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Satellite Image Classification Using Unsupervised Machine Learning

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Abstract. *In recent years, humans rely heavily on space Satellites are especially for communications, military defence, intelligence, science and Trade. As a result of the development of artificial intelligence technology, especially machine learning and deep learning, Time can be saved by using satellite images, which can offer a wealth of large-scale information on the Earth's surfaces quickly. Advanced image processing techniques have been used to improve the resolution of acquired objects with the emergence of sensors that give satellite images. Research on ways to apply it in various fields has been actively conducted. This paper summarizes research activities using machine learning using a search engine to survey the number of research proposals submitted in 2013 and 2024 and the number of papers published in the past five years, although the purpose of applying machine learning as there was a relatively large number of studies involving learning Automated. There has also been increasing interest in new methods such as reinforcement learning.*

Keywords: *Unsupervised, Google Erath Engine, Machine Learning, Satellites Image, Remote Sensing*

1. INTRODUCTION

The first satellite to enter Earth's orbit was launched in 1957 and was seen by everyone on Earth. Later, satellites used for additional functions including communication, commerce, and weather forecasting were developed and successfully launched in the early 1960s[1]. Applications in geology and geography, as well as weather forecasting and worldwide environmental monitoring, have been made effective use of data from these satellites since the 1970s[2]. Satellite technology allows researchers to gather data without being hampered by local air traffic restrictions. It also allows them to compare land covers across time, which is useful for long-term study projects.Ground measuring techniques, on the other hand, are labor-intensive, costly, time-consuming, and challenging [3, 4] The cost of satellite images has steadily decreased since commercial satellites were launched, and the regions of applications increase[5] [6].

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2. BACKGROUND

The data obtained by remote sensing, which involves using technology to sense an object without physically touching it, is obtained from satellite-hosted sensors or aerial sensors installed on drones, unmanned aerial vehicles, or other lightweight aircraft. Non-satellite methods have a highly constrained coverage area and need a lot of resources. The focus of this work is on data obtained via satellites [7].

There are several domains in which information obtained from satellite-based data can be utilized, such as meteorology, geology, and agriculture[8].

Since the 1970s, satellites have been utilized for agricultural purposes. In the early days, however, data was restricted to a small number of important visible and near infrared wavelengths. These days, data from a far wider range of wavelengths—from microwave to ultraviolet—is generally accessible. Thermal and hyperspectral sensing are the main areas of study[7]. Depending on the sensors each satellite is fitted with, the information the satellites deliver might be of a variety of resolutions and types. Images with resolutions ranging from 30 cm to 5 m per pixel can be obtained from high resolution satellites. A pixel in a low quality satellite image covers more than 60 meters. Satellites in the various spectral bands provide detailed information about cultivars[9].

Plant nutrient levels and soil moisture contents are included in this data.These satellites are in the public and private domains.

The most well-known public satellites are Sentinel, MODIS, Galileo, Lansat, and MODIS. Among the private ones, Spot, ImageSat, and China Siwei are noteworthy. The European Space Agency's (ESA) High Resolution Land Cover (HRLC) project has made a significant contribution to this subject [12]. Its primary goal is to use high-resolution photos, primarily from regions like Amazonia, West Africa, and West Siberia, to accurately describe the land cover and analyze changes in it. This project has significant applications in the areas of energy and climate modelingTraining automatizzato di sistemi Deep Learning per applicazioni di Ship Detection su dati satellitari SAR[10].

2.1 REMOTE SENSING

Remote sensing gathers data about items on the surface of the earth without physically reaching them. Sensors are instruments for carrying out research. It asserted that gathering data in dangerous or remote areas is viable[11]. Its uses monitor deforested areas such as the Amazon Basin, the relevance of climate variation in glaciers, and the Arctic and Antarctic regions with their pitch-perfect coastline sounds and ocean pitches. Both spectral and geographic resolutions are present in its data: The computation of the shortest

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pointed or linear parting between two objects—which could be ascertained using a sensor—is known as spatial resolution[12].

2.2 MACHINE LEARNING METHODS FOR REMOTE SENSING

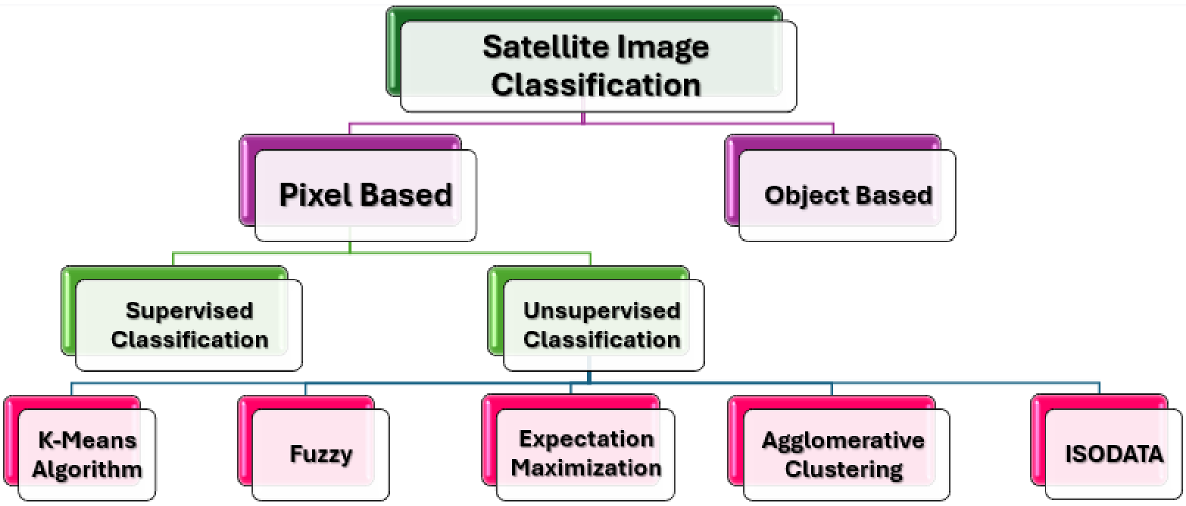
The majority of machine learning methods used in remote sensing applications are either supervised or unsupervised. Both methodologies are described in the next two subsections along with some instances of how they are applied to remote sensing[13].

2.2.1. SUPERVISED LEARNING

It works by first choosing representative pixels for each of the intended classes, after which an image's pixels are labeled with the information classes according to a single classification algorithm. The most used supervised technique in the literature is maximum likelihood classification[6]. For the pixel-based classification strategy, the most often used approaches are ISODATA and Maximum Likelihood Classification.

2.2.2 UNSUPERVISED CLASSIFICATION

Its foundation is the division of pixels into various spectral classes. The classes of interest are manually assigned labels to the spectral classes[6]. It's an unsupervised learning technique for classifying satellite images. It takes numerous parameters to regulate the number of clusters and number of iterations to be carried out, and it produces a certain number of unlabelled clusters in a picture.



Fig(1) Satellite Image Classification

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3. CHALLENGES AND LIMITATIONS

While there are many advantages to satellite imaging technology, there are also many drawbacks and restrictions.High-resolution photographs with a high degree of spatial resolution necessitate sophisticated sensors, which can be costly. For some purposes, photographs at a lower quality might not have enough detail. On the other hand, temporal resolution refers to how often a satellite may return to the same spot; this can have an impact on the capacity to track changes over time.The sensitivity of various sensors to various wavelengths varies. This may make it more difficult to collect some kinds of data, such as particular indicators of the health of the vegetation.Image quality can be impacted by a sensor's radiometric resolution, which is its capacity to differentiate between radiation intensities, especially in low light.

4. RELATED WORKS

Naji and Al-Tuwaijari proposed two approaches, k-means clustering and fuzzy c-means, to clustering Landsat-8 satellite images. The algorithms were implemented using different methods, pixel based and block based clustering. Both texture, features, such as,Gray Level,Co-occurrence ,Matrix (GLCM), and color were considered in the block based approach.). The performance of the algorithms was evaluated and compared based on their results in clustering satellite images. While the study provides valuable insights, both k-means and fuzzy c-means approaches have their inherent limitations. For example, k-means assumes clusters to be spherical and of similar size. On the other hand, fuzzy c-means may struggle with overlapping clusters due to its probabilistic cluster membership approach [3]. However, Prasad et al. provided a helpful technique for utilizing SVM to categorize multispectral satellite images in the land cover and use sectors. Pre-processing of the input image is done using the recommended classification method first. This pre-processing step involves applying RGB and Gaussian filtering to the Labcolorspace image. On the other hand, the SVM Classifier was used to classify multispectral satellite images using clustering. Multispectral satellite images were used for the experiment, and the research shows that the suggested method performs better than the conventional clustering approach [14, 15].

Although Ouchra et al. suggested comparing object-oriented classification with pixel-based classification because this kind of processing demonstrated significant promise for reasonably inexpensively monitoring wide areas. In order to compare various approaches' algorithms, techniques, image resolution, and image types, this research provided a comparison analysis. We will now exhibit and talk about the advantages and disadvantages of each approach. The OOC method is the most effective for classifying satellite images, based on earlier findings. Classification based on objects (OOC) [16]. As for Sathya and Malathi Using ANN and K-Means Backpropagation Algorithm for Classification and Segmentation in Satellite Images

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This paper describes the implementation of two algorithms, ANN and K-Means backpropagation algorithm on a large database of images. It provides a tool for segmentation and classification of remote sensing images. This classified image was given to the K-Means algorithm and the ANN back propagation algorithm to calculate the density number. The results showed high accuracy [14]. Fuzzy theory is used in FRANK Y. SHIH's novel two-pass unsupervised clustering approach to categorize each pixel in a Landsat image as a type of land cover. vector and the mean vector of each type. Experimental results show that the developed fuzzy clustering algorithm produces a more reasonable explanation of the phenomena than traditional rigid partitioning technique[17].

Soha Mohamed used Landsat-8 data to extract land cover in her study comparing methods for classifying satellite images in Alexandria, Egypt. To achieve an accurate extraction of land cover from remote sensing data, she examined, studied, and assessed the performance and efficacy of four classification algorithms: ISODATA, K-means, pixel-based, and sector-based classification techniques. The se.gment-based, K-means, ISODATA, and pixel-based classifications had overall accuracy rates of 81.82%, 77.27%, 92.42%, and 87.88%, respectively. Remaining a significant problem is accurately extracting different land cover types from themed maps utilizing satellite imagery [4] .

Chaitanya Malladi suggested in his study to use supervised and unsupervised learning methods to detect objects in satellite images. Where support vector machines and k-means are also observed, the resolution and silhouette have a low spread based on the standard deviation values. Also, object detection is confirmed by accuracy and silhouette scores along with normality values which show that SVM classifier has higher value compared to k-means clustering[18] .

Researchers Yang et al. proposed a method for effective detection of satellite images via K-MEANS clusters on the HADOOP system. A clear acceleration rate may be obtained in images of different sizes, and a speedup rate of up to 56.96 times is displayed maximum for large-sized images. Also, our method is about 1.79-1.87 times faster than CMeans on Hadoop[19] .

Khatidio and associates put forth a scheme for gathering land cover data and categorizing satellite images. Classification is the process of categorizing various land cover categories, such as plant, water bodies, and soil, using data from remote sensing. Every group symbolizes a distinct group of land cover, and the algorithm arranges the image's pixels according to how similar they are.The optimal number of clusters is ascertained using the algorithm. K-means clustering can be a quick and efficient method for classifying land cover when examining huge data sets. Land cover classification of satellite images is a supervised

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classification technique that maps the distribution of land cover classes over vast areas using segmentation and random forests. The benefits of hashing and random forest are combined in this technique[20] .

In order to minimize human labor and errors in the shortest amount of time, Goswami et al. suggested a nearby clustering technique for satellite images. However, the nearest clustering algorithm was evaluated and put into practice using a dataset provided by a domain expert. It was determined that this algorithm yields good outcomes. the nearest cluster image classification technique works well. Classification of satellite images Classification of satellite images[12] .

While object-based techniques and 3D convolutional autoencoders are employed to reassemble the obtained segments in Kalinicheva et al.'s method for clustering time series of unsupervised satellite images, a hierarchical clustering algorithm (HCA) applied to segment descriptors was utilized to assess the suggested clustering framework. They are contrasted with several time series clustering techniques, including our pipeline diversity without segmentation correction, object-based DTW, graph-based DTW, and 3D convolutional AE without NDVI branch. The enhancement of conventional segmentation techniques that were not initially adjusted to SITS, which results in a higher degree of NMI, is one of the suggested algorithm's primary benefits. Furthermore, we demonstrated that the clustering results can be enhanced by merely adding a transient NDVI branch to the AE model[12] .

Dhingra, Kumar suggested conducting a study on improving the Alwar region of India's classification accuracy by utilizing the right classifiers in conjunction with novel feature extraction methods and pre-processing procedures. It includes appropriate land cover characteristics including urban regions, water areas, vegetated areas, and rocky and desert areas. Additionally, a comparison between the original and categorized satellite image of the Alwar region is displayed, illustrating the categorization process. The best methods for increasing accuracy were SVM, K-nearest neighbor, and ANN (Artificial Neural Network)[21].

Hu et al. They proposed supervised classification methods based on partial transfer learning for unsupervised satellite images. A major problem for unsupervised satellite image classification is how to achieve high accuracy. They demonstrate a new end-to-end,unsupervised classification, method called Competitive Partial Domain,Adaptation (CPADA) for satellite,image classification[22] .

Kaur et al. proposed and automated the satellite image with different classification methods such as parallel classifiers and least distance classifiers[54]. They applied the hybrid and median clustering algorithm and the FFNN classifier to plan land rock cover, shade, and construction. The image processing is optimized using Artificial Crossed Bee Colony (ABC) algorithm which is implemented by intersecting ABC and Fuzzy cmes to find effective segmentation in satellite image and classify it using NN. The MATLAB 2013a simulation tool was used and its performance was evaluated in Xdb-Index and DB-Index. To design the framework in satellite images and classify its uses[23] .

Rivera and associates. In order to map crop species using satellite imagery, they suggested cluster analysis methods. These methods aid in accurate cultivar classification and monitoring[60]. Time series is typically employed as a pre-processing method and integrated with supervised learning approaches to construct models for identifying crop types in distant images[58]. Examine and evaluate the effectiveness of several unsupervised clustering techniques for identifying crop types on distant images[24] .

While Ouchra et al. compares the classification of satellite pictures using pixel-based and object-oriented methods,This kind of processing has demonstrated a lot of promise for reasonably priced, wide-area monitoring. For both military and civilian applications, the gathered ground data is tracked, examined, and processed. Although there are numerous options for mapping urban and other locations, the focus is on classifying satellite images, which uses various algorithms and yields results that are more accurate and high-quality. The weighted scoring model, or WSM, approach was used. It enables us to determine the final outcome for each comparison method by giving each criterion a weight.[10]

Li and others proposed a simple method for automatic multi-layer image feature recognition for satellite image scene classification, for unsupervised multi-layer feature learning for satellite image scene classification, and the data-dependent feature extraction is done independently. The performance of scene classification was evaluated on a data set. UCM-21 General. The results showed that the proposed approach can outperform many modern methods[24].

Lava flow mapping was discussed by Al Shehri and others. Thus, employing remote sensing and geographic information systems, together with self-organizing iterative data analysis technology (ISODATA) algorithms for high accuracy, they suggested an unsupervised categorization system in Harrat Lunar, Saudi Arabia. Finding the peak's spectral reflectance values is the aim. Using the atmosphere (TOA) to differentiate between layers of recent and old lava flows based on variation [25].

Ahmed They proposed a system that predicts river sediment deposition from satellite images that relies on unsupervised machine learning techniques. Because of the hydrological and riverine systems of the Earth's surface, the study,aims to prove that,unsupervised remote sensing,and machine learning,techniques combined with,an appropriate verification measure can,be used. To quickly predict areas subject to future river sediment deposition. The algorithmic approach is successful and necessary[26] .

In order to address the aforementioned issues with RGB images obtained from remote sensing, they suggested an unsupervised method of learning the classification of water bodies from images using convolutional neural networks (CNNs). To assess the strategy and demonstrate its varying degrees of

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efficacy, three datasets were used: (1) The SAT-6 dataset, which consists of high-resolution airplane images; (2) Sentinel-2, a low-resolution remote sensing image from EuroSAT; and (iii) PakSAT, a newly constructed dataset for this study. The initial dataset created by Sentinel-2 for the purpose of categorizing water bodies in Pakistan is called PakSAT. Results demonstrated the suggested algorithm's efficacy.[27]

An overview of the use of remote sensing in retrieving and efficiently monitoring water quality parameters (WQPs) like chlorophyll-a concentration, turbidity, and total substances was provided by Adjovu et al. They also discussed the drawbacks and advantages of using this technique. dissolving color and suspended solid. Total dissolved solids, organic matter, etc. Decision makers may now efficiently identify and track WQPs on a temporal and spatial scale thanks to RS applications. Two classes of RS, namely micro and optical sensors, have been used to estimate WQPs using RS spectral fingerprints. Based on the onboard platform, optical RS, which has been extensively used in WQP estimation, are constructed as airborne and spaceborne sensors [28, 29] .

Edun described how to separate solar panels into images using a convolutional neural network (CNN). a low-resolution satellite using the Hough transform and semantic segmentation. A novel unsupervised method for estimating the azimuth of a single solar panel from a convolutional neural network's anticipated mask is provided. The purpose of this pipeline was to extract metadata from a collection of latitude and longitude coordinates, all that is required for a solar installation. Results of azimuth forecasts are given for 669 distinct solar plants connected to 387 sites around the US. R-squared values of 90.9 and 90.6 are displayed in the results. The power conversion of the solar arrays was estimated using the predicted azimuth, and the AC and DC power were estimated using a completely automated algorithm with a mean absolute percentage error (MAPE) of 1.70% for the former and the power conversion for the latter [30].

Northwestern Polytechnic University (NWPU) developed the publicly available standard for Remote Sensing Imagery Scene Classification (RESISC), ChenG et al. offered a large-scale dataset known as ¥NWPU-RESISC45. Applications for remote sensing picture scene classification are numerous and varied. 31,500 images total from 45 scene categories (each with 700 images) are included in this dataset. NWPU-RESISC45 1) The scope of the concept is wide in terms of the total number of images and scene categories; 2) There are notable variations in terms of translation, spatial resolution, point of view, object posture, lighting, backdrop, and occlusion. and 3) Its interclass similarity and intraclass diversity are both strong. The community will be able to create and assess various data-driven algorithms thanks to the creation of this dataset [23] .

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AKGÜNa and colleagues conducted a study that compared several techniques for classifying satellite images: Utilization in the western Turkish area of Ayvalik. About 560 square kilometers make up its area. In order to achieve this, various supervised image classification techniques were used to classify the land uses in the research region, and the outcomes were compared. In this investigation, the IDRISI Klimanjaro image processing, the GIS package, and a Landsat 7 ETM+ satellite picture were employed. It was demonstrated that the maximum likelihood approach is the most practical and trustworthy for classifying satellite images. The parallel approach was found to produce less trustworthy findings when compared to other methods, however the minimal distance method produced more reliable results than linear discrimination procedures[31] .

In order to get a comprehensive representation of scene information, Zhao et al. suggested an importance-based multibagof-visual-word model for remote sensing picture scene categorization.One of the most widely used approaches is the multi-BOVW method based on two-stage classification; nevertheless, the effectiveness of multiBOVW methods in classification is impacted since this method ignores the feature importance information between different feature types in the fusion stage at the score level. According to experimental results, the suggested approach efficiently investigates feature importance information in multi-class remote sensing picture scene classification and outperforms conventional score-level fusion-based BOVW approaches [32] .

Using their parallel k-means image clustering approach, Han and Lee were able to quickly study land cover distributions without any prior knowledge. This method also produces training data for supervised (or deep learning-based) classification. In order to get a single set of class signatures and ensure consistency in the classification results across numerous images, the original k-means clustering (kMC) technique is improved with the introduction of the inter-image k-means clustering (IIkMC) algorithm. Due to the computationally demanding nature of IIkMC, parallel techniques utilizing numerous CPU and GPU cores were implemented to expedite the procedure. IIkMC has the ability to cancel the class identified in kMC and resolve the issue of incomplete hashing.Better than sequential processing by up to 12.83 times. With the GPU, the speed increased by up to 25.53 times, and with parallel downscaling, it increased by up to 39.00 times.[33]

Regmi showed how to use deep learning to segment unsupervised images. When using the FreeSOLO unsupervised instance segmentation method on satellite images. The technique evaluates itself using the PASTIS, CrowdAI, and iSAID datasets. On the iSAID dataset, 3.1% AP50 on the CrowdAI dataset, and 1.1% AP50 on the PASTIS dataset, the technique obtained the desired results. It obtained 1.2% AP50 in the iSAID dataset and 3.5% AP50 in the CrowdAI dataset for large objects [34].

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In order to test the methodology, the Mohammed bin Rashid Space Center dataset in Dubai and the UAH setting were used. Here, the model demonstrated its ability to separate trees, buildings, water features, roadways, and apartments. In a semantic segmentation challenge, this study also shows how well FreeSOLO-based weights perform in comparison to other well-known encoder weights based on supervised learning[1] .

Deep learning was suggested by Shafaey and others for the classification of satellite images. The evaluation of widely used methods for classifying satellite images and publicly available remote sensing datasets led to the classification of existing remote sensing classification techniques into four main categories based on the features used: manual feature-based methods, unsupervised feature learning methods, and learn supervised feature, object-based methods. Convolutional neural networks (CNNs), more precisely an AlexNet architecture, were constructed using the UC-Merceed Land Use standard audio dataset. Lastly, a comparison with alternative methods is provided [35] .

An image production and masking framework (Auto-CM) was proposed by Xie et al. An issue with Earth observation that affects several societal sectors, such as water, energy, and agriculture, is cloud masking. It is hard to accomplish this by hand. Because of the frequent distribution shifts in sensor-collected satellite images that depend on unique spectral signatures from multi- or hyperspectral bands, as well as the utilization of the dynamics of various events in both geographic domains and time series, producing trustworthy cloud masks and image composites is a significant challenge [36] .

Babbar and Rathee conducted a study on satellite image processing, as satellite image processing is considered one of the most important journals at the present time. The interest is in order to capture information from them. Satellite image analysis poses a great challenge for researchers due to high contrast, low accuracy, and large data. But a systematic review that would lead researchers to identify the problem and contribute to this field is missing[37] .

Throughout the optimization process, Pal et al. suggested a novel way to update the solutions by maintaining the variable length attribute. Multi-objective variable-length genetic clusters for high-resolution satellite image segmentation with the goal of multi-class change detection, where (MS) is a genetic cluster-based high-resolution image segmentation (VHR) technique. a number of variable-length targets Sensitivity to initialization, local optimal solutions, a fixed number of output sets, single-objective optimization, and other issues plague basic methods to the segmentation problem. This work suggests a novel pixel-level multispectral system to address these issues. It is difficult to detect changes in land use and land cover (LULC) in a congested area [38].

In order to create the proposed IT2SPFCM-PSO, Mai et al. proposed a hybrid method that combines Type II semi-supervised fuzzy potential clustering (IT2SPFCM) with particle swarm optimization (PSO). The proposed IT2SPFCM-PSO is intended for satellite image analysis. Industrial and is independent of the resolution of the picture acquisition apparatus and viewing conditions, offering a wealth of information about the Earth's surface. Frequently, the objects in the pictures are hazy. By using membership function (MF) values, the fuzzy clustering technique based on type 1 fuzzy set permits each data pattern to belong to numerous groups. It is particularly adept at handling data patterns with hazy and unclear borders.

This method's sensitivity to noise, outliers, and constraints for handling uncertainty is high. The outcomes demonstrated that the IT2SPFCM-PSO algorithm provides an accuracy of 98.8% to 99.39% in order to overcome these flaws. The findings of the analysis based on the indicators PC-I, CEI, DI-I, XB-I, t-I, and MSE also demonstrated that the suggested approach produces outcomes. Better in the majority of instances [39] .

Classification of Mantilla Satellite Images Using Rp Fuzzy C Method Unsupervised Categorization System In applications that use satellite imagery, segmentation is a crucial step. However, "The data in a multispectral image shows low statistical separation and a long amount of data" is the primary issue. Since remote sensing yields valuable information on the Earth's surface, it becomes imperative to study related techniques. In this paper, we suggest enhancing the elemental balance for groups. To evaluate the expected influence of each item in each group, we introduce a new word. This new word tries to increase differences between groups and can be interpreted as a dissonance factor [40].

The inspiration for this change came from a recently added word called New Fuzzy Centroid Cluster (NFCC). We employ cluster internal validity for tests. in order to contrast algorithms. As a result, we deduce that the additional term better arranges the elements since it prevents the algorithm's quick convergence. The findings demonstrate that the addition of this new factor leads in groups that have more elemental similarity and lower entropy. Mantilla [[37, 41]

Lafabregue et al. demonstrated distance-based grouping of satellite image time series and proposed the usage of dynamic temporal covariance scaling (DTW), which is occasionally employed for time series analysis. As a result, there is complication associated with the introduction of high-resolution techniques for time series sampling. Unsupervised approaches, however, disregard intuition and expert knowledge. In data mining, constrained clustering is becoming a more and more common technique.

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Two applications were used to arrive at these conclusions: crop clustering utilizing eleven multispectral Landsat images that were irregularly captured across the course of eight months in 2007. Using ten NDVI Sentinel-2 images that were sporadically taken between 2016 and 2017, recording detection [42] .

cpresented an ideal artificial neural network that uses kernel-based classification for satellite images (KFCMÍOANN). Thus, among the primary issues with satellite images are image segmentation and categorization.The KFCM algorithm is used to segment images using the collection of fuzzy kernel-based techniques for satellite image classification. After that, features from the segmented regions will be recovered, including color features and gray level co-occurrence matrix (GLCM) features. The OANN classifier is then provided with these extracted features. The zones are divided into building, road, shade, and tree categories based on these characteristics. The FRUIT algorithm is used to optimally select the weight values in order to improve the classifier's performance. According on the findings of the simulation, the suggested classifier operates more accurately than the current filters[43] .

An object-oriented framework was presented by Khiali et al. to address multi-year satellite image time series (SITS). The objective of this approach is to automatically analyze SITS in order to represent and describe the dynamics of regions, or how a region's land cover changes over time. While the analysis was conducted on three study areas to highlight the internal similarity (between study areas) and internal similarity (within the study area) of While following the development of basic phenomena, it is still difficult and time-consuming to detect spatial and temporal developments in time series of satellite images [37] .

To do this, Kavitha and Araswathi presented a multi-feature fuzzy clustering method based on fuzzy logic and clustering. Fuzzy sets quantify the image's content and resemblance while representing ambiguity in the user's query. According to preliminary data, the suggested strategy can improve computing efficiency while achieving notable accuracy and recall rates. Information needed for urban planning, meteorology, damage assessment, change detection, natural disaster management, and military target detection may be difficult to retrieve from satellite images. High retrieval accuracy and low processing complexity are still unattainable goals for the majority of the image retrieval techniques now in use.[38] Hamada et al proposed implementing pixel-based clustering for 12 channels using satellite image from the Sentinel 2 remote sensing satellite via k-means clustering. Remote sensing has played an important role in crop classification, crop health and yield assessment This is why K-means,clustering algorithm is a,better way to classify high-resolution, satellite images[44] .

A novel change detection method based on unsupervised manifold learning is put forth by Gupta et al. It finds the nonlinear structure of data that is concealed in the original space. There are two processing phases in the suggested structure. First, a novel method for feature extraction is put forth, which is based on unsupervised orthogonal discriminant projection (OUDP). Discriminative features can be obtained from the orthogonal basis vectors that were acquired by OUDP. Furthermore, a new radial-based clustering technique is introduced in the second stage, yielding superior clustering than the single clustering method. Additionally, the performance of OUDP technology is enhanced with the introduction of extended-core OUDP technology. [45]

The three points below describe what makes the suggested framework unique. Using non-overlapping chunks from the image, an eigenvector space is first created. The second method creates clean or transparent change maps by extracting characteristics by utilizing the local neighborhood data surrounding each pixel. The classification of variable and non-variable pixels is greatly improved by the pooling technique's last stage, the RBF stage. The efficacy of the suggested approach is validated by experimental findings on multispectral images from various sensors [40] .

Sridhar, et al. This study presents a new method for statistical discrimination to enhance contrast images. Satellite imagery using statistical methods is superior to similar methods and can be applied to pre-processed satellite images. Identifying objects in a satellite image is a pivotal task. Machine learning methods can be used for this purpose as there has been a significant amount of research in the field of image processing through machine learning[46] .

To handle SITS data, Guo et al. introduced deep iterative clustering (DTIC), a novel unsupervised learning technique. The suggested approach uses the standard clustering algorithm, K-means, to iteratively cluster the features produced by the feature extraction network and then uses the subsequent assignments as supervision to update the network weights[61]. This process simultaneously learns the parameters of the neural network and the cluster assignments of the resulting features. We use DTIC for neural network unsupervised training. The experimental results demonstrate that DTIC beats the state-of-the-art K-means clustering algorithm on two SITS datasets, demonstrating that the suggested approach successfully offers a novel concept for unsupervised training of SITS data. SITS has made extensive use of supervised machine learning techniques, however getting SITS samples The title takes time and effort[45] .

Manibhushan along with others. Fuzzy logic is used to classify satellite image of the Ranchi district according to the various land uses and land covers. IRS-LISS III For linear imaging, a self-scanning sensor was employed as an image. Fuzzy logic was used to classify the image according to various land uses and land covers, improving classification accuracy. When identifying remotely sensed images for various land uses and land cover categories, fuzzy logic is frequently employed.

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Using conventional maximum likelihood (ML) approaches, the image of the Ranchi region were categorized. Using ERDAS IMAGINE 9.1, fuzzy employs a supervised classification technique. After classifying the images, the confusion/error matrix was used to calculate the product accuracy, user accuracy, overall accuracy, and kappa coefficient values. The findings indicated that, in the preceding category, agricultural areas and natural plants shown the lowest accuracy, while stagnant water bodies displayed the highest accuracy (100%). Because the pixels in still water are crisper, it displays the maximum resolution [43] .

Yang et al. described a comprehensive review of the topic of Google Earth Engine and Artificial Intelligence (AI) where remote sensing (RS) plays an important role in data collection in many critical areas (e.g. global climate change, risk assessment and vulnerability reduction to natural hazards,Ecosystem resilience and urban planning). GEE also provides access to the vast majority of freely available, public, multi-temporal RS data and provides free cloud-based computational power for geospatial data analysis. This is why GEE's AI methods represent a promising path towards automated RS monitoring software[47].

A bibliometric analysis of the GEE platform was proposed by Montoya et al. in order to examine its scientific output. Because it makes geographical processing easier, this tool is extremely valuable to the academic and research community. The amount of geographic data is always growing, which has resulted in the development of tools, storage spaces, and cloud computing to handle the data. GEE has shown to be a developing web platform that can handle massive amounts of satellite data with ease. Furthermore, GEE is an interdisciplinary instrument with a wide range of uses in several academic domains[57].

Table for comparisons between previous studies

Authors	***Methods/ Technique***	***Advantage & disadvantage***	***Result***
[2] S.V.S Prasad et.al (2013)	SVM/CNN	Adv: When the suggested method is used instead of the conventional clustering approach, performance is increased. Dis: The subject is challenging due to the intricacy of landscapes and the resolution of both space and spectrum.	The accuracy value has fallen when neural networks are used in place of support vector machines (SVMs). In the case of land use classification, this has led to a decrease in peak accuracy values from 66% to 14%. These findings unequivocally show that using SVM raises the accuracy level.
[24] Zhao et al (2016)	(multi-BOVW)	Adv: Among the most often used methods. Dis: at the score-level fusion stage, ignores the information about feature relevance among various feature types.	In multiclass remote sensing image scene classification, the classic score-level fusion-based multi-BOVW approaches and efficiently examines the feature importance information.

[16] Li et al(2016)	unsupervised multilayer feature learning	Adv: automatically learn a multilayer image feature for satellite image scene classification Dis : lack high generalization ability	feature extraction approach can achieve better classification performance
[6] Chaitanya Malladi(2017)	SVM / K-mean	Adv : object recognition algorithms on satellite images. Dis : Generate data sets corresponding to the objects.	SVM =99.3%. k-means clustering generated a silhouette score of 0.3237.
[7] Yang et al(2017)	K-Means	Adv: effective detection of satellite images Dis : It requires high execution time	Detection speed and good scaleup while keeping accuracy
[22] Cheng et al(2017)	K -Means	Adv: a sizable data set known as "NWPU-RESISC45,"º a benchmark for remote sensing image scene classification (RESISC) that is accessible to the public, Dis: the tiny scene class and image number scales	learn more powerful (or multiview) feature representations.
[1] Naji and Al-Tuwaijari *(2018)*	k-means / fuzzy c-means	-Adv: Easy and simplified to classify the data -Dis : Fuzzy C-Means Clustering producing partitions in partition each pattern that returns to only one cluster	- k-means : gave better results with (74.2615 and 83.5906), fuzzy c-means gave results with (71.06933 and 81.7031)
[11] Dhingra& Kumar(2018)	ISODATA/ K-mean / SVM	Adv: The image created after classification makes it easy to perceive each feature, which is represented by a different color. Dis: If the proper feature extraction and classification techniques are not applied, the accuracy could decline.	SVM, K-nearest neighbor and ANN (Artificial neural network) are defined that are considered as best for enhancing the accuracy.
[3] P. Sathya and L. Malathi (2018)	ANN / K-Means	Adv : An exceptionally good-quality image Dis: Relying on appropriate ground truth data for every image of the examined place that is accessible is not feasible.	improved accuracy (K-mean), however it works with a single database at a time. However, once trained, a neural network can be applied to multiple databases. Additionally, neural networks offer high accuracy.
[13] Kanungo et al(2018)	K-mean	Adv: simple and efficient implementation Dis : many were incorrectly predicted	the algorithm runs faster as the separation between clusters increas

[27] Shafaey et al(2019)	CNN	Adv: required for numerous uses, including contemporary urban planning, farming, and environmental observation Dis: composed of multiple processing layers which is more applicable for large scale and remote-sensing image scene classification.	The accuracy that GoogleNet (*97%) achieved outperformed that of CaffeNet (*94%).
[18] Ahmed et al (2019)	K-mean	Adv: A validation metric can be used to rapidly predict areas that will be covered by river sediment deposition in the future. Dis: require ground truth data	Using the Silhouette Width validation index, the algorithm that yields the most interpretable result is consistently selected.
[34] Lampert et al (2019)	SITS	Adv: Compared to unconstrained clustering, the clustering issue becomes more accurate when constraints are added. Dis: is gaining popularity as a data mining method since it provides an answer to these issues.	highest accuracy
[12] Hu et al (2019)	CPADA	The suggested method, in contrast to earlier unsupervised satellite image classification techniques, introduces a partial transfer learning method into this field. Additionally, by down-weighting outlier satellite image classes and promoting weights of shared satellite image classes, the novel coordinate loss can eliminate negative transfer.	CPADA :89.96
[36] Khiali et al(2019)	Object-oriented image analysis	Adv: SITS to illustrate and describe the areas' dynamics Dis: This type of data analysis is still difficult and time-consuming.	distinguish spatiotemporal phenomena more effectively than when relying just on spectral bands.
[17] Al Shehri and Gudmundsson (2019)	ISODATA	Adv: Determine the differences in spectral top-of-atmosphere (TOA) reflectance values between old and recent lava flow layers. Dis: accurate geochronological timeline	three distinct basaltic units were identified to have the following ages: 15.1 ± 6.1 ka (4%), 15.0 ± 8.4 ka (6%), and 14.6 ± 23.1 ka (10%).
[39] Hamada et al (2019)	K-means	Adv: significant role in crop classification, crop health and yield assessment Dis: clearly defined the heterogeneity of the contours of the field	an improved system for categorizing high-resolution satellite images.

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[38] Kavitha et al(2020)	Fuzzy logic	Adv: enormous problem in generating data for urban planning, meteorology, natural catastrophe management, harm assessment, and change detection Dis: Retrieval outcome with higher retrieval accuracy but less processing complexity is still unsatisfactory.	approach can improve computational efficiency while achieving notable precision and recall rates.
[35] Kumar et al (2020)	Fussy c-mean	Adv: color features and gray level co-occurrence matrix (GLCM) Dis: segmented regions are classi¯ed as building, road, shadow, and tree	the performance of proposed classi¯er outperforms that of the existing ¯lters in terms of accuracy.
[23] AKGÜNa et al(2020)	K-mean	Adv: all visible and infared bands were corrected atmospherically and geometrically. Dis : , the urban sites on the map could not be identified, bare lands and olive trees could not be distinguished from each other.	the minimum distance method has given more reliable results than the linear discriminant procedures
[40] Gupta et al (2021)	K-mean	Adv: It entails analyzing multitemporal remote sensing pictures from one or more sensors. Dis: added as a result of outside interferences, which may cause the intra-class variability in multitemporal images to rise.	The efficiency of the suggested strategy is confirmed by multispectral images from several sensors.
[5] Soha A. Mohamed(2021)	k-mean / ISODATA	Adv: improving classification accuracy. Dis: 1. The misclassification of some land cover categories as a result of mixed pixels and class overlap. 2. The misclassification of naturally occurring, sparsely vegetated areas with bare soil areas because of their comparable reflectivity. 3. Because the spectral signatures of urban and bare soil locations were similar, it was challenging to distinguish between them.	The accuracy : ISODATA=81.82% K-means =77.27 % pixel = 92.42% segment-based classiications = 87.88%
[19] Abid et al(2021)	CNN	Adv : The described algorithm is unsupervised, hence it does not require labeled training data. Dis: challenges for remote sensing based RGB imagery	UCL and presented encouraging water classification results across the three datasets.

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[31] Mukhopadhyay (2022)	(LULC)	Adv :large-scale change detection method using the suggested picture segmentation algorithm as an application. Dis: Detecting changes in a crowded place is a difficult undertaking.	quantitative and qualitative analysis is performed to validate the superior performance of the proposed method with different state-of-the-art techniques.
[15] Ouchra et al(2022)	CNN	Adv: reasonably priced, wide-area monitoring Dis: When it comes to classifying satellite images with a high spatial resolution, the PBC approach is not the most effective.	the OOC approach is the most efficient for satellite image classification
[32] Mai(2022)	fuzzy c-Means	Adv: By using membership function (MF) values, each data pattern can be a part of numerous distinct clusters. Dis: little ability to handle uncertainties and very susceptible to noise and outliers	98.8% -to- 99.39%
[33] Mantilla(2022)	NFCC	Adv: A multispectral image's data exhibits both a large amount of data and a poor statistical separation. Dis:determine that the new term better arranges the items by preventing the algorithm from rapidly convergent.	Clusters with reduced entropy and higher elemental similarity are produced by the new component.
[41] Tang et al(2022)	K-mean	Adv: Deep Temporal Iterative Clustering (DTIC) to deal with SITS data.	DTIC significantly beats the most advanced K-means clustering technique, demonstrating that the suggested method successfully offers a fresh concept for unsupervised training of SITS data.
[9] Goswami et al(2023)	Nearst Cluster	Adv It's a nice algorithm because it's not parametric. Dis : Training datasets must be robust and consistent to give better accuracy	Accuracy more than 90%
[10] Kalinicheva et al(2023)	HCA	Adv: The growing image resolution Dis Since some items might change significantly from image to image and appear and disappear, segmenting a full time series can be challenging.	When compared to conventional machine learning techniques, DTW-based methods as deep learning techniques are able to extract more robust and complicated features.
[20] Adjovu et al (2023)	ANN, SVM	Adv: effectively retrieved by RS	Decision-makers can effectively measure and track WQPs on a spatiotemporal scale with the help of RS apps.

		Dis : Image acquisition errors may occur	
[26] Regmi (2023)	HCA	Adv: use in satellite images of the cutting-edge unsupervised instance segmentation technique FreeSOLO, which is benchmarked using datasets from iSAID, CrowdAI, and PASTIS. Dis: costly and time-consuming to acquire	FreeSOLO-based weights' performance in comparison to other widely used
[25] S. Han and J. Lee, (2023)	K-mean	Adv: utilized to swiftly investigate land cover distributions Dis: The issue of partial segmentation and class canceling that was identified in kMC could be resolved by IkMC.	Compared to kMC, IIkMC produced more trustworthy results, and its parallelism might make it easier to examine several images at once.
[29] Xie et al(2023)	(Auto-CM)	Adv: processed has fast-climbed to a scale Dis : problematic because of the ongoing changes in the imagery's distribution	Using many satellite platforms and a large range of data, Auto-CM beats current approaches.
[28] Kim et al (2023)	Convective clouds	Adv: Understanding the growth of tropical convective clouds (TCCs) Dis : Cloud optical thicknesses are distributed over a wide range, but thinning requires a particle radius larger than 20 mm.	the precipitation probability (PP)= 70% are consistent across regions and periods
[42] Manibhushan(2023)	Fuzzy Logic	Adv: Because standing water has more clear pixels, it displays the maximum precision.a	standing water body exhibits highest accuracy (100%).
[8] Kharat et al(2023)	K-mean	Adv : obtaining important knowledge for both the Earth's surface and upcoming interactions between environmental factors and human activity. Dis : many were incorrectly predicted	Accuracy =0.88091 Recall =0.88095 F1 score = 0.87974

4. CONCLUSIONS

In short, the use of satellite images to monitor changes occurring on the Earth's surface is extremely important in obtaining information. Satellite image data provide great advantages in studying the Earth's surface and are useful for monitoring changes. Optical or radar satellite image options are determined by

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the requirements of the research. Given the current state of technology, the outcomes of satellite image analysis can offer precise information to support conservation planning and policy making. Combining radar and optical data will enable image processing in the future to be much better. Since radar data complements optical data, it can be utilized to explore underground mining deposits more effectively.

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