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Categorization of Multiple Crops Using Geospatial Technology, Machine Learning and Google Earth Engine

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ABSTRACT

Accurate crop classification is crucial for agricultural monitoring and decision-making. Remote sensing's ultimate goal is the precise extraction and classification of crops. Based on a cloud platform, the study area of Guntur district, Andhra Pradesh India, presents a multi-crop classification approach using Sentinel-2 satellite imagery and machine learning techniques. The study area encompasses a diverse agricultural region with three major crop types. After pre-processing, spectral and textural features were extracted. It compares the traditional four machine learning algorithms employed, adding the NDVI, NDBI, MNDWI, and BSI vegetation indices for multi-crop classification enhances accuracy, and offers diverse and complementary information. The overall classification accuracy achieved 95%, with individual crop accuracies ranging from 85 to 96%. The scalable and simple classification method proposed in this research gives full play to the advantages of cloud platforms in data and operation, and the traditional machine learning compared with other algorithms can effectively improve the classification accuracy, and individual areas of crop production are calculated. The results underscored the reliability of GEE-based crop mapping in the region, demonstrating a satisfactory level of classification accuracy, surpassing 97% across distinct time intervals in overall accuracy values, Kappa coefficients, and F1-Score.

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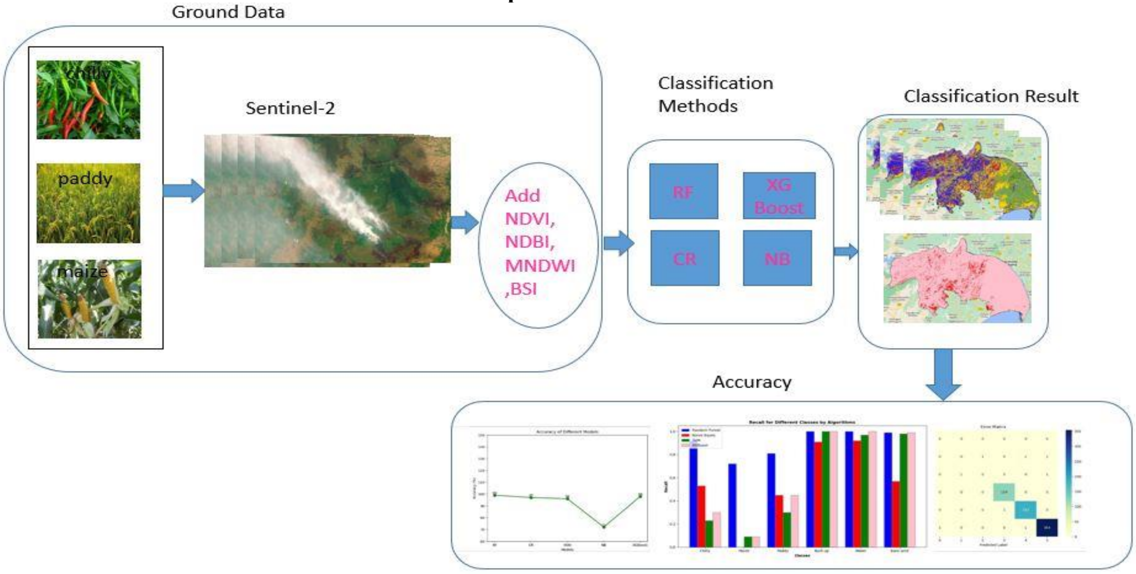
Graphical Abstract



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1. INTRODUCTION

Understanding the spatial arrangement of crops within farmland holds significant importance in shaping macro agricultural policies, guiding farmers' production practices, detecting food production trends, and predicting future yields (1-3).

Conventional crop classification methods heavily rely on extensive manual fieldwork, resulting in low data timeliness. Therefore, there's a growing need for instantaneous observation of regional crops (4, 5). The swift progress in recent advancements in agricultural RS technologies has offered robust technical assistance in promptly identifying and monitoring vast crop areas.At present, numerous studies have validated the viability of utilizing visuals from remote sensing for crop labelling. Li et al. (6) demonstrated precise identification of winter wheat by leveraging spectral features. Similarly, Jiang et al. (7) successfully retrieved data pertaining to rice from Landsat images, analyzing the evolving rice planting systems in Southern China. These studies affirm that spectral features serve as a viable basis for crop recognition. However, relying solely on single spectral features for multi-crop classification has limitations due to the "same matter different spectrum" and "foreign matter same spectrum" phenomena, particularly in areas with intricate planting architectural. RS images encompass diverse textural characteristics that mirror the ground object dispersion in space.

Incorporating these textural features enhances the differentiation between multiple crops and elevates classification accuracy (8). Researchers have examined a number of techniques for extracting textural features and confirmed their utility in crop classification (9, 10). Furthermore, environmental attributes significantly influence crop growth characteristics. Leveraging environmental indicators to discern crops based on environmental disparities can notably enhance classification accuracy (11). Zhang et al. (12) for instance, integrated agricultural categorization using spectral and environmental indices, producing very precise results.

Thus, devising an effective strategy that amalgamates these three types of information—spectral, textural, and environmental features— for the categorization of many crops to fulfil practical agricultural needs warrants further exploration. Machine learning (ML) models are often used in identification of crops, encompassing techniques like random forest (RF) (13), support vector machine (SVM) (14), K-nearest neighbor (KNN) based algorithms (15), naive Bayes (NB) which was utilized (16), artificial neural network (ANN) (17), and Extreme Gradient Boost (XGBoost) (18). For instance, Xu et al. (13) and Liu et al. (19) used RF to track winter wheat, investigating different feature combinations and how they affected the precision of categorization. Saini and Ghosh (20) demonstrated the superior performance of XGBoost over RF and SVM in crop mapping based on spectral features. Asghari Beirami and Mokhtarzade (21) integrated multiple data sources, discovering that RF and XGBoost exhibited the highest accuracy across different datasets.

Sentinel-1, using a semi-empirical WCM model in RS & GIS, assesses soil moisture in varied agricultural regions (22). The paper outlines a technique to identify topographical characteristics and design structure in the Abbassia reach of the Euphrates River (23). Employing Grim Schmidt spectral analysis on thermal satellite data, surpassing MH. This study refines the CD method for precise LU/LC pattern calculation (24). Study assesses optimal LU/LC mapping in Serdang, Selangor, Malaysia, comparing spatial resolutions (UAV, WorldView-2, Sentinel-2) with GS and Brovey algorithms for accuracy (25).

However, the selection of classification features and the quantity of classification indices significantly impact ML classifier performance. Inclusion of excessive indices can affect prediction efficiency and accuracy, while too few may not adequately represent crop characteristics, thereby reducing model accuracy. As a result, in order to maximize machine learning classifiers, index screening is frequently used to reduce redundant data and get crucial indices for crop identification.

In summary, this paper aims to mention challenges through a comprehensive comparative analysis, a topic that, to the best of our knowledge. The objective is to amalgamate spectral, textural, and environmental features to develop a more precise and efficient method for multiple crop classification, employing various ML classifiers. This study involves constructing multiple crop which have taken paddy, chilly, and maize crops with data from the ground truth points, and satellite images which apply the ML models by integrating four classifiers (RF, SVM, NB, and XGBoost) with diverse methodologies. For these algorithms to improve the efficiency we added the parameters of vegetation indices. Guntur, known for its flourishing agriculture, serves as the study area. Spectral, textural, and environmental variables are utilized to quantify crop growth characteristics, forming the foundation for the developed classification methods aimed at recognizing multiple crops. The evaluation of results will employ metrics like the Kappa coefficient, F1-score, and accuracy, and finally classify the individual crops and their crop production stages among additional improvements.

2. STUDY AREA

As depicted in Figure 1, the research encompasses the Guntur district situated in Andhra Pradesh, India. This region is bordered by the Bay of Bengal to the southeast, Bapatla District to the south, Palnadu District to the west, NTR District to the northwest, and Krishna District to the northeast. Covering an approximate area of 2,443 km^2 (943 mi^2). Its coordinates are located between 16.314209° N latitude and 80.435028° E longitude, pinpointed at 16° 18' 51.1524" N latitude and 80° 26' 6.1008" E longitude, Guntur district. The climate in the region is tropical, with an average annual temperature of 28.5°C (83.3°F) and a yearly rainfall averaging around 905 mm (36 in). The influence of the southwest monsoon is prominent, particularly in the months of June and July, witnessing the highest monthly rainfall, reaching up to 280 mm. Conversely, December records the lowest monthly rainfall at 1 mm. Utilizing sensing and GIS techniques, the study focuses on multi-crop classification within the coastal region. This area showcases varied land usage patterns, encompassing agricultural practices, water bodies, barren land, and forested areas. Notably, rapid urbanization has significantly impacted crop production management within this region.

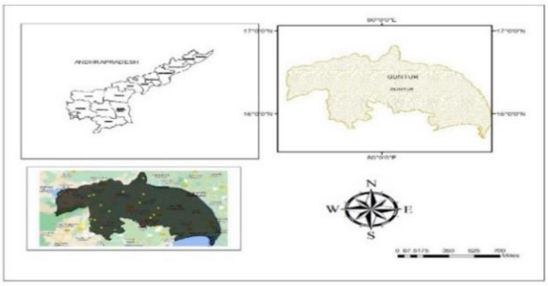

Figure 1. Regional geological map of the study area

3. METHODOLOGY

Figure 2 depicts the method of conducting research. The primary contents comprise: (1) Pretreatment and data acquisition; (2) Gathering of samples, examination of features in the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), and Bare Soil Index (BSI) as a component of the work done prior to categorization; (3) The Crops maps were identified using Random Forest, Classification and regression, Gradient Tree Boost classifier and , Naive Bayes, using feature collaborative data; and (4) Analyzing and assessing the outcomes and correctness of the classification.

3. 1. Acquiring and Analyzing Data within the Study Region

3. 1. 1. Data Source The dataset utilized comprises crop types and geographic coordinates extracted from the Guntur district crop dataset of 2022. This dataset primarily features chilies, paddy, and maize as the prominent crop types, aligning with the focus crops in this area. The sources of the remote sensing data used include the 2022 Sentinel-2 product, processed through image mosaicking and clipping procedures using ArcMap software and GEE.

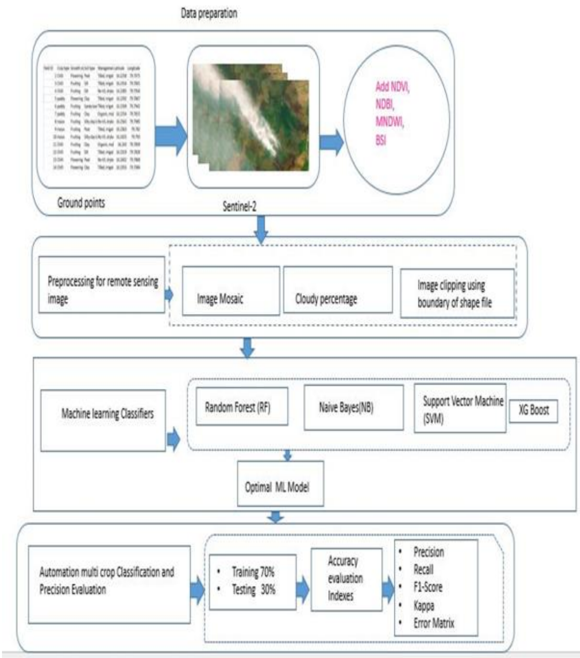

Figure 2. work flow of study region

3. 1. 2. Crop Phenology Information Phenology represents the cyclic alterations shaped by organisms' prolonged adjustment to diverse external factors like temperature and humidity, encompassing the growth and developmental rhythms synchronized with the surrounding environment. Various crops typically exhibit distinct phenological characteristics. The phenology specifics of the crop types under examination (e.g., Chilies, paddy, and maize) within the topic of study has been acquired by consulting a range of studies.

Figure 3 illustrates the dispersion of crop growth periods spanning from January to December, presenting the data from the time series encapsulating the crop calendar utilized in this study.

3. 1. 3. Sentinel-2 Data Sentinel-2 is an optical image with 14 bands of multispectral data offering acceptable spatial resolution. It comprises 4 bands at 10 meters (blue, green, red, and near-infrared), 6 bands at 20 meters (including red edge and swir bands), and 4 bands at 60 meters (covering aerosol, water vapor, cirrus, and cloud cover). For this study, the 20-meter and 60-meter reflectance was adjusted to 10-meter resolution using the nearest-neighbor method. Consisting of two satellites,

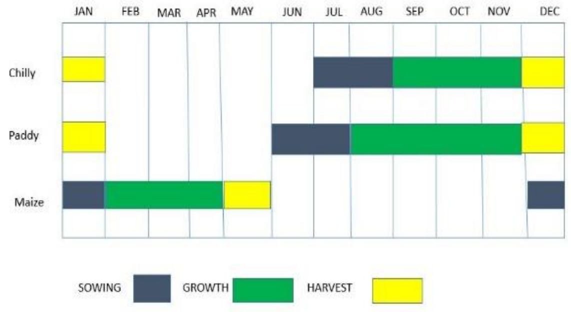

Figure 3. Crop calendar

Sentinel-2A and Sentinel-2B, this system grants a revisit time of ten days per satellite, with a five-day overlapping period between them. Cloud cover information obtained from Sentinel-2's cloud-masking band was essential for ensuring cloud-free operations in the study. The standard product, known as Level-1C ("COPERNICUS/S2"), delivers top-of-atmosphere reflectance data in Universal Transverse Mercator (UTM) map projection. Widely employed in crop type classification, Sentinel-2's Level-1C data has a minimal impact about crop labelling accuracy results.

3. 2. Construction of Spectral Indexes Several studies indicated that the different growth characteristics between crops are mainly reflected in the temporal sequence of the NDVI values, in this research progress to improve the accuracy of the algorithm to performance better way and compares to the other algorithms the spectral indices are to be utilized, where NDVI used for the vegetation NDVI's ability to capture variations in vegetation health and density is leveraged in crop classification studies to differentiate between various crop types, monitor their health, and assess changes in agricultural landscapes over time. NDBI's capacity to highlight built-up areas makes it a valuable tool in the context of crop classification by helping differentiate between urbanized and agricultural or natural landscapes within satellite imagery. MNDWI plays a crucial role in identifying and excluding bodies of water captured using satellite images, thereby refining the scope of crop classification analyses to focus specifically on agricultural or non-water land cover types, consequently enhancing the accuracy of classification models. BSI is valuable in identifying and isolating bare soil surfaces within satellite imagery, enabling the exclusion of these areas from analysis or specifically focusing on vegetated regions for crop classification, thereby refining the accuracy and precision of classification models.

3. 3. Machine Learning Classifiers The paper employed various classifiers, including Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB), and Extreme Gradient Boost (XGBoost). The optimization of these classifiers' hyper parameters was conducted by assessing the acknowledged error rate and employing cross-validation.

Random Forest (RF), based on decision trees, constructs multiple trees for classification purposes and has extensive applications in various fields related to pattern recognition and classification (21). This classifier requires establishing critical hyper parameters like the number of decision trees (NTREE) and the number of variables sampled randomly for building each tree (MTRY).

Support Vector Machine (SVM), a powerful nonlinear classification algorithm, was chosen due to the complex relationships between data and diverse crop types. SVM's selection involved configuring the kernel function (e.g., linear, polynomial and radial kernels) and tuning two crucial hyper parameters: gamma, influencing the class-dividing hyperplane's shape, and cost, used for misclassification penalization (26).

Naive Bayes (NB) is a straightforward probabilistic classifier rooted in Bayes' theorem, selecting the classification type based on the highest posterior probability. Tuning for the NB classifier involved considering the hyper parameter Laplace (26).

Extreme Gradient Boost (XGBoost), an advancement of traditional boosting, aims to create a robust classifier by combining weak classifiers' outputs. This involved tuning parameters such as the number of trees (nrounds), the learning rate (eta), and the tree's depth (depth).

3. 4. Accuracy Evaluation The paper assessed the effectiveness of a classification approach using accuracy, recall, precision, and F1-score. Recall signifies the ratio of accurately recognized positive samples from all actual positives.

Precision gauges the ratio of true positive samples among the predicted positives, while the F1-score represents the accuracy of positive sample predictions.

However, it is usual to find high recall with poor accuracy as well as high precision with low recall, which makes it difficult to distinguish between the efficacy of positive sample categorization. For instance, the recall and precision results are not comparable when the recall is 0.93 and the accuracy is 0.96 with an F1-score is 0.9. This problem is introduced as the harmonic value of recall and accuracy, which can be solved using the F1-score. As a result, rather than using recall and accuracy as assessment indicators, the F1-score was used. Furthermore, accuracy in Equation (3) is the percentage of the entire sample's accurately anticipated rate.

Moreover, the paper emphasizes the calculation of error matrices individually for algorithms using distinct training and testing datasets. Accuracy, representing the ratio of correctly predicted instances among the entire dataset, is highlighted as an essential metric (as outlined in Equations).

$$\text{Precision: P(c)} = \frac{TP_C}{TP_C+FP_C} \tag{1}$$

$$\text{Recall: R(c)} = \frac{TP_C}{TP_C+FN_C} \tag{2}$$

$$\text{F1-Score: F1(c)} = 2 * \frac{R(c)*P(c)}{R(c)+P(c)} \tag{3}$$

$$\text{Accuracy: A(c)} = \frac{Sum\ of\ correct\ \ Predictions\ for\ all\ classes}{Total\ Number\ of\ Instance} \tag{4}$$

where c is the crop type; TP_C is the true positive for crop class (c), FP_C is the false positive for crop class (c), FN_C is the false negative for crop class (c)

Recall, primarily designed for binary classifications, lacks the capacity to adequately assess the outcomes of multiple crop classifications. Consequently, in order to assess a multi-crop classification model's overall effectiveness, for this work introduced the kappa coefficient. Combining the use of Recall and the kappa coefficient provides a comprehensive evaluation of the model's performance, offering insights into the multi-crop scenario and classification efficacy. Based on prior research, specific thresholds for the kappa coefficient help categorize the effectiveness of the model A kappa coefficient below 0.2 indicates a slight model effect. A kappa value of 0.21 to 0.40 indicates a reasonable classification skill for the model. When values are more than 0.40 but less than 0.60, the model shows mediocre classification performance. A kappa coefficient ranging from 0.61 to 0.80 signifies substantial model performance. A kappa coefficient surpassing 0.80 denotes almost perfect model accuracy. In general, the evaluation of classification results commonly involves the consideration of the kappa coefficient, F1-score, and accuracy. These metrics collectively offer a comprehensive assessment of the model's effectiveness in multi-crop classification scenarios, providing a nuanced understanding of its performance across various dimensions.

4.RESULTS

4. 1. Classification Results Ground points from the study region were merged with Sentinel-2 satellite data to validate the results obtained from multi-crop classification. This validation process involved the application of six classifiers and the creation of four distinct models. The primary objective was to assess the precision of the classification of the crops and calculate the individual fields of the production area. For visual representation, the results generated by the ML algorithms are presented below. In these visual classifications: The color red signifies the classification of chilly crops. Yellow indicates the classification of maize crops. Green is assigned to identify paddy fields. Orange represents built-up areas. Blue is used to indicate bare land. The gray color is assigned to represent water bodies within the region. The outcomes of the four models are visually depicted in Figure 4. Then, finally knowing how much crops are growing in a particular area showcases the distinct categorization of various land types based on the multi-crop classification approach. The classifications of support vector, Naïve Bayes and XG Boost are shown in Figures 5 to 7, respectively. Figure 8 shows the overall accuracy of different models. Figure 9 depicts training and accuracies of different models.

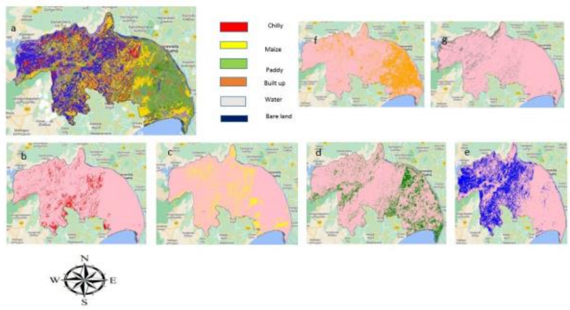

Figure 4. (a) Random forest classification, (b) chilly, (c) maize, (d) paddy, (e) bare land, (f) built-up, (g) water

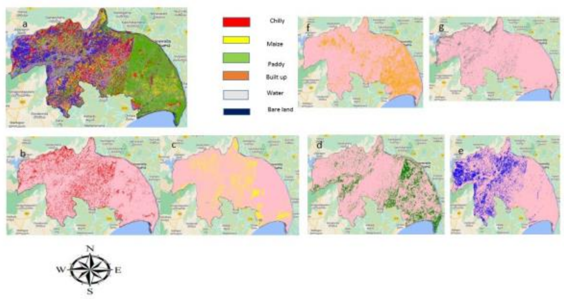

Figure 5. (a) Support vector (SVM) classification, (b) chilly crop, (c) maize crop, (d) paddy crop, (e) bare land, (f) built-up area, (g) water bodies

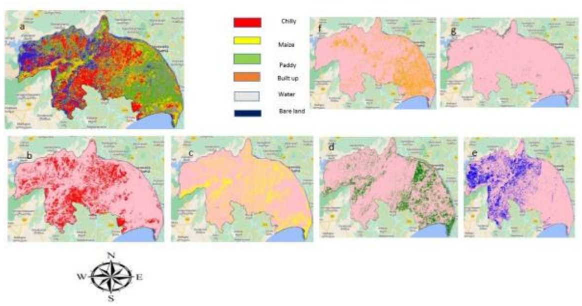

Figure 6. (a) Naïve Bayes classification, (b) chilly field, (c) maize crop, (d) paddy crop, (e) bare land, (f) built-up area, (g) water bodies

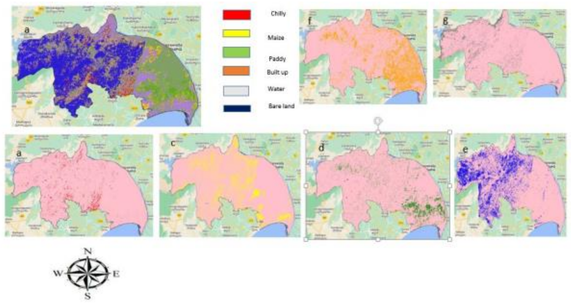

Figure 7. (a) XG Boost classification, (b) chilly area, (c) maize crop, (d) paddy field (e) bare land, (f) built-up region, (g) water bodies

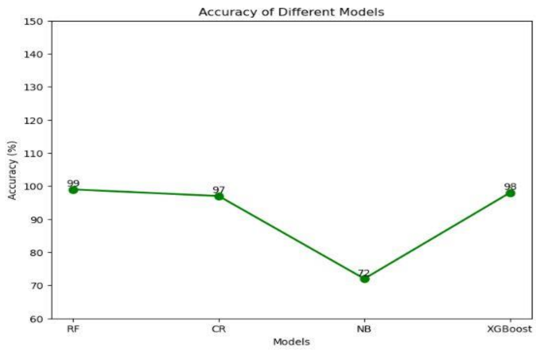

Figure 8. Overall Accuracy

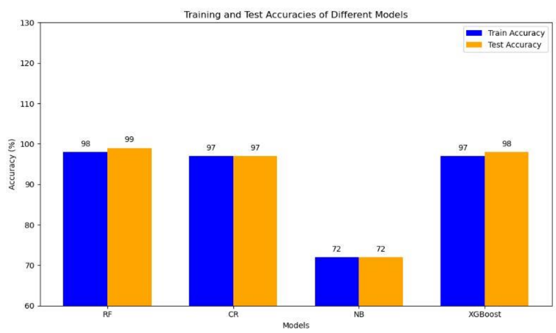

Figure 9. Accuracy of the models

4. 2. Evaluation Metrics Analysis

4. 2. 1. Accuracy It evaluates the general accuracy of predictions by indicating the proportion of correctly predicted instances out of the total. The random forest model demonstrates superior accuracy in comparison to others. In this approach, RF will get the highest accuracy when compared to other algorithms.

4. 2. 2. Precision Precision evaluates the percentage of actual positive predictions among all of the model's positive predictions. Table 1 summarized the Precision of the crops.

The precision of the chilly crop stands at 0.92, much greater than that of maize and other classes in comparison to various models. Among these models, the random forest demonstrates the highest precision when compared to the others for these classes. Figure 10 shows the precision of the models.

TABLE 1. Precision of the crops

	Precision			
Crop	**Random Forest**	**Naïve Bayes**	**XG Boost**	**SVM**
Chilly	0.92	0.05	0.8	1.0
Maize	1.0	1.0	1.0	1.0
Paddy	1.0	0.02	0.83	1.0
Built up	0.99	0.89	0.98	0.97
Water	0.99	0.99	0.98	0.99
Bare land	0.99	0.98	0.98	0.97

4. 2. 3. Recall The percentage of genuine positive predictions among all real positive cases in the dataset is calculated using recall. The recall samples reported in Table 2. Figure 11 depicts the recall representation.

4. 2. 4. F1-score The accuracy and recall harmonic means are represented by the F1-score. It provides a single score that strikes a balance between recall and

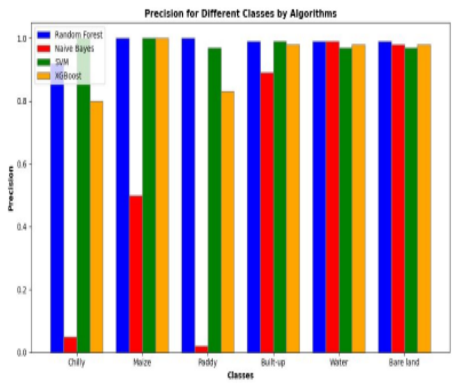

Figure 10. Precision of the Models

TABLE 2. Recall samples

	Recall			
Crop	**Random Forest**	**Naïve Bayes**	**XG Boost**	**SVM**
Chilly	0.92	0.53	0.30	0.23
Maize	0.72	0.3	0.09	0.09
Paddy	0.81	0.45	0.45	0.30
Built up	1.0	0.91	1.0	1.0
Water	1.0	0.92	1.0	0.97
Bare land	0.99	0.57	0.99	0.98

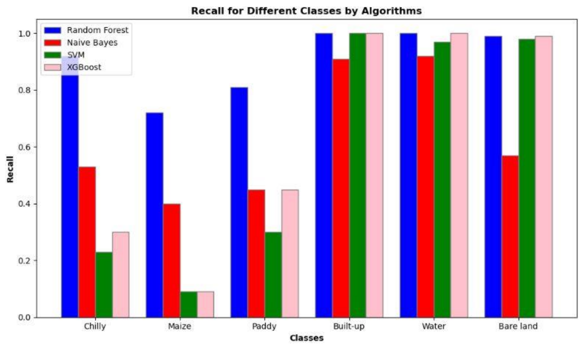

Figure 11. Recall Representation

accuracy. Table 3 summarized the F1-score values of the stated models. F1-score graph representation is illustrated in Figure 12.

4. 2. 5. Error Matrix (Confusion Matrix) This matrix tabulates the model's performance by classifying instances into true positives, true negatives, false positives, and false negatives across multiple classes. The confusion matrices of training and test analysis are shown in Figures 13 and 14, respectively.

4. 2. 6. Kappa Coefficient (Cohen's Kappa) The kappa coefficient measures the agreement between observed and expected classification results, adjusted for chance. It's particularly useful when evaluation classifier performance in multiclass scenarios. Kappa Coefficients of models for training and testing are shown in Figure 15.

TABLE 3. F1-score values of models

	F1-Score			
Crop	**Random Forest**	**Naïve Bayes**	**XG Boost**	**SVM**
Chilly	0.92	0.09	0.43	0.37
Maize	0.84	0	0.16	0.16
Paddy	0.899	0.03	0.58	0.46
Built up	0.99	0.89	0.98	0.96
Water	0.99	0.95	0.98	0.97
Bare land	0.99	0.72	0.98	0.71

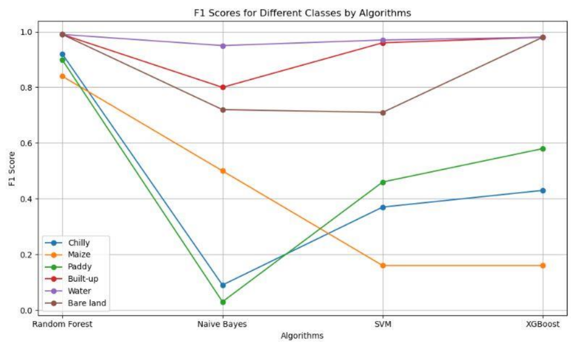

Figure 12. F1-score graph representation

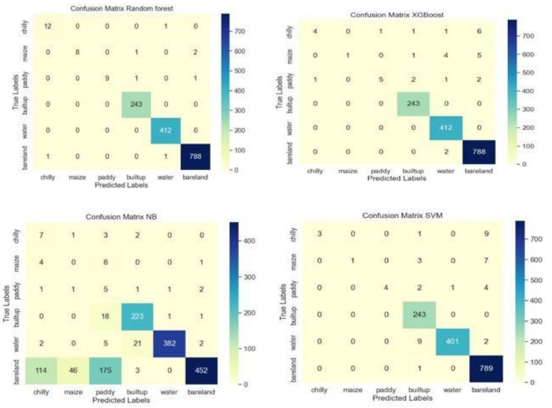

Figure 13. Confusion Matrix of training analysis

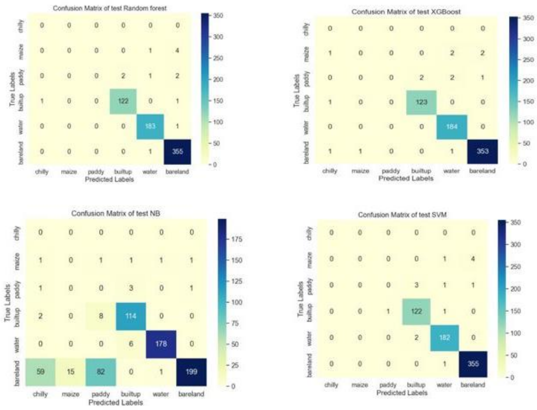

Figure 14. Confusion Matrix of test analysis

4. 2. 7. Crop Areas The crop production areas have been delineated using four machine learning models within the Google Earth Engine tool. Chilly crops are represented by the color red, maize by yellow, paddy fields by green, built-up areas by orange, water bodies by

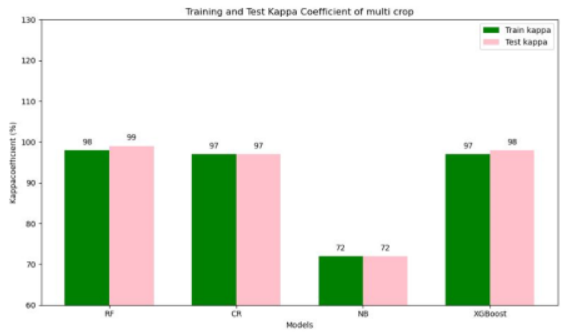

Figure 15. Kappa Coefficient of models

blue, and bare land by pink. This mapping process encompasses multi-crop classification across the specified regions. Figure 16 shows the crop production areas of all models.

According to Table 4 which represents the performance of multi-crop classification in conjunction with various crops and machine learning classifiers, as explored in existing references. These studies reported accuracies of 0.95 and 0.94, whereas our current research, employing four classifiers, demonstrates an enhanced accuracy of 0.97.

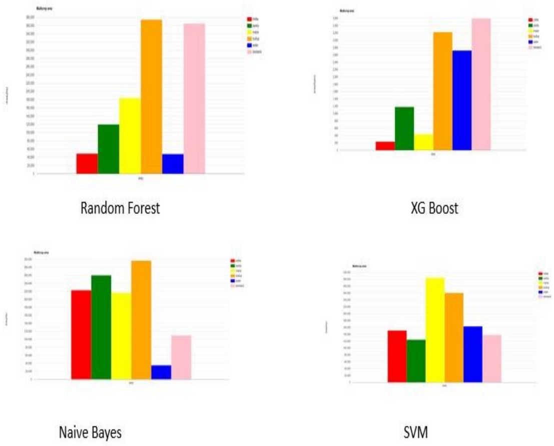

Figure 16. Crop production areas of all models

TABLE 4. Comparison table

Ref. no	crops	Metrics	Random Forest	SVM	Naive Bayes	XGBoost
11	Single crops	Accuracy	0.92	0.87	0.82	0.91
14	Two crops	Precision	0.95	0.86	0.81	0.92
17	Single crop	Recall	0.90	0.88	0.84	0.90
18	Two crops	F1-Score	0.88	0.87	0.82	0.91
This work	Three crops	All metrics	0.98	0.97	0.82	0.97

5. CONCLUSION

Generating comprehensive crop categorization maps for sustainable development in large regions like the Guntur district is challenging due to limited samples and vast areas for analysis. To address this problem, our article introduces a classification framework utilizing four algorithm Classifiers. These models leverage spectral, textural, and environmental indexes to ascertain the most efficient classification method. Our approach offers several benefits:(1) Government Survey Data Utilization: We used the government survey data that impact crop information of the three crops in Guntur. Using machine learning models, we establish an optimal strategy despite the region's constraints. Random Forest (RF), Support Vector Machine (SVM), Naive Bayes (NB), and XGBoost emerge as the best techniques for this region. (2) Integration of Indexes with Satellite Data: By merging various indexes into satellite data, we improve the enhanced classification accuracy. (3) Multi-Crop Classification: Our coupled approach facilitates automated result generation without in-depth prior knowledge of the area. This suggests broad applicability for our optimal classification method in diverse settings. Across all models, Random Forest consistently demonstrates higher accuracy, recall, and precision compared to other analyses and classified the individual areas to be classified and confusion matrices of the method. Our future work involves applying our coupling strategy to diverse machine learning classifiers, with a particular emphasis on its potential in smaller, fragmented crop areas, using high-resolution satellite images, and extending its application to various crops, including greenhouse crops.

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Persian Abstract

چکیده

طبقه بندی دقیق محصولات برای نظارت بر کشاورزی و تصمیم گیری بسیار مهم است. هدف نهایی سنجش از دور استخراج و طبقه بندی دقیق محصولات است. بر اساس یک پلت فرم ابری، منطقه مورد مطالعه منطقه Guntur، آندرا پرادش هند، یک رویکرد طبقه بندی چند محصول را با استفاده از تصاویر ماهواره ای Sentinel-2 و تکنیک های یادگیری ماشین ارائه می دهد. منطقه مورد مطالعه شامل یک منطقه کشاورزی متنوع با سه نوع محصول عمده است. پس از پیش پردازش، ویژگی های طیفی و بافتی استخراج شد. این چهار الگوریتم سنتی یادگیری ماشین را مقایسه می‌کند و شاخص‌های پوشش گیاهی NDVI، NDBI، MNDWI و BSI را برای طبقه‌بندی چند محصول اضافه می‌کند و دقت را افزایش می‌دهد و اطلاعات متنوع و مکملی را ارائه می‌دهد. دقت طبقه‌بندی کلی به ۹۵٪ رسید، با دقت محصول فردی از ۸۵ تا ۹۶٪. روش طبقه‌بندی مقیاس‌پذیر و ساده ارائه‌شده در این تحقیق به مزایای پلتفرم‌های ابری در داده‌ها و عملیات کاملاً نشان می‌دهد و یادگیری ماشین سنتی در مقایسه با سایر الگوریتم‌ها می‌تواند به طور موثر دقت طبقه‌بندی را بهبود بخشد و مناطق جداگانه تولید محصول محاسبه می‌شوند. نتایج بر قابلیت اطمینان نقشه‌برداری محصول مبتنی بر GEE در منطقه تأکید می‌کند و سطح رضایت‌بخشی از دقت طبقه‌بندی را نشان می‌دهد که از ۹۷٪ در فواصل زمانی متمایز در مقادیر دقت کلی، ضرایب کاپا و امتیاز F1 فراتر می‌رود.