EVALUATING THE POTENTIAL OF 8 BAND PLANETSCOPE DATASET FOR CROP CLASSIFICATION USING RANDOM FOREST AND GRADIENT TREE BOOSTING BY GOOGLE EARTH ENGINE

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ABSTRACT:

One of the challenging task in agriculture is mapping of crops using satellite images as spectral properties of the crops looks similar to each other, and there are many complexities which are there in the field such as small land holdings, heterogeneous and often distinct field patterns. In past, mapping with high resolution satellite images was not possible due to the non-availability of data and even they were costlier. However, with the free availability of PlanetScope dataset having 8 spectral bands, with daily revisit cycle and resolution of 3m, it is now possible to carry out mapping and monitoring of agriculture crops. The objective of the study is to classify major crops of rabi (December-April) season using single date PlanetScope imagery in the Haridwar district, Uttarakhand, India. Classification of crops has been carried out using an ensemble based machine learning algorithms within Google earth engine. Off late, Google Earth Engine (GEE), a cloud based platform has attracted the attention of remote sensing analyst since it expediates the classification yielding good results of high quality. In this study, Random Forest (RF) and Gradient Tree Boosting algorithm (GTB) have been used after performing hyper-parameter tuning and results shows that overall accuracy obtained by RF and GTB are 88% and 86.5% respectively. According to the results, both classifier performed well but RF achieved 1.5% high accuracy over GTB. Analysis of the results show that highest accuracy was attained by agriculture class (wheat) while other crops class exhibited lower accuracy. In this study, RF was found to be more competent as compared to GTB in classifying the crops and PlanetScope 8 band dataset has also proved its potential in classifying crops in heterogeneous fields.

1. INTRODUCTION

Mapping of crops is considered an important task in many different fields as it provides countless advantage for understanding the food system and yield prediction. It is also helpful during the challenging time caused due to climate change and also provides sustainable agriculture practice. Classification of crop provides useful information's for various agencies such as insurance agencies, geoportal, regional and national agricultural boards for decision making. Therefore, timely and accurate crop mapping is required which otherwise is often expensive, labour intensive and destructive process if performed manually.

Therefore, Remote Sensing data is considered a useful source of data for timely and accurately mapping and monitoring of crops. In the past years, freely available MODIS data with high temporal resolution, Landsat and Sentinel 2 data with 30m and 10m spatial resolution have been used for crop mapping (Zheng et al. 2015; Saini and Ghosh 2018). One of the biggest disadvantage with MODIS and Landsat data was spectral mixing due to low and coarse resolution data. In past, mapping with high resolution data was not possible because of its availability and cost, but now with free available PlanetScope dataset having a spatial resolution of 3m and daily revisit cycle is being used widely. Initially, PlanetScope provided 4 band surface reflectance data (Blue, Green, Red and NIR), but from 2022 onwards, it has started to provide a 8-band atmospheric corrected surface reflectance dataset which is data. There are many studies which reveals the advantage of 4 band PlanetScope dataset. A study has been carried out to compare PlanetScope dataset with Sentinel-2 dataset by (Mudereri et al. 2019) for mapping Striga weed in Kenya and results shows that PlanetScope dataset is more accurate in mapping as compared to Sentinel-2 dataset. Further, PlanetScope dataset has a great potential for producing the crops intensity maps at detailed resolutions (Rafif et al. 2021). The study used the 4 band data for mapping four different types of crop classes and found that NIR band to be most extensive for analysing and evaluating the cropping intensity. Acharki, (2022) deployed Random Forest machine learning algorithm for LULC classification using 4 band PlanetScope dataset, Landsat-8 and Sentinel-2 and the result show the potential of PlanetScope data which give an overall accuracy of 97%.

With the increase availability of free remote sensing data and improvement in the image resolution (radiometric, spectral, spatial, temporal), there is lot of scope for the researchers to adopt exhaustive techniques for data analysis. However, with improved spatial, spectral, radiometric and temporal resolutions, the volume of data has increased manifolds. This brought a shift in the working environment of traditional workstations to cloud- based platforms. Google Earth Engine (GEE) is one of the widely utilized cloud-based geospatial analytic platform which allow the researchers and users to tackle the difficulties faced while managing the huge dataset and processing. It provides the platform where user can analyse the available remote sensing images using Integrated Development Environment (IDE) code editor without downloading the dataset. In addition to this, GEE has large number of options of several machine learning algorithms. The use of GEE engine from 2013 is been increased drastically (Tamiminia et. al, 2020; Sharma et.al, 2022).

One of the advantage of 8-band and 4-band PlanetScope data is the introduction of Red-edge band (697-713 nm) between the red band and NIR band. This Red-edge band has huge potential in the area of vegetation mapping especially agriculture. Thus, one of the prime objective of the study is to explore the potential of 8-band PlanetScope data for classifying the major crops using machine learning algorithms. Here Random Forest (RF) and Gradient Tree Boosting (GTB) have selected for analysis using Google Earth Engine. The efficacy of RF and GTB algorithms are evaluated in the study for identifying different crops in the study area. The structure of the paper can be defined as follows: Section 2 highlights the characteristics of the study area followed by the satellite data-set utilized; Section 3 showcases the framework of methodological description of machine learning algorithms; Section 4 reveals and portrays the results and corresponding discussion and at last Section 5 presents the conclusive remarks and the future scope of the work.

2. STUDY AREA AND DATA USED

In this study, Hardiwar district is selected as a study area which is bounded between 29.58º N latitude and 78.13º E longitude covering an area of 2310.76 Km². The region lies within the close proximity of River Ganges on the east side and River Yamuna on the west side. The region has sandy loam soil with high porosity. It is located at the foothill of Himalaya and is mainly dependent on tourism, animal husbandry and agriculture. The major agricultural crops grown here are sugarcane (32%), wheat (18%) and rice (5%) and rest is cash crops such as groundnut, maize, mustard, potato and lentil etc. (https://haridwar.kvk4.in/district-profile.html). Thus, it is important to have accurate information regarding the crops being sown.
PlanetScope satellite data for 19 February 2022 has been used in the study as it corresponds to the peak winter season of crop growth. The 8-bands dataset has been used for classification to assess the utility of newly added bands. The satellite data was downloaded from https://www.planet.com/explorer/ and detailed specification of the PlanetScope dataset such as band name, spatial resolution and wavelength is given in Table1.

Ground truth data is collected using the Trimble Handheld Global Positioning System during the growing season (shown in Figure 2). According to the survey, the study area is split up into 12 different Land Use and Land Cover (LULC) classes such as: built-up, water, barren, sand, fallow-land, forest, shrub, orchards, wheat, sugarcane, mustard and other crops (wheat with trees, mustard with trees, vegetables etc.). Here, major crops in the study area are Wheat, Mustard and Sugarcane. Other Crop classes mainly consist of double crops, vegetable and many more. Orchard class mainly consists of a group of trees mainly guava trees during winter season and trees which are planted on the boundary of agricultural field. Figure 2. shows the False Color Composite (FCC) of the study area which was created using PlanetScope imagery.

Table 1. PlanetScope 8 Band Dataset Detailed Specification

Band No	Band Name	Resolution (m)	Wavelength(nm)
b1	Coastal Blue	3	431-452
b2	Blue	3	465-515
b3	Green	3	513-549
b4	Green	3	547-583
b5	Yellow	3	600-620
b6	Red	3	650-680
b7	Red-Edge	3	697-713
b8	NIR	3	845-885

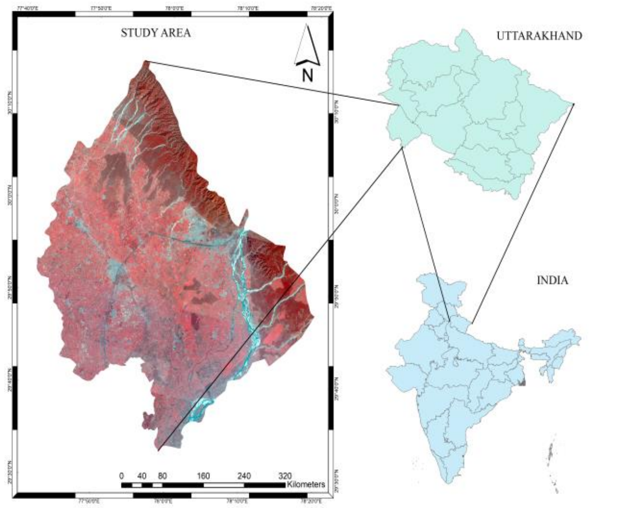

Figure 1. False colour composite (FCC) of the study area using PlanetScope Image

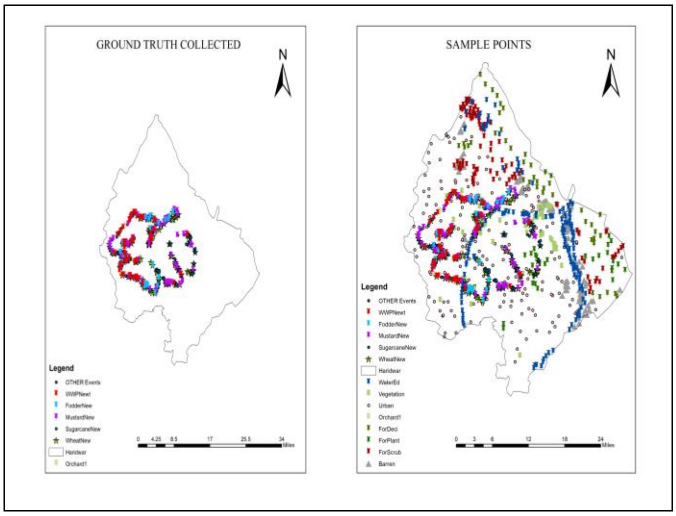

Figure 2. a) Ground Truth Data Collected for Major Crops and Sample Reference points generated for other classes using high resolution data.

3. METHODOLOGY ADOPTED

The methodology incorporated in the research work for crop classification is schematically presented in Figure 3. The main

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concentration of the study is for crop classification; therefore, Single date imagery of Planet scope was acquired during the growing season of winter crop. The study area is covering around 10 to 14 tile of planet data thus there is a need to mosaic the data before any processing. Mosaicking of dataset is performed in PCI geomatica outside the Google Earth Engine (GEE). Once the mosaicked image is generated the image is uploaded into GEE using its code editor.

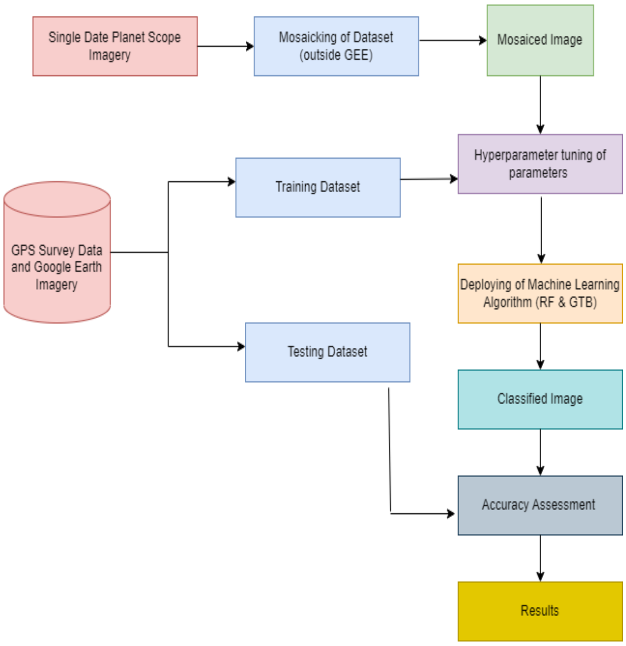

Figure 3. Methodology Adopted in Study

Table 2: No of Points used in Training and Testing of classifier for different classes

S. No	Class Name	Total Points	Training Points	Testing Points
1.	Built-Up	193	123	70
2.	Water	154	116	38
3.	Barren	115	80	35
4.	Sandline	253	195	58
5.	Fallow Land	85	60	25
6.	Deciduous Forest	71	50	21
7.	Shrub	113	79	54
8.	Orchards	76	53	23
9.	Wheat	169	118	51
10.	Sugarcane	145	102	43
11.	Mustard	110	77	33
12.	Other Crops	55	32	23

GEE is used in the study for further processing and analysis. Ground truth data was collected during the field survey using the Trimble GPS and sample for some classes were collected using high resolution google earth imagery which collectively creates a reference dataset (shown in Figure 2). Now with the help of GEE functions, the reference dataset is spited into 70% of training and 30% of testing data. RF and GTB machine learning algorithm have been used for classification. Both Algorithms are powerful and popular supervised machine learning algorithms with some pros and cons. The training dataset is further used for optimizing the parameters of RF and GTB to attain high accuracy. Now these optimized parameters (describe in Table 3) are used along with training dataset to train the models to predict the various classes in the input image. This helps in generating the classified map of the study area. Thereafter, testing dataset is used to test the accuracy of the models. In this study, for accuracy assessment F1- score has been used. It helps in accessing the accuracy of specific class, by combining the precision and recall of a classifier into a single metric by taking their harmonic mean of that particular class.

Table 3. Parameters used for Tuning by RF and GTB

Algorithm	Hyper Parameter	Tested values	Optimal Values
RF	numberOfTrees	[50,100,150,200,250,300]	250
	variablesPerSplit	[2,3,4,5]	3
	bagFraction	[05,0.6,0.7,0.8,0.9]	0.7
GTB	numberOfTrees	[50,100,150,200,250,300]	200
	Learning rate	[0.05,0.06,0.07,0.08,0.09]	0.08

3.1 Classification Algorithms

In the present study, two powerful classifiers such as Random Forest and Gradient Tree boosting are used for classifying the crops.

3.1.1 Random Forest Classifier (RF)

Random Forest (RF) algorithm (Breiman,2001) is a supervised Stastical classification approach which is based on the concept of learning strategy. It is an ensemble classifier and non-parametric algorithm, which combines the decision tree approach and aggregation approach. This classifier is capable of determining the variable importance and has revealed a high accuracy as compared to other tradition classifiers such as SVM, kNN and Decision tree (Saini & Ghosh, 2018; Lopes et al., 2020). RF classifier randomly selects the set of training data from the training dataset using the replacement policy which improves the accuracy by reducing the variance from the input data. It consists of a collection of tree structured classifiers and majority voting scheme is used to determine the output. RF classifier has three main tuning parameters which needs to be optimized. These parameters are: ntree (number of trees to grow), variablesPerSplit (number of variables per split) and bagFraction (fraction of input to bag per tree). From the literature, variablesPerSplit or Mtry and ntree is considered as the most critical parameters which had a great influence on classification results(Saini & Ghosh, 2018 ; Acharki, 2022). RF has come advantages (Breiman,2001):

i. RF performs well in many cases when compared to Adaboost.
ii. RF can handle huge amount of data easily.
iii. RF is robust to outliers as well as noise.
iv. RF can provide useful internal estimates of error, strength, correlation and variable importance.
v. RF can easily run on large datasets.

3.1.2 Gradient Tree Boosting (GTB)

The Gradient Tree Boosting (GTB) model (Friedman, 2001) comprises of an integrated decision-tree and boosting algorithms. The integrated algorithmic approach computes the residuals between predicted values and the actual value. Furthermore, in order to decipher the classification problem, the approach utilizes gradient, boosting as well as the decision trees. Additionally, this also assists in performing the process of

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regression for predictions. In general, boosting corresponds to numerous weak classifiers combined together for creating a prominent classifier. On the other hand, when the model executes and estimates the loss function, incremented flexibility corresponds to the gradient function. The GTB model contains less number of model parameters yielding higher computational speed and robust stability when compared to the conventional support vector machine model.

3.1.3 Accuracy Assessment

Confusion Matrix (CM) technique is used in the study for accuracy assessment (Foody et. al, 1992). In this technique, various statistics parameter is evaluated for all classified maps. Statistics parameter are as follows:

Overall Accuracy (OA):
Overall accuracy can be defined as "the ratio of correctly classified samples to that of the total sample space".

$$OA = \frac{Number\ of\ correctly\ classified\ samples}{total\ number\ of\ samples} * 100 \quad \text{....} \quad (1)$$

Precision (P): Precision can be defined as "the ratio of correctly classified pixels of particular class to the total number of classified sites". It mainly calculates the presence of correctly predicted training data.

$$P = \frac{Correctly\ classified\ pixel\ of\ class}{total\ number\ of\ classified\ sites} \quad \text{........} \ (2)$$

Recall (R): Recall can be defined as "the ratio of number of correctly predicted training data points of a class to the total training data points provided".

$$R = \frac{Correctly\ classified\ GroundTruth\ sites}{total\ number\ of\ GroundTruth\ sites} \quad \text{......} \ (3)$$

F1-Score: It can be defined as the harmonic mean of precision and recall.

$$F1 = \frac{2*(P*R)}{(P+R)} \quad \text{........} \ (4)$$

Where P is precision and R is recall

4. RESULTS AND DISCUSSION

In the study, Planet Scope images acquired in the growing season were mosaicked and the resultant image is used for the crop classification. All bands (except 'b1: coastal blue') at 3m resolution are used for crop mapping. The training and testing data used described in table 3 from which it can be observed that 70% of each class is been utilized by classifier for training purpose and 30% of data is utilized as a testing dataset. The total of 1539 data points is used from which 1072 points are used for training purpose while 492 points used for testing. This portioning of dataset is done using split function in GEE. In remote sensing, the quality of the classified map can be assessed with the help of accuracy assessment, the accuracy only defines whether the generated map can be used for the particular application (Foody, 2002). According to literature, for evaluating the process, confusion matrix and kappa coefficients is widely used. In this study, for evaluating the performance of both classifiers overall accuracy along with F1 score were evaluated. All these accuracy parameters were evaluated by using the optimal value of tuning parameters obtained from respective classifiers.

Table 4. Overall Accuracy by GTB and RF

Dataset	GTB	RF
OA (%)	81.99%	83.68%

The list of tuning parameters along with tested and optimal values are shown in table 3. In RF, numberOfTrees, variables per split and bagFraction are the three parameters which are optimized and can affect the classification accuracy. The testing value for numberOfTrees ranges from 50 to 300 with an interval of 50; variablesPerSplit ranges from 2 to 5 with an interval of 1 and bagFraction ranges from 0.5 to 0.9 with an interval of 0.1. The optimized value for the parameters are 250, 3 and 0.7 respectively for RF classifier. Similarly, for GTB classifier numberOfTrees and learning rate (shrinkage) were the tuning parameters and testing value for numberOfTrees range from 50 to 300 and learning rate or shrinkage value range from 0.05 to 0.09 with an interval of 0.01. The optimal values for GTB classifier are 200 and 0.08 respectively. With these optimal value classification is performed by both classifier and it was observed that GTB achieved 81.99% as the overall accuracy and 79.66% as the kappa coefficient while RF attained 81.99% as overall accuracy and 81.56% as kappa coefficient. The classified image for RF and GTB classifier is shown in Figure 4 and Figure 5.

It has been observed that both classifier performed well in the field of agriculture i.e. for crop classification. But from the result it can be seen that RF yields better result as compared to GTB. This can be because of the property of Random Forest that it is robust to noise and outliers while GTB is not. Table 4. shows the class specific accuracy, from which it can be inferred that in crops, wheat attains the high accuracy by RF classifier followed by Sugarcane and Mustard. This can be because during 19th February wheat crop must be at flowering stage attaining high level of chlorophyll content while mustard must be at ripening stage because during the mid of march harvesting of mustard starts in the study area and sugarcane is either harvested or if retains for next year. So, during this period it is easy to discriminate wheat from other crops and this can be observed from table 5 also that wheat is attaining high accuracy among all crops.

While Sugarcane has achieved 84.55% of accuracy by RF classifier and 89.56% by GTB. From the error matrix, it has been observed that maximum intermixing of Sugarcane pixels can be seen in shrub and other crop class due to the similar spectral characteristics. In other crops sample from double crops are also included which shows similar spectral behaviour and hamper the accuracy. Mustard crop is achieving 85.95 %of accuracy with GTB classifier and 88.08% accuracy with RF classifier. It has been observed that other crops (include double crops) attain lowest accuracy by both classifiers. While this can be a reason because few samples were collected for this class and due to double crops maximum pixels of this class is been misclassified into wheat or mustard class.

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Apart from crops from Table 5, it is also observed that Urban is not attaining a specific accuracy of 85% as it can be noticed that maximum pixels of urban is misclassified as Sandline and vice versa. This is because sand and urban have similar spectral reflectance and according to literature, SWIR band can help in discriminating Sandline from Urban but in PlanetScope data SWIR band is not present. This mainly reducing the accuracy of Urban as well as Sand line. However, other classes show nearly same accuracy with both classifiers but water attains high accuracy with RF Classifier as compared to GTB Classifier.

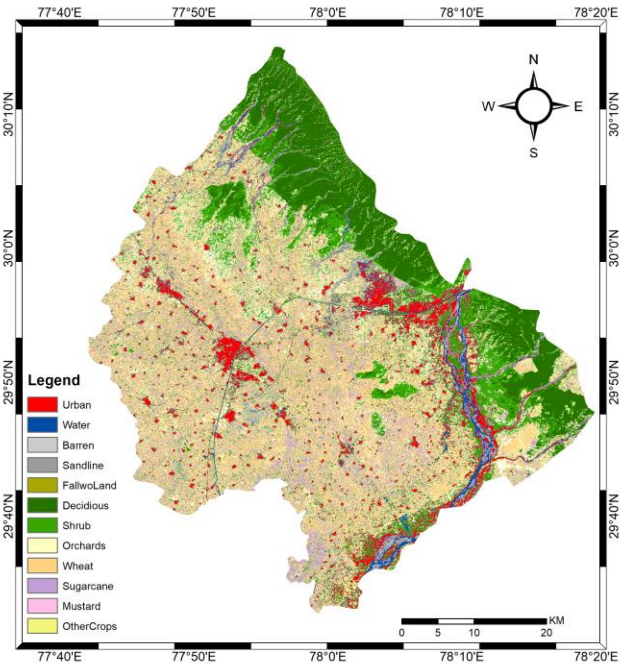

Figure 4. Classified Map generated using Random Forest (RF)

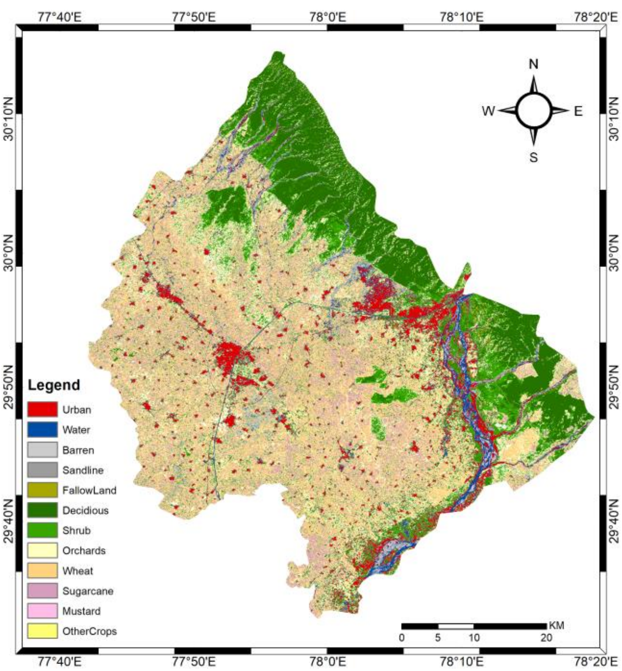

Figure 5. Classified Map generated using Gradient Tree Boosting (GTB)

Table 5. F1 score of all classes by RF and GTB

Class Name	GTB	RF
Urban	76.37	78.57
Water	82.66	92.10
Barren	95.64	95.89
Sand line	78.29	81.35
Fallow Land	84.30	87.66
Deciduous	72.96	76.97
Shrub	83.01	80.88
Orchards	87.09	88.19
Wheat	91.15	93.20
Sugarcane	89.56	84.55
Mustard	85.95	88.08
Other Crops	28.04	32.21

Table 6: Total No of Points Correctly Classified by RF and GTB

S. No	Class Name	Correctly Identified by RF	Correctly Identified by GTB	Total Points
1.	Built-Up	55	55	58
2.	Water	35	31	46
3.	Barren	35	33	36
4.	Sandline	46	44	76
5.	Fallow Land	21	21	25
6.	Deciduous Forest	16	16	21
7.	Shrub	45	46	54
8.	Orchards	20	20	23
9.	Wheat	48	46	51
10.	Sugarcane	36	39	43
11.	Mustard	31	29	33
12.	Other Crops	8	8	23

Table 6. clearly shows the correctly identified pixel by both classifiers. When the values of correctly classified pixel by RF and GTB is observed, it is seen that nearly equal no of pixels were correctly identified by both classifiers. But RF yield better accuracy as compared to GTB Classifier for nearly all classes especially for crops.

5. CONCLUSION

In this study, machine learning based two powerful classifiers RF and GTB were used for crop classification for Haridwar district. Hyper parameter tuning of important parameters were performed for both classifiers to attain highest accuracy. Planet Scope dataset consist of 8 bands from which 7 bands were utilized in the study leaving band 1 which is a coastal blue. The results of the classification reveals that RF classifier attains high accuracy as compared to GTB classifier. According to F1 score of specific classes it can be observed that wheat attains maximum accuracy in the crop classes followed by sugarcane and mustard. This is due to the reason of chlorophyll level being high in wheat during the February period as it attains its flowering stage while mustard must have shifted from reproductive stage to ripening stage. Other crops in both classifier attains minimum accuracy due to the presence of double crops. Barren attains high accuracy using both classifier while water attains high accuracy by RF classifier. Both classifiers perform well while RF attains high (+1.5) accuracy as compared to GTB. The results of the study can conclude that

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PlanetScope 8 band data has a great potential to classify crops by using RF classifier. But if we need to improve accuracy of some specific class than some spectral indices related to the application has to be integrated along with PlanetScope bands.

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