Application of Machine Learning on Remote Sensing Data for Sugarcane Crop Classification: A Review

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Abstract Sugarcane is a major contributing component in the economy of tropical and subtropical countries like India, Brazil and China. Sugarcane agriculture is empowered with the advancements in the remote sensing technology because of its timely, non invasive, and labor and cost effective capability. Remote sensing data with machine learning algorithms like Support Vector Machine, Artificial Neural Network and Random Forest are proven to be suitable in sugarcane agriculture. The aim of this paper is to present a review of studies that implemented various machine learning algorithms based on remote sensing data in sugarcane crop mapping and classification.

Keywords Machine learning · Remote sensing · Sugarcane crop classification

1 Introduction

Sugarcane is a semi-perennial and one of the most important crops across the world, especially in India, Brazil, and China. Brazil ranked first in sugar production and second in ethanol production, India is the second largest country followed by China. Sugarcane is a raw biological material that produces several products other than sugar, such as ethanol, bagasse, molasses, rum, cachaca. The growth of sugarcane highly depends on the plantation season and area along with other factors like soil type, precipitation, irrigation, and fertilization. There are three plantation seasons in

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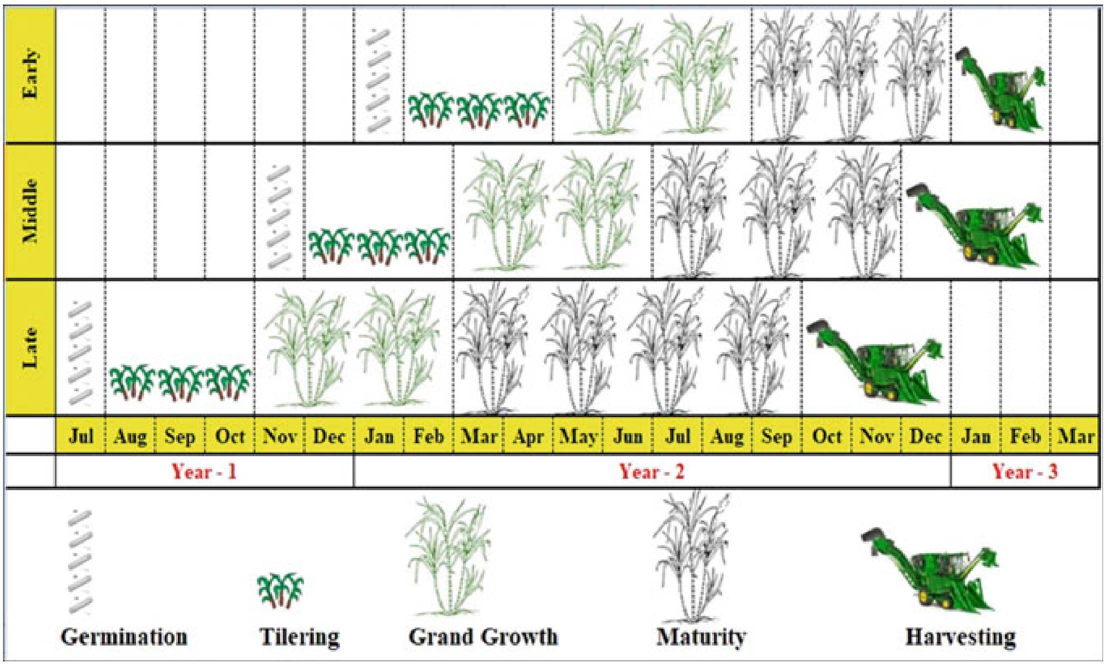

Fig. 1 Sugarcane crop calendar in South India

south India viz. early (Jan–Feb), mid-late (Oct–Nov) and late (Jul–Aug). It undergoes 4 growing phases i.e. germination phase, tillering (formative) phase, grand growth phase, and maturity and ripening phase in south and north India [1], (Fig. 1). Plantation and ratoon are the 2 types of practices to grow sugarcane crops whose plantation cycle is 12–18 months. After harvesting for the first time, it is allowed to grow again without completely ploughed out several times until its quality deteriorate (less no. of shoots), referred to as ratooning. Ratoon crops observed to be low in vigor and mature early than plantation.

Remote sensing (RS) provides an efficacious technique for monitoring crop growth, crop mapping and yield prediction due to its capabilities with regard to its spatial, temporal and spectral resolution [2]. Optical RS data, such as the Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper Plus (ETM+), Moderate Resolution Imaging Spectroradiometer (MODIS), SPOT-5 High Resolution Geometrical (HRG), High Resolution Imaging Camera (CCD) on board of China-Brazil Earth Resources Satellite-2 and—2B (CBERS-2 and—2B), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and ENVISAT Advanced Synthetic Aperture Radar (ASAR), have been utilized for mapping sugarcane planting areas, differentiating between sugarcane varieties.

Machine learning, a subsection of Artificial Intelligence (AI), has the power to process abundant data in a nonlinear system. RS generates innumerable data and therefore machine learning algorithms can produce promising results. Numerous machine learning algorithms like decision trees (DT), Support Vector Machine (SVM), Genetic Algorithm (GA), Ensemble Learning (EL) have been successfully applied on RS data in sugarcane crop mapping with good accuracy.

This paper aims to provide a review of the application of machine learning on remote sensing data to classify sugarcane crop. The rest of the paper is shaped as follows. Section 2, presents various image classification approaches and techniques. The literature on sugarcane crop classification is presented in Sect. 3. Section 4 gives a conclusion with future directions for researchers.

2 Remotely Sensed Data Classification Approaches and Techniques

One of the most high interest tasks in RS is to separate the land use and land cover of the earth's surface based on the spectral reflectance of the earth's object through a classification process. Image classification is defined as a process of obtaining extremely useful information from the gigantic satellite imagery and generating maps of classes by designating every pixel of the input satellite image to an information class. Information classes are categorical such as crop type, built up, rock, water body, forest type, tree species, different geological units, etc. Whereas groups of pixels that are nearly similar in their reflectance values in different spectral bands are called spectral classes. RS data classification is executed based on the spectral classes of different features of earth's surface. Different approaches with techniques to classify remotely sensed data are as shown in Fig. 2 [3, 4].

3 Application of Machine Learning for Sugarcane Crop Classification

Over the last 40 years, crop classification has been experimented using RS by many researchers still, it is a challenging task. In 2008, [5] presented a review for sugarcane agriculture which explains RS applications such as variety identification, yield prediction, crop classification, disease detection, health and nutrient status monitoring. The development in machine learning algorithm improves the crop classification task. In this section various ML algorithms in the area sugarcane crop classification based on remotely sensed data are reviewed. Table 1 presents comparative analysis of the research done for sugarcane classification in the form of features evaluated, classifiers used, training samples, input imagery, accuracy achieved, etc.

3.1 Decision Tree

Decision tree is a non parametric method that generates classification tree from training data was implemented by [1] on LISS IV images to identify sugarcane crop

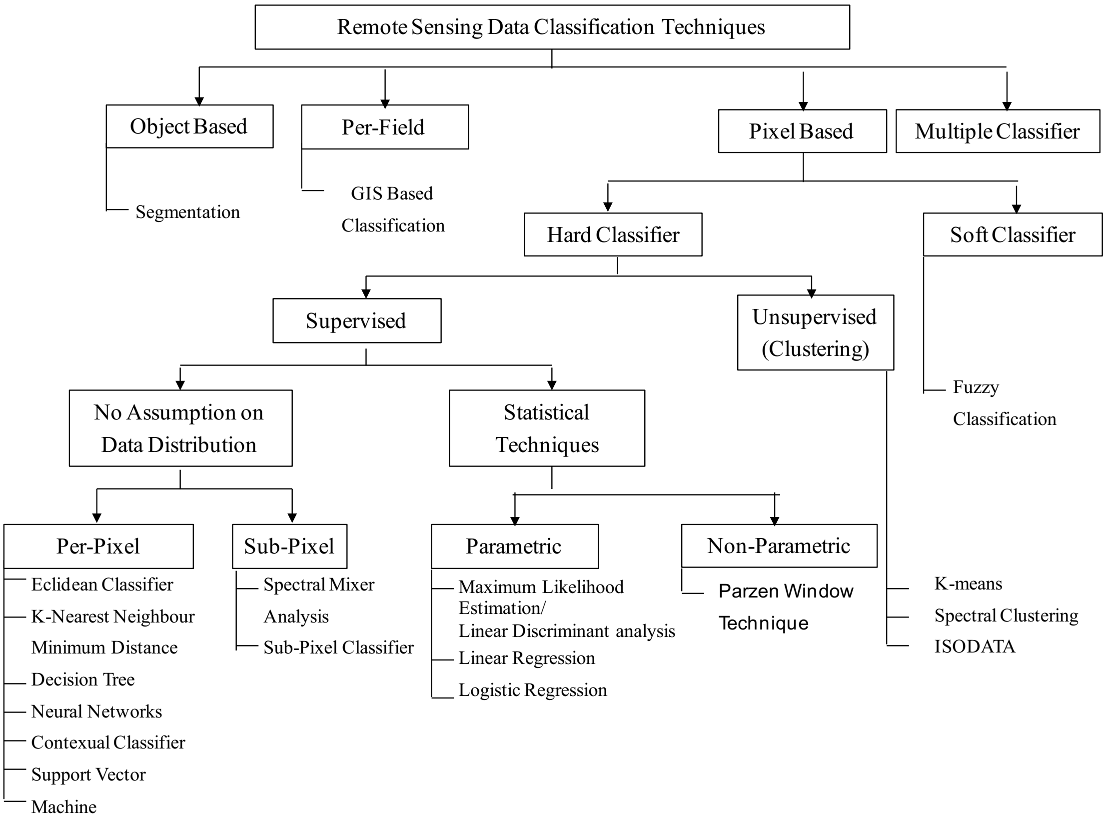

Fig. 2 Image classification approaches in RS

along with other 7 classes for the region of Chhapar village, Muzaffarnagar, India. Classification was implemented using three methods: ISODATA, Maximum Likelihood Classifier (MLC) applied on layered stacked image and DT on vegetation indices. 11 vegetation indices were experimented, among which Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Difference Vegetation Index (DVI), Optimized Soil Adjusted Vegetation Index (OSAVI) have a positive effect in the generation of decision tree. Decision tree approach outperformed with 87.93% of overall accuracy.

3.2 *Maximum Likelihood Algorithm*

Maximum probability Algorithm (MLA) is a parametric classifier which doles out a pixel to a class based on its likelihood of having a place with a class whose mean and covariance are demonstrated as forming a normal distribution in multispectral feature space. MLA is a basic classifier which was used widely before development in machine learning algorithms took place.

With the help of MLA, [6] mapped the sugarcane vegetation area in the region of Uttarkhand, India. To classify sugarcane crop and map its variety, authors evaluated the capability of ASTER satellite, by developing the spectral signature of sugarcane

Table 1 Comparative analysis of sugarcane classification studies using machine learning

Ref. No.	Features evaluated	Ground truth data, T-Training V-Validation	Dataset used	Classifier	Method	Overall accuracy	Advantages	Disadvantages	Observations
[1]	11 Vegetation indices	T- 400 V-253	LISS IV	DT	Based on 11 Vegetation indices	87.93	ISODATA and MLC producing acceptable results on single date imagery considering peak growing stage of sugarcane	ISODATA and MLC algorithms unable to classify sugarcane crop areas with acceptable accuracy	Vegetation indices along with high-resolution time series images of the entire crop cycle
				ISODATA	Layer stacking of NIR, Green and Red bands	62.07			
				MLC		76.18			
[6]	NDVI, 3 VNIR bands	T-2500 V-562 Pixels	ASTER (3rd Oct. 2004)	MLA	Using 3 VNIR bands	74.3	ASTER data have proven to be a useful resource to extract the sugarcane information	MLC was unable to separate different varieties of sugarcanes	Three crops are heavily mixed because of water content and crop variety. May not be useful for sugarcane variety mapping. Overall accuracies are low
					3 VNIR bands after NDVI	76.2			
					3 VNIR bands after Atmospheric correction	79.5			
[7]	NDVI, NDWI	T-960 V-320 Data fields	Landsat 8 20 images (Apr 2013–May 2014)	MLC	NDVI layered stacking with MLC	83.8	Landsat NDVI has shown great potential for detecting crop type, for medium sized farms over 1 hector	High resolution datasets are required to map sugarcane fields	NDWI is an effective indicator to detect harvest mode as it achieved high accuracy
					Temporal variations if NDVI and NDWI to detect harvest mode	90			
[8]	B2, B3, B4 bands	249 pixels	IRS LISS IV 2nd Oct. 2014	SVM	Classification on 3 bands	86.04	Good accuracy using spectral features	Paid dataset	Features extracted using GLCM approach outperformed raw band features
					GLCM 8 measures on 3 bands	90.29			

(continued)

Table 1 (continued)

Ref. No.	Features evaluated	Ground truth data, T-Training V-Validation	Dataset used	Classifier	Method	Overall accuracy		Advantages	Disadvantages	Observations
[9]	EVI	Training samples taken from EVI cubic image	Landsat 8 22 images (14th Jan–30th Nov 2015)	SVM	Phenology profile using EVI	90.78		Worked on less training samples	low temporal resolution of imagery creates gaps in data for profile creation	Pairwise multiclass strategy is used by training several SVM's
[10]	G, R, NIR, SWIR bands	500 observations	SPOT 5 (19th May 2016)	MD	Based on class means derived from the training data	74.6		Worked on raw bands, No idices calulation is required	Dataset is paid	Raw bands are useful for classifiation
				MAHD	Similar to MD with covariance matrix used in calculation	81.6				
				MLA	Based on probability of a pixel belonging to a class	87.4				
				SAM	Based on minimum spectral angle	68.2				
				SVM	Kernel based technique	86.4				
[14]	150 bands	2402 pixels and 84 paddocks	EO-1 Hyperion (2nd Apr 2002)			Variety	Cycle/class	Nine sugarcane varieties are classified with satisfactory classification accuracy	Dataset is paid	Machine learning algorithms outperforms the statistical approaches. Paddock level method is useful for sugarcane varieties discrimination
				LDA stepwise	Per pixel classification	76.4	57.4			
				LDA		76.8	57			
				PDA		79.7	62.3			
				RF		87.5	80.4			
				SVM		90	83.9			
				LDA stepwise	Per paddock classification	82.7	63.9			

(continued)

Table 1 (continued)

Ref. No.	Features evaluated	Ground truth data, T-Training V-Validation	Dataset used	Classifier	Method	Overall accuracy			Advantages	Disadvantages	Observations
				LDA		86.9		68.7			
				PDA		85.7		77.1			
				RF		100		97.6			
				SVM		98.8		100			
[15]	NIR, R, G, B bands	Data from field and google earth	Sentinel 2 (19th Feb 2018)	RF	Classification based on a single date layered stacking of NIR, Red, Green, Blue bands	84.22			Freely available dataset. Use of single date imagery	Not much accurate.	RF and SVM worked well on Sentinel raw bands
				SVM		81.85					
[18]	B-G, G, R,NIR,SWIR	No ground data	MSR5	K-nn	k-means clustering	98			No ground survey required	Human intervention required in imagery acquisition	Handheld radiometer was used
[22]	NDVI	Area1(A1)T-182, V-40 Area2(A2)-T-251,V-605 Area3(A3)-T-261,V-606	A1-13 images, A2-13 images, A3-21 images			***A1***	***A2***	***A3***	Significantly higher accuracy using pixel based and object based approach	Mixed results of classification in all three test areas	All classified crops have distinct temporal profile
				TWDTW	PB-NDVI time series	94.8	87.1	74.9			
					OB- NDVI time series	96.2	89.8	78.1			
				RF	PB- NDVI time series	97.1	87.4	88.8			
					OB- NDVI time series	97.6	86.3	88.3			
[28]	NDVI	Toposheets and field data	Landsat 8 12 images 12th Feb 2015–11th Nov 2015	No classifier	NDVI temporal values	90.91			Worked well for ratoon and plant cane discrimination	Covered only 2 phenologies of sugarcane	High accuracy

(continued)

Table 1 (continued)

Ref. No.	Features evaluated	Ground truth data, T-Training V-Validation	Dataset used	Classifier	Method	Overall accuracy	Advantages	Disadvantages	Observations
[30]	Polarimetric data (VV and VH)	Field visit	Sentinel-1 SAR 28 tiles	Knowledge based classifier	Object based crop cycle identification	82.17	Resolved issue of cloudy weather effect	Little low accuracy compared with other techniques	Use of SAR data provides scope to regions having cloud contaminated images
[31]	Objects	T 382, V-500	6 images	AdaBoost with bosted classifier	Time series of spectral, spatial texture and customized attributes	93.6	Good results with cloudy weather and highly mixed crop land having similar spectral reflectance	Need to calculate spatial and texture attribute values	Shown significance of sugarcane crop phenology in classification. Good accuracy in highly fragmented area

and determining the plant features. They worked on 3 bands but NDVI significantly improved the accuracy of the classification.

Reference [7] investigated spatial and temporal contents of Landsat 8 images to map cropping practices viz. sugarcane crop type and harvest mode in the sugarcane-based cropping system. To classify crop type, sugarcane map was generated using time series of NDVI images and then processed in 2 steps i. Firstly this time series was classified using ground survey data and MLC, ii. Recoding and assigning sugarcane classes into one class and other class for other land cover areas. For harvest mode classification, difference in NDVI and Normalized Difference Water Index (NDWI) was used. MLC is a good classifier if proper training samples are provided and giving good accuracy in the range of 75–90% in sugarcane classification.

3.3 Support Vector Machine

Support vector machine is a statistical learning approach to classify heterogeneous data with higher accuracy without assuming input data distribution. SVM learner has the intention of achieving Optimal Separation Hyperplane (OSH) that is a decision boundary between classes which minimizes classification error in training, by having maximum margin and later generalize to unseen data. The margin of the classifier is maximized with the help of support vectors. Support vectors are data points lie closer to the margin mainly contributes to fit the hyperplane. Other data points are discarded because they do not contribute in position and orientation of hyperplane.

Applying SVM on single data of IRS LISS IV with 3 bands (B2, B3, B4), sugarcane and other 6 classes have been classified by [8]. They extracted 8 statistical features using Gray Level Co-occurrence Matrix (GLCM) from 3 bands.

Reference [9] identified sugarcane plantation area and non-sugarcane area by applying SVM using Radial Basis Function (RBF) on time series Landsat data using (Enhanced Vegetation Index) EVI. Instead of ground truth survey data they developed phonology profile from EVI of the crop.

SPOT5 satellite imagery with four spectral bands, Green (G), Red (R), Near InfraRed (NIR), Short Wave InfraRed (SWIR), and 10 m pixel size was assessed by [10] for classification of five crops viz. corn, cotton, sorghum, sugarcane, and non crop. Five supervised techniques such as minimum distance (MD), Mahalanobis distance (MAHD), maximum likelihood, Spectral Angle Mapper (SAM) and SVM, were applied on the original satellite image and on two images generated from this original image. Their results showed that maximum likelihood and SVM performed better than other three classifiers. Original image with MLC achieved the best accuracy of 91.00 and 87.00% for two sites.

Combination of multispectral data from ResourceSat-I (IRS P6) satellite, hyperspectral data from ASTER and microwave data from RADARSAT/RISAT have been explored for classification of crops by [11]. Sub pixel level feature extraction was performed using statistical learning and contextual based algorithms. Additionally, SVM classifier was implemented for crop mapping, with the use of GA to optimize training set of SVM, and Differential Evolution Algorithms (DE), Comprehensive Learning Swarm Optimization (CLPSO) and Active Learning Algorithms to optimize the kernel parameters. SVM produces above 80% of accuracy in sugarcane crop land mapping (Table 1) and performs well with limited training samples [12] which is the main challenge in RS applications.

3.4 Random Forest

Random Forest (RF) is an ensemble learner [13] that is built by constructing many weak decision trees for classification and regression. It is a nonparametric machine learning algorithm. Bootstrap are randomly selected from an original dataset to construct multitudinous tress with the replacement of samples. The trees are grown in the best possible ways. Each tress is built independently on each other without pruning, based on the two user defined (hyper parameters—Ntree and Mtry) attributes, forms the forest. The majority vote of predictions of all the tress decides the ensemble's final decision. To test new data, it runs through all the produced trees and each tree votes for a class. The class receives maximum votes will be the final selected class.

Variety and crop cycle of sugarcane plants have been predicted using the EO-1 Hyperion hyperspectral data in Australia by [14]. A range of statistical approaches, Linear Discriminant Analysis (LDA) stepwise, LDA and Penalised Discriminant Analysis (PDA), and RF, SVM were implemented for classification firstly on pixel level, later enhanced to paddock level (Table 1). Paddocks usually contain only one sugarcane crop variety of a particular cycle. An object based classifier is good to predict on a per paddock basis using paddock vector boundaries. Paddock based classification method remarkably improved the classification accuracies.

Four bands, NIR, R, G and Blue (B), of a single date Sentinel 2 satellite imagery have been stacked by [15] to classify crops and other land cover. Classification of 11 classes including sugarcane crop was carried out by applying RF and SVM algorithms. The highest classification accuracy (Table 1) was gained by setting penalty parameter to 64, Gamma to 1 for SVM and ntree is 350 and mtry to 1 in case of RF. Feature importance was also computed whose results showed that NIR and B band for RF are of great importance, and NIR and R band contributed more in SVM classifier.

Supervised machine learning classification algorithms need to build training dataset consisting of ground truth observations during satellite overpass period. Such algorithms are unable to operate on other years without new reference data. Classifier generalization or extension [16] is an approach which is used to get rid of the above problem. Reference [17] listed many studies which uses a classifier trained on one reference dataset of a year and use it for another year. They produced three such generalized classifications for plant and ratoon cane classification, based on object based classification with reflectance indices for each object as listed below

- Same year—Training data for same application year

- Multiyear—Several years training data applied on another year
- Multiyear based map updating and change detection—Previous year reference map updating.

3.5 k Nearest Neighbor

k-Nearest Neighbor (k-NN) is a supervised classifier that classifies objects correctly if the dataset is appropriate. The created sample dataset was validated by [18] in their work to classify cotton and sugarcane using k-means. Five spectral bands B, G, R, NIR and SWIR, of Multispectral Radiometer (MSR5) were experimented as features and three clusters were chosen based on three objects bare land, sugarcane and cotton. k-NN was applied for classification on the validated reflectance dataset, resulted in significant increase in accuracy. Authors found all the 5 bands compatible with Landsat imagery, so argued that the same methodology can be experimented on Landsat image bands.

3.6 Dynamic Time Warping

In time series analysis, dynamic time warping (DTW) is one of the algorithms for measuring similarity between two temporal sequences. It was originally invented for speech recognition and recently is used in remote sensing applications. Paper by [19] have used DTW for Sentinel-2 satellite time series image classification to address following challenges—i. Lack of training (ground truth) data due to weather artifacts or labor intensiveness. ii. Unavailability of temporal data due to cloud coverage, iii. Changes in vegetation cycles. The original DTW is extended to multidimensional time series and modified to handle missing temporal samples and cloud covered images. Authors argued that DTW is evenly applicable for SAR images along with optical data. Further, [20] proposed an efficient time series analysis by reducing memory usage by more than a factor of 5, improved temporal classification results with the help of segmentation and reduction in an execution time.

Variation in DTW, time-weighted DTW, for land use and land cover mapping was proposed by [21] to address main issues of having crops phenological cycle more than a year and seasons variation. This TWDTW method gave remarkable results to classify double cropping, forest, pastures, and single cropping from time series pixel based EVI derived from MODIS data. Many existing cropland mapping studies have been focused on time series analysis on pixel based (PB). Reference [22] focused on object based (OB) classification of Sentinel 2 time series data by applying TWDTW on three different test areas and achieved significant accuracy (Table 1).

3.7 Other Techniques

References [23, 24] developed and evaluated a methodology to map sugarcane area ready for harvesting, in a given year using four dates Landsat-5 and Landsat-7 images. Reference [23] mainly focused on merging Object Based Image Analysis (OBIA) and Data Mining (DM) techniques of AI to improve the conventional method of sugarcane mapping from RS through visual interpretation. OBIA was used to represent the acquired knowledge and DM was applied to construct the knowledge model. They implemented the C4.5 algorithm to generate two models, one with the original training set and another by removing important attributes to evaluate the model's efficiency.

Another interesting RS application, the sugarcane field skips mapping was presented by [25]. The procedure is composed of crop rows identification, sugarcane classification, skip extraction and maps creation phases. Crop rows identification was carried out based on NDVI; OBIA was used for classification using ModelBuilder in ArcGIS. In future, they would work on determining the rate of skip increase in ratoons. OBIA also becomes more acceptable than pixel based classification [25] to process UAV images. UAV provides data with very high spatial resolution generates the multi temporal images of AVHRR/NOAA 16 and 17 from April 2001 to March 2010 were analyzed to monitor sugarcane fields by [26]. NDVI values of these images were analyzed using k-means clustering under the Dynamic Time Warping (DTW) function. Five clusters of each season from 2001/2002 to 2009/2010 were produced to monitor the sugarcane fields.

Logistic Regression (LR) was explored by [27] with a gradient descent algorithm to tune the parameters of the model, in order to classify sugarcane land. One of the poorly studied tasks of ratoon sugarcane discrimination and its growth monitoring was explored by [28]. By taking advantage of multi temporal characteristics, NDVIT, temporal values of NDVI, was utilized for ratoon crop identification. RAMiner (Rule Based Associative Classifier Miner), a developed method by [29] created a model using set of associated rules based on NDVI series to identify sugarcane fields with two way classification steps: conviction value and conviction based probability. RAMiner gave highest accuracy 83.4% in comparison with other classifiers.

Time series Sentinel 1 images have been utilized to identify harvested and non harvested sugarcane areas by applying knowledge based crop cycle analysis and segmentation [30]. K-means clustering initially segmented the data into 15 clusters from which crop types were identified based on crop cycle knowledge. Finally classification of three classes, sugarcane harvested area, non harvested area and other crops, was achieved with good accuracy.

Sugarcane cultivation areas in southern China face the challenges of cloudy weather and spectral mixing of crops, makes discrimination of sugarcane crop difficult using RS data [31]. Authors developed a methodology for the mapping of a large sugarcane area using middle resolution satellite data. It includes object oriented based image segmentation with the generation of attribute table followed by building a training set using the Adaboost algorithm and a boosted classifier. The overall training and testing accuracy, proved that middle resolution satellite data is suitable to classify sugarcane crops in the southern China.

Same problem of cloud coverage in images was dealt in [32] by employing time series of images, optical and radar data and cloud gap filling methods to classify crops, pastures and tree plantations at 4 levels, in the heterogeneous region of Sao Paulo, Brazil. Supervised object oriented classification and RF algorithm were used for their study. They concluded that advanced cloud filling methods and Sentinel 1 data did not contribute in overall accuracy. Conversely, time series images were helpful in classification. Reference [33] also observed issue of entire sugarcane growing season in the region of Suixi and Leizhou, South China along with cloud coverage problem. Sentinel 1A SAR data was used for their study along with optical Sentinel 2 data. They devised a technique for early season mapping of sugarcane using RF and XGboost algorithm on time series data. Their framework consists of two procedures:

i. Time series S1A SAR images generate initial sugarcane map which is refined by removing non vegetation area using Sentinel 2 optical data.
ii. S1A based incremental classification to test the framework.

3.8 Deep Learning

A method to extract sugarcane plantation area was proposed by [34] using deep learning with the help of four months multi temporal images of GF-2 and BJ-2. Firstly, non vegetation area was extracted and then temporal processing of sugarcane area was performed, using Deep Convolution Neural Network (DCNN). Input to DCNN were sowing period images, growing period images, matured period images and other data. Authors compared the proposed method with object oriented, DeepLab V3+ and ground data. The overall accuracy of the proposed method is 94.32%.

4 Accucracy Assessment Parameters

4.1 Cohen's Kappa Coefficient

Cohen's Kappa, a robust measure than simple percent calculation, measures the agreement between two raters who each classify number of (N) items into C mutually categories. It is defined by following function

$$k = \frac{P_o - P_e}{1 - P_e} = 1 - \frac{1 - P_o}{1 - P_e} \tag{1}$$

where

Po—Relative observed agreement among raters

Pe—hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observe randomly seeing each category. Zero value of the Kappa coefficient indicates no agreement between reference data and classified data, whereas value 1 indicates, classified image is totally identical to the reference image.

4.2 Overall Accuracy

The quantitative method of characterizing image classification accuracy is a confusion matrix or error matrix. It is a table that shows correspondence between reference data and classified data. Overall accuracy (OA) is defined as out of all of the reference data what proportion were mapped correctly. It is given as below

$$OA = \frac{\text{\# of correctly classified sites}}{\text{\# of reference sites}} \tag{2}$$

The overall accuracy is usually expressed as a percent, with 100% accuracy being a perfect classification where all the reference sites are classified correctly. Figure 3 presents comparative analysis of highest accuracies gained by machine learning and other techniques in the studies of sugarcane classification.

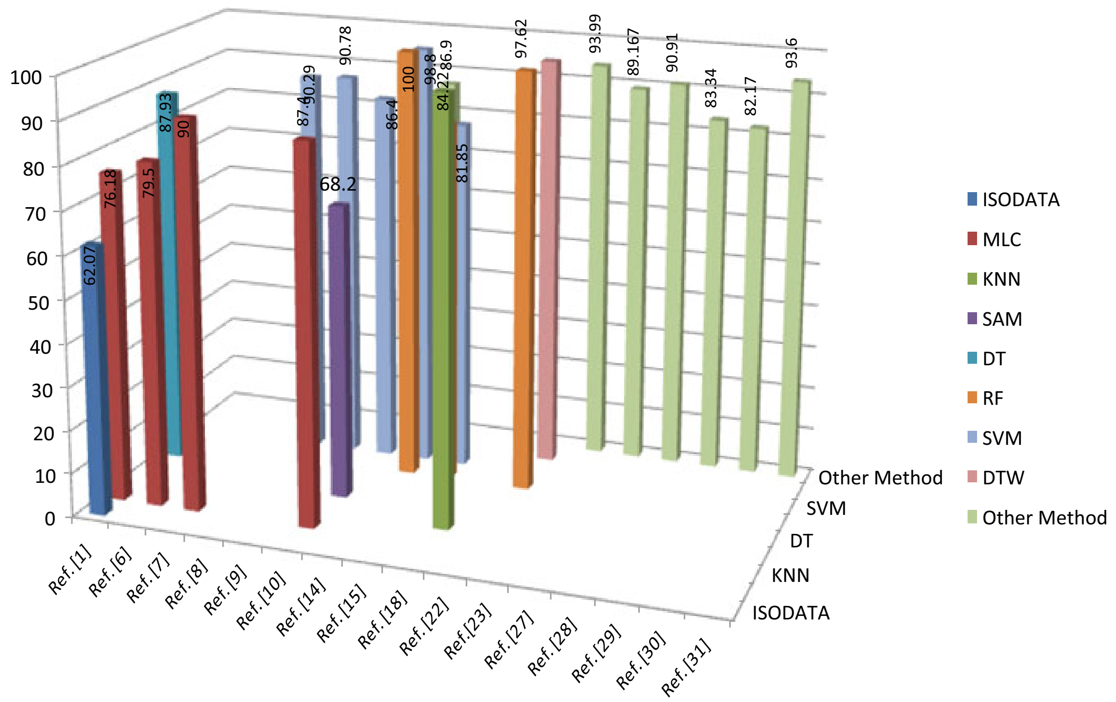

Fig. 3 Comparative analysis of accuracies achieved using machine learning and other algorithms in sugarcane crop classification

4.3 Producer's Accuracy

Producer's Accuracy (PA) is the map accuracy from the producer's point of view. This is how often are real features on the ground correctly shown on the classified map. It is given each classify number of (N) items into C mutually categories. It is defined by following function

$$PA = \frac{\text{\# of reference sites classified accurately of a class}}{\text{Total \# of reference site for that class}} \tag{3}$$

4.4 User's Accuracy

The User's Accuracy (UA) is the accuracy from of a map user's point of view. The User's accuracy indicates how often the class on the map will actually be existing on the ground. The User's Accuracy is defined by following function.

$$UA = \frac{\text{\# of correctly classified sites}}{\text{Total \# of classified sites}} \tag{4}$$

5 Conclusion and Future Directions

This paper presents the significance of machine learning with RS technology in sugarcane crop classification. From the review, it is revealed that object based image analysis outperforms pixel based analysis for sugarcane mapping. The accuracy of all classifiers which are reviewed is ranging from 74.63% to 100%. Classifier such as MLC yields good results when classifying on single date satellite imagery and for sugarcane classification its accuracy is around 74% irrespective of whether it is single date or multi-date imagery. However machine learning with different classification technique i.e. SVM, RF, DTW, AdaBoost, etc. successfully classify sugarcane crop with remarkable accuracy. Considering the fact that sugarcane is highly dynamic crop and its phenological characteristics play an important role in classification; it is concluded that the ML approach using RS data is certified to be applicable, with good accuracy, in sugarcane crop classification. Based on the study of recent work the future directions are identified as follows:

1. Variety Identification—The idea is that varieties have different canopies due to their particular morpho-physical characteristics; hence it might be possible to identify such differences through orbital spectral data. It would help institutions that breed sugarcane varieties for royalties charges, for the propagation of their genetic material.

2. Cloudy images—In southern India generally monsoon starts from June and lasts till September. So 4–5 months of optical satellite data is missing due to heavy cloud coverage over the land. This creates a gap in the data that represents particular growth stage of the sugarcane crop. However assimilation of optical and SAR data helps to cover that phenological stages data but does not produce optimum accuracy. So there is scope to investigate the technique to deal with cloudy images of optical satellite.
3. Satellite Sensors—The sensors in satellite, if can be enhanced enough spatially, temporarily and spectrally then mapping accuracy will definitely increase beyond expectations.

The future work will be to work on sugarcane variety identification, distinguishing between plant cane or ratoon cane and discrimination of sugarcane phenology in the south India area.

References

1. Verma AK, Garg PK, Prasad KSH (2017) Sugarcane crop identification from LISS IV data using ISODATA, MLC, and indices based decision tree approach. Arab J Geosci 10(1):16
2. Xavier AC, Rudorff BFT, Shimabukuro YE, Berka LMS, Moreira MA (2006) Multi-temporal analysis of MODIS data to classify sugarcane crop. Int J Remote Sens 27(4):755–768
3. Lu D, Weng Q (2007) A survey of image classification methods and techniques for improving classification performance. Int J Remote Sens 28(5):823–870
4. https://alan.do/remote-sensing-an-overview-of-common-pixel-classification-techniques-4827c4c3a9ff
5. Abdel-Rahman EM, Ahmed FB (2008) The application of remote sensing techniques to sugarcane (Saccharum spp. hybrid) production: a review of the literature. Int J Remote Sens 29(13):3753–3767
6. Vinod KVK, Kamal J (2010) Development of spectral signatures and classification of sugarcane using aster data. Int J Comput Sci Commun 1:245–251
7. Mulianga B, Begue A, Clouvel P, Todoroff P (2015) Mapping cropping practices of a sugarcane-based cropping system in Kenya using remote sensing. Remote Sens 7(11):14428–14444
8. Dhumal RK et al (2019) A spatial and spectral feature based approach for classification of crops using techniques based on GLCM and SVM. In microelectronics electromagnetics and telecommunications. Springer, Singapore, pp 45–53
9. S. Mulyono and others (2016) Identifying sugarcane plantation using LANDSAT-8 Images with support vector machines. In IOP conference series: earth and environmental science, vol 47, No 1, p 12008
10. Yang C, Everitt JH, Murden D (2011) Evaluating high resolution SPOT 5 satellite imagery for crop identification. Comput Electron Agric 75(2):347–354
11. Khobragade AN, Raghuwanshi (2015) MM Contextual soft classification approaches for crops identification using multi-sensory remote sensing data: machine learning perspective for satellite images. In artificial intelligence perspectives and applications. Springer, pp 333–346
12. Foody GM, Mathur A (2004) Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. Remote Sens Environ 93(1–2):107–117
13. Breiman L (2001) Random forests. Mach Learn 45(1):5–32
14. Everingham YL, Lowe KH, Donald DA, Coomans DH, Markley J (2007) Advanced satellite imagery to classify sugarcane crop characteristics. Agron Sustain Dev 27(2):111–117

15. Saini R, Ghosh SK (2018) Crop classification on single date sentinel-2 imagery using random forest and suppor vector machine. Int Arch Photogramm Remote Sens Spat Inf Sci
16. Botkin DB, Estes JE, MacDonald RM, Wilson MV (1984) Studying the earth's vegetation from space. Bioscience, 508–514
17. dos Santos Luciano AC et al (2018) Generalized space-time classifiers for monitoring sugarcane areas in Brazil. Remote Sens Environ 215:438–451
18. Shifa MS, Naweed MS, Omar M, Jhandir MZ, Ahmed T (2011) Classification of cotton and sugarcane plants on the basis of their spectral behavior. Pakistan J Bot 43(4):2119–2125
19. Petitjean F, Inglada J, Gançarski P (2012) Satellite image time series analysis under time warping. IEEE Trans Geosci Remote Sens 50(8):3081–3095
20. Petitjean F, Weber J (2013) Efficient satellite image time series analysis under time warping. IEEE Geosci Remote Sens Lett 11(6):1143–1147
21. Maus V, Câmara G, Cartaxo R, Sanchez A, Ramos FM, de Queiroz GR (2016) A time-weighted dynamic time warping method for land-use and land-cover mapping. IEEE J Sel Top Appl Earth Obs Remote Sens 9(8):3729–3739
22. Belgiu M, Csillik O (2018) Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. Remote Sens Environ 204:509–523
23. Formaggio AR, Vieira MA, Rennó CD, Aguiar DA, Mello MP (2010) Object-Based image analysis and data mining for mapping sugarcane with landsat imagery in Brazil. Int Arch Photogramm Remote Sens Spat Inf Sci 38:553–562
24. Vieira MA, Formaggio AR, Renno CD, Atzberger C, Aguiar DA, Mello MP (2012) Object based image analysis and data mining applied to a remotely sensed landsat time-series to map sugarcane over large areas. Remote Sens Environ 123:553–562
25. de Souza CHW, Lamparelli RAC, Rocha JV, Magalhães PSG (2017) Mapping skips in sugarcane fields using object-based analysis of unmanned aerial vehicle (UAV) images. Comput Electron Agric 143:49–56
26. do Valle Gonccalves RR, Zullo J, Romani LAS, do Amaral BF, Sousa EPM (2017) Agricultural monitoring using clustering techniques on satellite image time series of low spatial resolution. In: 2017 9th international workshop on the analysis of multitemporal remote sensing images (MultiTemp), pp 1–4
27. Henry F, Herwindiati DE, Mulyono S, Hendryli J (2017) Sugarcane land classification with satellite imagery using logistic regression model. In IOP conference series: materials science and engineering, vol 185, No 11, p 2024
28. Singla SK, Garg RD, Dubey OP (2018) Sugarcane ratoon discrimination using LANDSAT NDVI temporal data. Spat Inf Res, 26(4):415–425. Joao RS, Mpinda STA, Vieira APB, Joao RS, Romani LAS, Ribeiro MX (2018) A new approach to classify sugarcane fields based on association rules, In: information technology-new generations. Springer, pp 475–483
29. Joao RS, Mpinda STA, Vieira APB, Joao RS, Romani LAS, Ribeiro MX (2018) A new approach to classify sugarcane fields based on association rules. In information technology-new generations. Springer, pp 475–483
30. Murugan D, Singh D (2018) Development of an approach for monitoring sugarcane harvested and non-harvested conditions using time series Sentinel-1 data. In IGARSS 2018–2018 IEEE international geoscience and remote sensing symposium, pp 5308–5311
31. Zhou Z et al (2015) Object-oriented classification of sugarcane using time-series middle-resolution remote sensing data based on adaboost. PLoS One 10(11):e0142069
32. de Oliveira Santos C et al (2019) Classification of crops, pastures, and tree plantations along the season with multi-sensor image time series in a subtropical agricultural region. Remote Sens 11(3)
33. Jiang H et al (2019) Early season mapping of sugarcane by applying machine learning algorithms to sentinel-1a/2 time series data: a case study in Zhanjiang City, China. Remote Sens. 11(7):861
34. Zhu M, Yao M, He Y, He Y, Wu B (2019) Studies on high-resolution remote sensing sugarcane field extraction based on deep learning. IOP conference series: earth and environmental science 237(3):32046