Unsupervised Spectral Satellite Image Analysis for Classification of Crop Types

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Abstract

Satellite imagery has emerged as a valuable resource for monitoring and classifying land cover, particularly in precision agriculture. This work explores the field of unsupervised spectral analysis of Sentinel-1 satellite data for crop-type classification. Using the special properties of Sentinel-1's synthetic aperture radar (SAR) data. Sentinel-1 data provides a strong basis for agricultural surveillance because of its capacity to see through cloud cover and provide all-weather imagery.

These findings show how well unsupervised spectral analysis can distinguish different crop kinds in the German environment. We evaluate the advantages and disadvantages of each approach in capturing the nuances of agricultural land cover. I used Simple Linear Iterative Clustering (SLIC) and k-means clustering, two unsupervised clustering methods. By expanding the use of unsupervised spectral satellite image analysis in precision agriculture, the knowledge obtained from this work opens the door to more precise and effective crop monitoring techniques.

DECLARATIONS

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

STATEMENT 1

This dissertation is the result of my own independent work/investigation, except where otherwise stated. Other sources are acknowledged by giving explicit references. A bibliography is appended.

STATEMENT 2

I hereby give consent for my dissertation, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organizations.

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Date:14/12/2023

Contents

Chapter -1 Introduction

The core of food production has always been the use of traditional farming techniques, which have their roots in earlier practices in agriculture. However, the shortcomings of these conventional methods become more obvious as the world's population continues to grow and climatic uncertainty increases. Their labor-intensiveness, susceptibility to weather fluctuations, and inefficient use of resources must be addressed in order to meet the world's expanding need for food production. [25]. Innovative methods that may overcome the constraints of traditional farming are desperately needed in this situation in order to boost production and address the issues of the twenty-first century.

In the era of remote sensing, satellites flying far above the planet provide a new approach to monitoring and controlling agricultural landscapes. Satellites like Sentinel-1, Sentinel-2, and Landsat, each with specialized sensors that can gather crucial data about the Earth's surface, are among the mainstays of this technological paradigm. Sentinel-1 can image in all weather situations, day or night, because of its synthetic aperture radar (SAR) capabilities, which allow it to cut through atmospheric layers[4]. Sentinel-2's multispectral sensors enable it to collect high-resolution imagery that may be used to identify minute features in the land cover. An illustrious contributor to Earth observation, Landsat offers a wealth of historical multispectral data spanning several decades. These satellite data provide a dynamic and all-encompassing picture of the agricultural terrain.

Although remote sensing provides the framework for collecting large amounts of data, machine learning techniques are necessary to extract valuable insights from this massive datasetThe two primary methods in machine learning are unsupervised and supervised. Supervised learning employs tagged data to train computers to recognize certain patterns, whereas unsupervised learning looks for inherent patterns in the data without predefined labels[26]. Regarding crop type categorization, the unsupervised method is superior since it can identify subtle spectral differences, making it more adaptable to the changing conditions of agricultural landscapes.

In the project, the capabilities of unsupervised machine learning techniques with the power of remote sensing are embodied in satellites like Sentinel-1, Sentinel-2, and Landsat. Using Sentinel-1 SAR data's special powers and techniques like k-means clustering and Simple Linear Iterative Clustering (SLIC), this study seeks to go beyond the constraints of conventional agricultural evaluations. This project is significant because it has the potential to transform crop type categorization and has wider implications for tackling issues related to global food security.

1.1 Project Description

The intricate issues of crop type classification and monitoring have made it necessary to integrate state-of-the-art technology in the large field of precision agriculture[13]. The field of remote sensing, which is at the forefront of this technological frontier, allows us to see our agricultural landscapes from above, thanks to satellites circling far above the planet. Notable satellites in this project include Sentinel-1, Sentinel-2, and other widely-used platforms such as Landsat. All these satellites are important for Earth observation, but Sentinel-1 stands out because of its synthetic aperture radar (SAR) capabilities[2][10]. SAR has a distinct advantage over optical sensors because it can penetrate air conditions and collect data day and night and in all-weather situations. Sentinel-1 can monitor agriculture even with obstacles such as cloud cover and inclement weather that might block optical sensors because of this function[22].

The project's dataset is an extensive compilation of Germany's agricultural landscape spanning 122 timestamps. This wide temporal coverage offers a thorough understanding of the dynamic changes that transpire over time, enabling an in-depth examination of crop patterns, growth phases, and reactions to environmental influences. Germany was a logical option for the study region because of its varied agricultural techniques and well-researched land use patterns. Using such a dataset improves the overall effectiveness of the unsupervised spectral analysis by enabling a sophisticated investigation of crop kinds and their temporal history.

Unsupervised learning takes centre stage in the analysis methodology, steering away from traditional supervised methods that rely on labelled data for training algorithms. In the context of crop-type classification, unsupervised learning is a more flexible and adaptive approach. It allows the algorithms to explore inherent patterns within the data without predefined labels, making it particularly suitable for the dynamic and variable nature of agricultural landscapes. This project employs two prominent unsupervised spectral analysis techniques: k-means clustering and Simple Linear Iterative Clustering (SLIC). These methods work synergistically with the extensive Sentinel-1 dataset to discern meaningful patterns and classify diverse crop types, providing an innovative and data-driven approach to crop monitoring.

The importance of this initiative goes beyond its technical complexity to include its possible effects on world food security. Classifying crop kinds accurately and promptly helps to improve agricultural practices and makes decision-making processes more informed. This project aims to employ innovative methods to simplify Germany's complicated agricultural environment, creating the possibility of adaptable and scalable solutions that can be applied in a range of agricultural situations worldwide[27].

1.2 Project Aims

The main objective is to use a substantial dataset covering the agricultural landscape of Germany over 122 timestamps to enable a detailed examination of crop patterns, growth phases, and reactions to environmental influences. The study aims to identify significant patterns in the dataset by utilizing unsupervised spectral analysis approaches, namely Simple Linear Iterative Clustering (SLIC) and k-means clustering. By comparing various approaches, it will be possible to determine how well they identify different types of crops and gain important knowledge on how best to use Sentinel-1 satellite data for precise and successful agricultural surveillance. The ultimate goal of the study is to deepen our comprehension of the possible applications of unsupervised spectral analysis in precision agriculture and how it might transform crop type categorization for increased global food security.

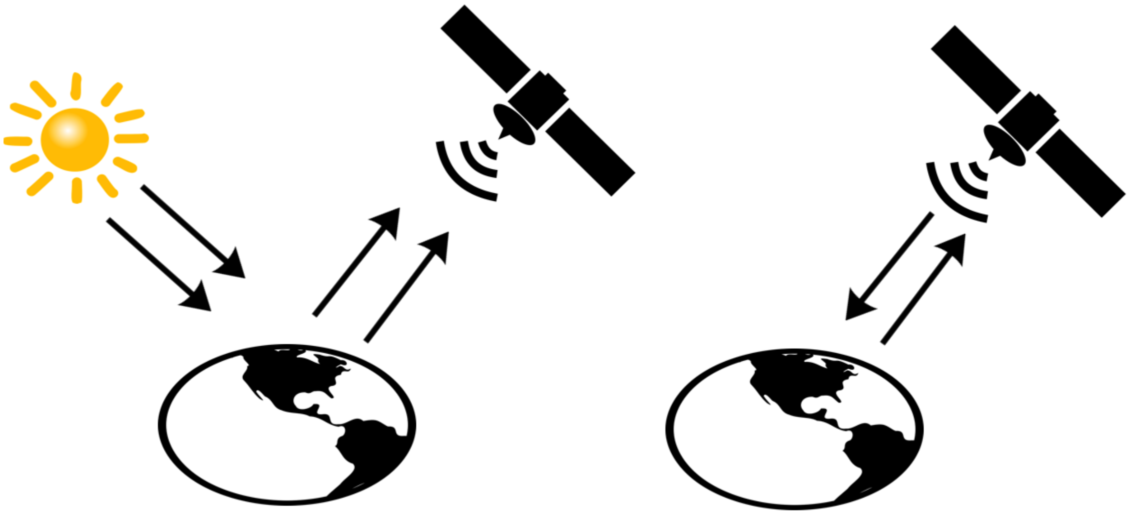
1.3 Research Objectives

1) Examine the literature to learn about the most recent developments, approaches, and difficulties in unsupervised spectral analysis, emphasizing satellite image analysis for crop classification.
2) Examine and prepare the large dataset that represents Germany's farming environment so that it is ready for unsupervised spectral analysis.
3) Analyse and explain why Sentinel-1 satellite data was chosen over alternative satellite datasets due to its capabilities for synthetic aperture radar (SAR) and potential for resolving long-standing issues with agricultural surveillance.
4) Develop and improve unsupervised spectrum analysis methods, such as Simple Linear Iterative Clustering (SLIC) and k-means clustering, ensuring that these methods can be tailored to the distinct features of the various crop kinds in the chosen dataset.
5) Perform a thorough evaluation of the classification accuracy of the unsupervised spectral analysis, taking into account precision.

Chapter-2 Background Research

2.1 Remote Sensing

In of remote sensing, which is an important tool for understanding and monitoring the surface of our planet, the choice of satellite technology is critical[28]. Remote sensing gathers information about the Earth's surface or atmosphere using sensors mounted on aircraft or satellite platforms. This technique detects electromagnetic radiation that is reflected or emitted by objects to produce multiscale and multitemporal pictures. There are two primary types of remote sensing: passive and active. Active sensing offers distinct benefits since it measures the return signal using its own energy source, as demonstrated by RADAR and LIDAR[29]. Passive sensing depends on sensors identifying electromagnetic radiation from outside sources, such as sunshine.



Sentinel-1 is a renowned satellite among the several utilized for remote sensing, and its remarkable Synthetic Aperture Radar (SAR) capabilities are the reason it was chosen for this project. To use SAR technology, microwave signals are sent toward the Earth's surface and reflected to be captured; high-resolution photographs produced by this procedure provide insights into the textural and structural properties of the Earth's surface, especially agricultural regions. Sentinel-1 can see through bad weather, including thick cloud cover, since it works in the microwave region of the electromagnetic spectrum [1][3][30]. This feature is revolutionary, especially in areas like the tropics, where cloud cover is common.

Sentinel-1's benefit becomes more apparent when considering the objectives of the project. A steady supply of high-quality data is necessary for unsupervised spectral satellite image analysis for crop type classification, and Sentinel-1 more than meets this need. With its day-and-night, all-weather imaging capabilities, its SAR technology guarantees a steady stream of data for processing. Because the research relies heavily on unsupervised techniques like Simple Linear Iterative Clustering (SLIC) and k-means clustering, Sentinel-1's capacity to overcome atmospheric obstacles and offer a clearer spectral signature of crop kinds is extremely beneficial.

In addition, Sentinel-1's 10-day return period and its twin's strategic orbital alignment guarantee a greater data-collecting frequency for particular Earth regions[3][7]. Because these satellites are phased 180 degrees apart, a unique characteristic that allows for a return duration of 5 days for any region greater than 100 km^2 makes it possible to examine changes in the agricultural landscape more dynamically and quickly.

In conclusion, Sentinel-1's strong SAR capabilities, which make it ideal for day-and-night, all-weather imaging, explain why the project relies on it[1][14]. This capacity is essential to effectively use unsupervised spectral analysis techniques for crop type classification, especially in regions vulnerable to unfavourable weather patterns. The project's goals are well aligned with Sentinel-1's special capabilities, which provide a complete and trustworthy dataset for studying and categorizing crop kinds in the selected geographic area.

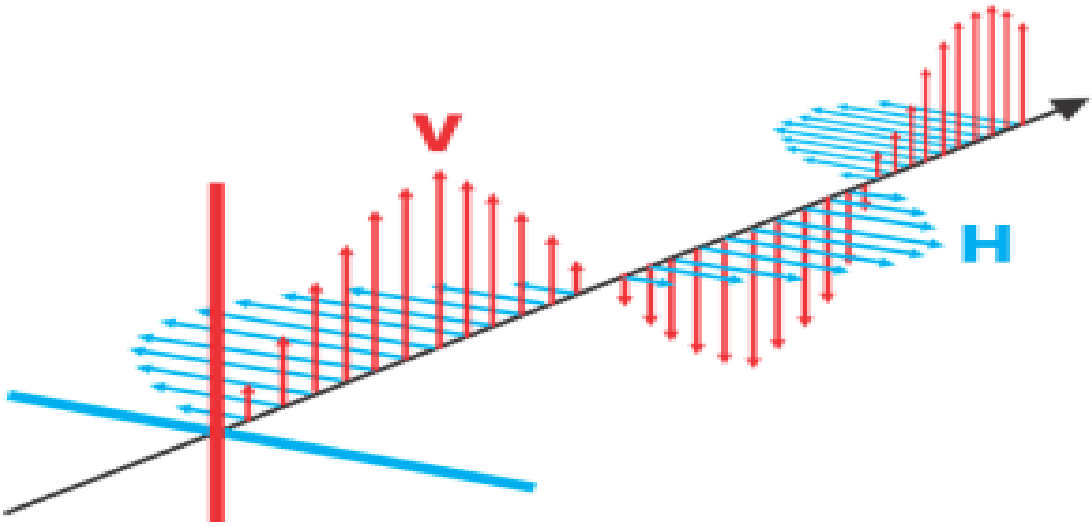
2.2 VV and VH Polarization

A crucial aspect of Sentinel-1 data lies in its polarization characteristics, ––specifically Vertical Transmit, Vertical Receive (VV), and Vertical Transmit, Horizontal Receive (VH)[18]. These polarizations play a pivotal role in capturing distinct signatures instrumental for accurate crop type classification.

2.2.1 VV (Vertical-Vertical) Polarisation:

In VV polarisation, the radar sends out microwave pulses that are oriented vertically and receive backscattered signals that are similarly polarised vertically. This indicates that the electric field vectors of the broadcast and received signals are directed vertically. The vertical structure and surface roughness of the surfaces that VV polarisation interacts with are important factors. It is frequently used to track vegetation changes and identify certain kinds of land cover.

VV polarisation offers Sentinel-1 a unique view of the Earth's surface by highlighting its sensitivity to surface roughness and structural characteristics. Rougher terrains like woods or cities show distinct VV responses from smooth surfaces like pools of water. The VV polarisation is essential for differentiating between different land cover types because it is particularly good at recording radar backscatter responses from varied surfaces. Crop-type categorization efforts depend on this polarization, which is essential to comprehending the structural features of various landscapes.



Refrence: https://support.capellaspace.com/hc/en-us/articles/360044738831-Sentinel-1-Polarization

Figure VV shows how vertical waves are transmitted and received to create a SAR image, whereas Figure VH shows how vertical waves are transmitted and received to create a SAR image.

2.2.2 Vertical-Horizontal Polarisation (VH):

In VH polarisation, the radar sends out pulses that are oriented vertically, while it receives backscattered signals that are polarised horizontally[18]. This indicates that the electric field vectors of the broadcast and received signals are pointed in distinct directions. Surface roughness and horizontal structure have an impact on VH polarisation. It can offer useful details regarding surface features, such as how various flora and soil types disperse. With a noticeable sensitivity to the density and structure of the vegetation, VH polarisation provides an additional layer of information to the investigation. Radar signal scattering in VH polarisation is greatly influenced by the intricate branching and leaf orientation of vegetation. Because of this, VH polarisation is very useful for differentiating between various plant kinds, including crops in agricultural areas. Comprehending VH polarisation is essential for deciphering the structural subtleties of plants, enabling enhanced differentiation between distinct crop varieties according to their distinct attributes**.**

Utilizing VV and VH polarisations simultaneously provides a more comprehensive understanding of the surface of the Earth. In crop-type classification, VV and VH data integration becomes especially powerful. Different crops respond differently to both polarisations, enabling a more precise and nuanced categorization. Increased discrimination is made possible by the varied structural characteristics of crops, such as row patterns and canopy density, which appear differently in VV and VH polarisations.

2.3 Visualizations

In remote sensing, visualization is the process of presenting complicated data—like satellite imagery—in a simple way for people to understand using graphics or pictures. Improving comprehension of patterns, correlations, and trends in the data entails generating visual representations of spatial information. Visualization is essential when displaying and comprehending the information obtained from the satellite images in the context of crop categorization using Sentinel-1 SAR data.

Exploring the Sentinel-1 SAR data with the help of visualization enables us to evaluate its attributes and quality. It is possible to see patterns, abnormalities, and problems affecting the precision of crop categorization algorithms by visualizing various bands and polarisations. Before using machine learning techniques, researchers may better understand the data using visualization.

For a time-series dataset, visualization enables the analysis of temporal changes in crop characteristics. By creating visualizations over different time intervals, I can observe the growth patterns, phenological changes, and variations in crop conditions. This temporal aspect is essential for understanding the dynamics of agricultural areas and improving crop classification accuracy.

Visualization is essential for assessing categorization outcomes. Confusion matrices, accuracy evaluations, and theme maps are displayed to help visualize the models' performance. I can improve crop categorization accuracy by fine-tuning parameters and algorithms through this visual input.

Visualization is an effective tool for feature analysis, data exploration, model training, and outcome interpretation in projects. It makes it easier to comprehend Sentinel-1 SAR data more thoroughly and improves crop categorization efforts.

2.4 Unsupervised Learning

This research heavily relies on unsupervised learning, a potent paradigm in machine learning. The programme investigates structures and patterns in the data in unsupervised learning without explicit instructions or predetermined labels. The main goal is to find underlying structures, clusters, or connections in the dataset, which is why it's especially useful for picture analysis and classification jobs.

The inherent complexity and diversity of agricultural landscapes are why unsupervised learning approaches are preferred over supervised ones in remote sensing and satellite image analysis. Unsupervised approaches, such as k-means clustering and Simple Linear Iterative Clustering (SLIC), independently discover underlying patterns in the dataset, in contrast to supervised approaches that depend on labelled training data for certain classes. This independence is especially useful when crop diversity and geographical distribution vary. Nuanced spectrum fluctuations are well captured by unsupervised approaches, which also respond well to the dynamic character of agricultural contexts. Unsupervised approaches provide a more adaptable and scalable approach by enabling computers to identify patterns naturally. This avoids the difficulties in obtaining large-scale labelled training datasets and considers the constantly changing features of crops and land cover.

The enormous volume of data that has to be interpreted is one of the main problems with remote sensing and satellite image processing. Unsupervised learning techniques overcome this difficulty by independently seeing patterns in the data, enabling effective and impartial analysis. Although there are alternative unsupervised techniques, the efficacy of k-means and SLIC in large-scale satellite picture segmentation and classification applications justifies their deliberate selection. The simplicity, computational economy, and capacity to capture both spectral and spatial properties necessary for precise crop mapping are all powerful features of these techniques. The accuracy with which Sentinel-1 satellite data may be interpreted is expected to be greatly aided by the robustness of both k-means and SLIC, which will eventually help achieve the project's main objective of accurately classifying crop types.

2.4.1 K-Means

K-means clustering is a popular method for splitting a dataset into k distinct, non-overlapping subsets or clusters. The technique minimises the total squared distances between data points and each cluster centroid repeatedly, improving the cluster assignments[31][5]. K-means clustering excels in assembling pixels with comparable spectral properties in the context of satellite image analysis. Large-scale picture segmentation and classification jobs benefit greatly from the algorithm's scalability, simplicity, and efficiency[5].

2.4.2 SLIC

In contrast, a superpixel-based segmentation technique called Simple Linear Iterative Clustering (SLIC) effectively groups pixels according to colour and geographic closeness[12]. SLIC is particularly well-suited for situations where spatial coherence is essential since it conforms to the inherent boundaries of objects in a picture[17]. By defining homogeneous and compact superpixels, the approach lowers the dimensionality of the data and increases computing efficiency. SLIC is useful for collecting fine features in satellite images, including crop borders, because of its capacity to maintain spatial connections.

The process of classifying crop types using unsupervised learning algorithms like k-means and SLIC involves the division of satellite pictures into areas or clusters that have significance. These clusters stand for areas with comparable spectral properties, and the system tries to identify differences that could be associated with various crop kinds. Sentinel-1 SAR data's spectral fingerprints and these unsupervised algorithms' ability to give spatial coherence enable the production of precise and in-depth crop maps.

In addition to k-means and SLIC, several additional unsupervised learning algorithms have been used to satellite image analysis, including Gaussian mixture models, PCA, and hierarchical clustering. In the project, k-means and SLIC are prioritised because of their effectiveness, simple use, and track record in comparable remote sensing applications.

Chapter -3 Literature Review

The article [6] discusses the specifics of Sentinel-1. Evaluating agricultural policy requires accurate mapping, and this work uses the Copernicus program—Sentinel-1 in particular—to accomplish continental-scale monitoring for 2018 with a spatial resolution of 10 metres [6].

The use of in-situ data, namely the LUCAS (Land Use/Cover Area frame statistical survey) Copernicus module, to gather land cover extent compatible with high-resolution sensors. The categorization models are trained using the LUCAS data. The study's goal of identifying the primary crop types in the EU-28 based on in-situ data is achieved by reorganizing the LUCAS survey [6].

The classification methodology involves a two-phase approach, stratifying the EU-28 based on climatic and ecological gradients. In remote sensing applications, Random Forest (RF) models are utilized due to their ability to withstand multi-collinearity and overfitting[6]. The authors carry out a thorough feature selection process to find the most important S1 backscatter properties and time periods for precise categorization. The study balanced sample size and stratification detail using a stratified random sample methodology based on key biomes[33][6].

After that, the Big Data Analytics platform is used to generate the classification results at the continental scale. The final map is carefully post-processed to remove regions and land cover classes that were underrepresented in the training data and high-altitude areas that need to be more relevant to the study [6].

Three methods are used to check accuracy: verification against published subnational statistics, comparison with Geospatial Aid Application (GSAA) data, and validation against LUCAS 2018 core points [6]. Every method adds to a thorough assessment of the EU crop map, guaranteeing accuracy and pertinence across several spatial dimensions.

The thorough study had an overall accuracy of 80.3% when combining the main crop classes, and 76% when considering each of the 19 crop type classes individually [6]. Remarkably, some crop types—like rape and turnip rape, for example—show exceptionally high accuracy levels that surpass 96%. Strong correlations, ranging from 0.93 to 0.99, have been found between remotely sensed estimated crop acreage and reported crop areas by Eurostat [6].

The discussion and conclusion sections comprehensively evaluate the study's methodology, findings, and consequences, which lays a strong basis for developing Sentinel-1 data-driven continental-scale crop-type mapping.

In article[19], the paper discusses the significance of timely and accurate crop distribution information for agricultural management and the formulation of regulatory policies. It highlights the areas for improvement of the existing crop classification techniques based on remote sensing, especially the supervised techniques that depend on large amounts of ground sample data. Three categories—historically-based classification, semi-supervised learning, and unsupervised classification—are used in the article to group current approaches [19].

Historical-Based Classification: This technique uses historical data's crop pixels that haven't altered the stability of crop planting structure as training samples for the current season [19]. The researchers note the limits in regions without historical samples, but they also provide examples of historical-based categorization that reached high accuracy.

Semi-Supervised Learning: These techniques use labelled and unlabelled data, enabling more economical data use [19]. Examples include matrix completion collaborative representation, random forest-based cooperative training techniques, and support vector machines with self-training algorithms.

Unsupervised Classification: This group comprises techniques that handle a lot of unlabelled samples without using sample information [19]. Examples include K-means, probabilistic neural networks, and ISODATA. The vulnerability of these algorithms to noise, high dimensionality, and outliers is highlighted in the research.

The research uses PCA (principal component analysis), a dimensionality reduction technique, to improve unsupervised classification accuracy. PCA is applied to extract features from remote sensing images, and the top k principal components are divided into equidistant bins using the novel approach of isometric binning [19]. The PCIB approach is based on merging bins that belong to the same category to create a class label [19].

The proposed PCIB method involves five key steps: data preprocessing, feature value selection (NIR, NDVI, NDWI), comparison of classification methods (RF, K-means, ISODATA, PCIB), category label determination, and accuracy evaluation. The classification workflow includes PCA dimensionality reduction and isometric binning for crop mapping.

The authors used multitemporal Gaofen 1 satellite (GF-1) remote sensing pictures over particular regions of China for crop mapping in 2016 and 2017 to validate the proposed PCIB approach [19]. The outcomes were contrasted with other widely used classifiers, including ISODATA, K-means, and random forest. According to the study, random forest and PCIB had the best classification accuracy, with PCIB showing potential for wide-scale crop mapping without a huge field sample size.

The literature review underscores the significance of accurate crop classification in remote sensing and the limitations of supervised methods. The proposed PCIB method, integrating PCA and isometric binning, presents a novel approach to overcome these limitations, providing promising results for large-scale crop mapping without extensive ground sample data[19]

The literature study[8] delves into the importance of Sentinel-1 time series data in agricultural mapping, highlighting its applicability for field and crop monitoring to enable the allocation of subsidies. Field visits and aerial photos are used as quality control methods in the European Commission's Land Parcel Identification System (LPIS), which is essential for Common Agricultural Policy (CAP) subsidies. Space-borne remote sensing data, especially Sentinel-1 synthetic aperture radar (SAR) data, were investigated in search of a more affordable option[8]. Given that Sentinel-1 SAR satellites can offer repeated collections every six days, the study focuses on the European Union's interest in ongoing crop monitoring utilising these satellites.

Several research studies have used the benefits of the C-band wavelength, which is appropriate for various SAR approaches, to monitor crops using SAR technology. The evaluation emphasizes how useful C-band SAR data is for crop inventories near the end of the growing season since it is sensitive to changes in crop structure throughout seed and fruit development [8]. The preference for C-band SAR data in crop mapping, particularly for areas with minimal vegetation, is highlighted in the trade-off between polarimetric and multitemporal information. The study area encompassed 10,287 agriculture parcels in the Eura site, with 119 different crop species or land management categories in 2017[8]. Numerous categorization strategies—from probabilistic mapping to clustering techniques—that employ Sentinel-1 time series data are discussed in the literature. The paper also discusses how the normalized difference vegetation index (NDVI) and SAR backscatter complement one another for use in agriculture.

Analyzing the time dimension of Sentinel-1 data gathering, it is found that reliable crop species prediction may be achieved using scenes from early June to mid-August. This paper highlights the significance of Sentinel-1 data collected in the latter half of the growth season, as scenes collected around this time of year greatly enhance accuracy. Furthermore, research utilizing various polarisations indicates that VV polarisation outperforms VH polarisation somewhat, especially later in the growth season[8].

For crop species categorization, two approaches were used: multinomial logistic regression and the improved k-NN (ik-NN) technique (k-NN method and its optimized version ik-NN). The ik-NN method's non-parametric structure allowed for flexible modelling of complicated relationships and optimized features using a genetic process. The authors compared various approaches using data splitting into training and validation sets and leave-one-out cross-validation [8]. To describe the radar backscatter, SAR characteristics such as averages, standard deviations, and ratios were computed for every field parcel [8]. The ik-NN approach was selected for further thorough examinations as it showed reduced prediction errors.

The results show that the ik-NN approach produces overall accuracies between 71% and 90%, particularly when using a genetic algorithm and taking bigger parcels into account[8]. The ik-NN approach is better than multinomial logistic regression for certain area thresholds, as demonstrated by a comparison.

The study concludes by showing the Sentinel-1 time series' strong potential for crop species monitoring and differentiation. An operational technique for crop mapping is developed using the ik-NN approach and insights into the best times to collect data and estimate uncertainty. The results have implications for agricultural land parcel identification systems and offer useful suggestions for land management and precision agriculture.

The paper[16] presents a comprehensive framework for deriving a 10-meter crop-type map from Sentinel-1 at a continental level, highlighting the momentum in combining Copernicus Sentinel fleet observations, extensive in-situ data, and cloud computing for monitoring agriculture consistently at fine spatial and temporal scales over large areas. The method and data developed are valuable for scientific modellers and policymakers alike.

The paper DENETHOR (DynamicEarthNET2 dataset for Harmonized, inter-operable, analysis-Ready) highlights recent advances in remote sensing products that enable near-real-time monitoring of the Earth's surface[16]. Although near-daily time series of satellite images are becoming more widely available, research has been done on deep learning techniques to use the temporal density of data. The main use of time series remote sensing data is crop monitoring, where phenological variations in the crop's growth cycle are frequently taken advantage of.

In the paper, DENETHOR is a dataset created for remote, daily crop monitoring. Sentinel-1 radar, Sentinel-2 optical time series, and daily analysis-ready Planet Fusion data are all included in the collection, with a particular emphasis on Northern Germany[16]. The collection includes data on crop types and field borders from the European Union's Common Agricultural Policy. The following are the nine high-level crop classes: Oil Seeds, Meadows, Root Crops, Rye, Barley, Oats, Corn, and Forage Crops[16].

The authors evaluate various deep-learning models for crop-type mapping using the provided dataset. The benchmark results show that for crop type mapping, convolutional methods using pixel average encoders achieve competitive accuracy [16]. On the other hand, models applied to a different temporal or spatial context show a significant decline in performance, highlighting the difficulties in making predictions outside of the year.

The article advances agriculture and remote sensing by assessing deep learning models for crop type mapping and offering a fresh dataset. Clear explanations of the difficulties in managing temporal transitions and efficient use of sophisticated data sources provide valuable insights for further study in this area.

The article [23] highlights the importance of offering insightful information on crop classification techniques. The researchers used Google Earth Engine (GEE) For analysis and calculations. The collection and processing of Sentinel-1 data, emphasizing the VH polarisation band to generate a time-series dataset, aligns with current crop categorization machine learning and remote sensing developments.

The authors researched different machine learning algorithms, which are Classification and Regression Trees (CART), Random Forest (RF), Gradient Boosting, and Support Vector Machine (SVM), and this highlighted the variety of methods that are taken into consideration for precise crop mapping [23]. The experimental findings thoroughly assess the classifiers' performance, which are displayed using confusion matrices and overall accuracy metrics. Interestingly, CART has the most accuracy, demonstrating its effectiveness in crop categorization [23].

In conclusion, this article [23] contributes to the growing literature on crop classification through remote sensing and machine learning. The emphasis on the Kendrapara region and the comparative evaluation of classifiers provides valuable insights for future research. The suggestion for further exploration across diverse crop types, geographic locations, and dataset sizes, emphasizing obtaining better ground truth information through field visits, sets the stage for continued advancements in precision agriculture.

The article [24] outlines the significance of classifying land cover in remote sensing, highlighting its uses in monitoring land cover change, agricultural monitoring, and urban planning. Synthetic Aperture Radar (SAR) can take pictures day or night, regardless of the weather; it is emphasized as a useful tool for monitoring land cover [24].

The study discusses the difficulties in interpreting SAR photos and the lack of labelled SAR images. As a remedy, unsupervised techniques are presented. The study divides these techniques into two primary phases: feature extraction and clustering [24]. The Principal Component Analysis (PCA), Kernel PCA, Eigenface, and Autoencoder feature extraction techniques are discussed. Remote sensing frequently applies these methods to get pertinent data from SAR images.

The outcomes of land cover mapping and ideal cluster sizes for various techniques and window sizes. For VH and VV polarisations, silhouette indices illustrate how well each approach works. It is noticed that user-defined features and KPCA are useful for VV polarisation, whereas Autoencoder and Kernel PCA are helpful for VH polarisation [24].

The paper's overall goal is to advance the area of SAR image categorization through unsupervised techniques and performance comparison. An in-depth discussion of the chosen techniques and their results offers valuable perspectives for the next studies in remote sensing and SAR image interpretation.

The article[3] explores the challenging task of crop-type classification using Earth Observation (EO) data, focusing on the fusion of Sentinel-1 and Sentinel-2 data for enhanced mapping accuracy. The synergy of optical and Synthetic-Aperture Radar (SAR) data allows for a comprehensive representation of biophysical and structural information, overcoming the limitations of single-sensor approaches, especially for crop types with similar phenological growth stages[3]. The research aims to evaluate the effects of parcel sizes, optical data availability, and feature selection on classification accuracy[3][32].

The introduction provides a comprehensive background on the significance of crop-type maps for agricultural monitoring and environmental assessments. It highlights complementary optical and SAR data, outlining how each contributes to our knowledge of plant health and structural traits [3]. This study summarizes the historical context of optical-SAR data fusion, highlighting the recent resurgence of interest in this area following the launch of the Sentinel-1 and Sentinel-2 satellites[3].

The research area in Brandenburg, Germany, is defined in the methodology section, highlighting the importance of crop type categorization for the area and the predominance of large-scale farms. The selection of 16 crop types is discussed, and using reference data from the Land Parcel Identification System (LPIS) for ground truthing is justified[3]. The pre-processing procedures for optical and SAR data are described in depth, covering the creation of different features and using gap-filling methods to address abnormalities in the data.

The methodology combines a robust approach with feature stacking and decision fusion comparison, Random Forest (RF) classification, and gFFS feature selection. Techniques for combining data, including feature-level, pixel-level, and decision-level fusion, are essential for increasing the precision of categorization. Many sensors' data are combined in pixel-level fusion, frequently using dimensionality reduction techniques[3]. While decision-level fusion combines categorization results based on established criteria, feature-level fusion incorporates data from several sensors. RF is frequently used in remote sensing research because it can handle high-dimensional data effectively and is noise-resistant.

To summarise, the literature review lays the foundation for an extensive investigation of crop type classification, emphasizing the significance of data fusion and the difficulties the selected technique tackled. The results of this study should greatly improve the precision of crop type mapping using EO data, with possible ramifications for environmental management and agricultural surveillance.

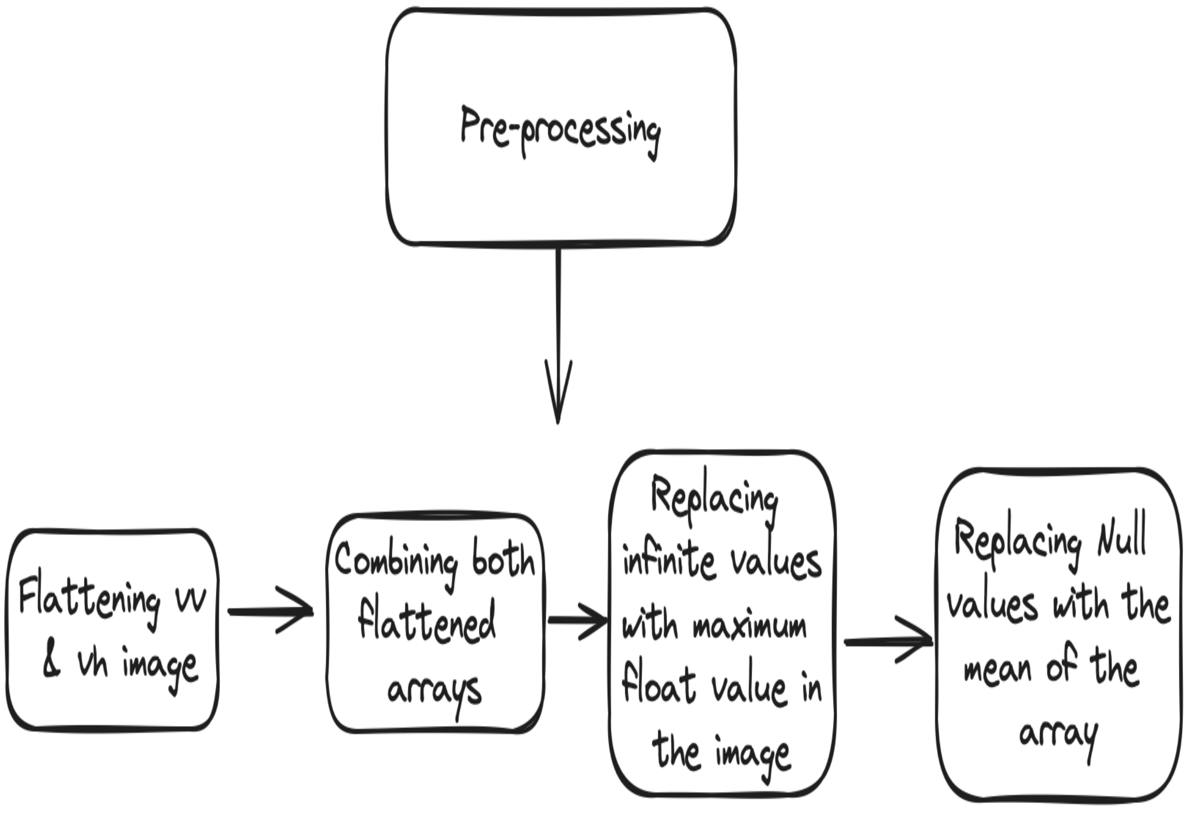
Chapter -4 Methodology and Results

4.1 Preprocessing

In the study, I extensively analyzed the provided satellite imagery, meticulously assessing the visual representations across two distinct spectra: VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive)[34][2][18]. This initial phase was crucial for understanding the characteristics and limitations of the data at our disposal.

Upon close examination using a visualization technique that employed a palette of 10 distinct colours, we encountered a significant issue. We discovered that the mask files, integral for delineating specific features in satellite imagery, were replete with noise. This noise rendered them unsuitable for our intended analytical purposes. The masks' inefficacy was a consistent problem across both spectrums (VV and VH), indicating a systemic issue in the data processing pipeline.

To address this challenge, we turned to an alternative source of information: a geojson file provided alongside the satellite data. This file proved to be invaluable, as it contained meticulously labelled information about various crops, along with precise geographical bounding polygon coordinates. Leveraging this data, we embarked on a process to create a new set of masks. These masks were tailored to align perfectly with the dimensions of the satellite images, ensuring a high degree of accuracy and relevance to our analysis.



FLOWCHART OF DATA PRE-PROCESSING

The second phase of our preprocessing involved a novel approach to enhance the distinction between different elements within the satellite images. Recognizing the limitations of traditional linear methods in differentiating subtle variations in satellite imagery, we applied a logarithmic transformation to each pixel. This approach was based on the hypothesis that a logarithmic scale would accentuate the nuances between pixels, facilitating a more effective differentiation of the features within the images.

This preprocessing step was especially critical for the subsequent application of unsupervised learning models, such as k-means clustering. By transforming the pixel values, we aimed to create a more pronounced distinction between different land covers and features, thus enabling the k-means algorithm to identify and group similar pixels more effectively. This technique has the potential to improve unsupervised classification accuracy in satellite imagery analysis, especially in varied and complex environments [35].

In summary, our preprocessing methodology involved a two-step approach: firstly, the creation of new, noise-free masks using geo-referenced crop labels, and secondly, the application of a logarithmic transformation to the pixel values of the satellite images. This comprehensive approach was designed to mitigate the original dataset's limitations and optimize the data for effective analysis using advanced unsupervised learning techniques.

4.2 Feature Extraction

In the feature extraction phase of our study, I focused on developing a robust method to extract and combine the distinctive features of satellite images captured in the VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive) spectra. This process is pivotal in enhancing the accuracy of subsequent analytical models, particularly those employed in remote sensing and agricultural monitoring.

My approach commenced with the concatenation of the VV and VH image arrays. This initial step was crucial in merging the unique characteristics of each spectrum into a single, comprehensive dataset. The rationale behind this concatenation was to leverage the complementary information provided by the VV and VH spectrums. While VV images are typically more sensitive to surface roughness and moisture content, VH images provide valuable insights into structural properties and biomass. I combined these datasets to create a more holistic representation of the observed landscape.

Following the concatenation, my next task was to address the issue of aberrant data values within the combined array. Satellite image arrays often contain infinite or null (None) values, which can significantly impair the performance of analytical models. To resolve this, I implemented a method to replace such values with the mean pixel value of the corresponding image. This approach was chosen for its effectiveness in maintaining the overall statistical integrity of the dataset, ensuring that the replacement values were representative of the general characteristics of the image.

The final step in my feature extraction process involved addressing the issue of excessively high floating-point values in the dataset. In digital image processing, pixel values that exceed the maximum permissible range can lead to distortions and inaccuracies in analysis. To mitigate this, we set a threshold by replacing any value that exceeded the maximum allowable float value in the array with the array’s maximum value. This strategy ensured that the dataset remained within a manageable and realistic range, thereby preserving the fidelity of the images for accurate feature extraction and analysis.

In summary, my feature extraction methodology was a multi-faceted process that involved the concatenation of VV and VH image arrays, normalization of aberrant data values, and the capping of excessively high pixel values. This approach was meticulously designed to ensure that the extracted features were not only representative of the true characteristics of the observed area but also conducive to effective analysis using various computational models in remote sensing and agricultural monitoring applications.

4.3 K-means

I applied two distinct methodologies to classify satellite imagery in the study, employing the k-means clustering algorithm as the core analytical tool. These methods were designed to capitalize on global and local features within the images, providing a comprehensive understanding of the underlying data.

4.3.1 k-means Algorithm

The k-means algorithm is frequently used in clustering analysis, commonly used in data mining and machine learning[36]. It operates on the principle of partitioning a dataset into 'k' distinct clusters, each characterized by the mean of its observations. The algorithm follows these key steps:

1. Initialization: Randomly select 'k' cluster centers from the data points.
2. Assignment Step: Assigning each data point to the nearest cluster center, typically using Euclidean distance as the metric.
3. Update Step: Recalculate each cluster's mean to determine new cluster centers.
4. Iteration: Repeat the assignment and update steps until the clusters reach a state of minimal change, based on predefined criteria such as a maximum number of iterations or a threshold for minimal variance within clusters.
5. Convergence: The algorithm concludes once the clusters have stabilized, and no significant assignment changes occur.

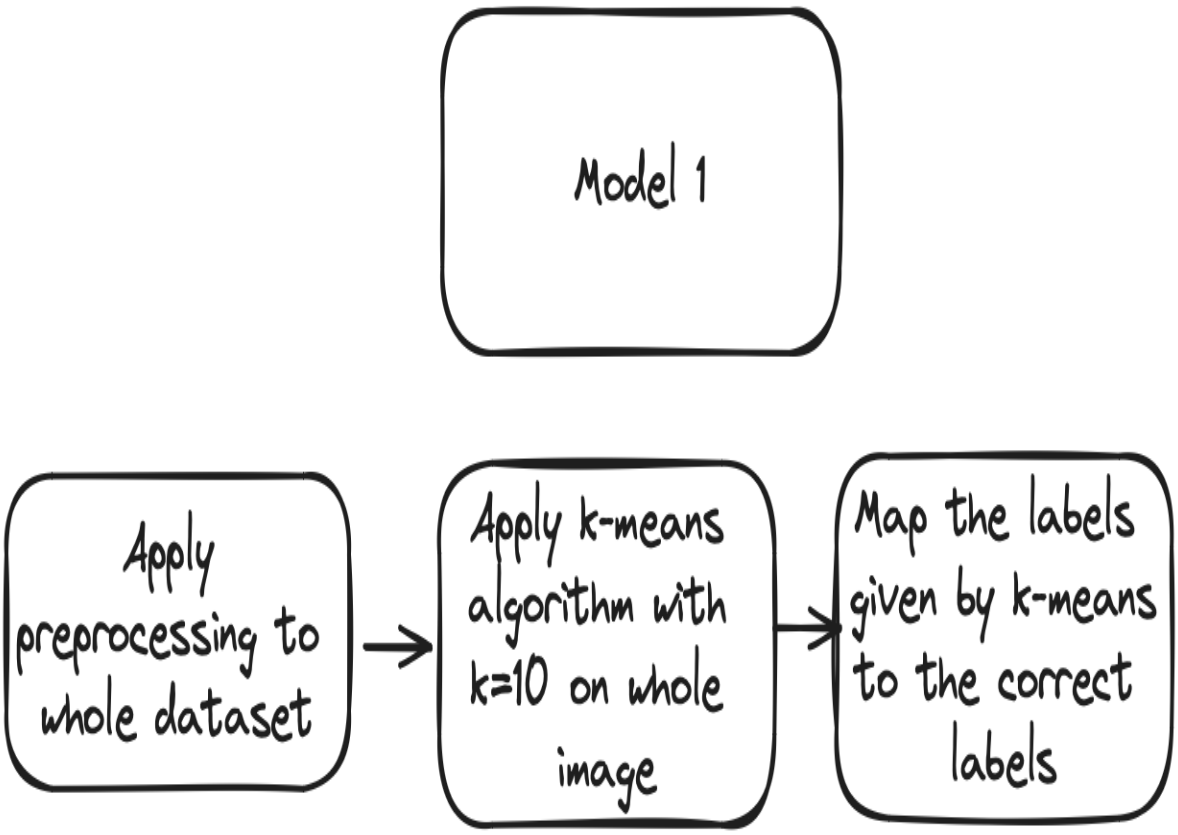
4.3.2 K-means (Model-1) Implementation

In the first method, I employed preprocessing and feature extraction techniques on each satellite image. For images in VV and VH spectra, I merged them into a single array by flattening, which allowed for a combined analysis of both spectral characteristics.

Then I applied the k-means algorithm to predict 10 clusters for each feature vector. The resultant clusters were reshaped into two different sizes to represent the final image segmentation.

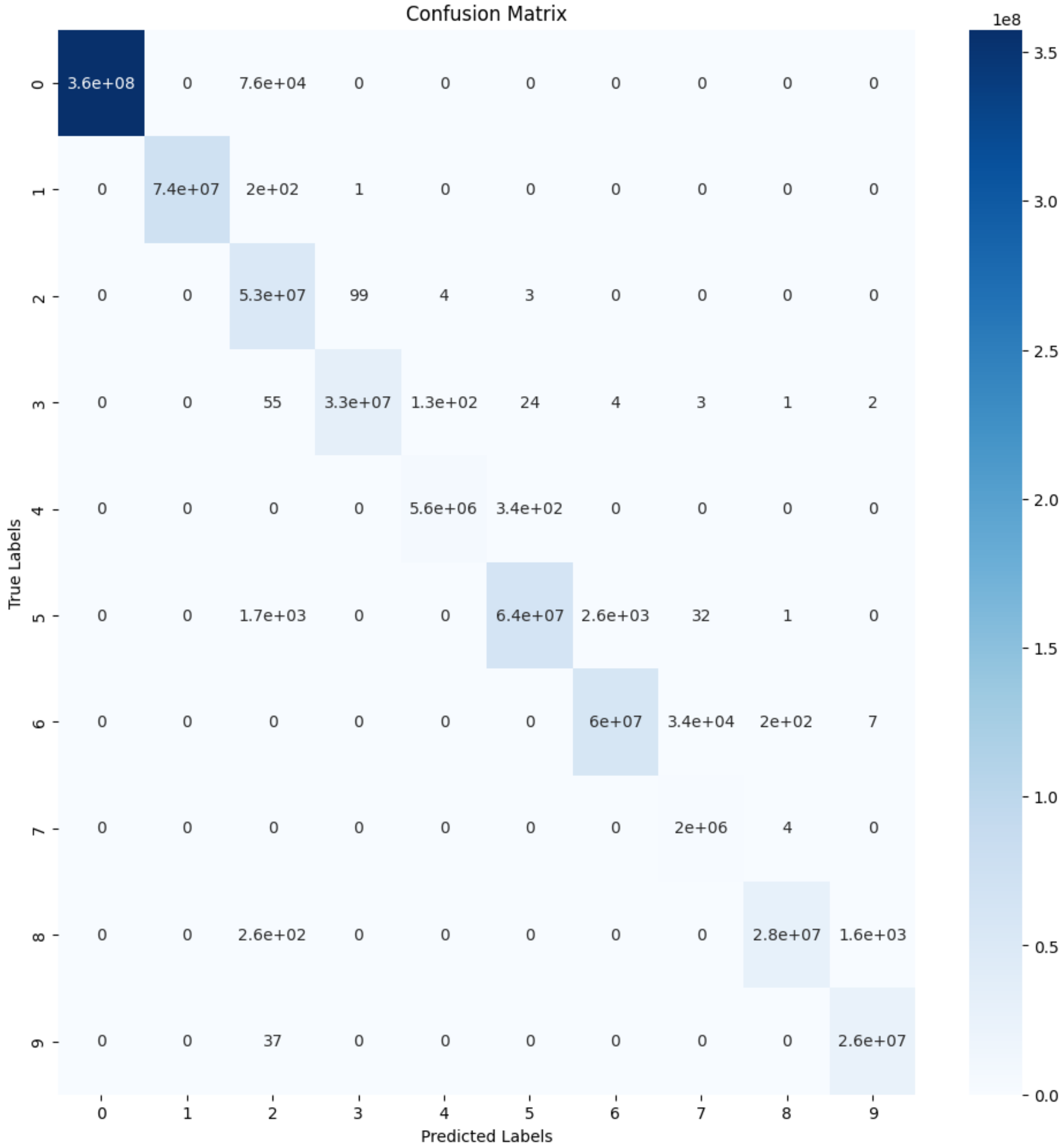
An inherent characteristic of k-means is its unsupervised nature, which means it does not consider the true labels of the data points and assigns labels independently. To align the predicted labels with true labels, we utilized a confusion matrix. This approach involved mapping each predicted label to the true label that was most frequently associated with it. For instance, if a significant number of points labelled '5' by the algorithm predominantly had a true label of '3', we reassigned all points with the predicted label '5' to the true label '3'. This process was replicated for all 10 labels to achieve a more accurate representation of the true classifications.

Finally, the confusion matrix was visualized to assess the accuracy and effectiveness of the classification, providing insights into the performance of the k-means algorithm in this context.



Flowchart of K means Algorithm

4.3.3 Method 1 Results

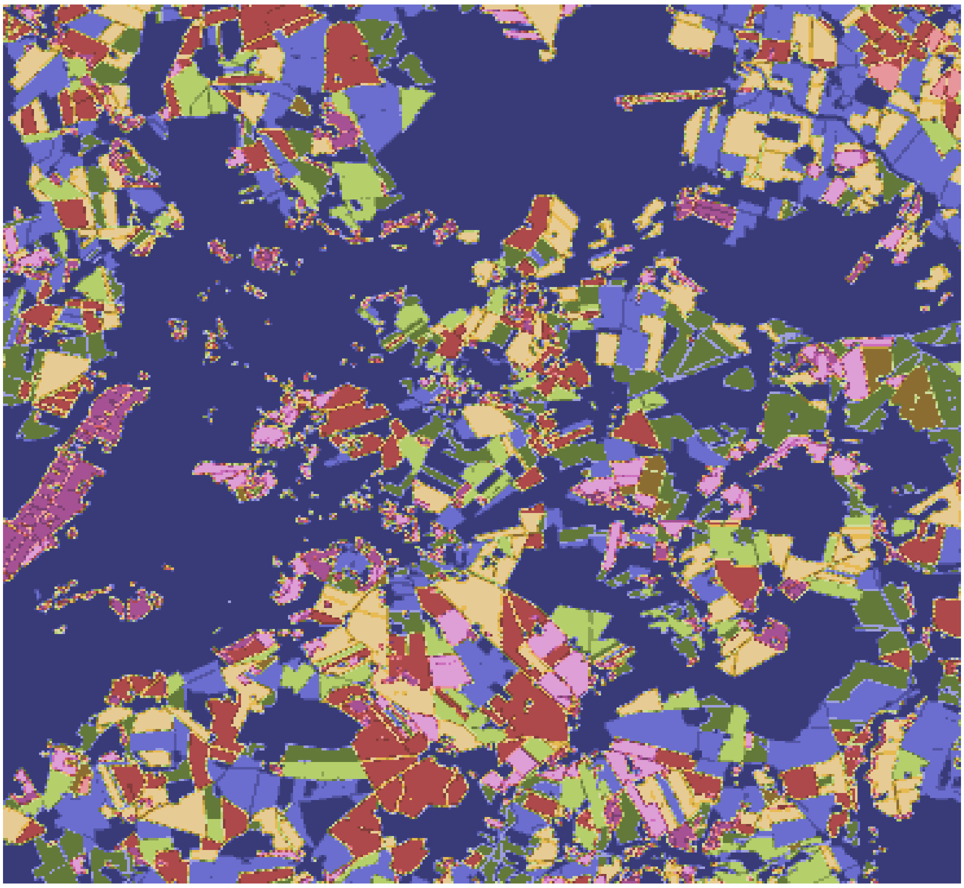


Confusion matrix of all the satellite images combined.

Method 1 K-Means gives us an accuracy of 99.98%.

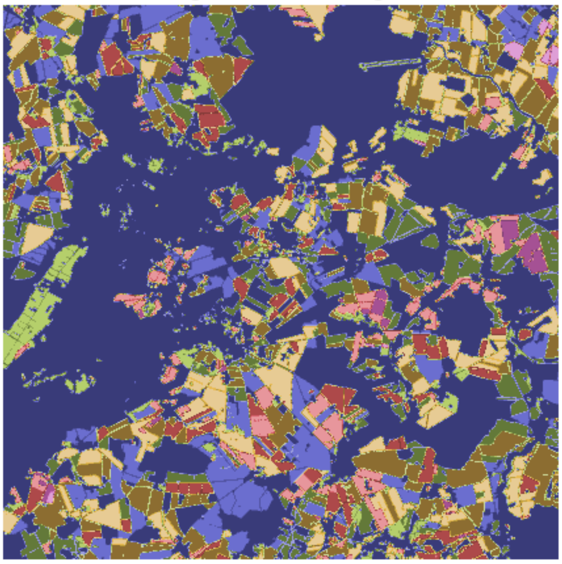
A single example of method 1 compared with the original mask: Below is the original mask generated by labels. geojson

Custom Mask

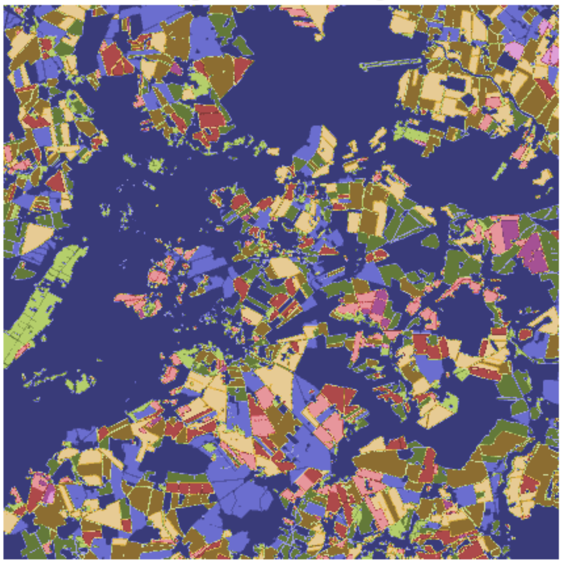


Below are the predicted VV and VH masks.

Segmented VV Image



Segmented VH Image



4.4 SLIC(Simple Linear Iterative Clustering)

We combined two powerful algorithms: Simple Linear Iterative Clustering (SLIC) for superpixel generation and Canny edge detection for precise boundary delineation. This method was designed to address the common challenges of over-segmentation and under-segmentation, aiming to achieve a more accurate and detailed representation of the features within the satellite images.

4.4.1 SLIC(Simple Linear Iterative Clustering)

Superpixels are an important concept in computer vision and image processing, serving as a foundational element in various applications such as image segmentation, semantic labelling, object detection, and tracking. They are defined as groups of pixels that share common characteristics, such as intensity, offering a more meaningful and perceptually relevant representation than individual pixels. Superpixels carry more information and provide a compact representation of images, which is particularly beneficial for computationally demanding tasks.

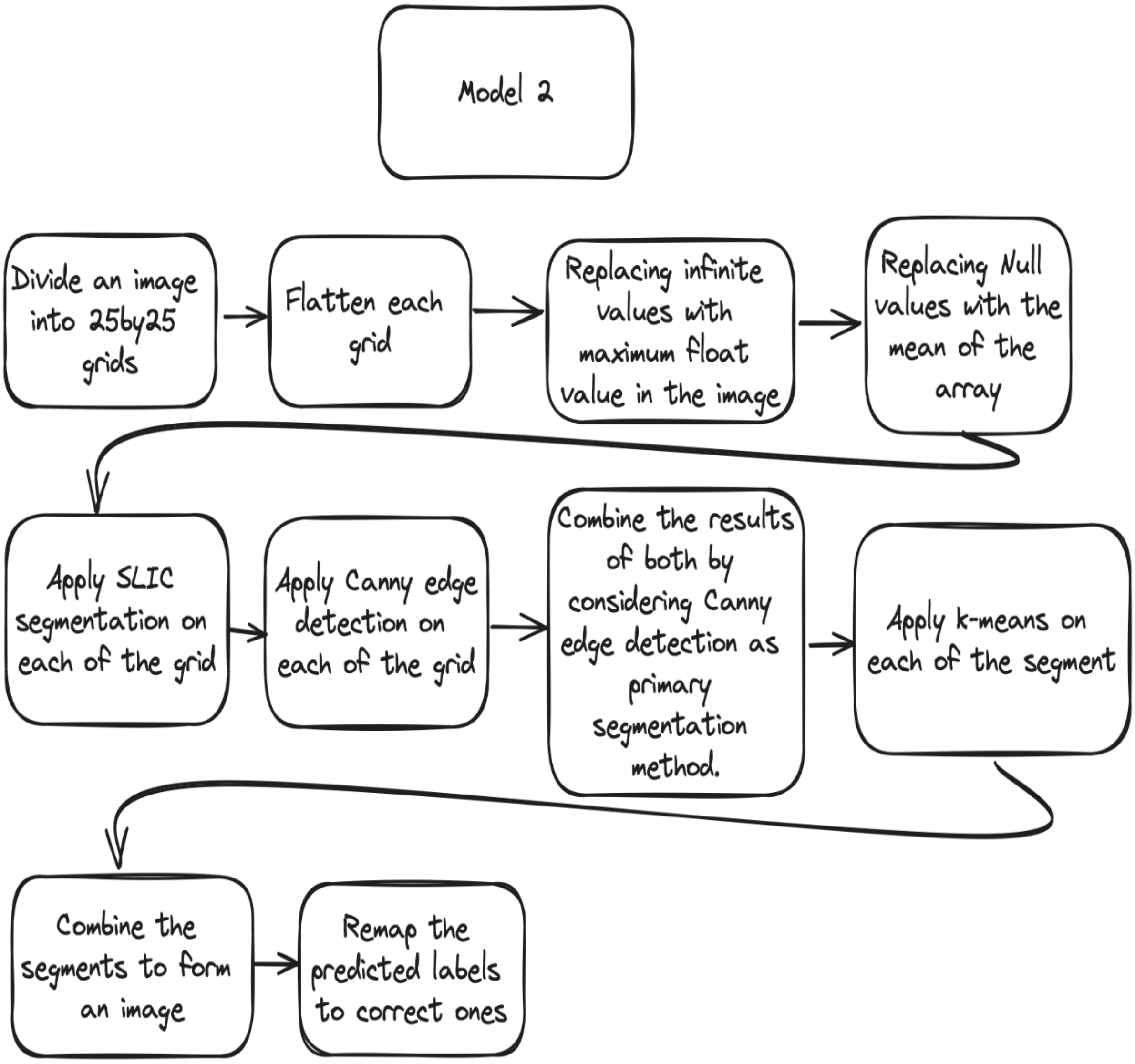
The SLIC algorithm is a prominent method for generating superpixels. It operates by clustering pixels based on their color similarity and proximity in the image plane. This clustering is conducted in a five-dimensional space composed of the CIELAB colour space (l, a, b) and the pixel position (x, y). The algorithm begins by determining an initial set of superpixel centers and iteratively refines these centers and their associated pixels.

A key aspect of SLIC is its distance measure, crucial for clustering in the five-dimensional space. This measure combines colour similarity (in the lab space) and spatial proximity (in the xy plane), allowing for the creation of superpixels that are color-consistent and spatially coherent. The algorithm also introduces a compactness parameter that influences the tightness of the clustering, balancing colour similarity and spatial proximity.

The implementation of SLIC involves several steps:

1. Initialize superpixel centers at regular grid intervals and adjust them to low gradient positions to reduce the chance of edge placement.
2. Assign pixels to the nearest cluster center and update the center based on the average color and position of the pixels.
3. Iterating the assignment and update steps until convergence.
4. Enforcing connectivity in the final step to ensure coherent superpixel shapes.

SLIC is particularly noted for its efficiency and simplicity, making it a popular choice for various image-processing tasks. Its ability to generate superpixels that respect image boundaries and exhibit uniform size and shape is a significant advantage in many applications, from medical imaging to video surveillance.



Flowchart of SLIC Algorithms

4.4.2 Canny Edge Detection in OpenCV

Canny Edge Detection is a frequently used technique in image processing for detecting edges in images. Developed by John F. Canny in 1986, it is a multi-stage algorithm designed to effectively detect a wide range of edges in images[37]. Implementing this algorithm in OpenCV, a popular open-source computer vision library, has made it accessible for a wide range of applications in research and industry.

The key stages of the Canny Edge Detection algorithm are as follows:

1. **Noise Reduction:** The first step in the process is to reduce noise in the image, which is typically achieved through a Gaussian filter. This smoothing process helps to mitigate the impact of false edges caused by noise.

2. **Gradient Calculation:** The algorithm then calculates each pixel's gradient magnitude and direction. This is done using edge detection operators (such as the Sobel operator), which highlight regions of the image with high spatial derivatives. The gradient direction gives the direction of the edge[38].
3. **Non-maximum Suppression:** The algorithm applies non-maximum suppression to provide a thin edge. This step involves scanning the image to suppress any pixel value (gradient magnitude) that is not considered an edge. This means that only the local maxima are retained, while all other pixels are set to zero.
4. **Double Thresholding:** Canny uses two thresholds (a low and a high threshold) to determine the strong and weak edges. Strong edges are defined as those that have an intensity gradient higher than the high threshold. Weak edges are those that are above the low threshold but below the high threshold. All other edges are discarded.
5. **Edge Tracking by Hysteresis:** The final stage involves edge tracking by hysteresis. Here, weak edges are only retained if they are connected to strong edges. This step ensures that the edges are continuous and not fragmented.

4.4.3 Implementation

I implemented a comprehensive and intricate method for segmenting high-resolution satellite imagery. Our primary objective was to effectively capture both the global and local features within the images, a challenging task in the realm of remote sensing and image analysis. To achieve this, we developed a multi-faceted approach that synergizes two advanced segmentation techniques: Simple Linear Iterative Clustering (SLIC) and Canny Edge Detection. This methodology was meticulously designed to address the complexities inherent in satellite image segmentation.

Detailed Implementation Process

1. **Initial Image Division:** We divided the entire satellite image, measuring 2400x2400 pixels, into smaller, more manageable grids. Each grid was sized at 25x25 pixels, a dimension determined through extensive experimentation. We assessed various grid sizes by visualizing the segmentation results, seeking the optimal balance to yield the most accurate segmentation.
2. **SLIC Segment Generation:** Within each grid, we generated 20 distinct SLIC segments. The SLIC algorithm was configured with a compactness parameter of 0.5, a setting that we found to strike an effective balance between color homogeneity and spatial proximity in segment formation.
3. **Canny Edge Detection:** Concurrently, within the same grid, we applied the Canny Edge Detection algorithm. This method is renowned for its precision in delineating clear and concise edges, thereby identifying the boundaries of various features within the satellite imagery.
4. **Comparative Analysis of Segments:** The core of our methodology involved a detailed comparison between the segments generated by SLIC and those identified through Canny Edge Detection. We meticulously evaluated each SLIC segment to determine whether it intersected with segments from the Canny process. If no intersection was found, the Canny segments were retained in their original form.
5. **Segment Refinement and Merging:** In cases where SLIC and Canny segments intersected, we employed a nuanced approach. If the intersecting Canny segment and the neighbouring SLIC segments were dissimilar, the Canny segment was subdivided us-

ing the borders of the SLIC segment. Conversely, if neighbouring segments were similar, we merged them into a single segment. This similarity was assessed using a combination of histograms, Histogram Oriented Gradients (HOG), and Gray-Level Co-occurrence Matrix (GLCM). The threshold for determining similarity was established through a rigorous process of trial and error, aiming to achieve the most accurate segmentation possible.

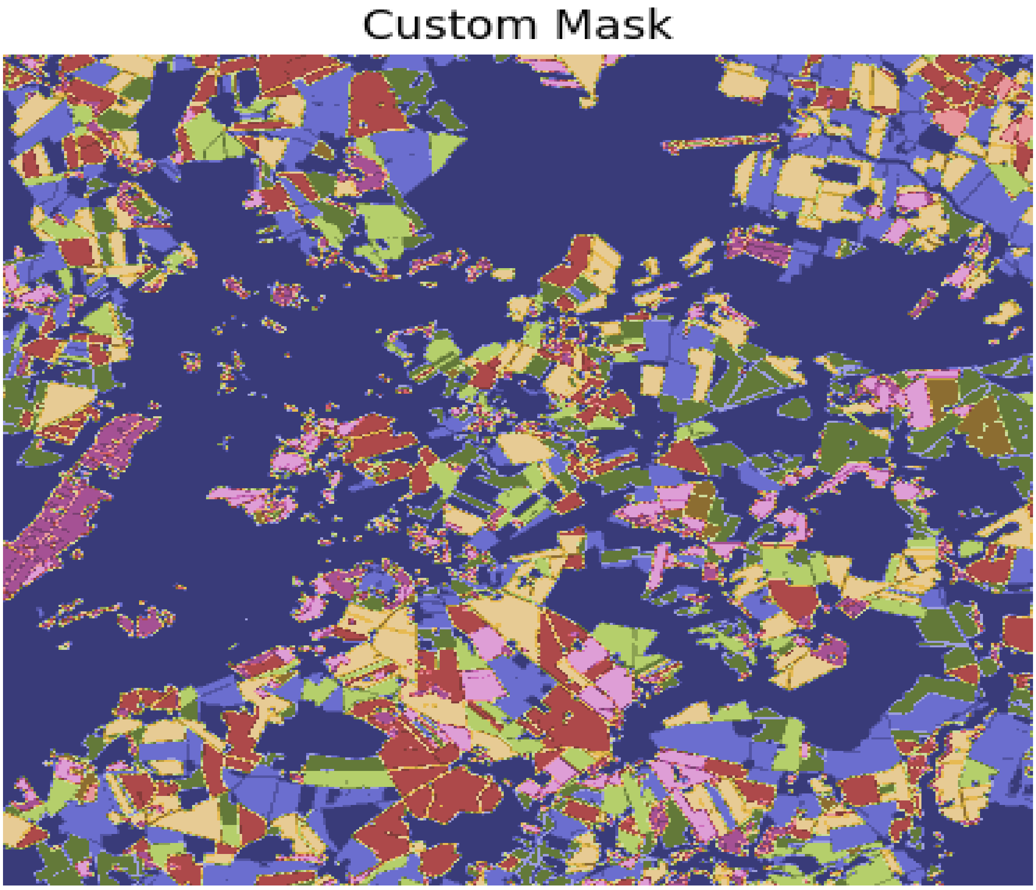
6. **Final Segmentation and Feature Extraction:** Upon completing the segmentation process for all grids, we reassembled the image, creating a cohesive segmented map. We then calculated the GLCM matrix for each segment, using the sum of the GLCM values as the feature vector. This process allowed us to capture the textural and structural nuances of each segment.
7. **Label Prediction Using K-means Algorithm:** The extracted features of each segment, alongside the grid labels, were then input into the K-means algorithm. This algorithm assigned a single label to each segment, thereby facilitating the classification of the satellite image into distinct categories.
8. **Exploratory Feature Testing:** In addition to using GLCM values as features, we experimented with another feature set: the Standard Deviation (STD) of pixel values within each segment. This was done to explore the potential of alternative feature vectors in enhancing the accuracy of the segmentation.

4.4.4 Outcomes and Reflections

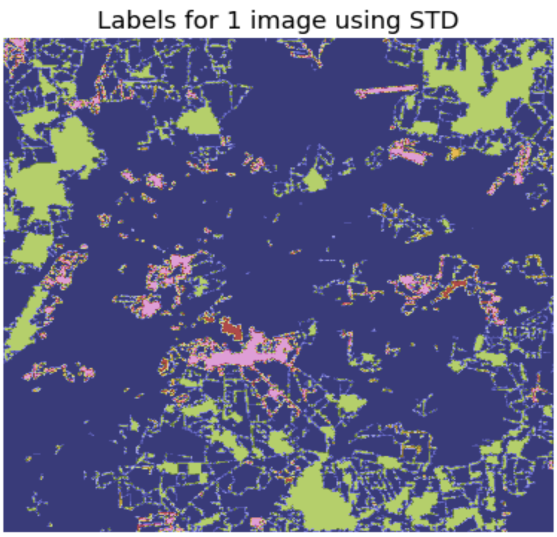
Despite the intricate design and sophisticated integration of SLIC and Canny Edge Detection algorithms, the results of this method did not align closely with our initial expectations. The visualized outcomes, when compared to the original mask image, revealed a significant divergence. This discrepancy underscores the challenges inherent in satellite image segmentation and the need for ongoing refinement of methodologies. The complex structure and the innovative combination of segmentation techniques, while theoretically sound, did not yield the anticipated level of accuracy in practical application. This outcome provides us with valuable insights and directs us towards further research and development in this field, aiming to refine our approach and achieve more accurate and reliable segmentation results in future studies.

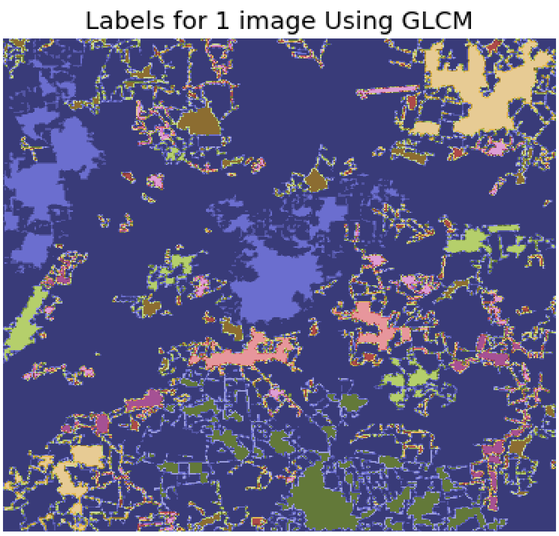
4.4.5 Method 2 Results

Below is the original mask generated by labels.geojson



k-means result using Standard Deviation **K-means result using GLCM**





Chapter -5 Discussion

Sentinel-1's Synthetic Aperture Radar (SAR) capabilities make it a suitable choice for this project. Sentinel-1's capacity to see through clouds guarantees a steady supply of excellent, all-weather data. This is especially important for areas like the tropics where cloud cover is common since it enables continuous crop type categorization and monitoring. Using both Vertical-Vertical (VV) and Vertical-Horizontal (VH) polarizations in Sentinel-1 data significantly contributes to the accuracy of crop type classification.

The preprocessing phase, involving the creation of noise-free masks and logarithmic transformations, demonstrates the necessity of addressing challenges in the original dataset. The geojson file is a valuable alternative for creating accurate masks, highlighting the importance of diverse data sources in overcoming limitations. The logarithmic transformation, designed to accentuate nuances in satellite imagery, enhances the dataset's suitability for unsupervised learning models. By combining the VV and VH spectra, the feature extraction process highlights how complimentary these datasets are to one another. The integrity of the dataset is preserved by normalizing aberrant data values and limiting abnormally high pixel values, which offers a strong basis for further investigation.

Two different approaches are used for satellite picture categorization, each utilizing the strength of k-means clustering. Method 1(K-Means) uses a mix of VV and VH masks to reach an amazing accuracy of 99.98%. Method 2 (SLIC) presents a more complex method by combining SLIC with Canny Edge Detection. Even with the advanced mix of algorithms, the visual results show a substantial divergence from the original mask picture, highlighting the difficulties in attaining correct segmentation. The results obtained from Method 2 highlight the intricacy involved in the segmentation of satellite images. The expected degree of accuracy is not reached in real-world applications, even with a careful design and integration of sophisticated algorithms. This disparity emphasizes how remote sensing and image processing techniques need to be continuously improved and explored.

The difficulties in Method 2 offer chances for more investigation and improvement. Subsequent research endeavours might investigate substitute segmentation strategies, feature extraction methodologies, or a blend of both. Furthermore, the accuracy of crop type categorization in satellite data may be improved by combining machine learning models with deep learning architectures.

Overall, The project's results add to the field of remote sensing applications and precision agriculture as it develops. Sentinel-1 data, VV and VH polarisations, and unsupervised learning methods all show potential for improving crop monitoring's precision and effectiveness. Ongoing efforts to enhance techniques will contribute to the advancement of remote sensing technology for agricultural and environmental assessments.

Chapter- 6 Conclusion

In conclusion, this research has delved into precision agriculture, leveraging the capabilities of Sentinel-1 satellite data for unsupervised spectral analysis in crop-type classification. The study highlights the value of Sentinel-1's Synthetic Aperture Radar (SAR) technology, especially its capacity to offer day-and-night, all-weather photography while getting over atmospheric impediments like cloud cover. A critical component that provided a more thorough picture of the Earth's surface and improved crop type classification accuracy was the use of both Vertical-Vertical (VV) and Vertical-Horizontal (VH) polarisations in Sentinel-1 data.

The research results demonstrate the efficacy of unsupervised spectrum analysis using techniques such as k-means clustering and Simple Linear Iterative Clustering (SLIC). The durability of this technique was highlighted by Method 1, which combined VV and VH masks with the k-means algorithm and showed an amazing accuracy of 99.98%. However, Method 2, which combined SLIC with Canny Edge Detection, offered a more complex approach. While it has difficulties and does not match the original plans, it clarifies the difficulties in satellite picture segmentation and calls for more research and development in this developing area. The limitations found in Method 2 provide opportunities for further study, encouraging studies into other feature extraction techniques and segmentation strategies to improve the precision of satellite picture segmentation.

This research offers important new information on precision agriculture and remote sensing applications. Sentinel-1 data, VV and VH polarisations, and unsupervised learning methods may all be used to improve crop monitoring's accuracy and efficiency. It also highlights the ongoing need for research and development in remote sensing and image processing. To improve crop type categorization accuracy even further, future research projects may investigate combining machine learning models with deep learning architectures as technology advances. The findings of this study, taken as a whole, advance the area of precision agriculture by opening new avenues for the use of remote sensing technologies for agricultural and environmental evaluations.

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