

Statistical Perspective on Hyper Spectral Classification Systems for Accuracy Improvement

Rajashree Gadhawe, R. R. Sedamkar



Abstract: Classification on a hyperspectral imagery data is a multi-domain problem, it involves segmentation, followed by feature extraction (FE) & selection and finally classification. The vast majority of work in processing of hyperspectral imagery data is done in the field of image classification itself, due to the fact that most of the hyperspectral images are captured in order to evaluate the areas where a particular type of event is occurring, these events range from crop growth, forest covers and military applications. These systems use an algorithm for each of the given steps individually in order to evaluate the accuracy of the system under test. Thus, various algorithms have been proposed in order to evaluate the classification performance of hyperspectral systems. Due to so many algorithms in the field of research, there is a lot of confusion as to which approach should be selected for an effective system. Thus, we need to find approaches which have good accuracy. In order to find the best approaches for classification, researchers have to generally study a plethora of papers, so in this paper, we compare a set of algorithms used for hyperspectral image classification and compare their performance so that the researchers reading this text can analyse these algorithms and select the ones which are best suited for their particular application. Moreover, recommendations are also made in order to further improve the performance of these systems.

Keywords: Convolution Neural Network, Classification accuracy, Hyperspectral imaging (HSI), Machine Learning, crop

I. INTRODUCTION

HSI is created by using imaging Spectrometers. To develop the HSI images, two principal methodologies named as Remote Imaging and spectroscopy are used. HSI's goal is to obtain the spectrum for each pixel in the image of a scene, to find objects, identify materials, or to detect processes. HSI has been efficiently utilized in various remote sensing applications requiring estimation of physical parameters of more surfaces as a complex [1]. HSI classification is classy and occasionally terrible; several minimum sample-size enthused methods had been just established. On the other side, there is still some controversy due to the unsupervised classification which is the main challenge leads to a robust and complicated high dimensional data observation that is

suggested in a more fabulous combination of spectral information. HSI spread in many areas for that application image classification to identify the pixel label is the essential step [1]. Even though a large amount of hyperspectral image classification methods has been analyzed that there are still some of the issues faced in training samples. Using the unsupervised manner classification accuracy is one of the most critical parameters that has been analyzed in various articles using training samples as these are aware that training samples are some of the most limited in the number of numbers for HSI classification. There is still some controversy due to the unsupervised classification, which is the main challenge that leads to a challenging and complicated high dimensional data observation that is suggested in a more magnificent combination of spectral information [2].

Image classification has been a topic of research for more than 2 decades now, it includes multiple levels of processing for the input image. These levels are depicted with the help of figure 1 where, the input images can be normal images, hyperspectral images or military images, the flow always remains constant. The images are collected and labeled according to the classes needed at the output. For example, for crop classification, we need the output to contain classes like cotton crop, wheat crop, bajra crop [3], among other types, so we collect images and label them with the given classes, this step is critical, and defines the accuracy of the overall classification process, a thoroughly selected dataset ensures better classification results. The collected images are then given to a pre-processing and noise removal block, where the images are cleaned of any noises and are processed so that they are ready for feature extraction [4].

In this paper, we have compared various algorithms for classification for the hyperspectral image classification system, and identified the optimum algorithms used for a given application, the next section describes the algorithms in brief, followed by the comparison of results between the algorithms. Finally, we conclude the paper with some interesting observations about the compared algorithms and proposed the future work which researchers can perform in order to further analyze these algorithms.

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II. LITERATURE SURVEY

Remote sensing or hyperspectral image classification has limited training datasets, the ones which are used are listed as in Table I. There are other data sets as well, but some parameters of these are still unclear, so we use the words “not-sure” to replace the unknown values in the table,

Table 1. Datasets used for evaluation

Type	Range	Number of Bands	Kinds of objects	Image Size	Spatial resolution
Indian Pines	0.4-2.5 μ m	224	16	144*144	20m
University of Pavia	0.43~0.86 μ m	115	9	610*340	3.7m
Salinas	not-sure	220	16	512*217	1.3m
Radarsat-2	0.43-0.9 μ m	not-sure	19	4952065	5.2-7.6m
UC Merced	not-sure	not-sure	21	256*256	0.3m
KSC	0.4-0.25 μ m	224	13	512*614	18m

A case-study defining the use of deep learning algorithms for classification of hyperspectral images is defined in [1]. In [1] researchers Yabin Hu, Jie Zhang, Yi Ma, Xiaomin Li, Qinpei Sun and Jubai-An have proposed deep convolutional neural network (DCNN) for classifying Huanghe (Yellow) River Estuary coastal wetland images. These images were taken in real-time and both spectral & textural features were selected for classification. Classes like Reed, Tamarix, Spartina, Water, Tidal flat, Farmland and OCA [1] were selected. Accuracies of SVM-linear, SVM-polynomial, SVM-RBF, SVM-sigmoid and the proposed DCNN were compared. It was found that the proposed DCNN algorithm outperforms the other algorithms in terms of core accuracy by more than 8%, and thereby can be used for real-time hyperspectral classification applications. The kappa coefficient (which is a measure of an algorithm’s effectiveness) is also evaluated, and results indicate that the proposed DCNN is at least 10% better than the others in terms of kappa. While DCNN is found to be superior to SVM, the work done by Yanhui Guo, Xijie Yin, Xuechen Zhao, Dongxin Yang and Yu Bai in [2] uses SVM with a guided filter to improve the classification performance. The guided filter acts as a feature improvement algorithm, and helps in describing the images with better accuracy. Thereby improving the effectiveness of the algorithm. In their work [2], the researchers have compared the results with SVM, SVM-EPF, Co-SVM, Co-SVM-EPF, GF-SVM & the proposed GF-SVM-EPF. They found that the proposed GF-SVM-EPF outperforms the other algorithms by at least 6%. The comparison of GF-SVM-EPF with DCNN is

not done, which can be interesting research to be pursued by any reader of this text. DCNN is a variant of CNN, in [3] the researchers Hongmin Gao, Yao Yang, Chenming Li, Xiaoke Zhang, Jia Zhao and Dan Yao have proposed the use of simple small CNNs for spectral-spatial classification of multi and hyper spectral images. They have proposed a small-level architecture for the classification of these images. Using their architecture, the images are divided into different sectors, and each sector is able to perform one task very precisely. For example, the first sector is for pre-processing of images using gaussian filters. This section performs the task and makes sure that all images are properly processed using the filter. Similarly, there are multiple such sectors which perform a small but effective task for hyperspectral classification. They have compared 6 different CNN architectures, and found that their proposed architecture gives better accuracy than others. This proposed CNN can be combined with deep CNNs to further optimize their accuracy. CNN, SVM & deep CNN are classes of deep learning. The research done in [4] proposes different algorithms for deep learning-based hyperspectral classification. They have compared SVM, EMP, JSR, EPF, 3D CNN, CNN-PPF, Gabor-CNN, S-CNN, 3D GAN and DFFN models in order to evaluate the best working algorithm. From their extensive research, it is found that the DFFN (Deep feed forward network) can be a good option for classification in the hyperspectral space. Their analysis is done on more than 10 classes, and thus can be considered as a good starting research and study point for any researcher.

Similar to DFFN, the work done in [5] uses Cascaded Recurrent Neural Networks for classification of hyperspectral images. They use the concept of adding multiple networks together in order to perform classification. From their study the combination of 10 recurrent neural networks with a loss function and a sum operator is enough to obtain accuracies in the range of 90% to 95%. They have compared the accuracy rates of CasRNN, CasRNN-F, CasRNN-O and SSC as RNN, and found that the proposed SSC as RNN [5] method is excellent in performing the classification tasks. It outperforms the other algorithms by more than 15% in terms of core accuracy. SVMs are nonparametric factual methodologies for tending to regulated arrangement and relapse issues. In this way, there is no presumption made on the hidden information dispersion. The numerical establishment of the SVMs can be found in [6], [7], and [8]. In the first plan of SVMs, the technique is given an arrangement of information tests, and the SVM preparing calculation intends to decide a hyperplane that segregates the informational index into a discrete predefined number of classes in a manner predictable with the preparation precedents [9].

The term ideal isolating hyperplane is utilized to allude to the choice limit that limits misclassification achieved amid the preparation stage. Learning alludes to finding an ideal choice limit to isolate the preparation examples and after that to isolate test information under a similar arrangement [10]. An itemized depiction of the SVM calculation as an instrument for example acknowledgment can be checked on in [11] and [12]. The vital part for any piece-based method, including SVMs, is the best possible meaning of a portion work that precisely mirrors the closeness among tests.

Some generally utilized parts to create distinctive SVMs and other portion-based classifiers fulfilling Mercer's condition [13] are straight bit, polynomial piece, outspread premise work (RBF) bit, sigmoid bit among others.

3D CNNs have made their mark in hyperspectral classification. The work done in [14] is a milestone in the research on hyperspectral classification, because they have been able to successfully apply CNN's 3D model for the task of classification. They have further used transfer-based learning mechanisms to further improve the system performance. It is found that the proposed system is able to achieve more than 98% accuracy, which is a commendable number. Moreover, the algorithm is free from any bottlenecks, and thus can be used for real time applications. Another CNN design is presented in [15], wherein fully automatic classification is proposed. They have combined 1D CNNs with 3D CNNs in order to get the advantages of both the architectures in terms of feature processing and classification respectively. The resulting system is able to achieve more than 95% accuracy across multiple datasets. The results have been compared with RF-200, MLP, L-SVM, RBF-SVM, RNN, 1D CNN, 1D DCNN and the proposed model. The proposed model outperforms all the other models by atleast 5% in terms of core accuracy values. Another interesting piece of work is done in [16], wherein researchers have used Discriminative Compact Representation for learning features and classifying hyperspectral images. The results showcase that boosting of the features is able to increase the accuracy of the classification system, therefore boosting has a place with a group of calculation or procedures that are skilled to change over feeble student to solid student. When all is said in done, frail student can be characterized as a student or model that is somewhat superior to the random speculation. Then again solid student execution is near most exact outcome. Boosting is a general technique for enhancing the execution of any learning strategy. In [17] it is proposed the boosting system that depends on an idea that a powerless student can be supported to a solid student. Boosting is a forward added substance display [18] and boosting utilizes the whole informational collection as each stage. This technique consolidates the yields from numerous classifiers with the end goal to create an amazing board of algorithms [19].

Random forest is one of the well-known group classifier increased much consideration by scientist in the most recent decade. This group strategy deal with the idea of various choice trees by utilizing randomly chosen subset of preparing information and factors [20]. Random Forest turns into a famous decision for picture characterization in the field of remote detecting since it delivered great order precision. Random Forest [21] demonstrated its quality in various application area [22-24]. RF classifier is an arrangement of CARTs (Classification and Regression Tree) for definite expectation [25]. Trucks are produced by illustration the subset of preparing information through bagging approach. This expresses one same preparing test might be utilized commonly then again, some example may not be utilized even once. Around 70% of the example utilized for the preparation of the trees, these examples are otherwise called in-pack tests and every single outstanding example are known as out-of-the sack tests. These out-of-sack tests are utilized in inside cross approval strategy to assess the execution of resultant RF show. This mistake is alluded as out-of-pack blunder. This strategy requires two parameters

that should be set purchase client: first parameter is Ntree (number of tree) and Mtry (number of highlights). Every hub in the tree is part by utilizing Mtry parameter. RF created trees that have low predisposition and high difference [26]. For definite grouping averaging of class task probabilities determined by all tree in the forest [27]. A few examinations in writing demonstrated that characterization precision is less touchy to the parameter Ntree when contrasted with the other client characterized parameter Mtry [28]. RF is considered as computationally effective classifier. Much research demonstrated that the estimation of parameter Ntree set to 500 the reason is that mistake settle at this esteem [29]. Be that as it may, in writing numerous specialists have tried the execution of RF classifier by utilizing distinctive estimation of Ntree parameter 5000 [30], 1000 [31], or 100[32]. Be that as it may, a few specialists have demonstrated that the estimation of Ntree parameter might be accepted little when contrasted with the above said an incentive for an explicit application and accomplished great characterization result. Work in [33] utilizes RF to arrange oil slicks from SAR information and presume that the quantity of tree (Parameter Ntree = 70) give great order result. Then again, the parameter Mtry is considered as the square base of the quantity of info variables [34]. In one research [35] the estimation of Mtry is taken as the estimation of aggregate number of variable however this expansion the computational multifaceted nature of the calculation. A few investigations demonstrated that RF classifier perform superior to anything other classifier like Linear Discriminant Analysis, Artificial Neural Network, Binary Hierarchical Classifier and Decision tree [37]. Support Vector Machine is a machine learning procedure classifier that delivered incredible outcome regarding precision for different applications. A few investigations have demonstrated that the execution of RF classifier is near the SVM [38], and RF creates great outcome for hyperspectral information (high dimensional information). Work in [39] utilized RF classifier for multi-scale question picture analysis (MOBIA) on EO hyperspectral symbolism and got extremely all-around characterized pictures. Elhadim Adam looked at the execution of SVM and RF classifier on Rapid Eye symbolism and break down the significance of different groups of Rapid Eye satellite. Then again, some exploration revealed that SVM give better arrangement in the field of Object based Image Analysis (OBIA). Baoxun Xu proposed an enhanced rendition of RF classifier and guaranteed that it gives preferred outcome over unique RF strategy.

Picture arrangement will be directed utilizing managed methods feed-forward neural network which is backpropagation calculation. Prior to preparing and arrange LU/LC of picture satellite, the standardized procedure of preparing test has been performed. This procedure is to maintain a strategic distance from the immersion during the time spent network broadcasting. In BPNN process numerous concealed layers for feed-forward will be utilized, and the quantity of shrouded layers can be changed dependent on caution. The quantity of neurons in yield layer will be equivalent to the quantity of classes (N), which depends on coding, pursued the yield.

The quantity of shrouded layer neurons is proposed concurring the a few criteria incorporate the quantity of concealed neutrons ought to be in the range between the span of the info layer and size of the yield layer. Back-propagation is the most well-known technique which has just modified to make the network demonstrate and to show the networks. These days have other present-day techniques for prepared the information which is conjugate angle strategy and the Lavenberg-Marquardt strategy. These strategies have their very own favourable position which is they are quicker. Be that as it may, such preferred standpoint happens just in the event that when the issue ought to be illuminated by the neural network with discovering the strategy for its answer on the premise prepared process. This undertaking favours utilizing backpropagation calculation contrasts and present-day calculation in light of the fact that BPNN is the technique that works freely from what so ever hypothetical suspicions. That is to say, in opposition to other cunning calculation which once in a while works, the backpropagation techniques dependably work.

III. PROPOSED METHODOLOGY

In our work, to address the limitations of previous records and present a comparative survey on HSI for improving classification accuracy using Neural Network. To consider the different problem with the neural network by in-depth learning approach. Our significant contribution in the paper can be summarized as follows:

- Discussion on the various performance of deep learning techniques such as CNN, ANN, SVM, and KNN
- Classification of different approaches
- Identification of specific gaps and research challenges to the production of about present status on using neural network

The main motive of this paper is to introduce new algorithm on HSI data to achieve greater accuracy using a neural network.

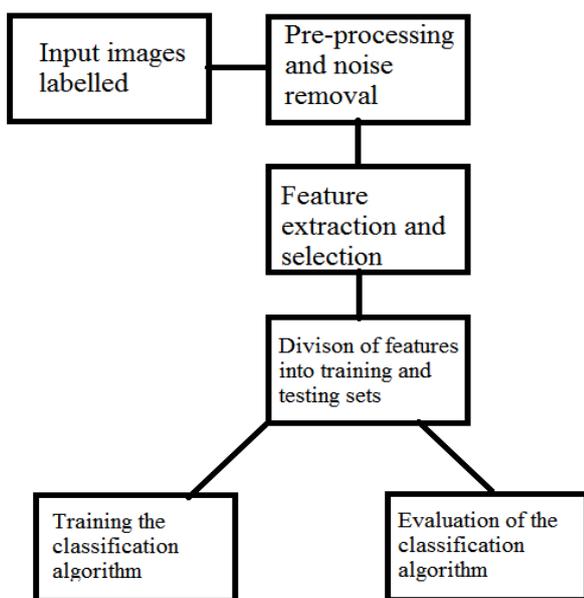


Figure 1. Flow of image classification

The processing includes, image fusion, segmentation of the image, and any morphological structure operations on the image, among other steps which are usually application dependent. The processed image is then given to the feature extraction unit, where the features of the image are evaluated. Feature evaluation is another very critical step, it defines the accuracy with which features are evaluated for the image, many methods including Speed up Robust Features (SuRF) and others have been proposed specifically for hyperspectral image processing in order to have better feature extraction capability. Feature evaluation is usually accompanied with feature selection for large datasets, in order to remove any redundancy from the extracted features.

After feature extraction, the classifier is trained with the input features, training is done with the images extracted from the training set, while the actual classification is done from the evaluation block, where the trained classifier is used with the input features from the given image. The training and testing (evaluation) sets are decided based on the application, usually 70% of the data is used for training, while remaining 30% of the data is used for evaluation. The evaluation process identifies the accuracy of the classifier used for the process, and can be used to re-train the algorithm in order to improve the accuracy based on the steps followed by the system.

In this paper, we have compared various algorithms for classification for the hyperspectral image classification system, and identified the optimum algorithms used for a given application, the next section describes the algorithms in brief, followed by the comparison of results between the algorithms. Finally, we conclude the paper with some interesting observations about the compared algorithms and proposed the future work which researchers can perform in order to further analyse these algorithms.

IV. RESULTS

The consequences of the characterization are relying upon the accuracy evaluation and Kappa coefficient esteem. The level of accuracy of arrangement result for all classifiers was determined by dissected with disarray network and furthermore called mistake grid.

Next to this, there is some marker that used to demonstrate the arrangement results, for example, by and large accuracy, producer accuracy, user accuracy and Kappa coefficient esteem. Producer accuracy was determined by partitioning the quantity of right questions of an explicit class with the genuine number of reference information objects for that class. While the user accuracy was controlled by isolating the quantity of right questions of an explicit class by the aggregate number of articles doled out to that class. To play out the producer accuracy the extent of named question in the reference information was educated accurately. User accuracy, notwithstanding, evaluates the extent of items allotted to an explicit class that concur with the articles in the reference information. User accuracy shows the likelihood that an explicitly marked question likewise has a place with that explicit class as a general rule. It can demonstrate the commission mistakes.

The following table indicates the classification performance of the mentioned algorithms,

Table 2. Performance comparison of the algorithms

Algorithm	User Accuracy (%)	Producer Accuracy (%)	Kappa	Delay (ms)
DBN	82	81	0.815	7.8
CNN	85	86	0.855	9.1
AE	62	63	0.625	1.3
SVM (RBF)	74	70	0.72	8.2
Bagging	61	59	0.6	1.1
Boosting	65	61	0.63	1.5
Random Forest	83	80	0.815	9.4
Cascaded NN	80	82	0.81	7.3

All the algorithms were compared with the KSC dataset, with 1200 images for evaluation. The delay evaluated is the mean delay for classification of a single image with 70% training and 30% testing dataset. It can be observed that DBN, Random forest and CNN outperform all other algorithms in terms of raw accuracy, but Random forest and CNN have high delay when compared with DBN, thus DBNs can be used for any real time hyperspectral classification applications with high accuracy and high speed. Other algorithms are good as well, but bagging, boosting and AE are not advisable to use due to their low levels of accuracy and low kappa values.

V. CONCLUSION

From the results we can observe that the deep belief networks are the most suitable option for hyperspectral image classification followed by random forest and convolutional neural networks. Other algorithms like support vector machines and cascaded neural networks are equally useful, but they do not have that level of accuracy as produced by the DBN, RF or CNN algorithms, and thus should be used only in case of very high speed applications where accuracy is not the primary concern, and moderate level of accuracy will also suffice, like land detection applications for town planning. Researchers can further check the performance of these algorithms on different datasets and check their results in order to suit the application in use. Thus, we conclude that from this review the deep learning-based algorithms provide a better accuracy when compared with their conventional counterparts. Combination of more than one deep learning algorithm will always be beneficial to the system accuracy, but it will increase the computational complexity of the algorithm. Moreover, combining algorithms must always be done intelligently so that the nuances of one algorithm are covered up by the other algorithm(s). Redundancy during combining algorithms must be reduced as much as possible.

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