Dear reviewer RC2:

Thank you very much for the insightful comments. Thank you for giving us a choice to correct the shortcoming of our manuscript. We already carefully read your comments and revised the manuscript according to your suggestions. We hope that this revision will make our manuscript meet the publisher. The responses to the comments point by point are listed below. Please feel free to contact us with any questions. If the revised manuscript maybe exists the shortcomings, please tell us. We will try our best to continue to revise our manuscript in order to improve our manuscript. Really thank your insightful comments and help again!

Yours sincerely，

Regards,

Xianging Zhou

Reviewer #1:

The authors proposed a hyperspectral remote sensing image classification method based on texture features and semi-supervised learning. The LBP is employed to extract features of spatial texture information from remote sensing images and enrich the feature information of samples. Then the multivariate logistic regression model is used to select the unlabeled samples with the largest amount of information, and the unlabeled samples with neighborhood information and priority classifier tags are selected to obtain the pseudo-labeled samples after learning. By making full use of the advantages of sparse representation and mixed logistic regression model, a new hyperspectral remote sensing image classification model based on semi-supervised learning is constructed to effectively achieve accurate classification of hyperspectral images. However, it requires further improvements.

(1) In the abstract section, I would suggest that the author should provide to the point and quantitative advantages of the proposed method.

(2) In the introduction, the authors should clearly indicate the contributions and innovations of this paper.

(3) All acronyms and variables in equations must be defined in the article.

(4) In Section 3.2, how to realize the sample labeling by using neighborhood information and priority classifier?

(5) Figure 2 and Figure3 are not clear, please provide some clear figures.

(6) Why did you use the selected evaluation criteria? What are their advantages?

(7) There are some grammatical mistakes and typo errors. Please proof read from native speaker.

(8) Please add what the next work of this article is.

(9) Some new references should be added to improve the reviews the literatures.

COMMENT 1: In the abstract section, I would suggest that the author should provide to the point and quantitative advantages of the proposed method.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to provide to the point and quantitative advantages of the proposed method. In this study, local binary pattern (LBP), sparse representation and mixed logistic regression model are introduced to propose a sample labeling method based on neighborhood information and priority classifier discrimination. Then, a hyperspectral remote sensing image classification method based on texture features and semi-supervised learning is implemented. The experiment results show that the proposed classification method obtains higher classification accuracy and shows stronger timeliness and generalization ability. Please read our revised manuscript, thanks!

Abstract:Hyperspectral images contain abundant spectral and spatial information of the surface of earth, which increase the difficulties of data processing and analysis, and sample labeling. In this paper, local binary pattern (LBP), sparse representation and mixed logistic regression model are introduced to propose a sample labeling method based on neighborhood information and priority classifier discrimination. Then, a hyperspectral remote sensing image classification method based on texture features and semi-supervised learning is implemented. The LBP is employed to extract features of spatial texture information from remote sensing images and enrich the feature information of samples. The multivariate logistic regression model is used to select the unlabeled samples with the largest amount of information, and the unlabeled samples with neighborhood information and priority classifier tags are selected to obtain the pseudo-labeled samples after learning. By making full use of the advantages of sparse representation and mixed logistic regression model, a new classification model based on semi-supervised learning is constructed to effectively achieve accurate classification of hyperspectral images. The data of Indian Pines, Salinas scene and Pavia University are selected to verify the validity of the proposed method. The experiment results show that the proposed classification method obtains higher classification accuracy and shows stronger timeliness and generalization ability.

COMMENT 2: In the introduction, the authors should clearly indicate the contributions and innovations of this paper.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to clearly indicate the contributions and innovations of this paper in the introduction. Please read our revised manuscript, thanks!

The main contributions of this paper are described as follows.

1) A novel a hyperspectral remote sensing image classification method based on texture features and semi-supervised learning is proposed, which introduces local binary pattern, sparse representation, hybrid logistic regression model and so on.

2) The local binary pattern is used to effectively extract the features of spatial texture information of remote sensing images and enrich the feature information of samples.

3) A multiple logistic regression model was used to optimally select unlabeled samples, which are labeled by using neighbourhood information and priority classifier discrimination to achieve pseudo-labeling of unlabeled samples.

4) A hyperspectral remote sensing image classification model based on semi-supervised learning is constructed to effectively achieve accurate classification of hyperspectral images by making full use of the advantages of sparse representation and mixed logistic regression model.

COMMENT 3: All acronyms and variables in equations must be defined in the article.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to define all acronyms and variables in equations. Please read our revised manuscript, thanks!

COMMENT 4: In Section 3.2, how to realize the sample labeling by using neighborhood information and priority classifier?

RESPONSE: Thank you very much for the insightful comments. In this study, the ground objects are closer, the correlation is stronger. In the research of sample labeling, spatial neighborhood information based on training samples is widely used. The label of any pixel on a hyperspectral image must be consistent with the label of one pixel in its neighborhood. This property can be applied to label the unlabeled samples. The label information of training samples around the unlabeled samples can be used to discriminate the unlabeled samples. The labeling discrimination method based on neighborhood information centers on the sample to be labeled. The labeled samples appearing around it are labeled with a block diagram. Then, the labeled samples are used as training samples to train the classifier and classify the unlabeled samples. Therefore, a sample labeling method based on priority classifier discrimination is proposed. For unlabeled samples with the neighborhood information, the classifier with the highest priority is used for prediction. Please read our revised manuscript, thanks!

3.2 A sample labeling method based on neighborhood information and priority classifier

The features of hyperspectral images have some correlation. The ground objects are closer, the correlation is stronger. In the research of sample labeling, spatial neighborhood information based on training samples is widely used. However, due to the unknown central pixel and the lack of sufficient determination information, the neighborhood information of unlabeled samples is relatively less in the research of sample labeling. Generally, the label of any pixel on a hyperspectral image must be consistent with the label of one pixel in its neighborhood. This property can be applied to label the unlabeled samples. The label information of training samples around the unlabeled samples can be used to discriminate the unlabeled samples. The labeling discrimination method based on neighborhood information centers on the sample to be labeled. The labeled samples appearing around it are labeled with a block diagram. All the occurrences of sample labels are recorded and denoted as the neighborhood information set. Then, the labeled samples are used as training samples to train the classifier and classify the unlabeled samples. Determine whether the predicted sample label by the classifier appears in the neighborhood information set of the unlabeled samples. If it appears, the predicted label by the classifier is the sample label. Otherwise, the samples are put to be labeled back into the unlabeled sample set. One of the most important problems is whether the unlabeled samples which satisfy the neighborhood information can be reliably labeled by the classifier. At present, some studies use multiple classifiers to discriminate together and achieve good classification effect. However, a problem is how to determine the determination of labels, when the predicted labels by multiple classifiers are inconsistent, but all appear in the neighborhood information set of unlabeled samples.

Therefore, a sample labeling method based on priority classifier discrimination is proposed in this paper. For unlabeled samples with the neighborhood information, the classifier with the highest priority is used for prediction. If the obtained prediction marker appears in the neighborhood information set, its marker is determined. Otherwise, the classifier with the lowest priority is used for prediction. Then judge whether the label can be determined until the end of the sample labeling. The sample labeling method based on neighborhood information and priority classifier discrimination is shown in Figure 2.

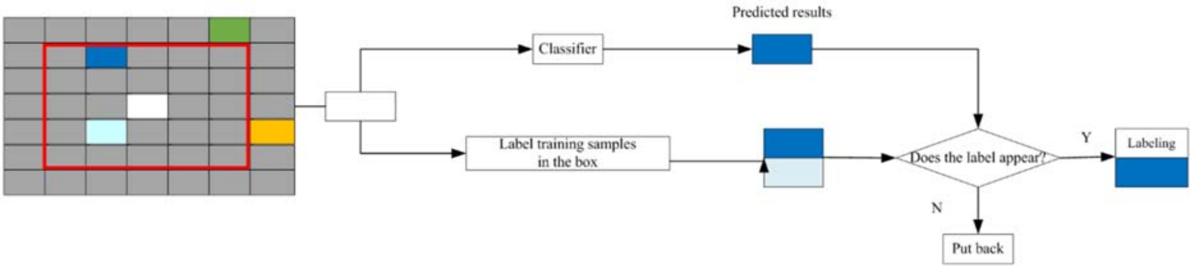

Figure 2. *Sample labeling process based on neighborhood information and priority classifier discrimination*

This labeling method is a cyclical iterative process. Although it is not possible to ensure enough training samples around all unlabeled samples at the initial stage of sample labeling, it can ensure that some unlabeled samples are sufficient. The unlabeled samples are then labeled and extended to the training set. With each iteration, the training set grows. Those unlabeled samples whose neighborhood training samples are not sufficient may reach the label condition at a certain labeling time. This sample labeling method with replacement ensures the accuracy of sample labeling to a certain extent, and improves the performance of classifier step by step.

COMMENT 5: Figure 2 and Figure3 are not clear, please provide some clear figures.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to provide some clear figures. Please read our revised manuscript, thanks!

7		…		28
	79	26	78	
	132	68	10	
	30	202	252	
24		…		59

Figure1. The quantized texture feature form of one region

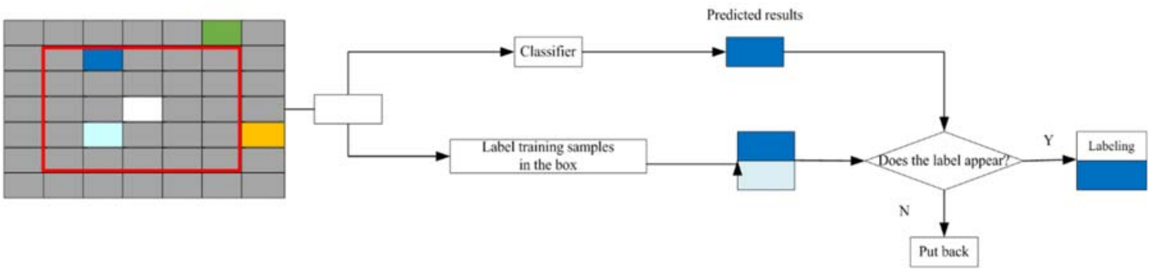

Figure 2. Sample labeling process based on neighborhood information and priority classifier discrimination

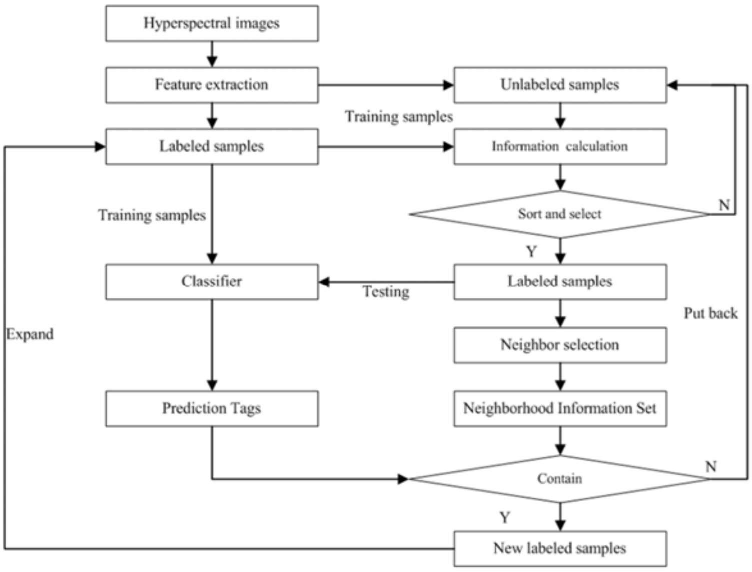

Figure 3. Hyperspectral image classification model based on texture features and semi-supervised learning

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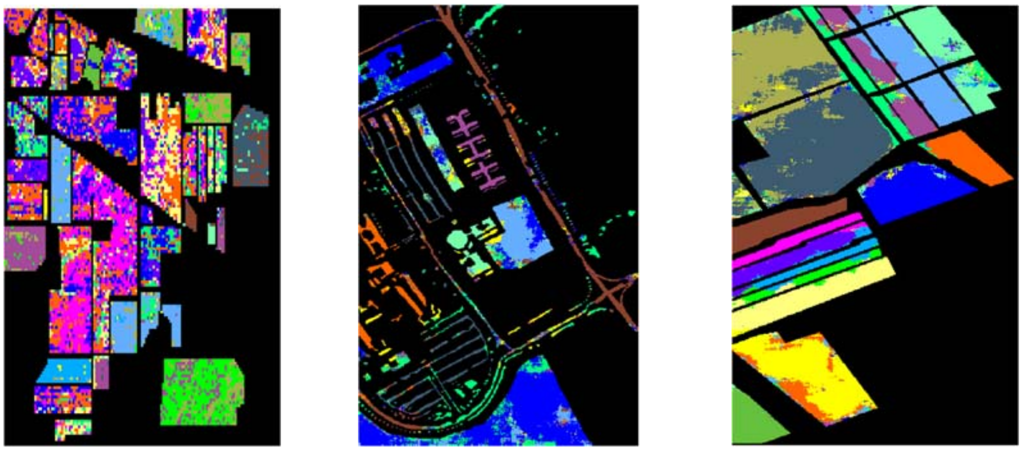
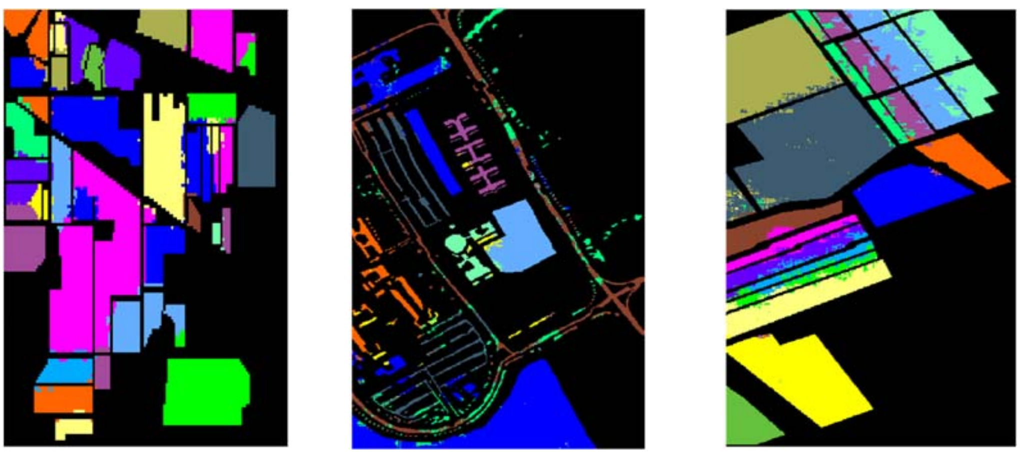


(a)Indian Pines (b)Pavia University (c)Salinas Scene

Figure 7 The classification results of the initial samples



(a)Indian Pines (b)Pavia University (c)Salinas Scene

Figure 8 The classification results of the labeling samples

COMMENT 6: Why did you use the selected evaluation criteria? What are their advantages?

RESPONSE: Thank you very much for the insightful comments. Confusion Matrix (CM) is usually used in the classification and evaluation of hyperspectral images. Based on the confusion matrix, three classification indexes can be obtained, which are Overall Accuracy (OA), Average Accuracy (AA) and Kappa coefficient, which comprehensively considers the number of objects correctly classified and the error of being misclassified on the diagonal of the confusion matrix. Please read our revised manuscript, thanks!

5.1. Evaluation criteria

Confusion Matrix (CM) is usually used in the classification and evaluation of hyperspectral images. A confusion matrix is generally defined as follow.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{14}$$

where, n denotes the number of objects in the category, p_{ij} *represents the number of samples belonging to class i that were assigned to class j. The total amount of data in each row denotes the true number of objects in that category. The total amount of data for each column represents the total number of samples.*

Based on the confusion matrix, three classification indexes can be obtained, which are Overall Accuracy (OA), Average Accuracy (AA) and Kappa coefficient.

$$OA = \frac{\sum_{i=1}^{n} p_{ii}}{N} \tag{15}$$

where, N represents the total number of samples participating in the classification. p_{ii} *represents the number of correctly classified samples of class i. It represents the probability that the classified result corresponds to its true label for each random sample.*

$$CA_i = \frac{p_{ii}}{N_i} \tag{16}$$

where, N_i *represents the total number of samples for the first category in class i.* CA_i *represents the probability that category i is correctly classified.*

$$Kappa = \frac{(n(\sum_{i=1}^{N} p_{ii}) - \sum_{i=1}^{N}(\sum_{j=1}^{N} p_{ij} \sum_{j=1}^{N} p_{ji}))}{n^2 - \sum_{i=1}^{N}\left(\sum_{j=1}^{N} p_{ij} \sum_{j=1}^{N} p_{ji}\right)} \tag{17}$$

The Kappa coefficient comprehensively considers the number of objects correctly classified and the error of being misclassified on the diagonal of the confusion matrix.

COMMENT 7: There are some grammatical mistakes and typo errors. Please proof read from native speaker.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to eliminate a number of grammatical errors and spelling errors. In addition, we have invited an English teacher whose native language is English to check the manuscript carefully in order to improve the written English level and avoid solecism and spelling mistakes. Let the revised manuscript be more readable. Please read our revised manuscript, thanks!

COMMENT 8: Please add what the next work of this article is.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to add what the next work of this article is. Please read our revised manuscript, thanks!

However, the proposed classification method has the more computing time, so the next step should be more in-depth research to reduce the time complexity.

COMMENT 9: Some new references should be added to improve the reviews the literatures.
RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to add some new references to improve the reviews the literatures. Please read our revised manuscript, thanks!

And so on, please read our revised manuscript. We thank the comments and the opportunity for us to improve our manuscript. As much as possible, the questions were taken into account during the preparation of the revised manuscript. We hope that the manuscript is now suitable for publication.