Dear reviewer RC1:

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 results look encouraging and motivating. But some contents need be revised in order to meet the requirements of publish.

(1)The abstract should be improved. Your point is your own work that should be further highlighted.

(2)The parameters in expressions are given and explained.

(3) The method in the context of the proposed work should be written in detail.

(4) The values of parameters could be a complicated problem itself, how the authors give the values of parameters in the used methods.

(5) The literature review is poor in this paper. You must review all significant similar works that have been done. I hope that the authors can add some new references in order to improve the reviews and the connection with the literatures.

(6) The main contributions of this paper should be further summarized and clearly demonstrated. This reviewer suggests the authors exactly mention what is new compared with existing.

(7) The conclusion and motivation of the work should be added in a clearer way.

(8) There are some grammatical errors seen in the paper. Check carefully for a few clerical errors and formatting issues.

COMMENT 1: The abstract should be improved. Your point is your own work that should be further highlighted.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to clearly describe the abstract and highlight the contributions. 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 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. 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: The parameters in expressions are given and explained.
RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to explain the parameters in expressions, such as expression (1), expression(4), ….. Please read our revised manuscript, thanks!

COMMENT 3: The method in the context of the proposed work should be written in detail.
RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to write the method in the context of the proposed work in detail. 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.

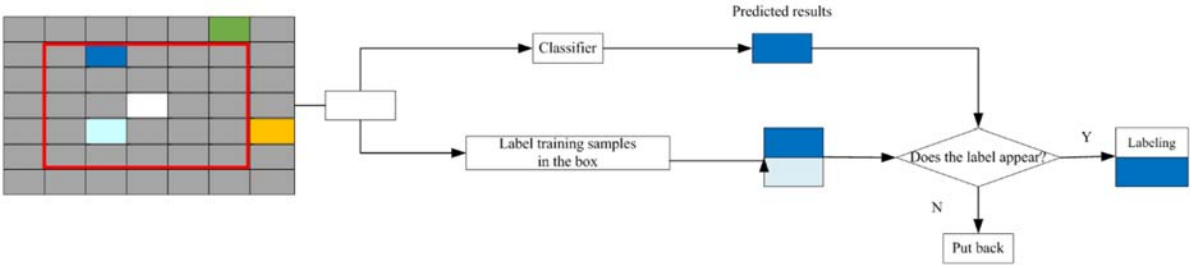

Figure 2. *Sample labeling process based on neighborhood information and priority classifier discrimination*

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.

4.1 The idea of hyperspectral image classification

Hyperspectral images consist of pairs of continuous spectral bands, which contain rich spectral and spatial information of earth surface features. So that some objects that cannot be identified by conventional remote sensing means can be identified in hyperspectral images. However, the abundant data information increases the difficulty of data processing and analysis, and there are problems such as the difficulty of sample labeling. In order to improve the accuracy of hyperspectral image classification, a new hyperspectral image classification method based on texture features and semi-supervised learning is proposed in this paper. Firstly, aiming at the problems of high correlation between bands, information redundancy, high data dimension and complex processing, LBP is employed to deal with the hyperspectral images. The texture features of hyperspectral images are effectively extracted to enrich the feature information of samples. Then, to solve the problem of limited label samples, a new sample labeling method based on neighborhood information and priority classifier is proposed. And a sample selection strategy is designed to find some samples from a large number of unlabeled samples. Secondly, the selection samples are labeled by using the neighborhood information and the priority classifier. Finally, the classifier is applied to achieve accurate classification of hyperspectral images.

COMMENT 4: The values of parameters could be a complicated problem itself, how the authors give the values of parameters in the used methods.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to give the values of parameters in the used methods. In our study, a large number of alternative values are tested, and some classical values are selected from literatures, then these parameter values are experimentally modified until the most reasonable parameter values are determined. These selected parameter values have obtained the optimal solution, so that they can accurately and efficiently verify the effectiveness. Please read our revised manuscript, thanks!

COMMENT 5: The literature review is poor in this paper. You must review all significant similar works that have been done. I hope that the authors can add some new references in order to improve the reviews and the connection with the literatures.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to review all significant similar works and add some new references in order to improve the reviews and the connection with the literatures. Please read our revised manuscript, thanks!

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COMMENT 6: The main contributions of this paper should be further summarized and clearly demonstrated. This reviewer suggests the authors exactly mention what is new compared with existing.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to further summarize and clearly demonstrate the main contributions of this paper. In addition, we exactly mention what is new compared with existing. In this study, a new sample labeling method based on neighborhood information and priority classifier discrimination is developed to implement a new hyperspectral remote sensing image classification method based on texture features and semi-supervised learning. Please read our revised manuscript, thanks!

COMMENT 7: The conclusion and motivation of the work should be added in a clearer way.

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

6. Conclusion

For the difficulties of hyperspectral image processing and analysis, a new sample labeling method based on neighborhood information and priority classifier discrimination is developed to implement a new hyperspectral remote sensing image classification method based on texture features and semi-supervised learning by introducing local binary

*model, sparse representation and mixed logistic regression model. The local binary pattern is employed to deal with the hyperspectral data and extract the texture features of the hyperspectral remote sensing image. 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. The problem of limited labeled samples of hyperspectral images is solved. The data of Indian Pines, Salinas scene and Pavia University are selected in here. The experiment results of the BT method are obviously better than those of other methods. The block window of Indian Pines dataset is 7*7. The block windows of Pavia University and Salinas scene are 25 * 25 and 20 * 20, respectively. The combination of MLR and SRC can get better classification results. The obtained classification results by the classifier and the labeled samples are smoother and has fewer discrete points, which indicates that the generalization ability of the classifier is improved by labeling the samples from the classification visualization. For Indian Pines data, the classification results of AA, OA and KAPPA are 84.7%, 94.42% and 0.914, respectively. For Pavia University data, the classification results of AA, OA and KAPPA are 81.87%, 88.53% and 0.848, respectively. For Salinas Scene data, the classification results of AA, OA and KAPPA are 87.76%, 92.64% and 0.918, respectively. Therefore, the classification method obtains the higher classification accuracy.*
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 8: There are some grammatical errors seen in the paper. Check carefully for a few clerical errors and formatting issues.
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!

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.