dimensional color features analyzed by PCA, achieving an accuracy of 96.43%, which is better than that of SVM and BP neural networks.

4.2.6 XGBoost
The XGBoost algorithm is a supervised ensemble machine learning algorithm implemented on the basis of the concept of gradient boosting, where the constructed model is integrated from multiple tree models (or linear models) based on the boosting method. They undergo multiple iterations during the construction process, with each iteration adding a new weak learner. The weak learner generated by the iteration trains and fits the performance of the existing weak learners and finally integrates all weak learners into one strong learner, that is, the output of all weak learners is superimposed as the final prediction result of the model. Pei Wencan et al. [59] found that both feature data and type data are floating-point types. Therefore, XGBoost was selected to build a maturity and SPAD value correlation model, with an F1 score of 95.27%.

Unlike statistical recognition methods, machine learning methods can handle high-dimensional data and complex nonlinear relationships, have good scalability, and can handle larger datasets by increasing computational resources. In tobacco leaf maturity discrimination, machine learning-based methods can achieve high accuracy and efficiency with appropriate feature data support and have become the mainstream classification method in this field.

4.3 Deep learning methods
Deep learning is a subfield of machine learning that simulates the way the human brain processes information by building multiple layers of neural networks. Deep learning can automatically extract features from original data without the need for manual feature selection and extraction. This feature ensures that deep learning performs well in processing complex data such as images, speech, and text. Deep learning has also made many achievements in the field of crop image classification. Sparse autoencoder, CNN [15], residual network (ResNet) [67], You Only Look Once (YOLO) series of models [17-18], and MobileNet series of models [16] are the most commonly used deep learning methods in image classification studies.

4.3.1 Sparse autoencoder
Sparse autoencoder is mainly used for unsupervised learning. The hidden layers of the model are made sparser when representing data by learning the compressed representation (i.e., encoding) of data and introducing sparsity constraints, thereby extracting more meaningful features. Wang Jie et al. [68] used a sparse autoencoder to classify the maturity of tobacco images, achieving an accuracy of 98.63%.

4.3.2 Convolutional neural network
CNN is a deep learning model specifically designed for processing data with grid structures, such as images and audio. It is widely used in computer vision tasks such as image recognition, object detection, and image segmentation. The core network layers of CNN include convolutional layer, pooling layer, fully connected layer, and batch normalization (BN) layer.

Convolutional layer is the core part of CNN and is used to extract local features from input data. The convolutional layer convolves the input image using a convolutional kernel (or filter) to generate a feature map. A convolutional kernel is a small weight matrix used to detect specific patterns in an image. Each convolution kernel slides (or scans) on the input image, performs dot product operation on each position, generates a scalar value, and finally forms a feature map. Multiple types of local features can be extracted through multiple different convolution kernels.

The pooling layer is usually located after the convolutional layer and is employed to reduce the spatial dimension of the feature map, decrease computational complexity, and model parameters. The most common pooling methods are max pooling and average pooling. Max pooling selects the maximum value within a small region of the feature map, while average pooling selects the average value of that region. Through the pooling layer, important features can be retained while reducing the size of the feature map and improving the robustness of the model.

The fully connected layer is usually located in the last few layers of the network and is used to comprehensively process the features extracted from the previous layers and output the final classification result. Each neuron in the fully connected layer is connected to all neurons in the previous layer. Learning the weight matrix transforms the feature map into a fixed-size vector for classification or regression tasks. The output of the fully connected layer can be converted into a probability distribution using functions such as softmax, which can be used for multiple classification tasks.

The BN layer is employed to accelerate the training process and improve the stability of the model. BN reduces internal covariate shift and makes the training process more stable by normalizing the activation values on each batch of data. BN layers are usually located after convolutional or fully connected layers and used in conjunction with activation functions to significantly improve the training efficiency and accuracy of the model.

The CNN structure forms a powerful feature extraction and classification model through the combination of the above layers. Each layer undertakes specific tasks, working together on input data, gradually extracting high-level features, and ultimately completing classification or other tasks.

Chen et al. [69] used CNN to extract and classify features from near-infrared spectral images and constructed a tobacco leaf maturity identification model. The model achieved identification accuracies of 96.18%, 95.2%, and 97.31% at three different leaf positions, respectively. Wu et al. [70] used a three-dimensional CNN architecture to extract spectral and spatial features from 150 raw hyperspectral images, and the average accuracy of the model reached 99.93%.

4.3.3 Residual network
A residual block is a core component of ResNet, designed to address degradation issues in deep neural network training. Its main feature is that it achieves residual learning by introducing skip connections, allowing the network to learn the residuals (i.e., differences) between input and output, rather than directly learning the mapping from input to output. The ResNet network structure is shown in Fig. 4.

ResNet allows the feature matrix to be added in layers, where *F(X)* is the result obtained through two convolutional layers, and *X* is the original feature matrix. The so-called addition is the addition of numbers at the same position in the feature matrix. The added matrix as input can effectively solve the problem of deep network degradation and improve the depth of the network.

Sun et al. [71] designed a semi-supervised learning framework on the basis of the ResNet50 backbone network and combined with maturity structure constraints. This framework only needs to label 25% of tobacco leaf samples to achieve the same recognition accuracy as supervised learning.

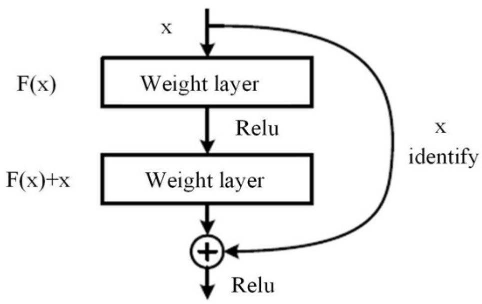


Fig. 4. ResNet network structure

4.3.4 YOLO series models
The YOLO series of models are a set of object detection algorithms that are popular in the field of computer vision for their high efficiency and real-time performance. The object detection algorithm includes two parts: image classification and object detection. It can select and classify multiple objects from the image. For fresh tobacco leaves in situ in the field, the object detection algorithm has high practicality.

The YOLO series has been updated to YOLO v9 so far. YOLOv5 is one of the most widely studied and applied models in the series. The network structure of YOLOv5 consists of four main parts: input, backbone, neck, and head. The input includes mosaic data augmentation, image size processing, and adaptive anchor box algorithm. The backbone includes the focus module, which performs slicing operations on the original image size set by this model, and then connects them through concat operation. Feature maps downsampled by 8, 16, and 32 times are used as the feature layers of the detection target, improving the detection speed. The neck layer integrates extracted semantic and positional features, while the backbone layer and detection layer enrich the model’s feature information. The head outputs the category probability, score situation, and bounding box position information vector of the detected object.

Wang Ruiqi et al. [72] introduced the lightweight object detection model YOLOv5s to recognize the maturity of fresh tobacco leaves, and the mAP values in all three tobacco leaf part models reached 0.9 or above.

4.3.5 MobileNet series models
The MobileNet series of models are a set of lightweight CNN models designed specifically for mobile devices and embedded systems, aiming to provide efficient performance and lower computational complexity. The MobileNet series currently has three versions: MobileNet v1, v2, and v3. These network structures are centered around depthwise separable convolutions, which optimize the network structure and reduce the number of parameters to achieve efficient model operation, making them particularly suitable for resource-constrained devices. For fresh tobacco leaves in the field, the MobileNet model has strong scene adaptability and is convenient for embedded applications in agricultural machinery.

Li Junxian et al. [73] designed a lightweight tobacco leaf maturity discrimination model based on the MobileNetv2 structure, which reduces the model size and number of operations compared with other classical deep learning models. Zhang Y. et al. [74] proposed a field in-situ tobacco leaf maturity discrimination model that combines feature pyramid network, attention mechanism, and MobileNetv1. This model has high robustness in complex environments.

The biggest advantage of deep learning methods over the previous two methods is that they can learn more thorough and abstract feature details through complex neural networks and have stronger feature extraction capabilities in structurally complex images.

The characteristic comparison of the above tobacco maturity classification methods is shown in Table 4. The statistical recognition method has strong interpretability and can achieve good classification results in small sample tobacco leaf discrimination. Machine learning methods, with their powerful feature processing and classification capabilities, have become the cornerstone models for many scholars. Deep learning methods have demonstrated powerful feature extraction and complex pattern recognition capabilities, but studies in the field of tobacco maturity discrimination are still in their infancy. The main reason may be related to the sample size of the tobacco maturity discrimination task and the current development status in the field. However, with the advancement of information technology and the continuous deepening of studies, the potential application of deep learning methods in the field of tobacco maturity discrimination cannot be ignored, and it may usher in a wider range of applications and developments in the future.

Table 4. Comparison of classification methods

Methods	Applicable features	Characteristics
Statistical recognition	Low-dimensional, structured, and highly interpretable features	High computational efficiency, strong interpretability, and high requirements for features
Machine learning	Structured and unstructured features	Strong flexibility, requiring feature engineering and diverse models

Deep learning	High-dimensional, unstructured, and complex features	End-to-end learning; complex features require high data volume and consume significant computational resources

5. Conclusions and Future Directions

5.1 Conclusions

The review summarizes the studies on tobacco leaf maturity discrimination based on machine vision, providing a comprehensive overview from the aspects of feature engineering and classification methods. In terms of feature selection, multispectral image features exhibit the advantage of being less susceptible to human factors and external environmental influences compared to color and texture features, though they require costly equipment to acquire the necessary data. In terms of classification methods, machine learning approaches, unlike statistical methods, do not require prior knowledge and have gained widespread application in the field of tobacco leaf maturity classification, demonstrating superior performance in handling nonlinear and medium-scale batch classification tasks. As an emerging approach, deep learning methods eliminate the need for feature engineering, enabling the completion of maturity discrimination tasks with a single deep learning model. However, to achieve optimal performance, large-scale sample datasets are required in deep learning, which is a challenge that currently remains unmet. In conclusion, machine vision technology shows broad application prospects and research potential in the field of tobacco leaf maturity discrimination, yet further research and technological innovations are essential to enhance the accuracy and practicality of tobacco leaf maturity identification systems.

5.2 Future directions

In summary, future studies on tobacco leaf maturity discrimination can focus on two key areas.

First, a comprehensive tobacco leaf sample dataset needs to be developed. Currently, the majority of studies utilize samples sourced from a single variety, specific harvest year, and limited in quantity. Both traditional machine learning and deep learning methods often suffer from insufficient sample sizes. Establishing a large-scale and diverse tobacco leaf sample database is crucial for enhancing model robustness, reducing overfitting, and widening the scope of practical applications.

Second, integrating multi-domain feature fusion inputs is critical. Beyond visual features, data related to tobacco growth—such as cultivation practices, transplanting schedules, topping timings, and fertilization records—should be incorporated as supplemental feature data. These variables exhibit a strong correlation with tobacco leaf maturity and can significantly enhance the accuracy and practical application of machine vision technology in assessing tobacco leaf maturity.

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