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Comparing ANN and Other Machine Learning Algorithms in the Study of Feature Classification Based on Multi-spectral Remote Sensing

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Abstract. Due to the complexity and diversity of features, accurately recognizing their classification accuracy is significant for remote sensing data processing. Machine learning algorithms have high accuracy and can be applied to a variety of classification problems, providing excellent solutions to the problem of feature classification. In order to achieve fast and accurate classification of features and screen out the best model, this paper takes forests and airplanes as an example and compares and analyzes the accuracy effects of Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN) and AdaBoost (Adaptive Boosting) on feature classification based on multi-spectral remote sensing images collected by aerial. The results show that among the four models, SVM has the highest average accuracy, the best stability, and the fastest solution time, and can be used as the optimal model. ANN and AdaBoost are the next best, and RF is the worst. This paper can provide reference and guidance for feature classification model selection.

Keywords: Multi-spectral; machine learning; feature classification.

1. Introduction

Multi-spectral telemetry is a technology that utilizes multi-spectral photographic systems or multi-spectral scanning systems to perform simultaneous photographic telemetry on different spectral bands of the electromagnetic spectrum and obtain images of vegetation and other features in different spectral bands. Multispectral telemetry can not only identify the features according to the differences in the morphology and structure of the images but also according to the differences in the spectral characteristics, which enlarges the amount of information in telemetry. The multispectral photography used for aerial photography and the multispectral scanning used for land satellites can obtain telemetry information in different spectral bands. The images or data in the spectral bands can be processed by photographic color synthesis or computer image processing, which can obtain richer images than the conventional methods, and also provide possibilities for the identification and classification of the feature images through computers.

In recent years, the continuous development and improvement of multispectral telemetry technology makes it widely used in civil fields such as environmental monitoring [1], urban planning, land use, geological exploration, major disaster detection, medical diagnosis and auxiliary treatment, nondestructive testing of substances, identification of pests and diseases, anticounterfeiting identification of banknotes, and detection of hidden objects. In addition, multispectral telemetry technology has been emphasized in the military field of battlefield environment monitoring as well as key target reconnaissance and combating.

At present, the main methods for feature classification using UAV multispectral images include traditional supervised classification and unsupervised classification [2], object-oriented image classification, machine learning classification and deep learning classification [3]. Among them, machine learning plays a crucial role in the classification of multispectral remote sensing images. Yang Shu Qin et al. optimized Deeplab V3+ based on UAV multispectral images using deep semantic segmentation algorithm and used it for field crop classification, and the optimized result improved the classification accuracy by 17.75% relative to SVM [4]; Yang Hongyan et al. classified the vegetation of desert grassland based on human-computer multispectral images by using RF method, which made the overall classification accuracy reach 91.06%, achieving more excellent results [5]. In addition, other algorithms in the field of machine learning, such as AdaBoost, are also instructive for the study of multispectral imagery. The AdaBoost model is very flexible in that it can be used to construct weak classifiers using a variety of regression classification models. AdaBoost has a very high accuracy, and the training error decreases at an exponential rate. Compared with the bagging algorithm and RF algorithm, AdaBoost considers each classifier's weight. At present, the classification of multispectral remote sensing images based on the AdaBoost algorithm is rare, and the discussion of the comparison cases with the accuracy of other algorithms is rarely reported.

In this paper, we utilize multi-spectral remote sensing images collected by air, and the collected images are subjected to feature extraction and PCA dimensionality reduction. On this basis, SVM, ANN, RF, AdaBoost and other algorithms are used to classify the unknown features, calculate the accuracy of different algorithms, compare the advantages and disadvantages of the algorithms, and screen out the best algorithm.

2. Method

2.1. Data sources and data processing

2.1.1. Feature extraction

The image datasets in this paper are airplane and forest. Each dataset has 100 image data (Fig. 1), in order to be able to transform the image data into data that can be used in machine learning methods, the features of the images need to be extracted. In extracting the pixel features, two types of features are extracted using color and texture, for color features are extracted by converting the image into HSV color space with Hue histogram, Saturation histogram and Value histogram. The above three histograms are converted into one-dimensional vectors and stitched together as color features for this data. For texture features, the GLCM method is used to calculate the Contrast, which describes the degree of difference between gray levels; Energy, which indicates the uniformity of the statistical distribution of textures in an image; Correlation, which measures the linear correlation of textures in an image; Homogeneity, which means the homogeneity of textures in an image; and the GLCM method, which is used for the calculation of texture features in an image. Homogeneity): used to represent the local consistency of the texture. These four features are transformed into one-dimensional vectors and stitched together as texture features of this data.

Fig. 1. Examples of the data sets

Fig. 2 and Fig.3 show the HSV color space made from one image each of the two datasets of aircraft and forest, with Hue histogram, Saturation histogram and Saturation histogram. It can be seen that there are some differences between the histograms of different categories, for example, the Hue histogram is the most obvious, the distribution of the forest's hue is more average, while the aircraft's hue distribution has a low numerical magnitude.

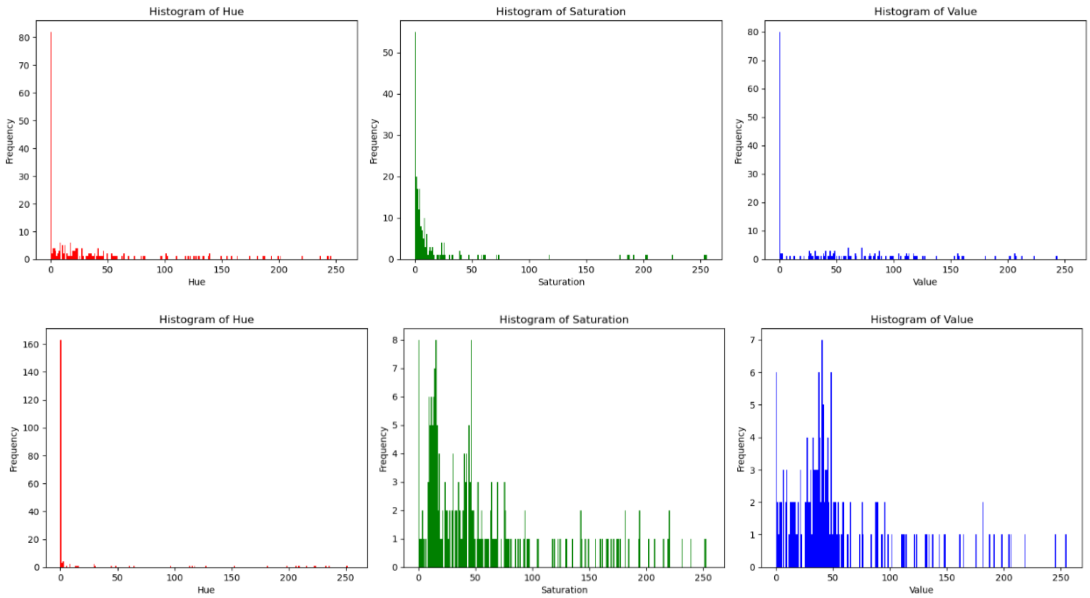

Fig. 2. Histogram of HSV color space of aircraft dataset

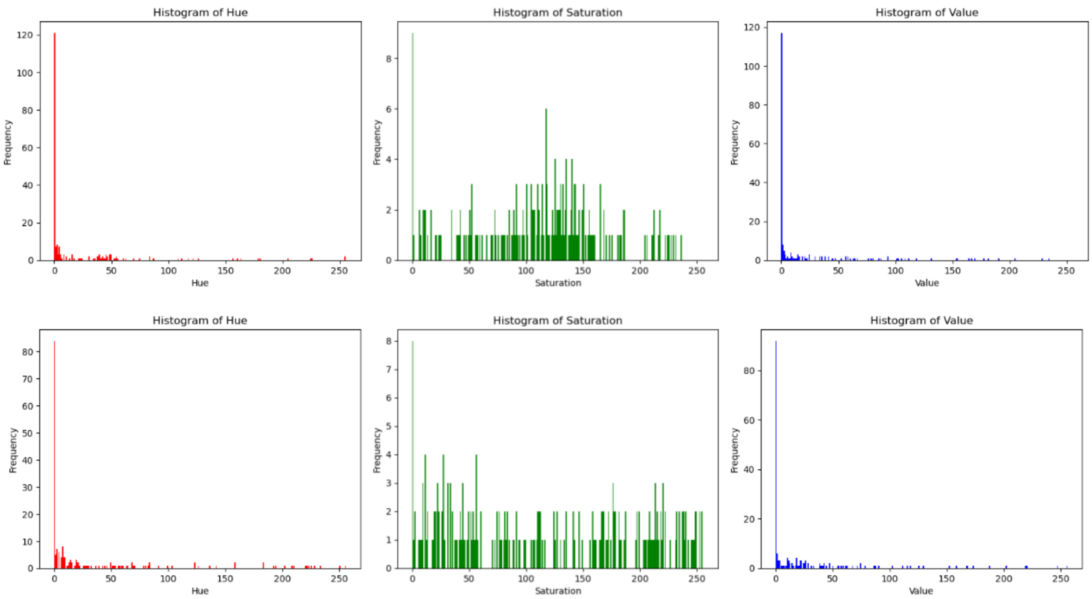

Fig. 3. Histogram of HSV color space for the forest dataset

2.1.2. Normalization and label assignment

Since the scales of different features are completely different, such as the scales of texture features and color features, it is necessary to carry out normalization operations on the above features, in this paper, we adopt the Min-Max normalization method, the labels of the dataset are designed as airplane and forest and the assignment of labels is carried out, the label of an airplane is set to be class 1, and forest is set to be class -1.

2.1.3. Data downscaling

Due to the complexity of the classified features, image enhancement processing of multi-band images is required. Due to the large dimensionality of the processed image features, which may lead to a long time for model training, the features of the dataset are downscaled using PCA.PCA converts the high dimensional data into a low dimensional representation while retaining as much information as possible from the original data. Multi-band images can be downscaled using PCA, improving the vegetation index, texture features and reflectance of features in the target study area [6], making it easier for the model to perform classification.

2.2. Models

In this paper, Support Vector Machines, Artificial Neural Networks, Random Forest, and AdaBoost algorithms are used to classify features.

Support Vector Machine (SVM) is a commonly used supervised learning algorithm for classification and regression tasks. It can handle both linear and nonlinear problems and performs well in many real-world applications.

Artificial Neural Network (ANN) is an information processing system based on modeling the structure and function of the human nervous system. The signal mapping in the previous layer of the neural network is converted to a low-dimensional signal by a defined propagation function and kernel function, and then the mapping function in the output layer is activated [7].

Random Forest (RF) is an integrated learning method based on decision trees. Random Forest consists of multiple decision trees, and each decision tree is independent of each other. Random Forest has the following advantages: it can deal with high-dimensional data and large-scale data; it can effectively avoid the overfitting problem; it has good generalization ability and is suitable for various types of data; it is insensitive to noisy data and has strong robustness [8].

AdaBoost (Adaptive Boosting) is an integrated learning algorithm for improving the accuracy of classifiers. It iteratively trains a series of weak classifiers, each adjusted to the previously misclassified samples to focus more on the misclassified samples. Eventually, the results of all the weak classifiers are weighted and voted to get the final classification result.

2.3. Page Numbers

The whole experimental procedure is to use GridsearchCV algorithm to tune the parameters and 5-fold cross-validation of the selected 4 models, get the average accuracy of 5 times cross-validation of the 4 models and the time of the model solution and record it, change the random seed of cross-validation to avoid chance, repeat the experiment for 30 times, plot the box plots of the accuracy of the 4 models and output the average of the accuracy of the 4 models and the time to solve. Then the dataset is divided with 0.7 training set and 0.3 test set to train and predict the 4 models, and the corresponding ROC curve, PR curve and confusion matrix of the 4 models are plotted.

2.4. Evaluation indicators

The algorithms are compared by the following metrics for the different models' outputs.

Use accuracy to represent the ratio of correctly classified samples of the model to the overall samples. Confusion matrix is used to represent how well the model classifies samples of different categories. The average solution time exhibits the time consumption of the model run.

3. Result

The SVM, RF, ANN, and AdaBoost models are used to analyze the principal component transformed image and plot the following curves and images.

Fig. 4 shows the ROC curve and PR curve. It can be seen that the effect of SVM ends up with 100% accuracy, followed by AdaBoost and Random Forest, and ANN has the worst effect of 98%. The higher classification accuracy may be due to the smaller number of samples.

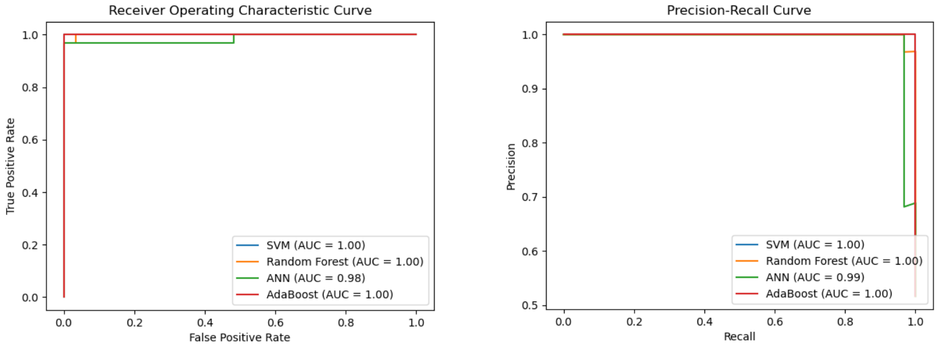

Fig. 4. ROC and PR curves of the four models

The confusion matrix is shown in Fig. 5. In the confusion matrix, SVM classifies all correctly, while AdaBoost and Random Forest are wrong by one and ANN is wrong by four. By combining the two images, it can be seen that SVM has better accuracy while ANN has more classification errors.

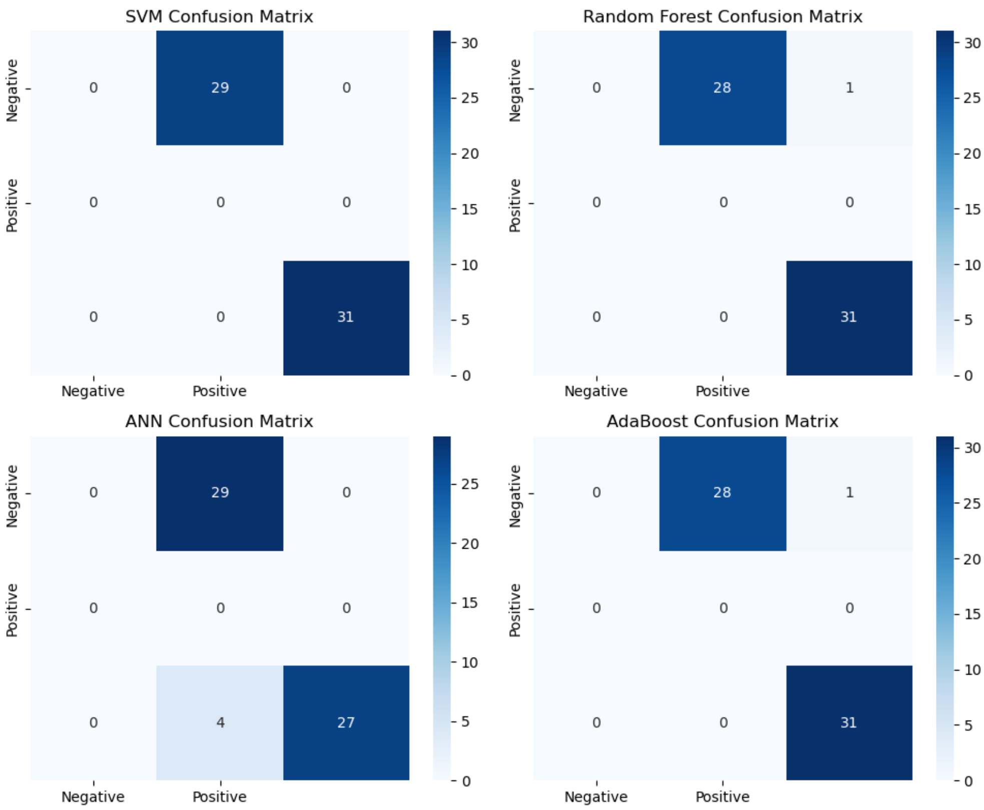

Fig. 5. Confusion matrix of the four models

The accuracy error box plot is shown in Fig. 6. According to the accuracy error box plots obtained from 30 experiments, the median accuracy of SVM is 98.5%, the median accuracy of ANN is 97.5%, the median accuracy of RF is 96.8%, and the median accuracy of AdaBoost is 98%. The variance of the accuracy of the SVM and AdaBoost models is 0, and the variance of the accuracy of the ANN and RF models is larger. This shows that SVM and AdaBoost models have better stability.

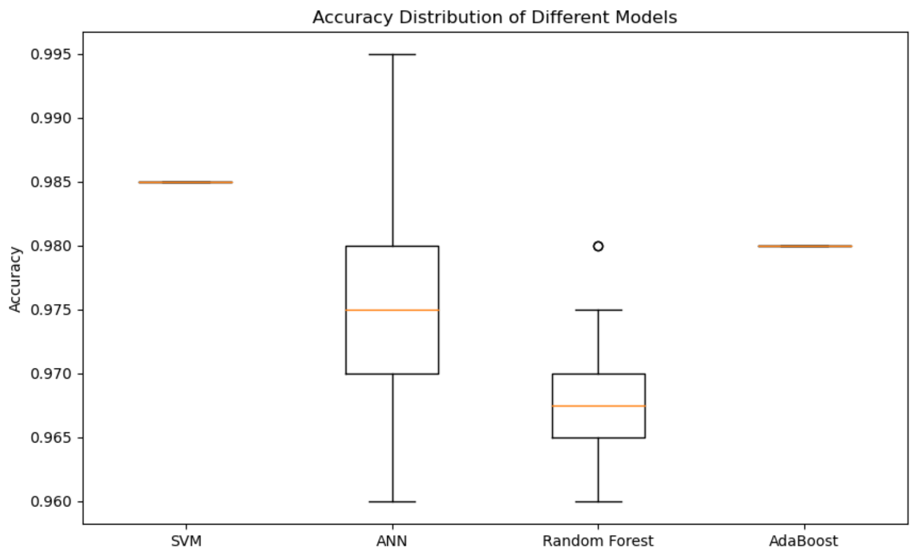

Fig. 6. Box plots of accuracy error for the four models

The average accuracy and solution time of the output models are summarized in Table 1. From the comparison of the average accuracy and solution time in Table 1, it can be seen that the accuracy of SVM is 98.5%, the highest among all the models, and the average solution time of 0.01 seconds is the shortest among the four models. AdaBoost has the second place with an accuracy of 98%, and the solution time of 0.55 seconds, then ANN with an accuracy of 97.5%, and a solution time of 0.55 seconds. 97.5% accuracy with a solution time of 0.06 seconds, and Random Forest had the lowest accuracy of 96.9% with a solution time of 0.20 seconds.

Table 1. Average accuracy and average solving time of the four models

model	Scheme 1	Scheme 2
SVM	98.5%	0.01
ANN	97.5%	0.06
RF	96.9%	0.20
AdaBoost	98%	0.55

Summarizing the above results, among the four models, SVM has the highest average accuracy, the best stability and the fastest solving time. The AdaBoost model has good accuracy and stability, but the solution time is the longest among the four models. The performance of ANN and RF models is weak compared to SVM and AdaBoost. Therefore, SVM is the best model among the four models.

4. Conclusion

In this paper, the multispectral images collected from aerial survey are applied to feature classification, and the model is constructed by using the vegetation information and spectral information. The SVM, ANN, RF, and AdaBoost algorithms are used to study the feature classification, and the performance gap and advantages and disadvantages between the algorithms are compared, and the most suitable SVM model for feature classification is selected. The SVM model is the most suitable model for feature classification, as it provides a certain reference value for the study of feature classification.

Among the four classification models, SVM has the highest average classification accuracy of 98.5%, the smallest error in accuracy, and the shortest average time for classification solving of 0.01s. In a comprehensive comparison, the SVM classification model, as a binary classification model, can solve the classification of features well with fewer training samples.

From the comparison between AdaBoost algorithm and other algorithms, it can be seen that AdaBoost algorithm has a more excellent performance, but it also has defects such as longer solving time. In order to improve the performance of the model, the AdaBoost algorithm can be optimized by considering the use of tighter generalization error bounds, more accurate iteration stopping conditions and other methods.

However, this experiment still has shortcomings, such as fewer classification samples and lower complexity of samples. In the future, such problems can be solved by increasing the sample size and sample complexity to obtain the model performance more accurately and reduce the error and chance. In addition, in order to have a more comprehensive understanding of the model performance, the performance test of the model in the case of multiple classification categories can be considered. Relevant experimental studies are still urgently needed.

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