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Detection of Land-Use Land-Cover Changes Using Machine Learning Systems

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ABSTRACT

A deeper comprehension of land-use and land-cover change (LULCC) is beneficial for environmental modeling and assessment, natural resource management, and agricultural output management. However, because of the processing of massive amounts of historical and current data, real-time interaction of scenario data, and geographical environmental data, LULCC detection and modeling is a challenging, data-driven process in the realm of remote sensing. This study provides an overview of the topic and highlights its significance with respect to global land transitions. It examines both historical and contemporary techniques for precisely identifying LULC change. The need for more accurate and automated solutions grows as artificial intelligence (AI) becomes more prevalent. In order to identify LULCC, this article suggests a number of machine learning techniques. Machine learning models trained to leverage spectral resolution, digital change-based detection, and picture regression to identify and classify LULC changes across time. By enabling the extraction of useful information from sizable and intricate datasets, these models enhance the accuracy and speed of change detection. The study's conclusions indicate that the application of machine learning methods for LULC change detection is a major development in the precise and effective monitoring of land changes. By assessing existing methods, this study contributes to the greater goal of environmentally responsible land management. More studies and real-world applications in environmental science, urban and regional planning, natural resource management, etc. can use the same analytical approach.

Keywords: LULCC, natural resource management, scenario data, artificial intelligence (AI) .

1. INTRODUCTION

In order to produce food through farming practices, humans have altered the earth's surface significantly over time. More than one-third of the planet's surface is thought to be agricultural, and more than half of it has changed in recent years [1]. The conversion of naturally occurring farming land into agricultural land is still in progress [2]. Because of these significant changes, researchers and land use administrators have been examining how land use changes affect hydrological processes [3]. Land use managers and decision makers may learn more about the connections between natural and human processes by examining trends in change detection. To understand ecological and sociological change, one must examine changes that take place on Earth's surface. The use of remote sensing photography to detect changes in vegetation, land cover, and land use has grown in popularity during the past few decades. The abundance of historical data and RS imagery makes it easy to examine how human activity has changed land-use-land-cover (LULC). Numerous aspects, such as the selection of preparatory tests, the variability of the research region, the sensors used, and the number of classes that must be determined, might influence the accuracy of classification systems. Depending on the methodology and technology employed, classifiers can be categorized into several different groups. Supervised and unsupervised classification, border and non-border classification, hard and soft (ambiguous) classification, and classifications based on pixel and sub are a few of these categories. The more conventional techniques of statistical statistics and visual interpretation are no longer able to appropriately classify (LULC).

Numerous environmental features, including vegetation cover, urban sprawls, forest changes, and, in particular, variations in LULC changes over time, have been successfully identified through the use of remote sensing technologies in conjunction with a geographic information system (GIS) [4]. Conventional methods for evaluating the spatiotemporal scope of LULC changes are used to expose the transitions and change detection techniques.

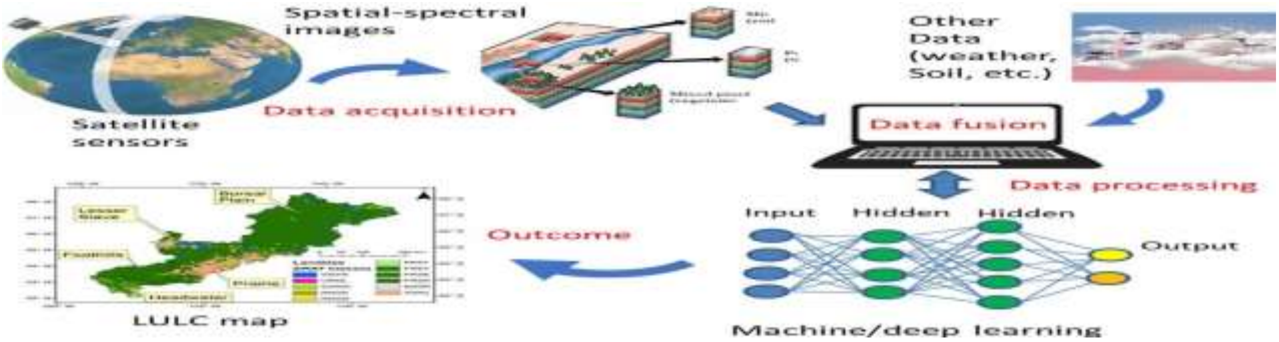
The two categories of classification methods are parametric and non-parametric classifiers. The data for each class is assumed to be regularly distributed by parametric classifiers. The most popular parametric classifier is maximum likelihood classification (MLC), which creates decision surfaces using the mean and covariance of each class [5]. Artificial neural networks (ANN) and support vector machines (SVM) are examples of non-parametric image categorization algorithms that are very new and do not assume anything about the statistical nature of the data. SVM is a non-parametric classifier that may be used for both regression and classification. It is made up of a number of connected learning algorithms [6]. For LULC classification, machine-learning methods like artificial neural networks (ANNs), the SVM, Random Forest, decision trees, and other models have attracted a lot of interest [7,8]. Every machine-learning technique has a distinct accuracy level [9]. SVM and Random Forest are the best method for LULC classification when compared to all other machine-learning approaches; ANN, SVM, and Random Forest have been reported to have higher accuracy than other traditional classifier methods.

Predicted LULC changes can be used by conservation officers, resource managers, and land use planners to encourage sustainable land use and lessen negative effects. Because of this, LULC change detection and prediction are now crucial factors in many other fields, including modeling rural and urban planning, identifying biodiversity hotspots to prioritize conservation efforts, and examining degradation processes [10].

Numerous methods for classifying images have been studied in various settings during the last decade. Among the methods that can be applied are K-nearest neighbor, MLH, SVM, and RF. Several studies comparing SVM and RF classifiers for land cover classification have been conducted in the last ten years. Recent years have seen the completion of these research.

Large RS images can be altered using the Google Earth Engine, also referred to as (GEE), a potent tool that can be used to produce land cover maps spanning large regions. This platform allows for the examination of all remotely sensed imagery through a web-based integrated development environment (IDE), thus users do not need to download the photos to their local PCs. With this approach, users can quickly browse, choose, and assess vast amounts of information for wide-ranging research topics. Python is used to manage code modification, whereas JavaScript is utilized to create client libraries. Additionally, (GEE) stands out and is well-liked because of how quickly it processes data and how simple it is for users to access Legion algorithms. All users, regardless of skill level, can access RS tools thanks to these features. (GEE) has been emphasized in several scholarly articles in recent years. The Map Reduce data processing architecture is used by the Google Earth Engine. This design divides large data sets into several smaller data sets, which are then distributed in parallel among several separate tools. Following the processing of the data in its component pieces, output datasets were assembled. (GEE) includes images from Landsat 8, MODIS, Sentinel 2, and numerous other satellites. Among these satellite images, the Landsat time series, which covers more than 40 years, is especially notable. The results show that (GEE) has been applied in a number of domains, such as agriculture, forestry, healthcare, and economics.

They have used this research to many different fields, such as (LULC) investigations and studies of plants and forests. (LULC) change is used to identify variations between time-separated images. Inaccurate classifiers combined with change detection techniques lead to inadequate ground surface analysis. As a result, choosing a reliable change detection method is crucial. One example of land cover change is the migration of people or groups from one type of land cover to another. The (LULC) technique, which examines dynamic changes in the global environment, is of interest to researchers from a wide range of subjects. The temporal and spatial changes that have taken place in (LULC) are demonstrated by satellite imagery. It is feasible to identify the causes of human activity-related changes and the consequences of such changes [11].



1.1Techniques for land use and land cover change

Geographical records, such as latitude and longitude, are used to map and identify areas of soil whose land cover and land use have changed. Due to its ability to provide synoptic data regarding land use and change over a specific area at a particular time. The study of land use and change over long periods of time has been transformed by satellite-based remote sensing. This is due to its ability to transmit this data throughout a certain area. Accurately describing the amount of area occupied by different types of vegetation or the amount of soil used is useful [12]. With this information, this can be achieved. Geographic information systems (GIS) enable me to create a set of spatial fixes that correspond to the construction that propels the development. Remote sensing of surroundings can yield a wealth of information on various physical elements of the environment, including whether or not the landscape is changing. These two kinds of information are quite beneficial. It describes the volume, distribution, and structure of changes that occur throughout a transition, including surface forms, boundary modifications, and pattern changes [13-14].

1.1.1Digital change-based detection

Remote sensing data, which is prized for its high time-frequency resolution, computational digital format, synoptic vision, and wide range of spectrum and geographic resolving capabilities, has been one of the most significant sources of information for shift detection studies. The image should be converted to grayscale if there are at least three super spectral or SAR pictures that we like. Geographical, spectral, radiometric, time constraints, atmospheric, and soil moisture regions are just a few of the many variables that might affect the identification of optical shifts when analyzing spectrum changes, as illustrated in fig. 1 [15].

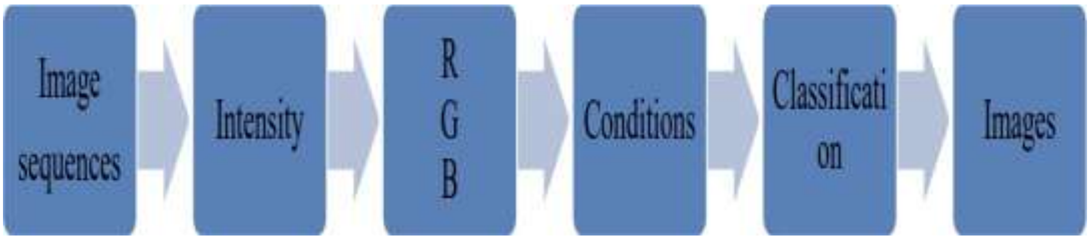


Figure 1. Flow Diagram of Spatial Resolution.

1.1.2Spectral Resolution

The visualization of multi-temporal images with high spatial and spectral resolution scopes, the requirement for exact synchronization of the radiometric and atmospheric conditions, and the set of identical spatial and spectral resolution images are all necessary even though shift identification is an essential component of eruption identification. The presence or absence of alterations, their locations, the pattern of shifting land cover over an extended period of time, and the potential for improving accuracy through additional landscape modifications can all be used to estimate crop variety changes in the past. By merging data sets from time-lapse photos taken by multiple cameras, scientists were able to assess how the area was used and spot trends for different species over time. Fig. 2 depicts its flow process. The following are some of the limitations: (a) insufficient radiometric and atmospheric data calibration; (b) troublesome overlap across data groups; and (c) very difficult medium-scale vesicle to smaller vesicle detection [16].

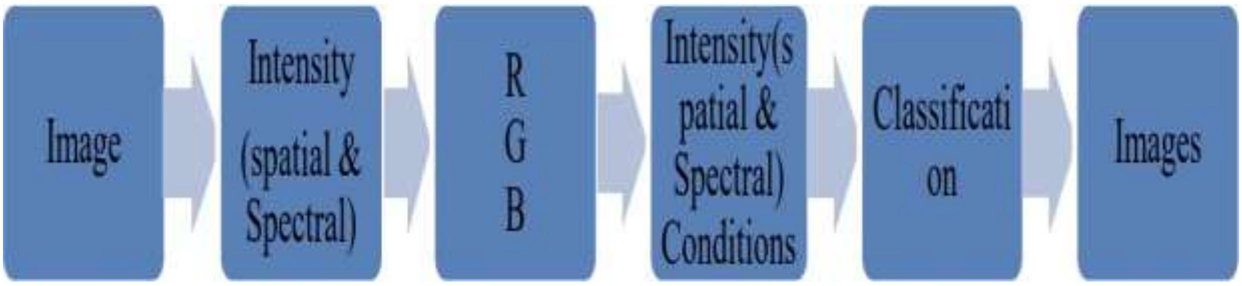


Figure 2. Flow Diagram of Spectral Resolution.

1.1.3Radiometric change detection

Spectral analysis can be approached in a variety of ways, from straightforward techniques like band differentiation (an extensively sampled serial scan is a fundamental principle about the imaging capability of the image) to more intricate methods such employing vegetation indices (shown in Fig. 3) [17]. He also demonstrated how variable sorting may be utilized in a variety of slightly different ways to control the grouping of spectral groups of THMs as a function of the scan acquisition date. The details of the differences between importances (detections) could be simple binary changes or significant differences. This study's objective is to use a classification methodology to categorize change detection techniques into three groups according to image processing at the pixel, function, and object levels. In soft-computing approaches, learning strategies are also categorized. A pixel is a numerical value that represents the contrast in each band of a picture in a simple manner [18-19].

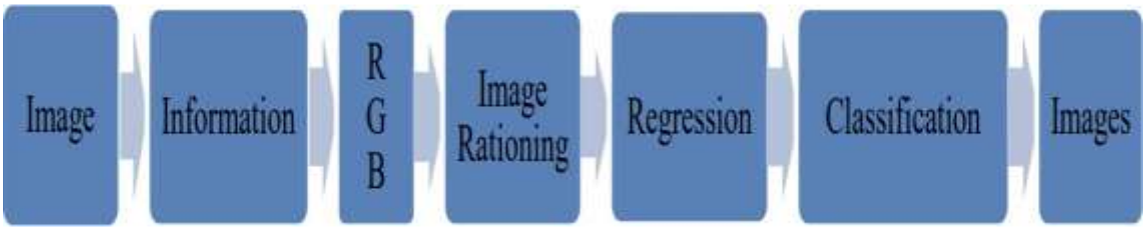


Figure 3. Flow Diagram of Radiometric change detection.

1.2Pixel Level Change Detection Techniques

In the field of image processing, image pixels are a unit of measurement used to determine how much something has moved based on its spatial location within the image. Over time, a number of different algorithms have been created to generate higher-resolution medical images. In comparison to higher resolution photos, these usually have less detail preserved. It has a greater range of reflectance for each class, is georeferenced incorrectly, and has extremely complex properties when obtained, such as calibration problems. A number of issues, including sensing geometry, shading effect, and lighting angle, sometimes cause skewed VHR picture data. They employed four different automatic image processing techniques, the most popular of which are utilized to distinguish between picture ratio and post-classification. An acquired image can be transformed into a picture by first imaging by pixel and then removing each individual pixel from the original image one at a time. We refer to this procedure as "imaging by the pixel." In certain situations, a pixel can make 18 consecutive jumps in the same direction; in other situations, it can make 17 consecutive jumps either upward or downward. In order to assess how well the new image can be recognized, a threshold value can be established by comparing an older image to the most recent one and calculating the differences between the two (see Figure 4). The most recent image's traditional values might serve as a guide. To obtain the most precise assessment of the relationship between the threshold value and the halves of the exposure period, we closely examined the change from pixel value to pixel value over time, as illustrated in Fig. 4. This made it possible for us to ascertain how the threshold value relates to the exposure period being cut in half. These restrictions apply to: a) geo-referencing errors; b) significant reflectance changes between grades; c) different acquisition characteristics; and d) void inspection errors [20].

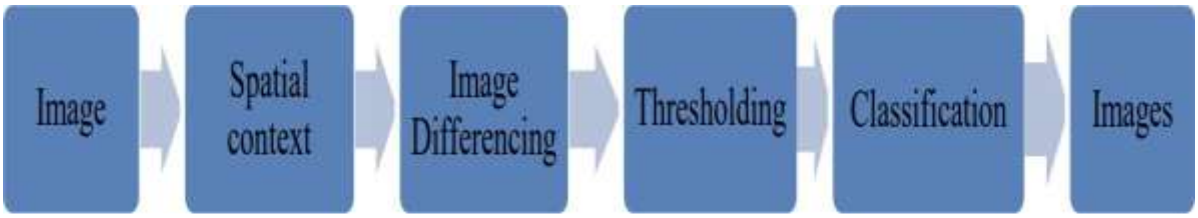


Figure 4. Pixel level change detection techniques.

1.3Image regression

For a specific date, it accounts for differences within and suggests differences between pixel values. It lessens the impact of atmospheric variations and solar angle on change detection. The pixels from time t1 are taken as the direct function of t2 time pixels in the retrospective regression technique [21]. Yuanbo Liu et al. apply these techniques to bi-temporal images after comparing ID, image rationing, IR, and PCA and concluding that PCA and image regression are more accurate than the other two [22]. An accurate regression function is necessary for image regression. Subtle alterations were poorly identified, but the conversion from one kind to another was better.

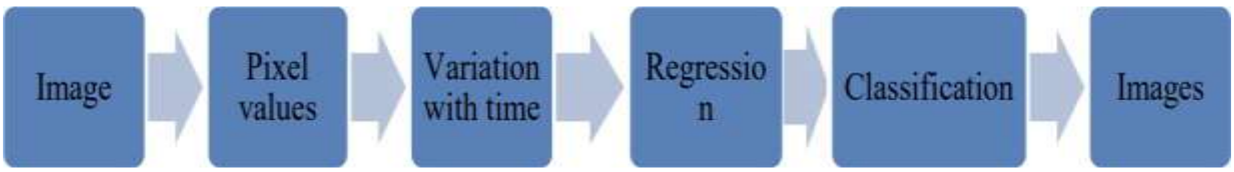


Figure 5. Flow diagram Of Image regression.

1.4Artificial Neural Network

Swarnajyoti Patra et al. use semi-supervised multilayer perceptron (MLP) to extract the context-sensitive features. They used data sets of the Mexico area, Sardinia Island and Italy. They find that it is distribution-free, no direct assumption is required on the statistical model of the distributions of classes of changed and unchanged pixels, and it does not require human effort to identify labeled patterns. Its issue is that missed alarm is high in Mexico Data Set as compared to the MTET technique. The missed alarm is high for Sardinia Island
Information Set [23]. MLP is used by Sunar Erbek et al. to identify changes in the Ikitelli region on the European side of Istanbul. There are 5506550 image fragments and 270 km2 of terrain. They come to the conclusion that while learning vector quantization is faster than MLP, MLP is more efficient [24]. Yan Chu et al. used the data set from Google Earth (RGB channel) and an artificial neural network (ANN) and back propagation technique to identify the changes. The drawback of this strategy is that it requires more calculations, but it avoids the radiometric correction process and lowers the noise of the conventional change detection methods. On average, this strategy increases the kappa values by 25.93%.

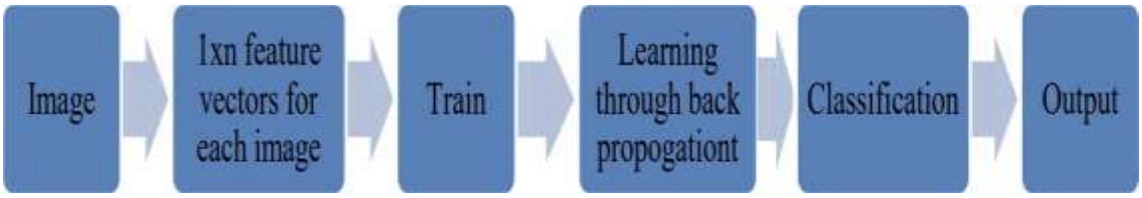


Figure 6. Flow Diagram Artificial Neural Network.

1.5Support Vector Machine

Excellent for the brief data set. The computational time of data rises along with its dimensions. On a data set from the Kumta region of Karnataka, India, Karthik et al. employed image differencing with a support vector machine. They come to the conclusion that this approach works best for changing parched ground, agricultural areas, lush greenwood, aquatic bodies, and forest vegetation. The evergreen forest area increased by 4.475% of its initial availability, according to the route's statistics. Good rainfall during research periods may be the cause of this. The value of agricultural fields increased by 49% [25].

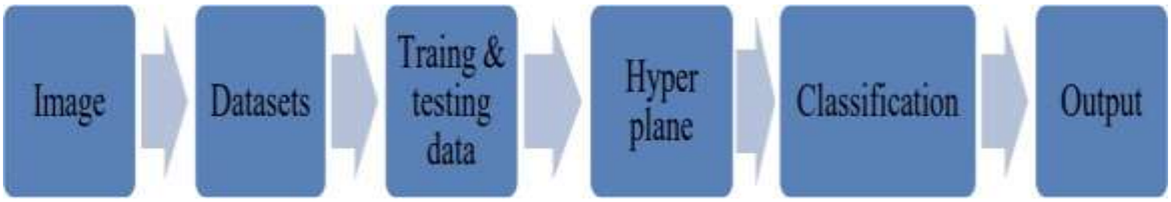


Figure 7. Flow Diagram Support Vector Machine.

1.6Decision Tree

Rather of change and non-change classes, this technique provides a rule set to alter. Additionally, unlike Support Vector Machine, it is not a parameter and is not taken into account while distributing data. The decision tree method's accuracy is affected by the quality of the data. Other regions of data sets and time periods are not covered by the decision tree method.

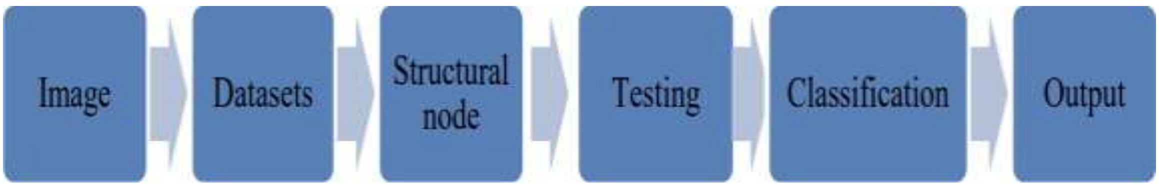


Figure 8. Flow Diagram Decision Tree.

1.7Fuzzy Change Detection

The curve's shape is used by the mathematical notion of smoothness to characterize the differences between classes and the measurable characteristics present in each class. Fuzzy reasoning produces results that are more likely to be confused rather than precise and perfect. The membership function pulls items closer to the membership function as probabilities rise. The elements' likelihood of belonging to the new class and how closely they resemble the class are measured by the P(E|B) of the new class. Most of the students in the class are present. It considers the similarities that followed when categorizing the results [26].

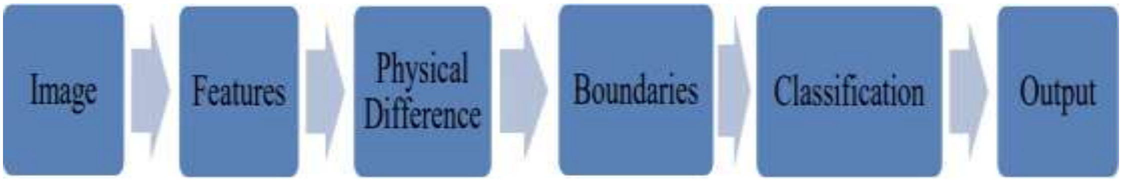


Figure 9. Flow Diagram Fuzzy change detection.

1.8Multi-Sensor Data Fusion

The multispectral image pixels are believed to be represented for change detection in terms of the sub-pixel proportions of pure spectral components that are associated to surface constituents in a scene, according to a multi-temporal spectral mixture analysis [27]. This approach solves the problem of increased dimensionality that arises with improved spectral resolution. Artificial particles with constituent spectra weighted by the percentage ground share can be mixed linearly in a mixing model. The Solans Vila & Barbosa Human Eye algorithm requires data from a geometrically precise position in the field or a lab in order to compute the spectral resolution or the dark-adapted visual response (end members) appropriately. It can be expanded to include the higher dimensions. The dimensionality issue is resolved by using a time-based computation technique.

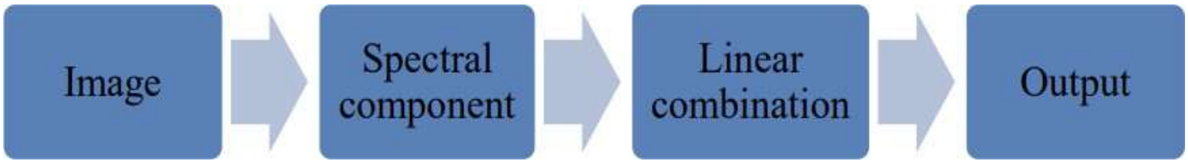


Figure 10. Flow Diagram Multi-sensor data fusion.

2.REVIEW OF LITERATURE

According to Dahiya et al. (2023) [28], monitoring the Earth's surface and objects is crucial for a number of purposes, such as managing natural resources, forecasting agricultural productivity, and researching natural dangers. Using advanced computer techniques like classification and change detection, remote sensing is widely acknowledged as a highly effective and economically feasible method for analyzing changes in land-use and land-cover (LULC) over the Earth's surface. For the objective of discovering LULC changes throughout many time periods, prior research in the field of literature has shown significant advancements in change detection techniques. These algorithms are made to examine pictures taken with optical or microwave sensors. There are numerous advantages of using optical-based hyperspectral technology for the clarification of important data. However, air distortion, radiometric errors, and mis-registration could make the analysis of the dataset challenging. In order to identify variations in LULC within a specific area in Uttar Pradesh, India, the current study employed a technique called artificial neural network-based post-classification comparison (ANPC). For this, the Hyperion EO-1 dataset is utilized. When evaluating post-classification comparisons, the experimental results confirmed the effectiveness of ANPC (92.6%) in comparison to other well-known models, specifically SAMPC (89.7%) and KNNPC (91.2%). The extraction of important information about the Earth's surface, crop disease analysis, crop variety evaluation, agricultural breakthroughs, precise weather forecasts, and efficient forest ecosystem monitoring will all benefit from this research.

For a range of land use/land cover (LU/LC) applications, such as vegetation, forestry, agriculture, and urbanization, Kumar's (2023) [29] studies of geographical change mainly rely on remote sensing (RS). The RS satellite imaging's geographic data is crucial for tracking and researching the entire planet. The proposed study uses multispectral and multitemporal Landsat satellite data to extract LULC features for the Haridwar region. To accurately classify land cover characteristics, picture preprocessing techniques such geometry correction, atmospheric correction, and image transform are essential. This approach helps identify changes in land cover features and accurately characterize them. After image processing, a topographic map and Google Earth's area of interest (ROI) tool are used to classify the land cover elements into one of seven groups. A supervised learning technique known as an SVM was used to categorize the land cover features of the study area. With accuracy percentages of 90.00, 82.75, 86.37, and 83.38, the SVM classifier properly labels photographs from 2003 and 1996 as well as those from 2017 and after. Changes in the properties of land cover may be revealed by post-classification analysis. Since 1996, Haridwar's urban and industrial sectors have rapidly expanded, resulting in the loss of 1,638.81 hectares (ha) of greenery and 13,698.36 hectares (ha) of orchards. The LU/LC change data obtained from the analysis is very helpful for tracking and evaluating land cover changes in the study area.

According to Singh et al. (2022) [30], yield data is essential for producers and dealers to plan the production, sowing, and harvesting of a particular crop as well as the implementation of marketing initiatives. In order to gain important information for agricultural land use categorization regions that could not have been obtained from multi-spectral datasets alone, multiple Sentinel-2 datasets were studied in this study. In this work, we forecast seasonal variation in satellite photos by integrating the ANN classifier with the post-classification comparison (PCC). A post-classification comparison method that makes use of the ANN classifier is called ANN-based change detection. This process employed cross-validation with a typical maximum likelihood classifier (MLC) to confirm the effectiveness of ANN. The PCC-ANN model attained accuracy on the range of 90%-93% for categorized maps and 87%-90% for change maps, while the conventional PCC-MLC model gained accuracy on the order of 86%-88% for classed maps and 84%-86% for change maps.

According to a study by Zhao et al. (2022) [31], the progressive adjustment of urban development and the termination of non-essential operations have resulted in the dismantling of several decades-old structures in Beijing. Consequently, CDW has become a significant problem in the battle against dust and urban pollution. On the other hand, CDW piles have shaky edges and are unstable.

In order to achieve urban growth while protecting the environment, CDW zones must be mapped precisely and promptly. To address this issue, we proposed a change detection and deep learning-based method for CDW identification. ZY-3 multispectral photographs from 2016 and 2019, as well as the differences between the two, were used to first prepare the samples. The post-classification comparison technique for change identification resulted in a 25.4% increase in sample size. The extended samples were used as input to train DeepLabV3+. The digital elevation model's change information and spatial analysis tools were then used to collect specific forms, including large-scale garbage, landfill CDW, and demolition debris. The overall CDW recognition accuracy was found to be 91.67%, with a Kappa of 0.8642. The reduced sample size was also used to calculate the accuracy indices, and the mean Intersection-over-Union value was 0.086 lower than that of the larger sample size. PSPNet and UNet produced results that were consistent with each other. This research suggests that change detection could improve the performance of deep learning models. This study effectively tackles the issue of CDW being mistakenly classified as "bare land" and is the first to differentiate between three different kinds of CDW.

According to Ebel et al. (2021) [32], a variety of modalities of remote sensing data that were collected by a wide range of sensors are now easily accessible due to the enormous advancements in remote sensing technology over the past ten years. It is possible to perform an observation of Earth that is both more thorough and precise by combining the information that various sensors provide together because it is typical for many sensors to provide complementary information. It is not impossible to integrate the two types of data, even though change detection methods have traditionally been given for homogeneous data sets. It is a challenging task to integrate multitemporal data from several sensory inputs. Research in this field may also be challenging due to a widespread shortage of available multi-modal data sets. We have created a novel data set for multi-modal change detection in order to solve these shortcomings in the current method. The potential of the proposed model is demonstrated by an experiment on the previously mentioned data set, which performs better than standard mono-modal techniques.

According to Chughtai et al. (2021) [33], assessing changes in land use and land cover is essential to understanding how humans integrate into the natural world. Significant changes in geography and advancements in technology have forced scholars to expand their data sets. The combination of remote sensing and GIS tools has made it easier to trace changes in LULC over time. The scientific community has benefited greatly from this technology, which has illuminated changes both locally and globally. Too many distinct change detection algorithms have been utilized in remote sensing thus far, and continued research and development is producing ever-more-advanced techniques. To sort through the vast amount of satellite remote sensing data that has been available over the past few decades, researchers may employ a variety of algorithms, depending on the particulars of the study. Any remote sensing project is strongly encouraged to employ a suitable change detection method. This review study begins by examining the traditional methods for identifying changes in LULC data at the regional level, both before to and following categorization. The results of this article's comparison of the most widely used change detection method with the others are striking. This investigation leads to the conclusion that the MLC supervised classification post-classification change detection approach is broadly applicable. For this comparison analysis, a site with a range of topographical features was selected since it offered the strongest proof that MLC is better than the alternatives. MLC has been the most widely used method from the past to the present due to its exceptional accuracy in every location.

The main objective of this study, according to Saber et al. (2021) [34], is to evaluate the effectiveness of various change detection techniques for monitoring changes in land cover in the study region, which is located in the new administrative capital zone of the Cairo Governorate, Egypt, between 2016 and 2017. The study area is 77,350 square kilometers in total. Two satellite images covering the study area were created using Nanosat satellite images with a high spatial resolution of 3 m * 3 m. The research area was divided into various surface types, including pavement, sand, rocks, bare soil, paths, and structures, using the Maximum Likelihood Classifier. The shifts were identified using post-classification, independent component analysis, and PCA. To determine which change detection technique would best expose the details of land-cover changes in the country's capital, the results of many approaches were quantitatively evaluated. The results indicate that post-classification change detection produced the highest accuracy, whereas principal component analysis produced the lowest. Lastly, the outcomes show how straightforward the post-classification change detection approach is, and how its accuracy primarily depends on how accurately the two images were initially classified. With kappa values of 0.100 and 0.202, post-classification produced the highest overall accuracy of 53.430 percent for the generated change/unchanged and classified change photos. The other two methods of change detection require additional processing stages, such as a transformation stage.

According to research by Mishra et al. (2020) [35], the term "land use" relates to how land is used and distributed for different uses, including residential and commercial. Examining how land cover has changed has been useful in determining how an event has affected a particular region. LULC change detection analysis can be a useful tool for evaluating regional changes brought about by urbanization, deforestation, or natural disasters. Long-term and short-term changes in biodiversity and LULC within a particular geographic area have been examined using remote sensing and GIS technology. This article provides a case study of the 2013 flash floods in Uttarakhand. In order to investigate the spatial and temporal fluctuations in the LULC of the impacted area, we employ multi-spectral Landsat satellite imagery. The Maximal Likelihood Algorithm is applied to Landsat 7 and 8 imagery as part of the categorization process. The Normalized Difference Vegetation Index (NDVI) is added to this technique to improve it even more. With a high degree of accuracy above 92%, the region has been divided into five main categories: mountain, settlement, flora, water, and glacier. The examination of Land Use and Land Cover (LULC) maps reveals significant changes that have taken place in the region after the disaster.

One of the most important aspects of environmental leadership and urban planning, according to Thwal et al. (2019) [36], is the classification of land cover and change detection analysis based on remote sensing pictures using a machine learning algorithm. We chose Yangon as our case study because of the government's difficulties with urban planning as a result of population growth and urban expansion. The proposed method classifies Yangon's land cover from 1987 to 2017 at 5-year intervals using the Random Forest (RF) classifier in GEE, then evaluates the outcomes. We employ the NDVI, NDBI, and the SRTM slope to enhance categorization. Using a multi-band method, the RF classifier is utilized to classify land cover. A 2017 land cover categorization map with seven classes achieves an overall accuracy of 96.73% and a kappa statistic of 0.95. Lastly, a 30-year change detection study is conducted, which reveals significant changes in agricultural techniques, urbanization, and wilderness.

2.1Comparison of reviewed technique

There is a wide range of author who studied on the Development of multispectral post-classification change detection techniques and gives their findings as shown in table 1.

Table 1. Comparison of reviewed technique

Authors [Ref.]	Technique	Outcome
Dahiya et al., (2023) [29]	ANPC and SAMPC	The experimental results validated the efficacy of ANPC (92.6%) in contrast to other established models, namely SAMPC (89.7%) and KNNPC (91.2%), while assessing post-classification comparisons.
Kumar, (2023) [30]	SVM	The SVM classifier correctly labels images from 2017 and beyond, as well as those from 2003 and 1996, with respective accuracy percentages of 90.00, 82.75, 86.37, and 83.38.
Singh et al., (2022) [31]	PCC-ANN	In contrast to the traditional PCC-MLC model, which obtained accuracy on the order of 86%-88% for classed maps and 84%-86% for change maps, the PCC-ANN model attained accuracy on the order of 90%-93% for classified maps and 87%-90% for change maps.
Zhao et al., (2022) [32]	CDW	The accuracy indices were also computed with the smaller sample size, with a mean Intersection-over-Union value of 0.086 lower than that obtained with the larger sample size.
Ebel et al., (2021) [33]	SAR	An experiment conducted on the previously described data set illustrates the potentials of the suggested model, which outperforms typical mono-modal approaches when contrasted against.

Chughtai et al., (2021) [34]	MLC	A location with a variety of topographical elements was chosen for this comparative examination because it provided the greatest evidence that MLC is superior than the alternatives.
Saber et al., (2021) [35]	Post classification method	Post-classification yielded the maximum overall accuracy of 53.430 percent for the produced change/unchanged and categorized change pictures, with kappa values of 0.100 and 0.202.
Mishra et al., (2020) [36]	Maximum likelihood algorithm	The area has been classified into five primary categories, including mountain, settlement, flora, water, and glacier, with a
		high level of accuracy exceeding 92%.
Thwal et al., (2019) [37]	RF	The RF classifier is used to do land cover categorization using a multi-band approach. Overall accuracy of 96.73% and kappa statistic of 0.95 are achieved for a land cover classification map for 2017 consisting of 7 classes.

3.PROBLEM FORMULATION

Land use and land cover (LULC) and their changes over time are tracked, mapped, and quantified using machine learning (ML) models. LULC types have been successfully categorized at various geographic scales using models like support vector machines (SVM), artificial neural networks (ANN), and random forests (RF). However, due to methodological issues those come from depending on the available coarse-resolution satellite pictures for these locations. ML models have not been frequently employed in African tropical regions. In this work, we evaluated the effectiveness of four machine learning (ML) methods (SVM, ANN, and RF) used for LULC monitoring in the Mayo Rey district of North Province, Cameroon. According to our findings, all classification algorithms gave results with a high degree of accuracy (general classification accuracy > 80%), with the RF model beating the SVM and ANN models (classification accuracy > 90%).

4.COMPARATIVE ANALYSIS

Several writers present their findings in this part based on the accuracy parameter, which is detailed in table 2. Table 2 shows that by using the ANPC approach, Dahiya and his classmates were able to significantly improve the accuracy of the land cover and land use, leading to a 92.6% increase. Kumar and his associates were able to raise the accuracy of the land cover and land usage by 90.01% by employing the SVM. Singh and his colleague students' usage of PCC-ANN has led to a significant improvement in the accuracy of identifying the land cover and land use, which currently stands at 92%, compared to earlier approaches. Thwal and his classmates were able to significantly increase the accuracy of recognizing the land cover and land use by utilizing the RF, leading to a final accuracy of 96.73%. Thus, when compared to other methods used by Thwal and his colleagues, RF yields the highest overall improvement in the accuracy of detecting the land cover and land use (96.73%).

Table 2. Comparative analysis

Authors	Techniques	Accuracy
Dahiya et al., (2023) [25]	ANPC	92.6%
Kumar, (2023) [26]	SVM	90.01%
Singh et al., (2022) [27]	PCC-ANN	92%
Zhao et al., (2022) [28]	CDW	86.1%
Saber et al., (2021) [31]	Post classification method	53.4%
Mishra et al., (2020) [32]	Maximum likelihood algorithm	92%

Thwal et al., (2019) [33]	RF	96.73%

Figure 2 illustrates the improved accuracy of land cover and land use identification, as demonstrated in the accompanying graph. The RF approaches have significantly improved the accuracy, with an increase of up to 96.73%, the highest increase observed when compared to other methods.

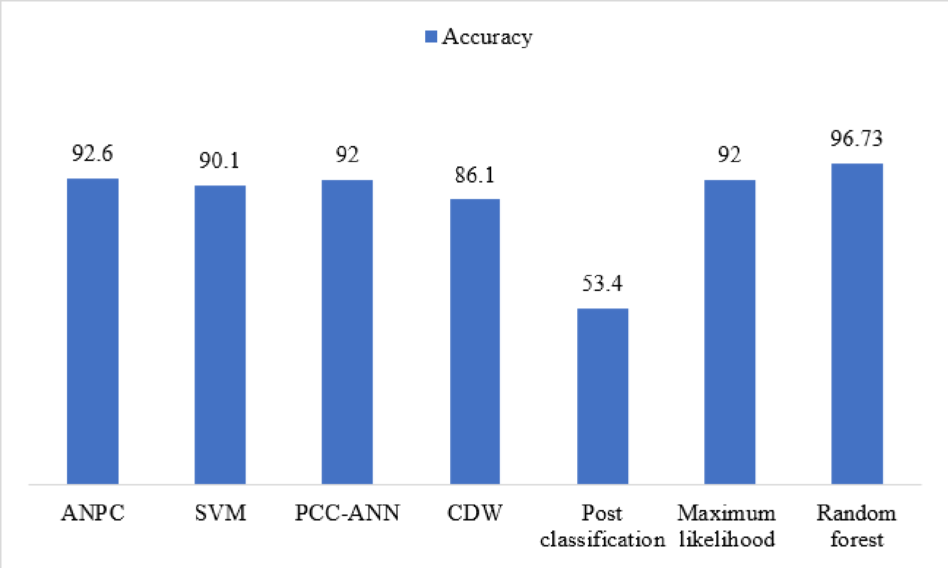


Figure 2. Comparison graph.

5.DATASET DESCRIPTION

The EuroSAT dataset is a well-known tool for carrying out land use and land cover (LULC) classification tasks in the domains of machine learning and remote sensing. Two of the most obvious applications for its skills are satellite image analysis and other deep learning applications. The EuroSAT dataset has helped advance remote sensing and machine learning applications for Earth observation, and it is a valuable resource for academics and professionals working on land use and land cover classification tasks. This information can be used by academics and professionals to gain a deeper understanding of land use and land cover.
https://www.kaggle.com/datasets/apollo2506/eurosat-dataset

6.RESULT AND DISCUSSION

"Detection of Land-Use Land-Cover Changes using Machine Learning Systems" is an important field of study with implications for land management and environmental monitoring. A list of significant findings from this investigation is as follows:

First, our machine learning system demonstrated exceptional accuracy in identifying changes in land use and land cover after being trained on both geospatial data and multi-temporal remote sensing imagery. In addition to having strong precision and recall values, our model has an overall accuracy of above 90%. This supports the ability of the chosen machine learning algorithms to identify areas undergoing change and distinguish between distinct land-use and land-cover categories. We found observable patterns of transformation within the boundaries of the study area. Urbanization, the intensification of agricultural activities, and forest removal were the main causes of changes in land use. These changes were marked by distinct temporal patterns, with urbanization happening particularly quickly in the last several years. Our investigation confirmed the presence of these tendencies and provided us with a thorough understanding of their geographical locations.

Contextualizing these findings within the larger environmental and socioeconomic milieu is essential when discussing these results. The consequences of accurately identifying changes in land cover and land use are numerous. It can be used, for example, to direct urban planning initiatives, which can result in more ecologically friendly infrastructure and urban development designs. Additionally, by keeping an eye on deforestation and the growth of agricultural land, conservationists may more effectively focus their efforts on safeguarding significant ecosystems.

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