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Satellite-Based Crop Typology Mapping with Google Earth Engine †

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Abstract: Crop classification plays a pivotal role in agricultural remote sensing, offering critical insights into planting areas, growth monitoring, and yield evaluation. Leveraging the power of Google Earth Engine, this paper centers on the agricultural landscape of Krishna District as its study region. It explores the efficacy of multiple machine learning approaches, specifically Random Forest (RF), Classification and Regression Tree (CART), Naive Bayes, and Support Vector Machine (SVM), in composition of Sentinel-1 and Sentinel-2 satellite imagery for crop categorization. By meticulously assessing and contrasting the evaluations of these four classification methods, the results highlight the efficacy of RF. The overall accuracy (OA) regarding RF classification reaches 0.86, surpassing the results obtained by Naive Bayes (OA = 0.68), CART (OA = 0.63), and SVM (OA = 0.78). This scalable and straightforward classification methodology harnesses the advantages of cloud-based platforms for data handling and analysis. The timely and precise identification in crop typing holds immense importance for monitoring alterations in harvest patterns, estimating yields, and issuing crop safety alerts in the Krishna District and beyond. This paper contributes to the agricultural geospatial sensing domain by providing an innovative approach for accurate crop classification, with broad applications in precision farming and crop management.

Keywords: Sentinel-1; Sentinel-2; Random Forest; CART; Google Earth Engine

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1. Introduction

Agriculture continues to serve as the bedrock of the Indian economy, wielding significant influence over GDP and serving as the lifeblood for a substantial segment of the population. Effective agricultural land management and monitoring take on paramount importance to ensure both food security and sustainable development. Krishna District, nestled in the southeastern Indian state of Andhra Pradesh, serves as a prime region. It boasts diverse cropping patterns, with prominent cultivations including paddy, sugarcane, and cotton.

Traditional methods of crop supervision and classification tend to be laborious and time-intensive, rendering them impractical for extensive agricultural regions. The quest for timely, precise information regarding crop types, health status, and spatial distribution has propelled the integration of remote sensing capabilities and deep learning techniques into agricultural monitoring practices [1,2]. Remote sensing methods in agriculture facilitate data collection across various spatial and temporal resolutions. When it comes to agricultural uses, the Sentinel satellites are among the most valuable sources of remote observations, delivering high- quality optical and radar imagery and being well suited for monitoring crops throughout the growth cycle [3,4]. The pre-existing systems for crop segmentation have predominantly relied on traditional methods, frequently hampered by their inability to furnish real-time data. The assimilation of machine learning approaches

into the scrutiny of remote imagery has ushered in new possibilities for automated and precise crop classification [5]. Machine learning techniques have risen to prominence for their capacity to process large volumes of remote imagery and distill meaningful insights [6].The overarching goal is to harness an automated, high-precision crop classification system scrutinizing multiple machine learning approaches (Random Forest, CART, Naive Bayes, and SVM) for crop categorization practices, not only in Krishna District, but also in analogous agricultural regions [7–9].

2. Study Area and Datasets

2.1. Study Area

The research field is in the regions of Penumatcha, Narapalem, Kondavaram, and Pedamuttevi (Figure 1). Krishna District, located in Andhra Pradesh, India, exhibits an average altitude of 9 m and has a tropical climate.

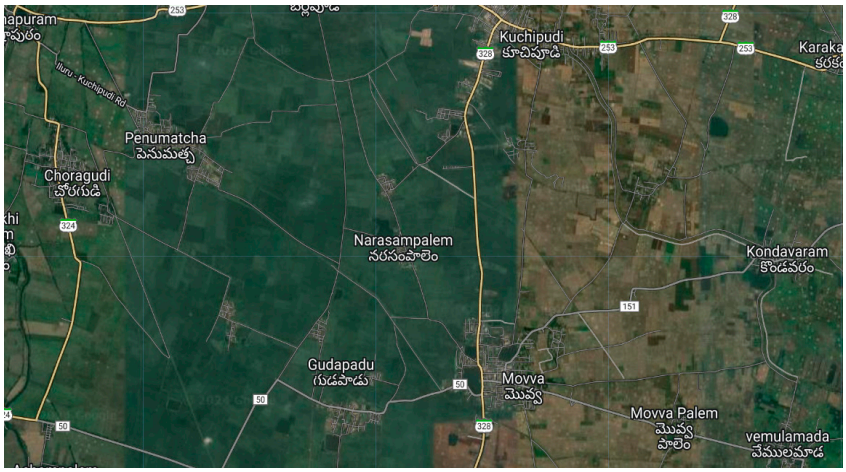


Figure 1. Region of interest. Source: Google Earth Engine.

2.2. Datasets

Sentinel-1, a radar satellite, provides precise photographs of Earth using Synthetic Aperture Radar technology and offers useful insights like soil moisture and surface roughness via its dual-polarization capabilities. Sentinel-2's multispectral optical satellite gathers data across many spectral bands. It supports applications including agriculture and forest monitoring and land use mapping.

3. Proposed System

The primary objective is to analyze the spatial facets of major crops within the Krishna District. The study follows a systematic methodology to achieve these objectives.

1. Data Acquisition: The study begins by obtaining satellite images with high spatial and temporal resolution, opting for Sentinel-2 and Sentinel-1 images, which cover Krishna District.
2. Data Preprocessing: To enhance data quality and mitigate the effects of atmospheric conditions, the study conducts essential preprocessing. This includes cloud masking to remove cloudy portions and image normalization to standardize the data values.
3. Data Preparation: This step involves the creation of training and validation datasets tailored for crop classification. Representative areas for each crop are identified within the study region, and an adequate number of instances are generated and then split into training and validation sets while maintaining a suitable ratio to ensure robust training and evaluation.
4. Feature Extraction: Relevant spectral, spatial, and temporal characteristics are acquired from the satellite images. This encompasses vegetation indices, polarization values, and other metrics to capture the distinctive attributes of diverse crops.

5. Classification Algorithm Selection: The study opts for the use of the Random Forest algorithm as the classification method, primarily due to its proven efficacy in crop segmentation.
6. Model Training: The RF classification model is trained using the training dataset. The input features utilized are acquired from the satellite imagery that underwent preprocessing, encompassing bands, vegetation indices, and other relevant information.
7. Classification and Evaluation: The trained RF model is applied to generate a classification map. The precision of the results is assessed by contrasting them with ground truth data or validation samples. The results are meticulously compared.
8. Visualization and Analysis: The classified crop distribution map is visualized utilizing Google Earth Engine. The map is scrutinized to obtain valuable insights into crop patterns within Krishna District.

Architecture Diagram

Figure 2 represents a systematic process for conducting machine learning-based crop classification. Beginning with data collection, it encompasses the acquisition of essential data. Following this, preprocessing steps are crucial to correct atmospheric influences and normalize values. Feature extraction identifies relevant attributes from the data, including the spectral bands vital for distinguishing various crop types. Feature selection reduces dimensionality and optimizes model efficiency. Classifier selection, such as Random Forest or SVM, depends on data characteristics and classification requirements. The algorithms are trained using labeled data, leading to classification. Visualizing the results on a map provides a spatial representation of the classified areas, and evaluation via a confusion matrix quantifies model performance.

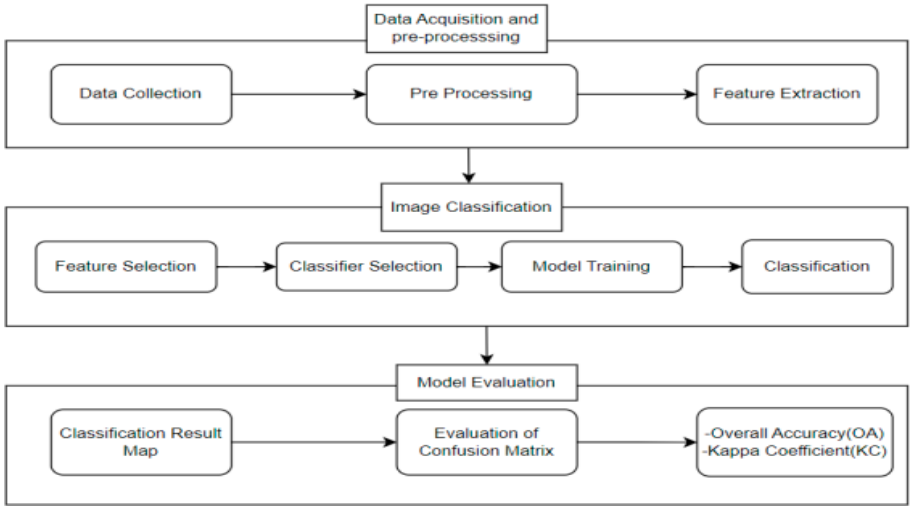


Figure 2. Architecture diagram for classified image.

4. Implementation and Results

This section provides a comprehensive representation of the outcomes obtained through the implementation of the specified algorithms, with the results displayed for each one (Figures 3–7).

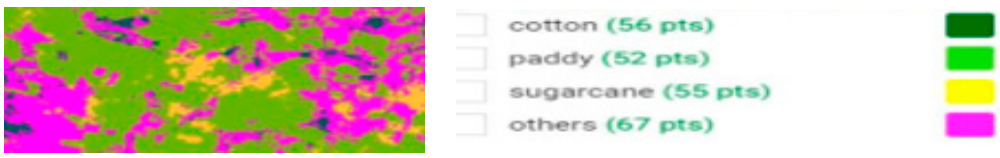


Figure 3. Classified image.

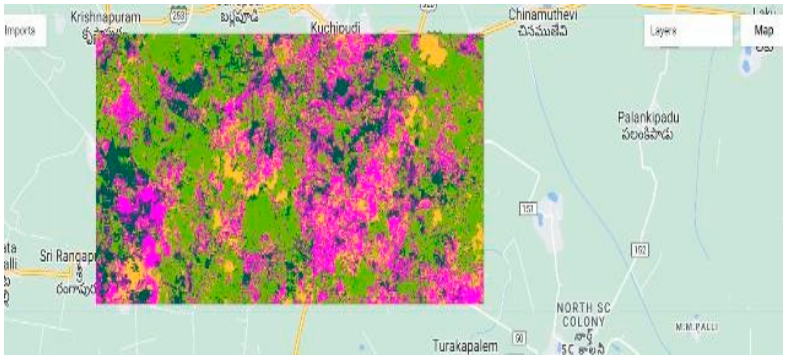


Figure 4. Classified crop image using Random Forest.

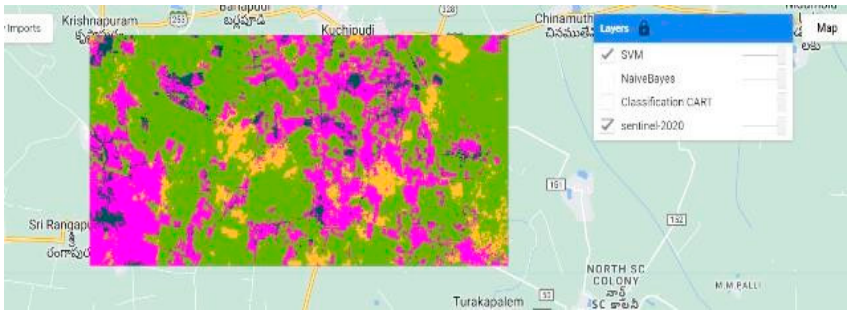


Figure 5. Classified crop image using SVM.

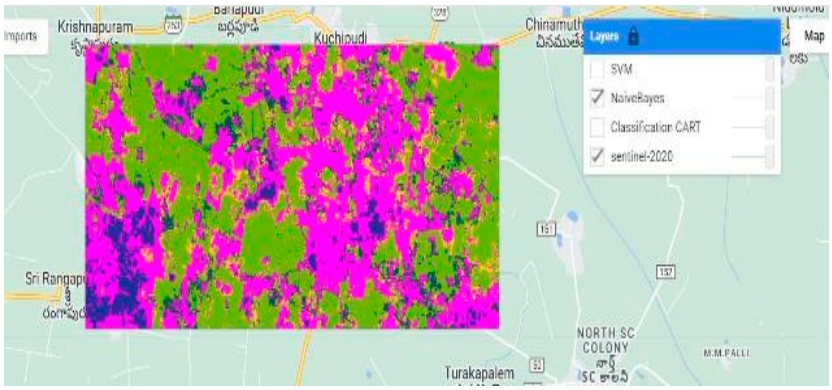


Figure 6. Classified crop image using Naive Bayes.

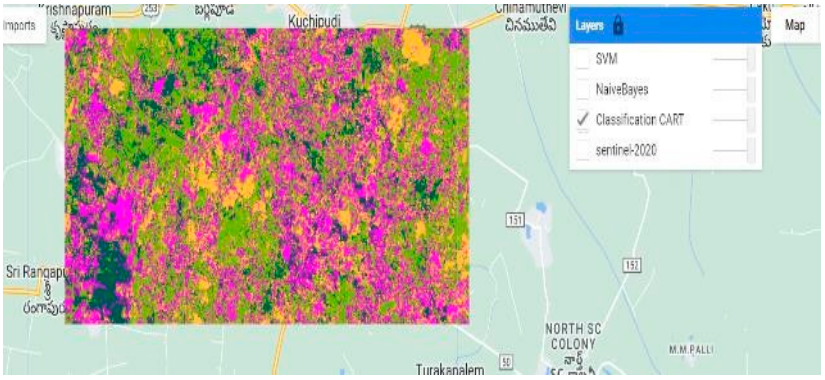


Figure 7. Classified crop image using CART.

In the above classified figure, the green color indicates paddy, dark green indicates cotton, yellow indicates sugarcane, and pink indicates other crop types.

4.1. Comparative Studies

To appraise the model's proficiency, we incorporated precision, recall, and F1 score as evaluation metrics and summarized in Table 1, which were computed utilizing the following formulas: TP denotes true positives, FP denotes false positives, FN denotes false negatives.

Table 1. Performance metrics table.

Classifier	Accuracy	Precision	Recall	F1 Score
Random Forest	86	0.83	0.96	0.89
SVM	78	0.79	0.81	0.80
Naive Bayes	68	0.61	0.67	0.64
CART	63	0.47	0.59	0.64

4.2. Results Obtained

The results obtained highlight accuracies across the algorithms under consideration. RF exhibited the highest accuracy at 86%, closely trailed by SVM, which achieved an accuracy of 78%. CART and Naive Bayes produced lower accuracy rates of 63% and 68%, respectively. Furthermore, the evaluation of kappa coefficients gauged the algorithms' performance. RF demonstrated exceptional consistency, boasting a kappa coefficient of 0.83. SVM had a substantial level of agreement, as indicated by its kappa coefficient of 0.75. Conversely, CART and Naive Bayes exhibited 0.60 and 0.67, respectively.

5. Conclusions

In conclusion, this paper demonstrated that the use of a combination of Sentinel-1 and Sentinel-2 data in tandem with machine learning approaches, particularly Random Forest, holds promise for accurate crop typing in Krishna District. We achieved classification accuracies of 85% with RF, highlighting its effectiveness in this context.

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