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A Survey on Hyperspectral Image Classification and Object Detection Techniques

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ABSTRACT

Machine Learning is vast field which finds its application in almost every field. The image classification is one of the important application of Supervised Machine learning algorithms. Image classification is basically concerned with identifying the objects in the images. The complexity of this task is dependent on the image features and type of images. For the research work here, the hyperspectral images are considered for deep learning based image classification. The object detection in the Hyperspectral images have applications in various areas including defense, precision agriculture, atmospheric analysis, environmental analysis, anomaly detection, fraud detection , etc. The work presented here is divided into broad survey of image classification methods using machine learning and deep learning methods. Continuing with this work, the further work presents object detection methods in ML and DL. The later work presents the deep review of the research articles over Hyperspectral image classification using Machine Learning and Deep Learning Algorithms. A lot of challenges are present to solve the object detection problems in Hyperspectral images. The later section of this work describes the object detection based on Hyperspectral images survey in detail highlighting the major developments.

Keywords: Machine Learning, Deep Learning, Image classification, Hyperspectral images, Object detection

I. INTRODUCTION

The hyperspectral images are composed of the high spectral resolution information which can be utilized for the detection as well as the classification of variety of materials and real world objects in the image under consideration. With the wide development in the imaging technologies, high spatial resolution hyperspectral images can be obtained. There are variety of domains where these hyperspectral image processing can be utilized including military applications, medical applications, earth sciences, etc to name a few. Pixel wise study is possible when considering the hyperspectral images. The machine learning and deep learning algorithms can be utilized for developing the models for performing the indepth study of the areas and performing information extraction. The hyperspectral image classification problems can be defined as the grouping of the objects in the image into identified classes in order to bring out an arrangement of objects of interest. When the classification is done, the purpose of the analysis is to identify the relationships of the objects or items in a way that general statements could be found out form the classes of the objects in the image. When it comes to image processing, the basic functions include the extraction of the relevant information specific to the domain of the application, process the information and interpret to infer the needed information to be utilized in the application. The object detection is different from the image classification problem where the classification identifies the class whereas the detection detects the typical objects from the image. The object detection in the images has variety of applications including, security, surveillance, observation, prediction, face detection, text extraction, etc . The object detection in the hyperspectral images find applications in the fields of astronomy, agriculture, biomedical, geosciences, surveillance, etc. The applications utilize the spatial and spectral information for performing the relevant tasks of recognition, processing and detection. The work here discusses image classification using machine learning and deep learning, image classification using Hyperspectral imaging, object detection using Machine and deep learning and the object detection using hyperspectral images.

II. Research Survey Significance

The hyperspectral image classification and object detection algorithms which also forms the part of computer vision and artificial intelligence have been studied and analyzed by various researchers. To identify the significance of the survey, we have studied existing methods for hyperspectral image classification and object detection domains for finding the best optimal solution to be utilized in real time object detection. The recent study in the field of hyperspectral images is focused on utilizing the spectral and spatial information which performs which are used independently or dependently for image classification in order to update existing methods or add new ones. In the next sections of this work we have presented various findings of our research survey based on research work presented by various researchers in the field of hyperspectral image classification algorithms and object detection approaches.

III. Approaches for Image Classification & Object detection in Hyperspectral images

3.1 Hyperspectral Image Classification

B. Borasca, L. Bruzzone, L. Carlin and M. Zusi [1], the authors have proposed a fuzzy input-output support vector machines classifier. This SVM machine is able to take fuzzy input to the classification algorithm and produce a fuzzy classification output. The proposed method concentrates on the uncertainty in the input data along with the fuzzy information. It is highlighted that the model has the capability of one to many relation of the pattern and related classes in learning phase as well as the classification phase. The authors have considered hyperspectral data to test the efficiency of the technique described. The SVM learning algorithm is an effective algorithm which can also handle high dimensional input feature space. The SVM transforms the given feature space to the high dimensional feature space. It has the capability to define the hyperplane that maximizes the margin in the considered class used for classification. The SVM earlier was capable of handling the crisp inputs, but the capability of the SVM can be modified to handle the different information classes including the mixed pixels in image classification. The proposed fuzzy approach performs better in this area. The authors have analyzed both the crisp and the fuzzy accuracy. The learning parameters used in the work are the regularization parameter, the Gaussian radial basis (RBF) kernel function. To calculate and compare the accuracy the output of the fuzzy SVM was compared with the output of the fuzzy multilayer perceptron neural network (FMLP). The F2-SVM classifier described in the work are able to process both binary and multi category problems.

F. Melgani and L. Bruzzone [2], the authors have discussed Support Vector Machines in the implementation of Hyperspectral image classification from the Hyperspetral remote sensing imagery. It has been observed that the support vector machines have several advantages including ability to handle high dimensional data, requirement of few samples and robustness to uncertainty. The work moreover concentrates on the spatial information classification. The method have shown better accuracy for the case of hyperspectral imaging. The hyperspectral imagery technique considers short electromagnetic bands to obtain the image information in the form of short-banded and continuous data of the images in various parts of the electromagnetic wave. The spectral dimension of the ultraviolet, visible, near infrared, middle infrared and even hot infrared part are considered for classification. A 3D remote sensing is formed for the hyperspectral image classification algorithm. The authors have discussed about the hughes phenomena which can occur if the sample training set is not enough while performing the classification.

Based on the SVM method of classification, the spatial information extraction and classification process consists of the preprocessing, sample selection, kernel function mapping, building decision function and making classification process phases.

The decision function is built to construct segmentation hyperplane among the class features. The linear programming optimization methods could be used for the same. After the hyperplane is created, one can built the classification functions to obtain the classes of training samples. The results of this method can be further improved by applying different kernel functions and kernel function parameters further reducing the computation task and decision efficiency.

X. Wang and Y. Feng [3], SVM has been considered as a novel approach for hyperspectral data classification. The process of parameter selection is an important process in SVM in which cross validation is one of them. It has been observed that the process of cross validation in case of hyerspectral data takes more time. For reducing this time and improving the classification accuracy, authors have worked on the new combined method for parameter selection. The method is the combination of sequential minimal optimization, independent component analysis and mixture kernels. The SMO method has been used for optimizing SVM model, whereas ICA method has been used for dimensionality reduction and then the mixed kernels have been used for sample classification.

N. Alajlan, Y. Bazi, H. AlHichri and E. Othman [4], Authors have worked on the improvement of the classification accuracy of the hyperspectral images. The work mentions the combination of support vector machine classifier and the fuzzy c-means clustering algorithm. Here the SVM classifier is used to find the spectral based classification map and the FCM clustering is used to give an ensemble of clustering maps. The computation complexity while doing clustering is handheld by Markov Fisher Selector algorithm. A pairwise labeling procedure is used to label the classification map using voting rules. The aggregate of the set of spectro-spatial maps through two fusion methods based on voting rules and the used MRF concept. The authors have fused the supervised and unsupervised learning algorithms. A special kernel function called as polynomial kernel function has been used to solve the subset selection problem and then it is handled using the MRF optimization techniques. To generate the final classification result, the fusion of the SVM-FCM method along with the MRF theory uses spatial and inter-image contextual information during the fusion process. For the experimental purpose the Indian pines dataset which is created using Airborne Visible Spectrometer sensor has been used. In the dataset, the ground truth images used to assess the sixteen land-cover classes.

A. Villa, J. Chanussot, J.A. Benediktsson, C. Jutten, R. Dambreville [5], the authors have considered the hyperspectral images of low spatial resolution for the classification. The classification and detection of the surfaces or elements from the hyperspectral images is a challenging task as it contains wide spectral range with high spectral resolution. The issues with the hyperspectral images is the variance in the spatial resolution from few to tens of meters. The image received through the sensor devices may be degraded because of induced atmospheric scattering, illumination effects, sensor noise, etc. This can cause the spatial resolution an expensive issue to be improved in the capturing devices. The Hyperspectral images face the problem of mixed pixels which can be defined as the mixture of other materials. The authors in this work have concentrated on the technique for spectral unmixing and unsupervised classification to create a thematic map of more finer spatial scale. The flow of this work is shown in the figure below:

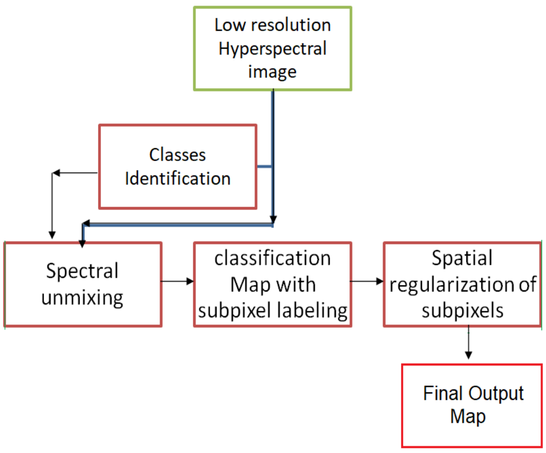


Figure. 3.1. Workflow for the spectral un-mixing and final map generation

The ROSIS data was acquired over the University of Pavia, Italy which had 103 bands ranging from 0.43 to 0.86 μm. Another dataset called as the AISA dataset. This dataset contains high resolution images of agriculture land. The authors majorly concentrated on the unsupervised classification in the situation where mixed pixels data was present. The method involves source separation, unsupervised classifiers and spectral unmixing algorithms to determine the classes at sub-pixel level. The advantage is that the method provides better classification in the case of mixed pixels as compared to other unsupervised learning algorithms.

A. Samat, P. Du, S. Liu, J. Li and L. Cheng[6], authors have introduced Ensemble Extreme learning machine for high dimensional image classification as ELM has advantages like fast operation, strong generalization, etc. The method allows to handle the randomness of the input weights and bais. The authors have introduced bagging-based ELM and AdaBoost ELMs to better the classification task. Later the support vector machines are used to evaluate the performance. The datasets ROSIS and AVIRIS were used to evaluate the performance of the classification based on the spectral and spectral-spatial sets. To perform the spectral-spatial classification, the spatial feature have been extracted using the extended extreme learning machine. The hyperspectral image capturing sensors are capable of capturing fine and abundant spectral information in the form of continuous narrow spectral bands. The Ensemble learning has its own advantages which makes it powerful than other classification algorithms. The ensemble learning is developed with the combined work of weak learning algorithms to better their performance. The authors in this work have used the eLM on hyperspectral image which contains high dimensional data. For the experiments, ROSIS Hyperspectral dataset, Kennedy space center Hyperspectral image dataset and Salinas Hyperspectral Image datasets have been considered. The ELM is much faster than SVM. But the proposed method discussed has large variation in the final output. It has been observed that as compared to BagELM and Adaboost ELM , SVM is more sensitive to model parameters.

The accuracy of the method was compared with RMKL and RBMKL over hyperspectral images and achieved better accuracy.

Yanhui Guo, Siming Han, Han Cao, Yu Zhang, Qian Wang[7], the hyperspectral image classification is based on the spectral information available in the image. When the spectral information is extracted from the HIS data, certain information loss may be seen. In this work the authors have used Long short term memory model. The spectral information is being considered as the sequential data which has relevance with the near pixel values. The novel guided filter method in RNN model has been used here to bring the model to a steady state. The major issues to be handled while performing the classification of the HIS images is the High dimensionality and the training samples used in the model. The basic task includes categorizing the pixels into any of the relevant classes according to their spectral features. The authors have highlighted the problem of hughes phenomenon which can be handled by the methods of feature extraction and feature selection. The Principal Component Analysis and the independent Component Analysis are the ways of Feature Extraction. Band Selection and Subspace Projection methods are the ways for performing Feature selection. The RNN is capable of solving the sequential input problems as considered in this work. The LSTM process applied here for HIS classification considers 5 sections: Input Gate, Output Gate, Forget Gate, Cell Input and Cell Output. In LSTM, the cell state operates on the current data considering the previous state.
The Guided filter method is applied for improving the classification accuracy by smoothing the noise and reducing the inconsistency. The authors have designed the improved LSTM named GF-LSTM. The result are obtained on two datasets i.e. Indian Pines and Kennedy Space Center. The overall accuracy of GF-LSTM is observed around 93 %.

Maryam Imani, Hassan Ghassemian[8], the hyperspectral images are represented in the cube structure, where the two of the three dimensions contain spatial information whereas the third contains the spectral information. The information collected in this structure has high dimensions and can be applied to analyze the materials at a greater details. The authors state that the fusion of the spectral and the spatial information will definitely improve the HSI classification accuracy. The fusion methods of the spatial-spectral information is described below:

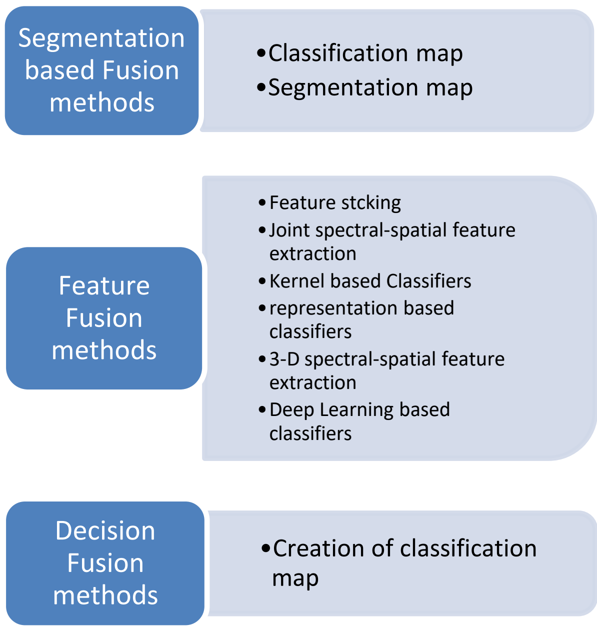


Figure. 3.2. Spatial-spectral fusion methods of feature extraction

In the feature fusion based methods, the spectral and spatial features are extracted either individually or simultaneously at the same time. Then the classification map is achieved by potential classifier. The decision fusion method, different classifiers are applied to same feature set to obtain the classification map or individually over various feature set. The majority voting or joint measures method can be used to obtain the classification maps. The objects are then classified utilizing features. For the hyperspectral image classification, an image which contain useful features is explored in detail through different perspective and the extracted features are fused together to better the classification accuracy.

Gizem Ortac, Giyasettin Ozcan[9],the work presents multidimensional deep learning methods for implementing hyper spectral image classification. In this work one dimensional, two dimensional and three dimensional convolution models have been described to improve the classification performance. The spatial, spectral and the fusion of both have been applied for classification. The available pixel based image classification methods concentrates on identifying the objects based on spectral values. Each pixel is classified in this scheme based on the numerical values of bands. The authors have developed convolution models which includes extraction of input data, design processes of convolution and searches of parameters and finally check the output.

One dimensional convolution neural network has been successfully applied for the classification of Hyperspectral images on pixel level. 2D-CNN is useful in solving the problems related to computer vision, object detection or depth optimization. The Diagram below shows the use of the types of CNN.

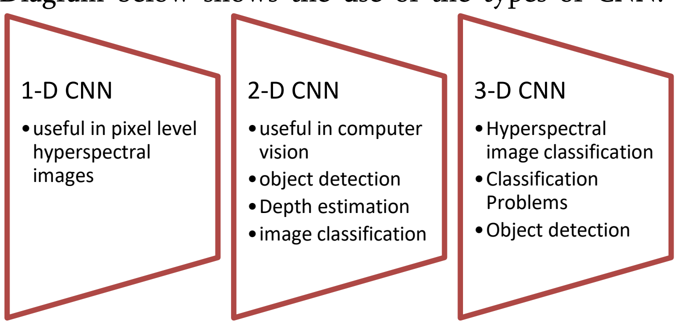


Figure. 3.3. Use of Types of CNN

The 1-D CNN can be used to extract the spectral attributes for creating the input data whereas, 2-D CNN extracts the useful attributes from the raw input image. When it comes to hyperspectral image classification, the 2-D CNN model processes the input data in the spatial dimension but the spectral information is not saved. The 3-D CNN model works on both the spatial as well as spectral information of the input data. The 3-D CNN preserves the spectral data which plays an important role in HIS classification. .

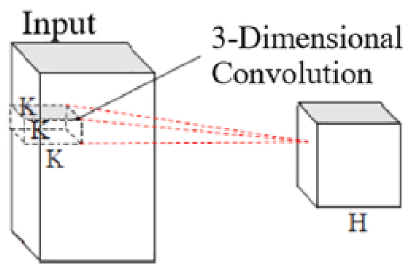


Figure. 3.4. Process of 3-D Convolution of HSI

Sezer Kutluk, Koray Kayabol, Aydin Akan[10], the hyperspectral image classification to be successful it is most important to select a good optimization algorithm and a large proper dataset. The authors in this work have discussed about a CNN based training algorithm. This algorithm uses a first and second order derivatives for training the layers in the model for classification. The backpropagation is applied along with the first order derivative for training the layers in the model except for classification layer. The number of training iterations needed is smaller as compared to other methods. High classification accuracy can be achieved in this way as well. The authors have integrated CNNs with a probabilistic spatial model and later applied this for the problem of land cover classification in the area of HIS. Here the number of spectral bands is very huge, but the training pixels are very small in quantity. The use of CNN in HSI image classification problems is considered as it can handle spectral signatures. In this area of work, the 2-D or 3-D networks are basically harder to train and consume time. The steps in each iteration of the proposed training procedure are as shown in the figure below.

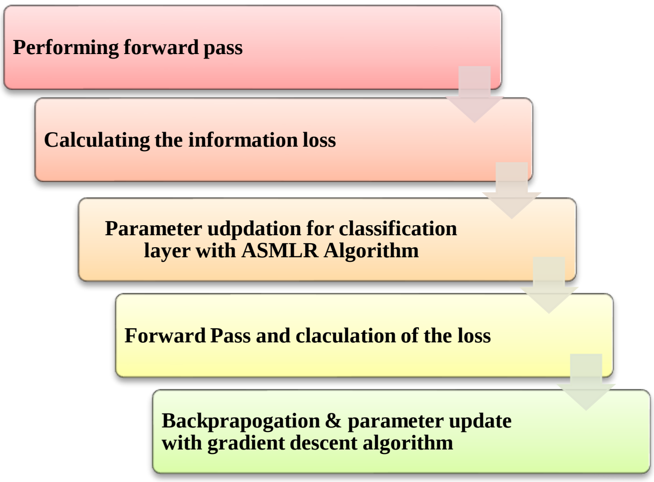


Figure. 3.5. Training Process of ASMLR

3.2 Hyperspectral Images : Object Detection

Park, KS., Cho, S.H., Hong, S. [11], the authors have discussed the reduced complexity algorithm for the real time target detection architecture in the context of HSI processing. This is applicable for high throughput applications. The pipelined processing architecture and the scalable multiple processing element architecture has been designed for detection. Data reduction algorithm is explored in HSI processing. The authors have proposed optimization structure for the better memory usage and avoiding memory bottleneck. The interconnection topology is also discussed for the multiple processing elements for improving the speed. For target detection, the architecture is implemented with the help of FPGA to check the hardware complexity and the execution throughput. The redundant information can be compressed by PCT between the hyperspectral bands. The system work sequentially so it needs the updated band index and libraries. This is done with the help of pipelined processing element model that is used to minimize the effect. Then the optimization of the memory usage is done with the help of data reduction algorithm. The hardware complexity and the execution throughput for better target detection are observed.

Zhang, B., Yang, W., Gao [12], the authors have worked over the spatial and spectral information extraction methods to be used for applying detection in the area of hyperspectral images. The limitation of the hyperspectral image data is the massive data processing which in turn limits the processing speed. Here, the authors have described the spatial spectral features extraction has been described in order to accelerate hyperspectral image processing. The model comprises of band selection and sample co-variance matrix estimation. The model for band selection utilizes completely the high spectral correlation for spectral image. The sample covariance matrix here utilizes the high spatial correlation of the sensing image. To select the sample pixels, effective scalar method has been applied. The system has been implemented over a DSP. The constrained energy minimization algorithm contains the data transferring model. The DSP implementation helps in improving the recognition rate and speeds up the data processing and also helps in the real time supervised detection.

The key used in this work for the target detection in hyperspectral images is the calculation of the covariance matrix or the correlation matrix, which takes most of the computing time in the process of target detection. The method of band selection is shown in the figure below:

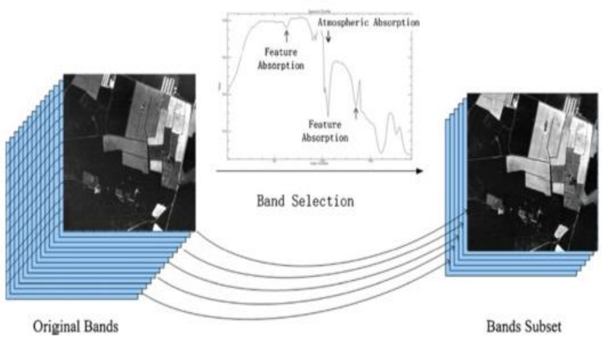


Figure. 3.6. Method of Band selection

After the band selection is done, a new HIS image is generated so as to represent the major information from the originally provided data. The covariance matrix method applied here is the most time consuming process in the target detection. It has been highlighted that the effective computing method is of high importance for the real time image detection.

J. Liu, Z. Wu, Z. Xiao and J. Yang [13], the authors have discussed the region based method called relaxed multiple kernel collaborative representation method. The spatial spectral classification of hyperspectral images is performed using this method. The figure below represents the R2MK method:

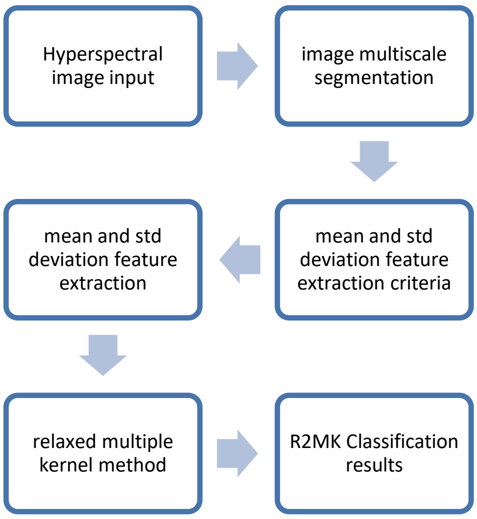


Figure. 3.7. R2MK Method for HSI processing

In the first stage the multiscale performs the superpixel segmentation over the HSI in order to capture the spatial spectral information. The image is segmented into several non overlapping spectrally same regions of ineterst. In the second step the mean and the standard deviation criterie are applied and computed over each region in order to generate the spatial features. Then a relaxed multiple kernel method is used to fuse the obtained spatial multiscale features and the original spectral features . Then the classificaton output is obtained. The method has informative criteria used to compute the features useful. Results demonstrate that it generates accurate classification and information extraction that can be further utilized to detect objects in the Hyperspectral images.

Ma, L., Lu, G., Wang, D[14], the authors have worked over the learning method that learns the variance between the tumor and the benign tissue for cancer detection. This is based on the hyperspectral images captured using an animal model. An autoencoder network here is trained to extract deep medical information in order to create the pixelwise prediction of the cancer or benign pixel. A hypothesis over each pixel is done in which each misclassified pixel will be again reclassified in the correct prediction direction using the concept of adaptive weights. This adaptive deep learning method highlights the pixels form the tumor region for the accuracy of the detection of the region under the cancer cells. The autoencoder are used for learning and recognizing the depth features of pixels in the hyperspectral images for the first cancer detection instance. Here, each pixel is assigned a weight according to the classification result value. The model is trained to reclassify the misclassified pixels during the previous stage classification. The model was able to produce a better sensitivity and specificity.

X. Sun, H. Zhang, F. Xu, Y. Zhu and X. Fu[15], the authors have discussed about the redundancy reduction. For the effective object detection, many clustering based band selection methods have been used. The authors have given a novel approach for the same. The authors have mentioned the many applications where the hyperspectral image detection is applied including the military and the civil fields. Due to this the methods for the low-correlation and band selection in order to reduce the redundancy of the information present in the bands. The authors in this work have proposed the novel Band selection method which is called as constrained –target BS with the subspace partition, in order to select the optimal subset having lower – correlation and have strong target representation for target detection from the input images. This technique is based on the correlation distance, where the method divides the hyperspectral bands into various unrelated subspaces. Then, according to the constrained target based prioritization criteria, the band with the highest priority in each subset is selected to form the optimal subset for specific target.

J. Hao, J. Li, C. Pan, C. Huang, T. Xu and H. Cheng [16], the authors have worked over the salient object detection in the context of hyperspectral images. The object detection algorithms in HIS mainly focuses on the utilization of the rich spectral information. This can aid in detecting objects from cluttered background. Most models in the previous work have been built on the color components model that considers spectral domain in order to detect the salient objects. The model fails to suppresses the background clusters effectively. Looking at the problem, this work highlights an effective model for performing salient object detection. The process of the said model is described in the figure below:

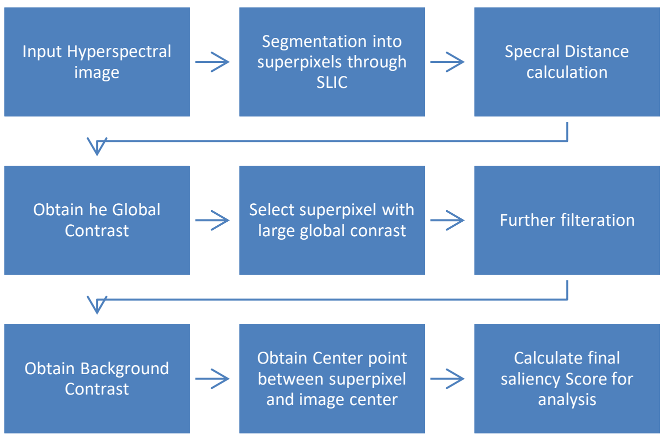


Figure. 3.7. Salient Object detection on Hyperspectral images

1. Segmentation of the input hyperspectral images in superpixels using Simple linear iterative clustering
2. Distance between spectral features of each subpixel and other superpixels is computed
3. Obtain the global contrast
4. Select the superpixels near the image boundaries with large global contrast
5. Further filteration of the superpixels with low spectral feature distance to foreground seed.
6. Obtain the Background contrast
7. Obtain the center point between the superpixel and image center
8. Incorporate global and background contrast , also the center to get the final saliency score for each superpixel

The previous methods for hyperspectral image object detection concentrates on the edge details but it does not give enough attention to the global features. With these methods are insufficient for suppressing background due o lack of information. In his work, the hyperspectral image input is given to the salient object detection method with the integration of global and background contrast. Then the image is at the basic stage segmented to generate superpixels. The global and the background contrast values for each of the generated superpixels based on the spectral features. This helps in generation of the background set to be used for suppressing the background information. The final saliency score is generated which is then used in the analysis of the spectral and spatial structures of the hyperspectral images.

3.3 Comparative Analysis of Existing Hyperspectral Image Classification and Detection Approaches

Sr. No	Author	Technique	Description	Pros	Cons
1	B. Borasca, L. Bruzzone, L. Carlin and M. Zusi	Fuzzy based classifiers- SVM	Hyperspectral image classification to be done using Fuzzy input-output SVM learning algorithm	Low computing complexity, simple architecture design, good generalization , good	Fuzzy information of data is required to be extracted

				accuracy	
2	F. Melgani and L. Bruzzone	SVM for Hyperspectral remote sensing imagery	Extracting and classifying city ground information from hyperspectral images	Good learning ability, classification efficiency, expressing Ability, better than other unsupervised learning	Training sample amount can be improved, difficult computations
3	X. Wang and Y. Feng	SVM, sequential minimal optimization, independent component analysis and mixture kernels	The SMO is used for optimizing SVM model, ICA is used for dimensionality reduction and mixed kernels have been used for sample classification	ICA can extract independent signal components, SVM can solve non linear classification problems, Fast ICA can be used for dimensionality reduction, increased accuracy	Time for cross validation can be improved.
4	N. Alajlan, Y. Bazi, H. AlHichri and E. Othman	SVM and fuzzy c-means clustering, Markov Fisher selector Algorithm	Spectral based classification map is generated by SVM, ensemble of clustering maps is given by fuzzy c-means clustering algorithm, MFS algo is used to reduce the computation complexity	Classification accuracy is good, needs more computation time	More robust learning algorithms for segmentation of hyperspectral images can be used, classification accuracy can be improved further
5	A. Villa, J. Chanussot, J.A. Benediktsson, C. Jutten, R. Dambreville	Fusion of spectral unmixing and super-resolution mapping	The integration of the spectral and spatial information to improve the image resolution.	No supplementary source is required	Spectral unmixing does not perform resolution improvement, has issue of intra-class spectral variability
6	A. Samat, P. Du, S. Liu, J. Li, L. Cheng	Bagging and AdaBoost-based ELM algorithms and SVM	Bagging is used for developing classifiers using bootstrapped replicas of training set, ADAboost performs resampling creating better training sets	Improves performance, provides most informative training set	Needs time for training and classification, statistical variation in final results
7	YanfengGu , HuanLiu	SVM-sample screening multiple kernel learning, Adaboost Strategy	SSMKL has been used to screen the training sample, AdaBoost to boost the screening of the training samples.	Limited samples classification is possible, improved classification accuracy ,better capability, higher flexibility	It obtains better results only over spectral features
8	Maryam Imani, Hassan Ghassemian	Spectral-Spatial fusion based methods	The method works by extracting useful features from the image and fusing the same to classify the image correctly	Improves accuracy	Needs significant amount of computation
9	Gizem Ortac, Giyasettin Ozcan	Multispectral Deep learning approaches	1-D, 2-D,3-D CNN	3D CNN models data in spatial as well as spectral dimension,dropout is applied to solve overfitting problem, good accuracy	2-D CNN requires trainable filter for classification, learning rate is reduced for CNN, more training samples are needed. Proper learning rate must be chosen for 3D CNN
10	Sezer Kutluk, Koray Kayabol, Aydin Akan	CNN based model-ASMLR	CNN, first and second order derivatives integrated with Backpropagation, 2nd order optimization for training classification layer.	Accuracy is good, no extra computation time required	Costlier to implement
11	Park, KS., Cho,	Real time target	Reduced complexity	Complexity is reduced,	The algorithm is

	S.H., Hong, S.	detection in Hyper spectral images based on deep learning	algorithm, efficient pipelined processing element, scalable multiple processing element architecture	data reduction increases speed	sequential so it needs updated band index
12	Zhang, B., Yang, W., Gao, L	Spatial spectral information extraction for hyerspectral image processing	Band selection for spectral image utilization, sample covariance matrix for handling the spatial information, DSP hardware with constrained minimization algorithms	Effective recognition rate, supervised real time target detection is possible.	Covariance matrix process is time consuming
13	J. Liu, Z. Wu, Z. Xiao and J. Yang	region-based relaxed multiple kernel collaborative representation method	superpixel-based spatial multiscale feature extraction and the relaxed multiple kernel technique	Applies effective fusion strategy,	Adaptive weights can be calculated and used
14	Ma, L., Lu, G., Wang, D	Adaptve Autoencoder method for improved learning of hyperspectral images	Hypothesis over pixel value is done. The pixels are classified as cancer or benign pixels, misclassified pixels are reclassified	Dimension reduction was done at a good level, better characterization of the cancer tissue	Auto encoder could be improved for other body parts cancer detection
15	X. Sun, H. Zhang, F. Xu, Y. Zhu and X. Fu	Creation of salient object detection data set for object detection	Removing distortion due to motion, calculation of the AUC for the correctness	Noise removal helped improve contrast in captured images	AUC can be further improved
16	J. Hao, J. Li, C. Pan, C. Huang, T. Xu and H. Cheng	Salient object detection method in Hyerpecral images.	Salient object deection in hyperspectral images with global and local conrast	Better accuracy, enhances suppression effect on subpixels	Global and background contrast must be calculated

IV. Interpretations and Observations

The Deep learning techniques available for performing the image classification, computer vision tasks and object detection have certain model evaluation metrics. These metrics are important to tune the parameters or the hyperparameters. The classification accuracy defines the measure of correctness of the observed outcome after the classification is done. One of the metric for the image classification tasks is the confusion matrix based on the following formula:

Classification Accuracy : (TP + TN) / (FP + FN + TP + TN)

The Confusion Matrix is shown below:

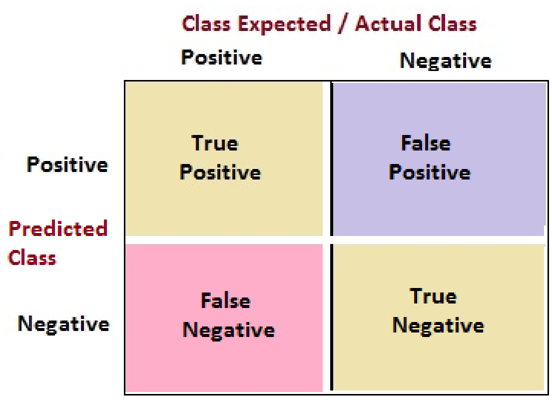


Fig 4.1. Confusion Matrix

- Sensitivity/ True Positive Rate:
  Sensitivity = True Positives/ (True Positives + True Negatives)

- Specificity / True Negative Rate:

Specificity = True Negatives/ (False Positives + True Negatives)

- False Positive Rate

  FPR = False Positives / (False Positives + True Negatives)

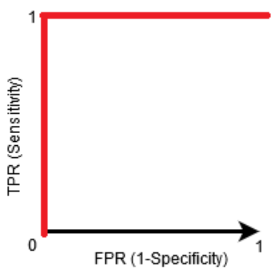
  FPR = 1 – Specificity

AUC ROC Curve:

Area Under Curve (AUC) along with ROC (Receiver Operator Characteristics) is one of the parameters for evaluating the classification performance. The parameter evaluates the plot or curve of the True Positive Rate against the False positive rate for the calculated threshold values. The AUC ROC metric is used to check the accuracy of the given classifier to identify classes. Higher AUC represents better performance of the model.

ID	Actual	Prediction Probability	>0.6	>0.7	> 0.8	Metric
1	0	0.98	1	1	1	
2	1	0.67	1	0	0	
3	1	0.58	0	0	0	
4	0	0.78	1	1	0	
5	1	0.85	1	1	1	
6	0	0.86	1	1	1	
7	0	0.79	1	1	0	
8	0	0.89	1	1	1	
9	1	0.82	1	1	1	
10	0	0.86	1	1	1	
			0.75	0.5	0.5	TPR
			1	1	0.66	FPR
			0	0	0.33	TNR
			0.25	0.5	0.5	FNR

Fig 4.2 Sample Table of Confusion matrix Values



From the table , it is observed that when AUC = 1, model classifier successfully distinguishes between the Positive and the Negative class points correctly. otherwise, the AUC would predict all Negatives as Positives, and all Positives as Negatives.

V. Conclusion

Hyperspectral images is dynamic area wherein the spectral and spatial information can be analysed and used in wide variety of real world applications. The work is the detailed survey about the research work in and around hyperspectral image classification. The review work done mentioned in this work highlights the algorithms applied and in use for the image classification over hyperspectral images. The evaluation parameters for the accuracy of the image classification approaches is discussed in few papers. The later work reviews the object detection approaches in , their uses, application areas in detail along with their evaluation methods and recent advances. Few research papers discussed here are based on the Hyperspectral image classification approaches and recent algorithms. The applications are discussed and evaluation parameters are highlighted. The last section of this review work highlights about effective object detection techniques and method for object detection in the hyperspectral images. The research finding mentions in brief about the methods and challenges for implementation of future work in the area of hyperspectral image classification and object detection.

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