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Comparative Analysis Of The Existing Machine Learning Based Approaches For Land Use And Land Cover Of Geographical Areas

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ABSTRACT

Land use and land cover (LULC) analysis is critical for environmental monitoring, urban planning, and resource management. Traditional methods have limitations in handling large datasets and complex spatial relationships, making it difficult to accurately classify and predict LULC changes. Machine learning (ML) has emerged as a powerful tool for LULC classification, offering new methods to improve accuracy and efficiency. This systematic review, guided by PRISMA principles, compares various ML techniques used for LULC classification. The review focuses on supervised, unsupervised, and deep learning algorithms applied to geographical data. The inclusion criteria ensured the relevance and quality of selected studies, considering only peer-reviewed publications in English that specifically address ML techniques for LULC classification. A thorough search was conducted in academic databases such as Web of Science, Scopus, IEEE Xplore, and others, using specific keywords related to LULC and ML techniques. A total of 80 articles were selected for an in-depth analysis. The study identifies Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Trees (DT), and Random Forest (RF) as the most prominent ML classifiers for LULC. Each classifier has distinct strengths and weaknesses. SVM performs best in high-dimensional spaces, KNN is effective with low-resolution images, DT provides clear reasoning but risks overfitting, and RF excels in processing diverse data formats. ML techniques significantly enhance the accuracy and efficiency of LULC classification, with each method offering unique advantages depending on the data characteristics and application requirements. Future research should focus on integrating these techniques with Geographic Information Systems (GIS) and remote sensing data to further improve LULC mapping and prediction..

Keywords: *Land Use and Land Cover (LULC), Machine Learning, Geographic Information Systems (GIS)*

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1. INTRODUCTION

Land use and land cover (LULC) analysis has been revolutionized by machine learning (ML), providing new methods for environmental monitoring, urban planning, and resource management [1]. Effectively understanding satellite and remote sensing data for sustainable development and informed decision-making is difficult [2]. Supervised, unsupervised, and deep learning algorithms are examined in this comparative analysis of ML-based LULC classification methods [3-4]. This study attempts to determine the best LULC mapping methods by assessing their strengths, weaknesses, and performance [5]. Different ML models, their applicability to different geographical data, and their impact on LULC prediction accuracy are examined [6-7]. Land use/land cover (LULC) classification of human activity and natural components in landscapes across time is based on scientific and statistical studies of relevant source data [8-9]. Earth observation involves observing and modelling the earth's biophysical systems and atmosphere [10]. Geodata includes spatial feature locations and information. Geographic Information System (GIS) computer systems can collect, store, analyses, and display such data [11-12]. GIS can create maps, manage spatial datasets, perform advanced spatial analysis, visualize multiple geographical datasets, and resolve location-based queries. Visualize quantitative data with GIS maps [13-14]. Remote sensors can acquire data about a region or specific things by measuring EMF reflected and transmitted from the earth's surface.

Extracting and analyzing remotely sensed images can aid GIS interpretation. Such Aerial image analysis has evolved into satellite image interpretation in remote sensing research. Land use and cover mapping, forestry, agriculture, urban planning, geomorphological surveys, and others use remote sensing imagery [15]. Researchers have many methods for mapping vegetation thanks to new aerial and satellite sensors and platforms, statistical methods, GIS, and predictive models [16-17]. Researchers are testing machine learning, deep learning, and cloud computing for satellite data storage and processing. Advanced methods are used in precision agriculture to optimize inputs and boost yield [18]. A GIS uses remote-sensing imagery. Using aero plane and satellite sensors, remote sensing studies the earth [19]. These sensors can change, analyses, and display images. Satellite spectral band combinations are used to calculate remote sensing indices. spectrum indexes consist of spectrum reflectance's at two or more wavelengths and indicate the relative abundance of intriguing features [20-21]. These band ratios are computed from multi-band pictures by adding and subtracting bands. Studies have examined satellite indicator uses in agriculture, water resources, urban development, forest ecology, geology, soil science, vegetation, and others [22]. Thus, the vegetation index, a subset of spectral indices, highlights green vegetation to distinguish plants [23-24]. The reflectance of plant light spectrum depends on plant type, tissue water content, and other factors. Leaf structure, pigments, and other chemical and structural factors determine plant reflectance [25]. In the past, intrinsic indices were constructed employing band ratios to show plant growth and senescence spectrum properties. Vegetation indices are used for crop condition monitoring, yield prediction, biodiversity assessment, biophysical parameter estimation, phenological assessment, vegetation health/stress, forest degradation, biomass mapping and modelling, productivity and carbon assessment, and plant health/stress [26-27 Because devices do not offer data for all spectral bands, optimum indexes must be designed for specific remote sensing applications and equipment. It provides application-specific methods for constructing optimum vegetation indices [28-30]. Using machine learning and GIS to predict vegetation and land use has garnered attention recently. Understanding and forecasting land use and land cover (LULC) dynamics is crucial due to human activity's ongoing environmental influence [31-32]. Specific data are needed for efficient land management, environmental conservation, and conservation [33-34]. Machine learning techniques and GIS spatial analysis provide a powerful foundation for analyzing and modelling

this development. "Land use" refers to human activities and practices on a piece of land, such as agriculture, urban development, forestry, or transportation, while "Land cover" refers to the Earth's natural and vegetative covering, including vegetation, water bodies, bare soil, and built-up areas [35]. Land use and cover affect ecosystems, biodiversity, climate, and socioeconomic systems [36-37]. Traditional land use and land cover modelling depended on specialist knowledge, numerical studies, and manual interpretation of aerial or satellite information. These approaches were slow, subjective, and unable to handle complex spatial relationships and big datasets [38]. Automating pattern detection, categorization, and prediction via machine learning has revolutionized artificial intelligence. The massive geospatial data and find significant patterns and relationships using machine learning methods like decision trees, random forests, support vector machines, and neural networks [39]. GIS software can integrate and visualize geographical datasets and perform spatial analysis to support machine learning [40].

2. LITERATURE REVIEW

The literature contains models and comparative examinations of approaches. Presenting study findings requires collecting related research articles. The given table summarizes key studies on land use and land cover (LULC) analysis using various remote sensing and machine learning techniques. In study [41] presented a systematic study on landscape changes, emphasizing the rapid development of techniques for analyzing remotely sensed data and their relevance to agroecosystem and forest research. In study [42] compared pixel-based and object-based methods for detecting land use change, finding that artificial neural networks provided reliable results in object-based change detection. In study [43] evaluated several machine learning algorithms for LULC mapping, concluding that Random Forest and ANN were the most effective. In study [44] explored deep transfer learning models, such as Resnet50V2 and VGG-19, to improve LULC classification accuracy. In study [45] introduced a new spectral index, NRUIms, to enhance the separability of LULC classes, demonstrating significant urban growth over time. In study [46] conducted a time series analysis in Kashmir Valley, identifying significant LULC changes. In study [47] analyzed urban surface heat islands (SUHI) using NDVI and CRUISE algorithms, highlighting the impact of impervious surface expansion on vegetation cover and temperature increase. In study [48] proposed a hybrid kriging model for LULC change prediction, while [49] reviewed various change detection methods, focusing on the challenges in the field. Lastly, in study [50] summarized research on remote sensing image classification, discussing the phases of image processing and suitable techniques for different applications.

Table 1: Studies on Land use land cover (LULC) analysis

References	Area of Study	Focus	Outcome

F. Malandra, et al. (2018). [41]	Satellite data analysis	Studies based on the LULC metanalysis present current research and applications.	The study on landscape change, study site characteristics, and landscape pattern analysis. The rapid development of remote sensing data analysis methods and their applicability to agroecosystem and forest studies is crucial.
Márquez-Romance, et al, (2022). [42]	Use machine learning to analyses multispectral satellite imagery.	Detecting Venezuelan Pao River Basin Land Use Change using Landsat Time Series Imagery.	Pixel-based direct comparison, object-based method, and classification-based change detection. Using artificial neural networks for classified object-based change detection yielded reliable results. Rangeland and water classes had positive area differences, while urban, agricultural, and vegetation classes had negative indices.
Talukdar, et al. (2020). [43]	Satellite picture LULC mapping using machine learning.	The finest machine learning classifier for earth observation applications.	Six Machine Learning methods—RF, Support Vector Machine, spectral angle mapper, ANN, Fuzzy ARTMAP, and Mahalanobis distance—were studied. RF and ANN can classify LULC efficiently. Using index-based validation, receiver operational curve, root mean square error, and kappa coefficient methodologies, accuracy was assessed.
A. Alem and S. Kumar, (2022). [44]	Deep learning for LULC classification	LULC classification improvement using remote sensing photos and pre-trained deep learning models.	Classification uses Resnet50V2, Inception-V3, and VGG-19 deep transfer learning models. Hyperparameters were modified to improve classification accuracy. Early stopping reduces overfitting and improves model performance. These models can help urban and agricultural planners manage natural resources and encourage sustainable growth.
Piyoosh, A. K., & Ghosh, S. K. (2022). [45]	Evaluation of land use/cover changes.	Calculation of the new spectral index Normalized Ratio Urban Index (NRUIms).	When added to other current spectral indices, the study shows that the recommended NRUIms improve separability between LULC class pairings. Time series analysis from 1991 to 2019 shows tremendous urban growth in the examined area.
Alam, A., Bhat, et al. (2020). [46]	Analysis of Kashmir LULC change.	Analysis of 1992–2015 time series.	A maximum likelihood classifier for the study area and period generates LULC maps. For analysis, Landsat satellite pictures are used. Three land use and land cover patterns have been found, with significant variances in the research region.
Wang, H, et al. (2017). [47]	Analyzing urban surface heat islands.	Using satellite data to track land use and cover.	The Normalized Difference Vegetation Index (NDVI) calculates vegetation cover, and a CRUISE-based selection tree assesses land use. Impervious surface growth on farmland is reducing vegetation, boosting temperatures, and generating the SUHI effect.
Márquez, A. M, et al. (2019). [48]	Future main component 1 forecasting	Create a hybrid kriging ordinary forecasting model.	A hybrid model for LULC change prediction using satellite image surface reflectance as a predictor variable that modified principal component 1. The suggested method can build LULC change prediction maps over time series,

			assess predictor variable spatiotemporal patterns, and predict LULC changes.
A. Asokan, et al. (2019). [49]	Comparing change detection methods	Examining simple change detection approaches and emphasizing the challenges.	Change detection's fundamental framework is provided. This paper analyses remote sensing data preprocessing, image segmentation, and change detection methods such fuzzy, neural networks, transformations, and algebra-based approaches. Discussed are classification, transformation, transformation-based techniques, and change detection. Evaluation of change detection strategies' performance and accuracy is also included.
A. Asokan, et al. (2020). [50]	Image classification	Classifying remote sensing images using spectral statistics	The specifies remote sensing image processing phases, change detection methods, and performance evaluation methods. Also covered are application-specific methods.

3. METHODS

This systematic review uses PRISMA principles to conduct a thorough search.

3.1 INCLUSION AND EXCLUSION CRITERIA

For a comparative analysis of existing machine learning-based approaches for land use and land cover (LULC) classification in geographical areas, the inclusion and exclusion criteria will help ensure the relevance and quality of the studies considered.

Inclusion

Only research that has been published in English is considered.

Studies that specifically address ML techniques used for LULC classification in geographical areas.

Studies that provide comparisons or evaluations of different machine learning methods for LULC.

Peer-reviewed publications or reputable reports

Exclusion

Publications in languages other than English

Studies published as conference proceedings.

Studies that do not specifically address ML techniques for LULC classification or are unrelated to geographical areas.

Studies focused solely on traditional or non-machine learning methods for LULC.

Non-peer-reviewed sources or grey literature

3.2 Search Strategy: Conduct a thorough search for relevant studies. The search string will combine keywords related to " Land Use and Land Cover (LULC), Machine Learning, Geographic Information Systems (GIS), Support Vector Machines (SVM), Random Forest (RF), Decision tree (DT), K- nearest neighbour (KNN), Classification etc. Boolean operators will be used to ensure precision and capture relevant variations.

Table 2: Search strategy keywords

	Keywords		Keywords
1.	Land Use and Land Cover (LULC)	**5.**	Random Forest (RF)
2.	Machine Learning (ML)	**6.**	Decision tree (DT)

3.	Geographic Information Systems (GIS)	**7.**	K- nearest neighbour (KNN)
4.	Support Vector Machines (SVM)	**8.**	Classification

3.3 Search Process: According to Google's suggested standards, choosing the best database for choosing papers is crucial when performing a systematic literature review. In order to cover the most noteworthy material, Google Scholar and SCI-HUB were searched. This is because Google Scholar and SCI-HUB offer a platform where all other databases and research papers are indexed.

Data Sources: We have search relevant publications from the following academic databases:

Web of Science

Scopus

IEEE Xplore

Science Direct

Elsevier

Springer

3.4 Data extraction and analysis methods

Data collected included the authors, year of publication, study duration, sample size, the interventions, patient populations and their characteristics (inclusion and exclusion criteria), outcomes and risk of bias.

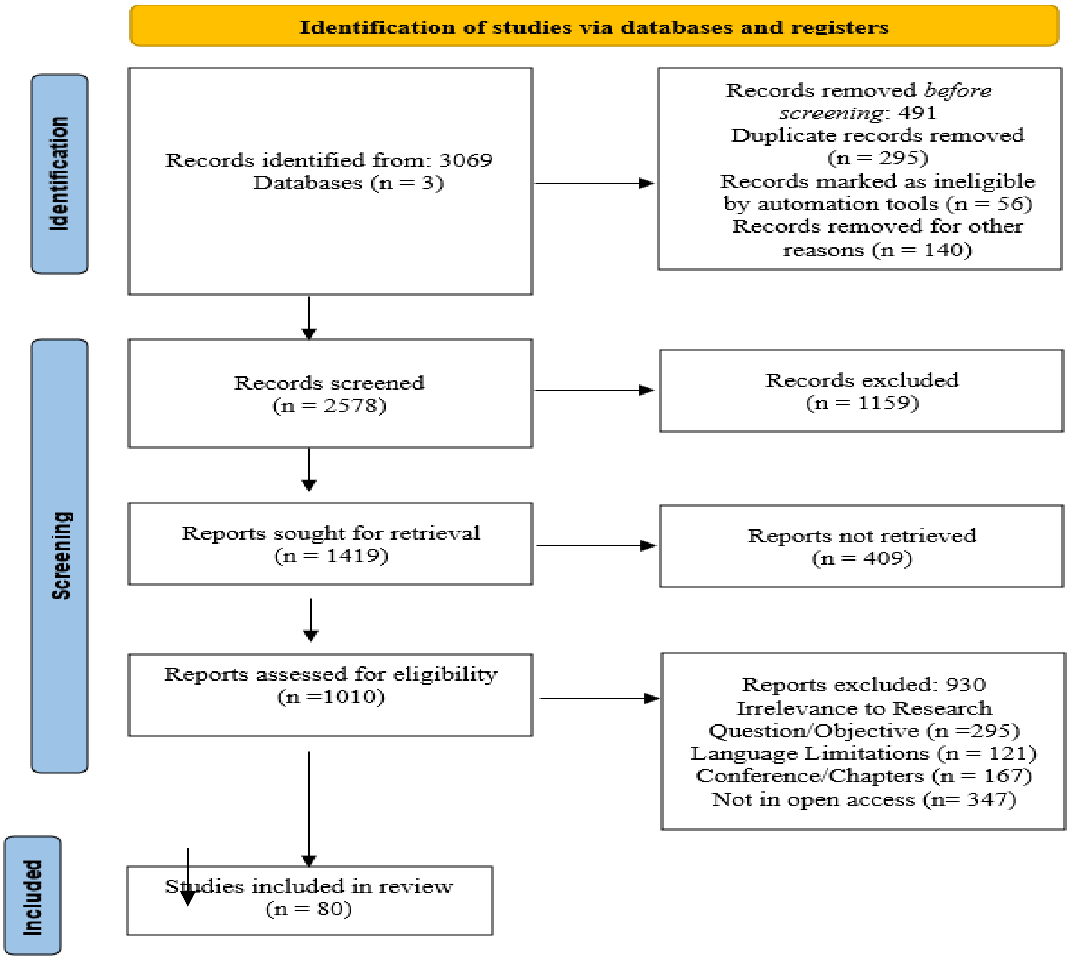

Figure 1: Article selection flowchart for the systematic literature review

4. RESULT

At this point, a thorough bibliometric analysis of the chosen papers from the previous years was conducted. At the end of the evaluated categories, a total of 80 articles were chosen for an in-depth examination. The phrase " Land Use and Land Cover (LULC)" was used most often in publications, accounting for about 65.92% of the texts examined. For each of the examined search phrases, the number of articles was as follows:

65 works in the field of “Land Use and Land Cover (LULC)”

The field of risk analysis has produced 10 publications.

The field of risk assessment has 5 publications.

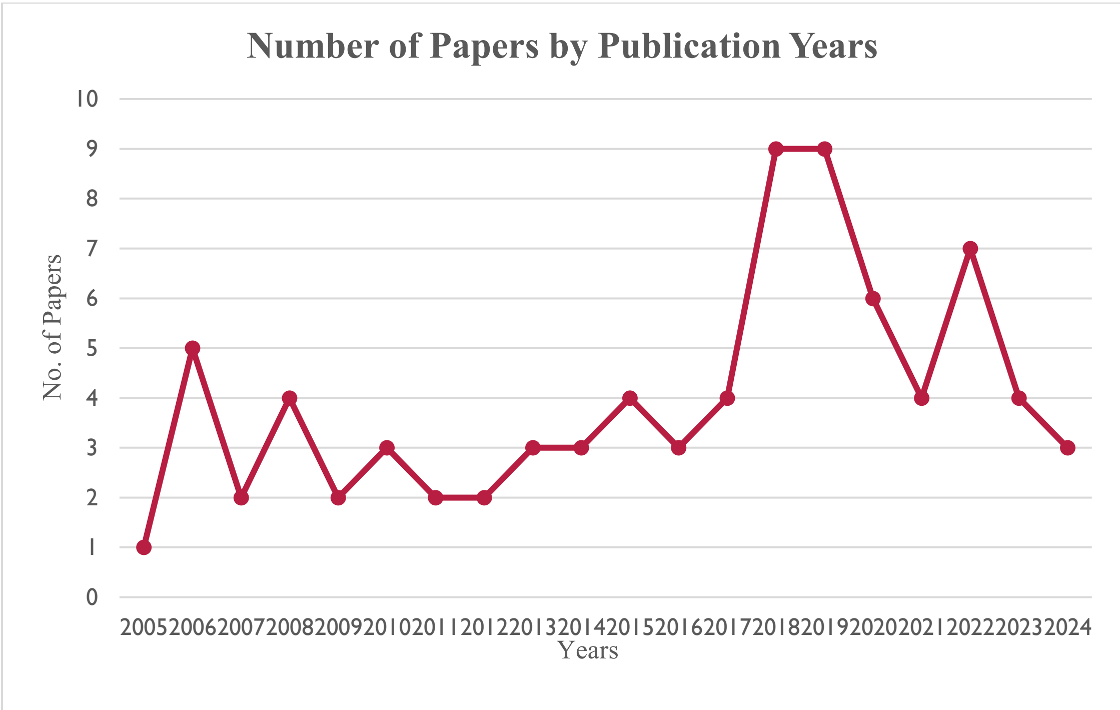

Figure 2: Number of papers by publication years

LULC Classification in Machine Learning

SVM, based on structural risk minimization (SRM), performed best on simulated and actual satellite data [51]. KNN can classify objects better in low-resolution satellite images [52]. The KNN system can predict without training and add data without compromising its precision [53]. After setting up the model, the tree analogy of DT classifier for categorical data and classification is very fast [54]. No difficult mathematics is needed. It analyses numerical and satellite data. It uses huge classification and regression tree ensembles for decision tree-based group learning [55]. This study classified LULC using the four most prominent ML classifiers, which have various image segmentation/classification advantages [56-59]. During QGIS model development, classifier parameters are set.

Support vector machine (SVM)

SVM was created for binary classification [60]. Developed on SRM. Data is classified using hyper-spectral planes. This procedure maintains a maximum margin width according to vectors [61]. SVM supports continuous, categorical, linear, and non-linear variables and samples with different class memberships. SVM margins and hyperplanes are defined by support vectors [62]. Although polynomial and radial basis function (RBF) kernels are used most often in remote sensing [63], RBF is the most accurate approach for LULC classification. The original SVM approach starts with data and seeks the optimal separating hyper-plane to partition the datasets into classes. SVM requires a decent kernel function to create hyperplanes and reduce classification errors [64]. SVM kernel type is crucial. SVM functionality is largely governed by kernel size, while smooth surface similarity is determined by kernel density. Genetically optimized SVMs excel on simulated and real-world hyperspectral satellites [65]. SVM's main task is to define the optimal boundary that maximizes support vector separation [66-67].

K- nearest neighbor (KNN)

The k-NN classifier is distinct from other classifiers due to the fact that it is not trained to produce a model. Rather than that, each sample that has not been identified is directly compared to the data that was used for training [68-69]. Among the k training samples that are closest to the feature space, the unknown sample is assigned to the class that occurs the most frequently. For this reason, a choice boundary that is exceedingly detailed is produced by a low k number, whereas a decision boundary that is more generic is produced by a higher k value. As the number of training samples rises, it is anticipated that k-NN classification will require a greater number of resources due to the absence of a trained model [70].

4.1.3 Decision tree (DT)

The DT is one of the machine learning classifiers that is the clearest in terms of reasoning. A mechanism for recursively separating the data that is provided is contained within this method. One way to segment the data is to determine whether the value in a given band is greater than or less than a threshold. For example, this might be done. An analogy of a tree is used to explain the general pattern of recurrent splits [71]. The branches of the tree indicate the potential paths between splits, while the leaves of the tree represent the eventual target values. On the other hand, the values of the leaf in a classification tree stand for classes, whereas in a regression tree, the leaf represents a continuous variable. An if–then rule collection is a visual representation that may be used to illustrate the reasoning behind the model. When categorical data is used, DTs may be utilized, and once the model is formed, classification can be accomplished very quickly. This is because there is no need for any additional difficult mathematics. The risk of DTs producing an inefficient solution and overfitting are two of the many problems associated with the use of DTs [72-73]. In most cases, the latter problem is remedied by conducting tree trimming, which comprises removing one or more levels of splitting (i.e. branches) [74-75].

4.1.4 Random Forest (RF)

The RF algorithm has been utilized widely in order to address environmental concerns such as the management of hydrological resources and disasters [76-77]. It is able to process a wide range of data formats, consisting of satellite photos and numerical data, amongst others [78]. The system is an ensemble learning system that is based on decision trees and combines enormous ensemble regression trees with categorization trees. In order to configure the RF model, there are two parameters that are necessary; these values are known as the method's base parameters. The first of these is the number of trees, which can be explained using the "n tree" approach, and the second is the number of features that are present in each split, which can be explained using the "m-try" method. The classification trees provide every person with the opportunity to choose or vote, and they precisely classify the trees throughout the entire forest in order to manage the vote of the majority [79-80].

5. DISCUSSION

The comparative analysis of machine learning (ML) approaches for Land Use and Land Cover (LULC) classification highlights significant advancements and persistent challenges in the field. This section synthesizes the key findings from the systematic review, offering insights into the strengths, limitations, and potential improvements for these approaches. In this comparative analysis of machine learning-based approaches for land use and land cover (LULC) classification, we examined various methodologies and their effectiveness in geographical applications. The approaches reviewed include traditional machine learning techniques such as Support Vector Machines (SVM), Decision Trees (DT), and K-Nearest Neighbors (KNN), as well as more advanced methods like Random Forests (RF).

The machine learning techniques rely heavily on feature extraction, which involves manually selecting and engineering features from raw data. This process can be time-consuming and prone to human error.

The techniques and data augmentation strategies are crucial to mitigate overfitting and enhance generalization. In contrast, traditional methods such as Random Forests, which aggregate predictions from multiple decision trees, tend to be more robust against overfitting due to their ensemble nature.

The methods such as SVMs and KNNs are also effective when the data dimensionality is manageable and when the focus is on specific land cover types with well-defined features.

The advantage of traditional machine learning models is their interpretability. Techniques like Decision Trees and SVMs provide clear insights into the decision-making process, which can be valuable for understanding model predictions and for regulatory compliance.

The integration of machine learning techniques with emerging technologies, such as satellite-based sensors and real-time data analytics, holds promise for enhancing LULC classification accuracy and efficiency.

6. CONCLUSION

In conclusion, this study compares land use and land cover (LULC) classification machine learning (ML) methods. The findings show that ML approaches have improved LULC analysis, particularly in handling huge datasets, classification accuracy, and geographical data interpretation. Each ML model—SVM, K-Nearest Neighbor, Decision Tree, and Random Forest—has benefits and limitations based on the application and geographical environment. SVM excels at hyper-spectral data classification, KNN at low-resolution pictures, DT at simplicity and speed, and RF at processing varied data formats and reducing overfitting.GIS and ML improve geographical data visualization and analysis, improving environmental management, urban planning, and agricultural monitoring decisions. Remote sensing and enhanced image processing have helped map precisely by collecting comprehensive LULC changes throughout time. Optimizing ML models for LULC applications, especially balancing accuracy and computing economy, remains difficult despite these advances. The next research should improve these models, investigate deep learning, and integrate ML with GIS for real-time LULC monitoring. Precision and efficiency in LULC categorization methods will increase as human activities damage the environment, making this area of study crucial for sustainable development

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