Noisy and Mixed Pixel Aware Hyperspectral Crop Classification

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Abstract. Hyperspectral imaging (HSI) is composed of both feature noise and label noise; thus, makes HSI crop classification extremely challenging. Recently, various feature noise tolerant machine learning and Deep learning mechanism have been presented for HSI crop classification considering; however, very limited have been presented considering presence of noise in training label. Existing model applied with presence of both label and feature noise in HSI exhibit very poor accuracies with higher misclassification. In addressing the research challenges in this paper noisy and mixed-pixel aware (NMA) HSI crop classification is proposed. The NMA-HSI provide a mechanism to obtain good quality spatial-spectral feature under presence of feature and label noise. The work introduces a modified SVM hyperplane to address class imbalance issues considering presence of noisy and mixed pixel within HSI. Experiment outcome shows the NMA-HSI achieves higher overall accuracies, average accuracies, and Kappa in comparison with existing HSI crop classification model using standard HSI datasets.

Keywords: Crop classification, Label noise, Machine learning, Mixed pixel, Spatial-Spectral features.

1 Introduction

Hyperspectral remote sensing is very much an essential approach for obtaining multiple incredibly small spectrally continuous imaging information in the electromagnetic spectrum's visible, thermal infrared, near-infrared, mid-infrared bands. The comprehensive spectral reflection properties allow for reliable differentiation (classification) of the vegetation cover of concern [1], [2]. Several HSI classification algorithms are developed in order to suit the various needs in vegetative monitoring and assessment, agricultural determination, diseases and pests' detection, and practical surveillance [3], [4]. These HSI classification methods are broadly classified into two types: supervised classification techniques and unsupervised classification techniques. The unsupervised type often includes segmentation or clustering, accompanied by expert class determination [5]. These classifiers use label information to build

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a decision vector using efficient machine learning models for projecting the labels of testing features. The present study is focused on strategies designed using supervised HSI classification approaches.

A few well supervised classification methods built using extreme learning machine (ELM) [10], support vector machine (SVM) [7], [8], [9], random forest (RF) [6], and deep neural networks [11], [12], [13] had already accomplished remarkably good classification accuracy [14], [15] by utilising the ingeniously gathered HSI databases. The majority of approaches presume that the training information obtained is of good standard. Obtaining sufficiently good standard labelled data, however, isn't really easy attributed to several factors [16]: 1) In process of encoding and decoding some information are lost, and 2) the diverse land cover with considerable inter-observer and intra-observer variations. Thus, using machine learning for classification crops using HSI in presence of label noise is main research issue for quite some-time [17]. Because classifying big data may be expensive and are prone to error, the advent of deep learning in Bigdata environment has influenced new effective label noise classification techniques [18]. Label noise cleansing algorithms and label noise-tolerant classification techniques are the two kinds of label noise strategies [19]. However, the objective of work is focused on designing label noise-tolerant HSI classification model. In meeting research objective this paper present Noisy and Mixed Aware (NMA) HSI classification model. The NMA-HSI first reduce the band size using Fusion methodologies [20]; then, design an effective spatial feature extraction mechanism that distinguish between shadow and crop inherent features. Finally, an improved SVM is employed for addressing the class imbalance issues [21] under presence of feature and label noise.

The significance of NMA-HIS is given below.

- Designed novel HSI classification model that retains good spatial-spectral feature even with of noise.
- The SVM introduced in this research work address class imbalance issues.
- The NMA-HSI is very good in achieving higher accuracies with presence of noisy feature within training label.

The paper is organized as follows. In section II, various existing hyperspectral crop classification have been studied. In section the proposed noisy and mixed pixel aware hyperspectral crop classification model have been proposed. In section III, the result outcome of noisy and mixed pixel aware hyperspectral crop classification model over existing crop classification model has been discussed. The significance of proposed model and its limitation are discussed in section IV.

2 Literature Review

In this section different hyperspectral classification have been studied. In particular the research focuses on studying noise nature of hyperspectral data impacting classification accuracies.

Table 1. Review of relevant studies

Author, Year	Methodology	Benefits and limitations
Shenming et al., 2022, [16]	The hyperspectral classification model combined random patch convolution with Gabor filter for extracting spectral-spatial features. The linear discriminative analysis and PCA are used for reducing the dimension of hyperspectral image and Gabor filter for retaining edge texture and spatial information. Then, using random patches the extracted spectral feature is convolved and spatial feature at different level are fused and are trained using SVM.	The model attains an overall classification accuracy of 98.09% and 99.64% for Indian Pines and Pavia University, respectively. The model can handle simple black pepper noise; however, presence of mixed pixel and noisy label is not taken into consideration for validating their model.
Wang et al., 2021, [11]	Designed a graph-based attention network for retaining high quality spatial-spectral features.	Good classification accuracies is achieved under publicly available HSI benchmarks. However, misclassification is slightly higher. Alongside, model is not tested under presence of noise.
Wang et al., 2022, [12]	The work presented improved HSI classification through enhanced multilayer perception network by combining with ResNet.	The model achieves very good classification; however, requires higher amount of training samples to achieves higher accuracies. Further, did validated the model under the presence of feature, and label noise.
Zhao et al., 2021 [13]	The model introduces a center attention network for capturing both spatial and spectral feature concurrently. Higher correlation exists among target pixels and central pixels aiding in generating more ideal and discriminative features.	The model achieves good accuracies for Indian pine, Salinas, and Pavia university benchmark. Alongside reduces training overhead through reduction of additional parameter during weight optimization.
Zhu et al., 2021 [14]	In retaining global spatial-spectral feature employed attention layer and long short-term convolution memory. The model addresses class imbalance issues through hierarchical SoftMax weighting mechanism and obtain ideal discriminative features by distinguishing identical crop types.	Good classification accuracies for Indian pines and Pavia university are achieved. Addresses class imbalance issues; however, under the presence of noise the model is not tested.
Wan et al.,	Presented HSI classification using	The model attains an overall

2022 [17]	graph convolution network through dual layer architecture. The model is efficient in retaining spatial information by fusing the edge information of different layers.	accuracy of 94.16%, 93.24%, and 97.61% for Indian Pines, Pavia University, and Salinas, respectively. However, the model is sensitive to selection of neighborhood size.
Jiang et al., 2019 [19]	The model designed a label cleansing mechanism through random label propagation algorithm. The model understands and extract spatial-spectral super-pixel for eliminating label noise.	Shows the impact of label noise affecting classification model. However, efficient machine learning or deep learning model is required to address class imbalance issues with presence of feature and label noise.
Jiang et al., 2022 [18]	Designed a multi-layer spatial-spectral graphs to obtains similarity among spatial-spectral region. First super-pixel segmentation is done, followed by similarity extraction and affinity graph is used to remove label noise.	The model achieves good classification accuracies on standard hyperspectral benchmarks. However, the model did not consider more complex and realistic noise types. Thus, increase higher false positive i.e., poor Kappa performance.

3 Noisy and Mixed Pixel Aware Hyperspectral Crop Classification

In this section a novel hyperspectral crop classification mechanism that work well even with existence of mixed pixel and presence of noise within hyperspectral image. The hyperspectral image is extremely large; thus, it is important to reduce the size of data by exploiting redundancy and at same time should retain quality feature both spatially and spectrally. The NMPA-HCC working process block diagram is shown in Fig. 1.

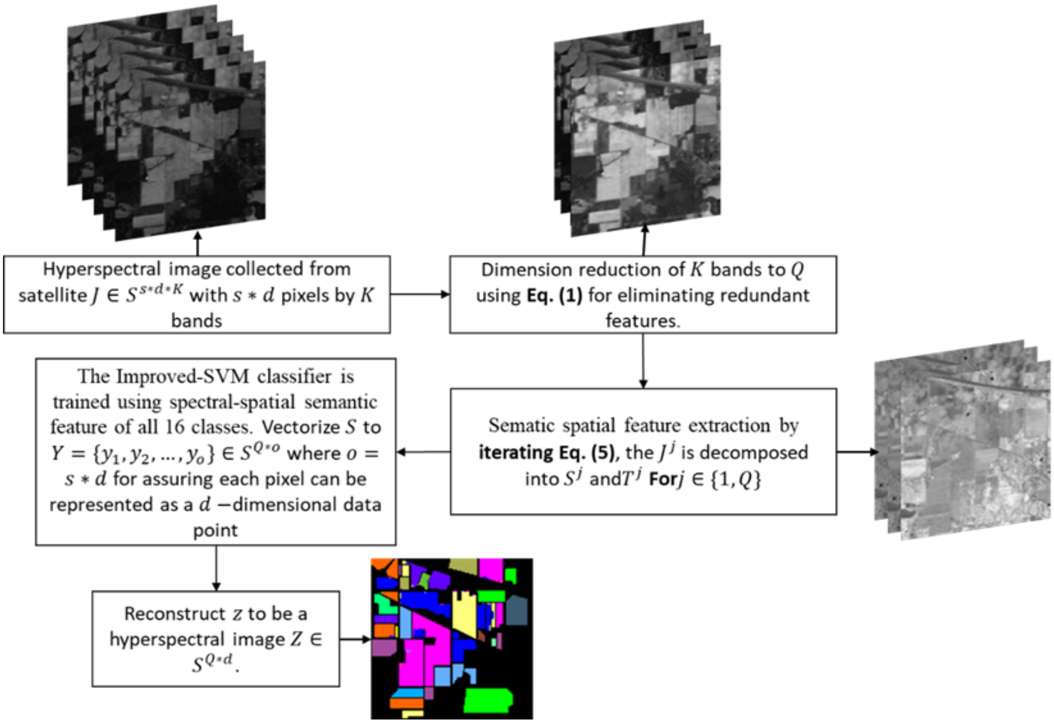

Fig. 1. Block diagram of proposed Noisy and Mixed pixel aware hyperspectral crop classification

In this work, the hyperspectral band size of K is reduced to Q bands using fusion mechanism presented in [20] as follows

$$J^l = \frac{\sum_{m=(l-1)n+1}^{ln} J^m}{n}, \qquad l = \lfloor \frac{K}{Q} \rfloor, \tag{1}$$

Using above equation, the redundant pixels are removed in different subgroup n. The parameter m and l define the band indexes of actual spectral and dimension reduced spectral band, respectively. The parameter J^m defines the noisy pixels and redundant information of different bands.

Each crops have different inherent feature which is impacted by climate and illumination changes. In this work the shading component are removed and only crop inherent features are kept using below equation

$$J_q = S_q T_q, \tag{2}$$

where q defines pixels of hyperspectral, J_q defines intensity features of hyperspectral image, S_q defines inhernet features and T_q shading component of inherent features. The S_q is computed as follows

$$S_q = \sum_{r \in O(q)} b_{qr} S_r, \tag{3}$$

where r defines pixel indexes, $O(q)$ depicts neighbor pixel q, and b_{qr} are affinity matrix. The neighboring pixel are defined as a Gaussian window as follows

$$GW = \exp\left(-\frac{\|q - r\|_2^2}{2\sigma^2}\right) \tag{4}$$

where σ defines its size. Later, in obtaining semantic feature the affinity graph is obtained using linear properties from Eq. (2) and (4) as follows

$$\begin{cases} S_r = \sum_{r \in O(q)} b_{qr} S_r, \widetilde{T}_q = \frac{1}{J_q} S_r, \end{cases} \tag{5}$$

where $\widetilde{T}_q = \frac{1}{J_q}$. Using above equation the intrinsic properties can be preserved by eliminating the unusable and noisy spatial information in shading element due to presence of noisy and mixed pixels.

The semantic features extracted are trained pixel-wise using SVM. The standard SVM for constructing hyperplane for hyperspectral crop classification (i.e., differentiating the training crop features T with no errors) is defined through following equation

$$\min_x \frac{1}{2} \|x\|^2 \quad such\ that\ z_j x^U \alpha(y_j) \geq 1, \ \ j = 1,2,3, \dots, n, \tag{6}$$

The standard SVM provide good outcome for binary classification problem. However, in this work it is adopted for multi-label classification problem. Let crops labels in HSI are defined through following parameter $Z = \{1,2,3, \dots, m\}$. After that, $m(m - 1/2)$ hyperplane is constructed for different pairs using Improved SVM. Then, using discriminant operation $f_{jk}(y) \in \{-1,1\}$, where $j \neq k$ & $j = Z$ binary classification between two classes namely j & k is done. Finally, prior to making prediction of y_q weight $T_j(y_q)$ for different class $j \in Z$ is established as

$$T_j(y_q) = \sum_{\substack{k=1 \\ k \neq j}}^{m} \mathrm{sign}\{g_{jk}(y_q)\}, \tag{7}$$

where $\mathrm{sign}(\cdot)$ defines binary classification function and crop with highest weight the classification of y_q is done as

$$j^* = \arg\max_{j \in Z} \{T_j(y_q)\}. \tag{8}$$

The ideal weight obtained aided the classification accuracy using improved SVM as outlined in experiment section.

4 Results and Discussion

In this section the performance of NMPA-HCC over existing model such as Dual Interactive Graph Convolution Network (DIGCN), 2022, [17], Multiscale Segmentation-based Multilayer Spectral-Spatial Graph (MSSG), 2022, [18], and Random Label Propagation Algorithm (RLPA), 2019 [19] is studied. In this work three dataset such as Indian pines, Salinas, and Pavia university hyperspectral images are used; the hyperspectral scene dataset is collected from following website [22]. All three dataset have different kind of crops with varying size; further, the dataset provides other material such as stones, bricks etc. which resemble real-time agriculture scenario; thus, testing the model using these datasets is important for real-time applicability in agriculture crops classification domain. The dataset encompasses of both feature and label noise which is varied from 0.1 to 0.5 similar to work presented in [18] and [19]. The average accuracy, overall accuracy, and Kappa coefficient are metrics used for validating models with presence of noise.

Indian Pines:

This section provides outcome classification outcomes achieved using Indian pines dataset. The Indian pines dataset is composed of total 16 classes such as Alfalfa, Corn-notill, Corn-mintill, Corn, Grass-pasture, Grass-trees, Grass-pasture-mowed, Hay-windrowed, Oats, Soybean-notill, Soybean-mintill, Soybean-clean, Wheat, Woods, Buildings-Grass-Trees-Drives, and Stone-Steel-Towers. The dataset is composed of total 10249 samples, out of which 5% of samples is considered for training and remaining sample is used for testing the classification models. More details of dataset cab obtained from [22]. The Fig. 2 shows overall accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher overall accuracies than DIGCN, MSSG, and RLPA. The Fig. 3 shows average accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher average accuracies than DIGCN, MSSG, and RLPA. The Fig. 4 shows average Kapa performance achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher Kappa performance than DIGCN, MSSG, and RLPA.

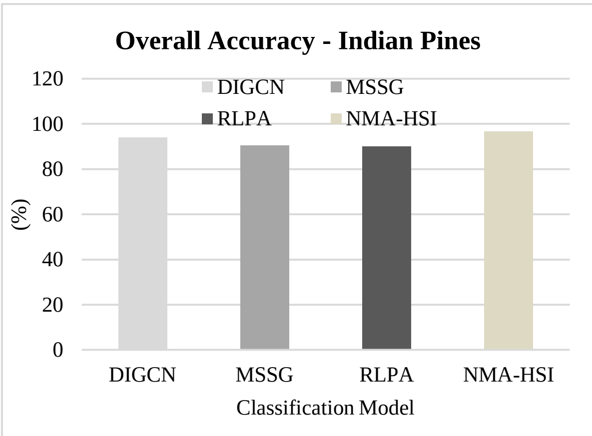

Fig. 2. Overall accuracy-Indian Pines

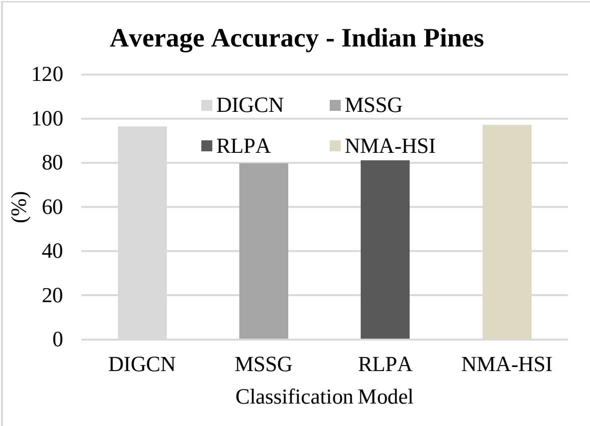

Fig. 3. Average accuracy-Indian Pines.

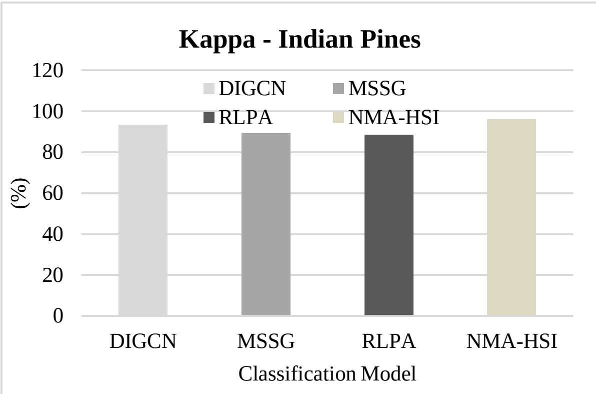

Fig. 4. Kappa coefficient-Indian Pines.

Pavia University:

This section provides outcome classification outcomes achieved using Pavia University dataset. The Pavia university dataset is composed of total 9 classes such as Asphalt, Meadows, Gravel, Trees, painted metal sheets, Bare Soil, Bitumen, Self-Blocking Bricks, and Shadows. The dataset is composed of total 42776 samples, out of which 5% of samples is considered for training and remaining sample is used for testing the classification models. More details of Pavia university dataset are obtained from [22]. The Fig. 5 shows overall accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher overall accuracies than DIGCN, MSSG, and RLPA. The Fig. 6 shows average accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher average accuracies than DIGCN, MSSG, and RLPA. The Fig. 7 shows average Kapa performance achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher Kappa performance than DIGCN, MSSG, and RLPA.

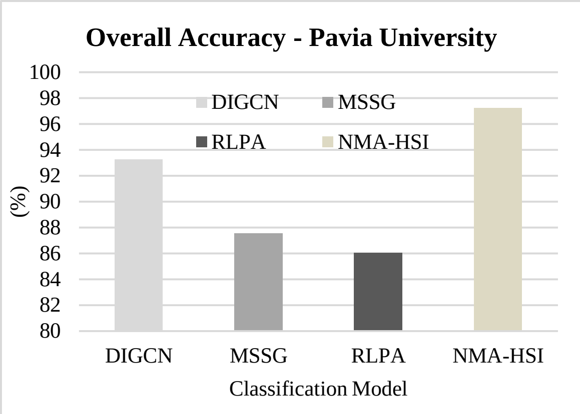

Fig. 5. Overall accuracy-Pavia University

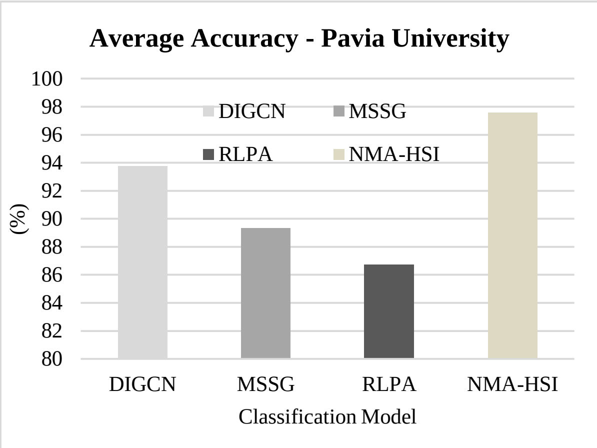

Fig. 6. Average accuracy- Pavia University.

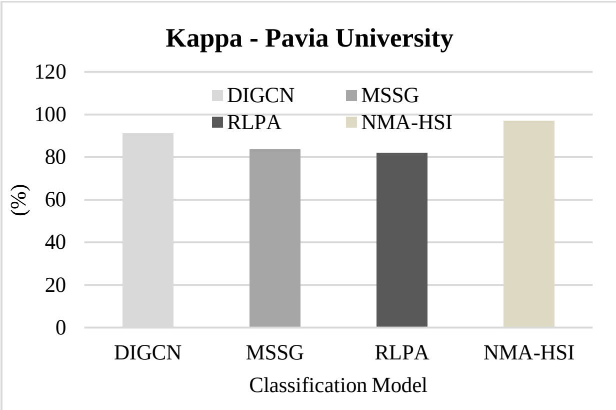

Fig. 7. Kappa coefficient- Pavia University

Salinas Valley:

This section provides outcome classification outcomes achieved using Salina Valley dataset. The Salinas valley dataset is composed of total 16 classes such as Brocoli_green_weeds_1, Brocoli_green_weeds_2, Fallow, Fallow_rough_plow, Fallow_smooth, Stubble, Celery, Grapes_untrained, Soil_vinyard_develop, Corn_senesced_green_weeds, Lettuce_romaine_4wk, Lettuce_romaine_5wk, Lettuce_romaine_6wk, Lettuce_romaine_7wk, Vinyard_untrained, and Vinyard_vertical_trellis. The dataset is composed of total 54129 samples, out of which 5% of samples is considered for training and remaining sample is used for testing the classification models. More details of Salinas Valley dataset are obtained from [22]. The Fig. 8 shows overall accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher overall accuracies than DIGCN, MSSG, and RLPA. The Fig. 9 shows average accuracy achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher average accuracies than DIGCN, MSSG, and RLPA. The Fig. 10 shows average Kapa performance achieved using proposed NMS-HSI and other existing HSI classification model. The result shows the NMS-HSI model achieves higher Kappa performance than DIGCN, MSSG, and RLPA.3.2 Research Methodology

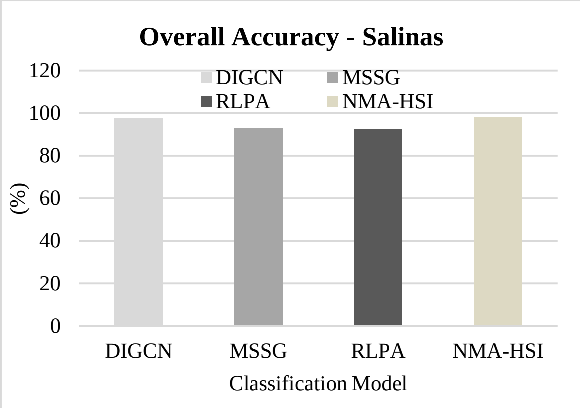

Fig. 8. Overall accuracy-Salinas Valley

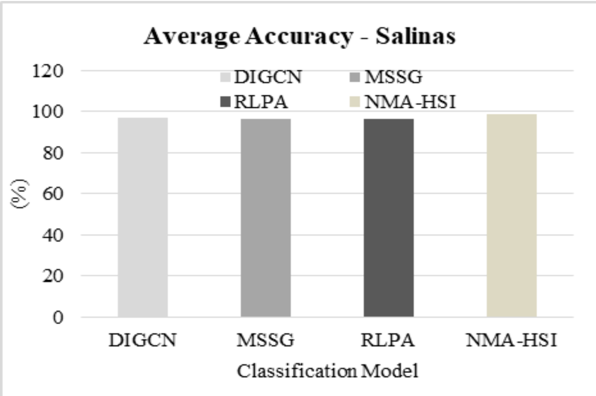

Fig. 9. Average accuracy- Salinas Valley

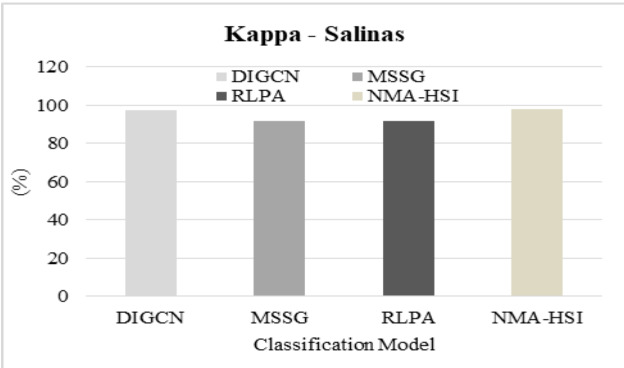

Fig. 10. Kappa coefficient- Salinas Valley

Result generalization: The accuracies achieved for Indian pine dataset using DIGCN is 96.94%, MSSG is 96.41, RLPA is 96.23%, and NMA-HSI is 98.45%. Similarly, the Kappa performance achieved using DIGCN is 97.34%, MSSG is 91.9%, RLPA is 91.53%, and NMA-HSI is 97.98%. The accuracies achieved for Pavia University using DIGCN is 93.76%, MSSG is 89.34, RLPA is 86.71%, and NMA-HSI is 97.56%. Similarly, the Kappa performance achieved using DIGCN is 91.14%, MSSG is 83.81%, RLPA is 82.05%, and NMA-HSI is 97.04%. The accuracies achieved for Salina valley using DIGCN is 96.94%, MSSG is 96.41, RLPA is 96.23%, and NMA-HSI is 98.45%. Similarly, the Kappa performance achieved using DIGCN is 97.34%, MSSG is 91.9%, RLPA is 91.53%, and NMA-HSI is 97.98%. The result achieved shows the proposed model achieves much higher accuracies than other existing model with less false positive. Thus, the proposed NMA-HSI can be adopted to solve various real-time classification problem of agriculture domain.

4 Conclusion

This paper introduced a HSI crop classification that work well with presence of both feature and label noise. The NMA-HSI provide a mechanism to obtain good quality spatial-spectral feature under presence of feature and label noise which can distinguish between shadow and crop inherent features. Alongside, the modified hyperplane added into SVM address class imbalance issues under presence of feature and label noise. Experiment is conducted for validating model NMA-HSI over DIGCN, MSSG, and RLPA using standard dataset such as Indian pines, Pavia University and Salinas Valley. The result achieved shows the NMA-HSI achieves higher overall accuracies, average accuracies, and Kappa in comparison with existing HSI crop classification model using standard HSI datasets.

The future work would consider validating model using other HSI dataset. Alongside, would further, design a label cleansing mechanism for eliminating noise prior to performing training.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest4.1. Introduction

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