

Crop Recommendation System using Satellite Images

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ABSTRACT

The "Crop Recommendation System Using Multi-Temporal Satellite SAR Data" is a creative project that combines cutting edge technologies to modernize agriculture. The study introduces a data-driven approach to crop selection by utilizing multi-temporal Synthetic Aperture Radar (SAR) data, deep learning, and machine learning. The method provides farmers with precise advice based on their specific agricultural needs by evaluating temporal fluctuations in SAR imagery. Comprehensive data analysis has yielded insights into crop dynamics, moisture levels, and soil health that guide these suggestions. By fusing advanced analytics with conventional agricultural

methods, the system encourages crop management that is both efficient and sustainable. By bridging the gap between conventional wisdom and cutting-edge technology, the project's holistic approach offers a revolutionary solution for improving productivity and resource usage. The technology seeks to transform agricultural decision-making processes by providing farmers with useful insights obtained from satellite data, promoting resilience and adaptation in the face of shifting environmental conditions.

Keyword: Crop Detection, Satellite Imagery, Image Processing, Agriculture, Machine Learning

1. INTRODUCTION

A new initiative at the intersection of modern technology and agriculture is the "Crop Recommendation System Using Multi-Temporal Satellite SAR Data" study. This work presents an innovative data-centric method to crop selection imaging, farmers can receive advice that are specifically customized to meet their needs.

These customized crop recommendations are based on important discoveries about crop dynamics, moisture content, and soil health that were made possible by the extensive data analysis carried out for this project. The system facilitates efficient and sustainable crop management tactics by fusing advanced analytics with conventional agricultural methods. This innovative method effectively combines the abundance of conventional agricultural knowledge with state-of-the-art technology to provide a comprehensive solution intended to maximize resource use and productivity in agriculture.

utilizing the power of multi-temporal Synthetic Aperture Radar (SAR) data in conjunction with advanced deep learning and machine learning algorithms. With the help of this innovative method, which examines temporal fluctuations in SAR

With the help of satellite data, this endeavor seeks to revolutionize agricultural decision-making by providing farmers with useful information. It ultimately transforms farming's future by fostering resilience and adaptation in the face of shifting environmental conditions. The system gives a continuous, detailed image of the agricultural environment by using multi-temporal SAR data, which helps to capture important data on crop growth stages, variations in soil moisture, and general field health. By using these information, farmers may maximize yields and reduce their impact on the environment by choosing crops wisely, planning planting dates, and allocating resources. Furthermore,

the incorporation of deep learning techniques improves the precision and applicability of the recommendations, guaranteeing that they are both flexible and accurate in a range of agricultural scenarios. This initiative demonstrates the revolutionary potential of fusing cutting-edge technology with agriculture, opening the door for a more resilient, productive, and sustainable agricultural industry. The "Crop Recommendation System Using Multi-Temporal Satellite SAR Data" represents the future of smart agriculture by bridging the gap between conventional farming methods and contemporary technological breakthroughs.

2. LITERATURE REVIEW

Constructing and validating a comprehensive crop recommendation system that employs ensembling strategies to increase crop output is the primary objective of the study "Boosting Plant Yield With A Plant Advice System Using Assembly Technique". This method combines many machine learning models with multi-temporal satellite data to deliver accurate, data-driven recommendations for crop choices. The following are the specific goals[1]. The study aims to increase crop recognition accuracy by using convolutional neural networks (CNNs) and synthetic photos that integrate different timings and spectral data. Improving agricultural monitoring is the goal since it will improve crop management, resource use, and overall productivity. To illustrate this method's potential advantages for farmers and other agricultural stakeholders, its efficacy will be compared to currently used procedures[2].

By using innovative image processing techniques, the study "Crop Detection Using Satellite Image Processing" seeks to create an accurate approach for identifying crops from satellite imagery. Its goals are to increase the precision of detection, facilitate well-informed agricultural decision-making, and encourage sustainable farming methods by making effective use of available resources. The study aims to enhance crop management, productivity, and sustainability in agriculture by verifying the suggested method's efficacy against benchmark datasets and current methodologies[3].

The primary goal of the study "A Novel Strategy for Field Kind Identification in Landsat Images Utilizing Mixed Deep Capsules an Autoencoder" is to use a hybrid deep capsule autoencoder to increase crop type mapping accuracy. By combining the advantages of autoencoders and capsule networks, this novel approach seeks to efficiently extract and represent spatial data from satellite photos for improved pattern identification. The project aims to enable more informed agricultural decision-making and sustainable land management practices by gaining higher precision in crop type identification[4]. The goal of the study "An Intelligent Crop Recommendation System using Deep Learning" is to create a complex system that can provide accurate crop recommendations by utilizing deep learning techniques. It seeks to increase crop selection processes' accuracy in comparison to traditional approaches by incorporating deep neural networks. Through the analysis of various agriculture information, including past crop performance, climate variables, and soil conditions, the system places an emphasis on enabling precision agriculture. It also seeks to promote environmentally friendly farming methods by recommending crops that maximize resource efficiency and reduce negative environmental effects. The goal of the research is to confirm its efficacy through real-world application, giving farmers access to cutting-edge instruments for increased production and sustainable agriculture management[5]. This article's primary goal is to discuss machine learning (ML) applications in agriculture, with a particular emphasis on disease detection, crop production prediction, and soil parameter prediction. It also discusses intelligent irrigation methods and the application of ML to animal production. The intention is to demonstrate how ML may improve the quality and production of sustainable agriculture[9]. This work proposes a recommendation system to address the problem of Indian farmers selecting the incorrect crop based on soil requirements. It makes highly accurate and efficient crop recommendations by using an ensemble model involving Randomized The Tree, CHAID, the k-n Others, and naive Bayes models with a majority vote. Increasing productivity through precision farming is the aim[10]. The paper seeks to emphasize

the use of soil analysis in contemporary agriculture as a means of maximizing crop yield and reducing environmental impact. It attempts to show how resource efficiency and sustainable agricultural methods can be improved by data-driven crop suggestions based on soil attributes. Enhancing yields and quality is the main goal, along with halting soil erosion and promoting food security[11]. The primary goal of the study “Machine Learning Techniques for Remote Sensing-Based Crop Identification Data in Fresno County, California” is to use machine learning and remote sensing data to reliably identify and classify various crop types in Fresno County. This seeks to improve agricultural management and monitoring through the application of cutting-edge technology[12].

3. METHODOLOGY

Data Acquisition:

First, multi-temporal SAR data is obtained from satellite sources and fed into the system. By capturing microwave signals reflected from the Earth's surface, satellites equipped with SAR sensors are able to produce high-resolution photographs of agricultural regions. These pictures are sent to ground stations so that they can be processed. The SAR imagery is gathered and arranged by the data gathering module, guaranteeing a steady and dependable data stream for analysis.

Preprocessing:

The collected SAR data is preprocessed to improve its quality and usefulness before analysis. This covers operations like calibration, radiometric correction, geometric correction, and noise reduction. In order to align SAR images with other spatial datasets, they might also require georeferencing or resampling. Accuracy and consistency are ensured during the preprocessing module's preparation of the data for feature extraction and testing.

Feature Extraction

The system's primary function is to extract significant characteristics from multi-temporal SAR data. DL algorithms are utilized to examine temporal

fluctuations in Synthetic Aperture Radar imaging and derive pertinent data concerning crop dynamics, soil health, and moisture content. To extract complex features from the SAR data, methods including polarimetric decomposition, texture analysis, and temporal change detection are used. The suggestion generation module uses these features that have been extracted as input.

Model Training:

The model training component complements the feature extraction module by imparting interpretative machine learning models that utilize the features that have been extracted. Models are trained on historical data employing supervised methods for learning such as support vector machines (SVM), random forests, and neural networks. By optimizing their predicting skills, the models discover patterns and connections between the crop results and the retrieved variables.

Recommendation Generation:

The recommendation generating module creates customized crop recommendations for farmers based on the collected information and trained models. To determine the best crop selections for a given set of agricultural conditions, the models evaluate historical trends, soil properties, and current SAR data. These suggestions are made with the intention of increasing agricultural productivity, reducing resource consumption, and advancing sustainable farming methods.

4. RESULT and ANALYSIS

Choice of Spectral Features.

Multispectral satellite images with $3\text{ m} \times 3\text{ m}$ pixels are included in the study. Every pixel has the ability to reflect four spectrum values, which are all Infrared radiation that is invisible and visible in RGB lights. The cadastral data is used to determine the values of the required pixels. The association between sixteen attributes—the average, standard deviation, maximum and lowest values of each pixel on each cadastre, and the number of days that cabbage develops—is then ascertained by analyzing the data (Figure 4). To demonstrate the values of the spectrum parameters, such as the mean, max, and min of the infrared radiation, a growth period of 20 to 60 days for

cabbage was chosen (Table 1).

| | day | mean_r | mean_g | mean_b | mean_nir | std_r | std_g | std_b | std_nir |
|----------|---------|--------|--------|--------|----------|--------|---------|--------|---------|
| day | 1 | -0.12 | -0.11 | -0.17 | 0.49 | -0.012 | -0.0053 | 0.045 | 0.39 |
| mean_r | -0.12 | 1 | 0.99 | 0.97 | 0.068 | 0.28 | 0.26 | 0.21 | -0.18 |
| mean_g | -0.11 | 0.99 | 1 | 0.98 | 0.065 | 0.3 | 0.28 | 0.23 | -0.17 |
| mean_b | -0.17 | 0.97 | 0.98 | 1 | -0.073 | 0.31 | 0.3 | 0.25 | -0.24 |
| mean_nir | 0.49 | 0.068 | 0.065 | -0.073 | 1 | -0.016 | -0.021 | 0.039 | 0.6 |
| std_r | -0.012 | 0.28 | 0.3 | 0.31 | -0.016 | 1 | 0.99 | 0.97 | 0.18 |
| std_g | -0.0053 | 0.26 | 0.28 | 0.3 | -0.021 | 0.99 | 1 | 0.98 | 0.19 |
| std_b | 0.045 | 0.21 | 0.23 | 0.25 | 0.039 | 0.97 | 0.98 | 1 | 0.27 |
| std_nir | 0.39 | -0.18 | -0.17 | -0.24 | 0.6 | 0.18 | 0.19 | 0.27 | 1 |
| max_r | -0.066 | 0.84 | 0.84 | 0.82 | 0.081 | 0.68 | 0.66 | 0.62 | -0.039 |
| max_g | -0.058 | 0.82 | 0.83 | 0.81 | 0.076 | 0.7 | 0.69 | 0.65 | -0.032 |
| max_b | -0.061 | 0.76 | 0.78 | 0.79 | 0.025 | 0.73 | 0.73 | 0.7 | -0.03 |
| max_nir | 0.48 | 0.04 | 0.039 | -0.089 | 0.95 | 0.085 | 0.084 | 0.15 | 0.77 |
| min_r | -0.1 | 0.97 | 0.96 | 0.93 | 0.1 | 0.11 | 0.093 | 0.049 | -0.21 |
| min_g | -0.095 | 0.96 | 0.97 | 0.94 | 0.1 | 0.12 | 0.095 | 0.055 | -0.21 |
| min_b | -0.15 | 0.95 | 0.95 | 0.96 | -0.036 | 0.11 | 0.093 | 0.042 | -0.3 |
| min_nir | 0.31 | 0.35 | 0.34 | 0.22 | 0.83 | -0.033 | -0.043 | -0.023 | 0.17 |

Figure 4: Relationship between spectral properties and the stages of growth of cabbage

Table 1 shows the coefficients of connection between the spectral properties and the developmental phases of cabbage.

| Spectral Features | Association Ratio |
|---|-------------------|
| average_nir standard deviation | NIR's 0.486128 |
| std_nir The NIR's standard deviation | 0.393943 |
| max_nir: NIR Maximum | 0.478906 |

Feature Selection for the Vegetation Index

This showing leadership factor the index (CMFI), infrared proportion index of vegetation (IPVI), the changed dirt organisms the index in changes (MSAVI), the width to height ratio (BR), the square root of the arrive relation (SQBR), the vegetable index (VI), the mean of the brightness the index (ABI),

NDVI, and the average the brightness index (ABI) were among the eight distinct kinds of vegetation indices that were computed using the spectral values of the pixels. The study examined the relationship between these markers and the cabbage's development phases, or growth days.employed sixteen features in total, included the mean as well as the standard deviation of each unique vegetation index. The results are presented in Figures 5 and 6.

There is a strong positive link with the vegetation indicators during the 20–60day timeframe. Specifically, Figure 6 demonstrates that the vegetation indicators have a stronger correlation compared to the spectrum data, with the cabbages' growth days. However, the bulk of vegetation indices are computed using values of red light and near-infrared light, which have a high association. As a result, Table 2 shows that only one of the three vegetation indices that are fully associated (correlation coefficients equal to 1 or -1)—the BR (SQBR), the V, or the NDVI. (IPVI, MSAVI, CMFI)—is was chosen.

| | day | ndvi_std | ipvi_std | cmfi_std | br | sqbr | vi | abi | msavi_std |
|-----------|------|----------|----------|----------|------|------|------|------|-----------|
| day | 1 | 0.47 | 0.28 | 0.47 | 0.28 | 0.44 | 0.39 | 0.46 | 0.37 |
| ndvi_std | 0.47 | 1 | 0.32 | 0.32 | 0.32 | 0.37 | 0.37 | 0.34 | 0.37 |
| ipvi_std | 0.28 | 0.32 | 1 | 0.32 | 0.32 | 0.37 | 0.37 | 0.34 | 0.37 |
| cmfi_std | 0.47 | 0.32 | 0.32 | 1 | 0.32 | 0.37 | 0.37 | 0.34 | 0.37 |
| br | 0.44 | 0.37 | 0.37 | 0.32 | 1 | 0.37 | 0.37 | 0.34 | 0.37 |
| sqbr | 0.39 | 0.37 | 0.37 | 0.37 | 0.37 | 1 | 0.37 | 0.34 | 0.37 |
| vi | 0.46 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 1 | 0.37 | 0.37 |
| abi | 0.46 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 1 | 0.37 |
| msavi_std | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 1 |

Figure 5: connections between the cabbage growth stages and the vegetation index's characteristics.

| | day | ndvi | ipvi | cmfi | br |
|-------|-------|------|------|-------|------|
| day | 1 | 0.47 | 0.47 | -0.47 | 0.4 |
| ndvi | 0.47 | 1 | 1 | -1 | 0.9 |
| ipvi | 0.47 | 1 | 1 | -1 | 0.9 |
| cmfi | -0.47 | -1 | -1 | 1 | -0.9 |
| br | 0.44 | 0.97 | 0.97 | -0.97 | 1 |
| sqbr | 0.46 | 0.99 | 0.99 | -0.99 | 1 |
| vi | 0.51 | 0.94 | 0.94 | -0.94 | 0.9 |
| msavi | 0.47 | 1 | 1 | -1 | 0.9 |

Figure 6. Strong or even perfect relationships exist between vegetation index featurepairs.

| Index of Vegetation | Coefficients of Correlation |
|---------------------|-----------------------------|
| NDVI | 0.47121 |
| IPVI | 0.47121 |
| CMFI | -0.47121 |
| BR | 0.443567 |
| SQBR | 0.458123 |
| VI | 0.508448 |
| MSAVI | 0.468535 |

Table 2 presents an analysis of the relationship between cabbage growth stages and vegetation indexes.

Selection of Texture Features:

Thirteen characteristics and six image gradient attributes (gx, gy, and gxy mean and standard deviations) (a total of 19 attributes) determined using the GLCM technique represent the various textural qualities of the satellite pictures under examination. Nevertheless, the correlation analysis reveals no relationship between any of the textural characteristics and the cabbages' growth days (Table 3). It's likely that the satellite imagery used had insufficient

resolution. As a result, the model training did not incorporate these properties.

| Texture Specification | Coefficients of Correlation |
|-----------------------|-----------------------------|
| haralick1 | -0.012057 |
| haralick2 | -0.011231 |
| haralick3 | 0.004898 |
| haralick4 | -0.029392 |
| haralick5 | 0.065032 |
| haralick6 | -0.123112 |
| haralick7 | -0.029654 |
| haralick8 | -0.054594 |
| haralick9 | -0.016616 |
| haralick10 | 0.016184 |
| haralick11 | -0.009838 |
| haralick12 | 0.060944 |
| haralick13 | -0.014681 |
| gxy_mean | -0.004639 |
| gxy_std | 0.022363 |
| gx_mean | -0.002482 |
| gx_std | 0.005792 |
| gy_mean | 0.000629 |
| gy_std | 0.045106 |

Table 3.relationships between growth phases of cabbage and textural characteristics.

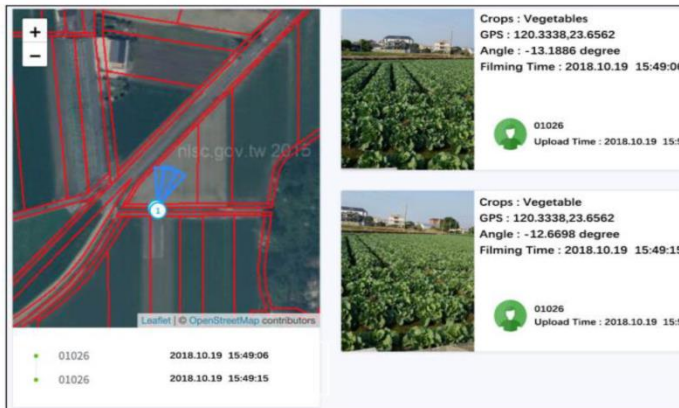


Figure 7:Backstage interpretations of the field survey images by an agricultural professional.



Figure 8 :Agricultural professionals interpret the growth days of cabbages according to the field survey images.

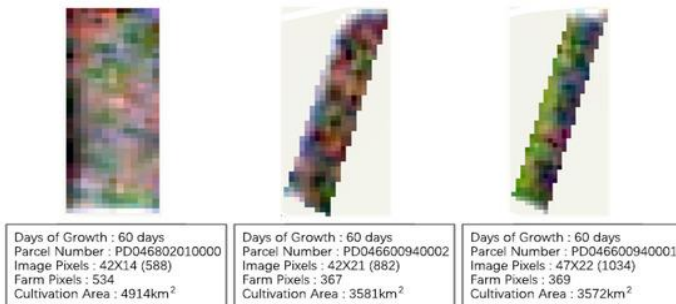


Figure 9: Satellite images of cabbages (60 days).

5. CONCLUSION

All things considered, the "Crop Recommendation System Using Multi-Temporal Satellite SAR Data" is a noteworthy development in agricultural technology. The system offers farmers accurate crop recommendations based on crop dynamics, soil health, and moisture levels by utilizing deep learning and SAR data processing. This fusion of cutting-edge technology and conventional agricultural methods encourages crop management efficiency and sustainability. Enhancing decision-making and optimizing resource utilization are the goals of the system, which provides farmers with useful insights from satellite data. Advances in satellite technology and continuous algorithmic refining will greatly increase the system's accuracy and usability. In the end, this approach aims to foster resilience in farming methods and environmental stewardship while boosting agricultural productivity.

6. REFERENCES

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