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Review Article

Advanced Deep Learning Approaches for Satellite Image Classification: Trends, Techniques, and Challenges

Kinjal Patel[1], Kaushika Patel[2*]

[1]*Gujarat Technological University, Gujarat, India.*
[2]*Department of Electronics Engineering, BVM Engineering College, Gujarat, India.*

[*]*Corresponding Author : kdpatel@bvmengineering.ac.in*

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Abstract - *For the purpose of detecting satellite images, researchers contributed a significant amount of effort and time over the course of many years in developing a broad number of different techniques. The vast majority of these models are intended to perform a certain task, with a specific kind of satellite image being the primary focus of their efforts. The classification accuracy of complex images continues to be inadequate, despite the fact that there have been developments in satellite image tools and object-based image analysis tools for the purpose of analyzing high-resolution temporal and spatial satellite images. It is possible that the primary reason for this inadequacy is due to the substantial variation in the spectral and spatial properties of the images, which makes the classification of diverse land cover classes more challenging. This paper explores recent advancements in satellite image classification, highlighting deep learning methodologies, multispectral and hyperspectral image analysis, and AI-driven strategies that combine machine learning with remote sensing. It also analyzes the function of transfer learning in satellite image classification, discussing significant challenges and opportunities. A comparative analysis of the available literature is presented, together with insights into existing challenges and future directions.*

Keywords - *Deep learning, Land cover classification, Remote sensing, Satellite image classification, Transfer learning.*

1. Introduction

Over the past several years, significant advancements have been made in the field of satellite imaging. The development of a large collection of satellite images with high resolution has become significantly more accessible as a result. With this approach, a significant number of researchers working in the field of satellite imaging and classification have been migrating from more conventional methodologies to more modern ones [1]. In order to get ground information through the utilization of satellite image technology, one must first utilize a variety of operational platforms to detect images from satellites and then continue to process the data. This methodology is commonly referred to as "ground truthing." As the technology behind satellite images continues to progress, the images need to be utilised appropriately to identify the area of interest, along with related challenges. Image classification using satellite imaging is a significant issue [2]. Through the application of cutting-edge Earth satellite technology, high-resolution satellite images may be obtained for the purpose of observing the surface of the planet. Despite that being stated, the processing of significant amounts of satellite images presents noteworthy challenges for the interpretation algorithms that are now in use [3]. Figure 1 shows a live satellite image for tracking live weather, hurricane tracker, and forecast maps of wind and temperature for a selected location. The study of ground image processing technologies is important for improving remote sensing [4]. Remote sensing and the applications that are associated with it are among the primary causes for the advancements that have been made in the world of communication. Images captured by satellites are extremely accurate and play a significant part in the distribution of geographic information. The use of remote sensing satellite images provides data that is both measurable and of high quality, hence reducing the amount of time and effort required for fieldwork and research. The Geographic Information System (GIS) techniques have grown outdated as a result of their excessive use over the years, which has resulted in insufficient results. Therefore, it is essential to maintain a close watch on the progression of technology to keep up with the developments in this sector.

Through the utilization of satellites, remote sensing assists in acquiring information about any entity from a remote location. These remote sensing images from satellites are of considerable significance in agriculture, military, medical, transportation, and many other fields [5]. This article discusses the range of applications from diverse satellite image data with advanced deep learning methods. Figure 2 shows the process of selecting articles for satellite image classification.

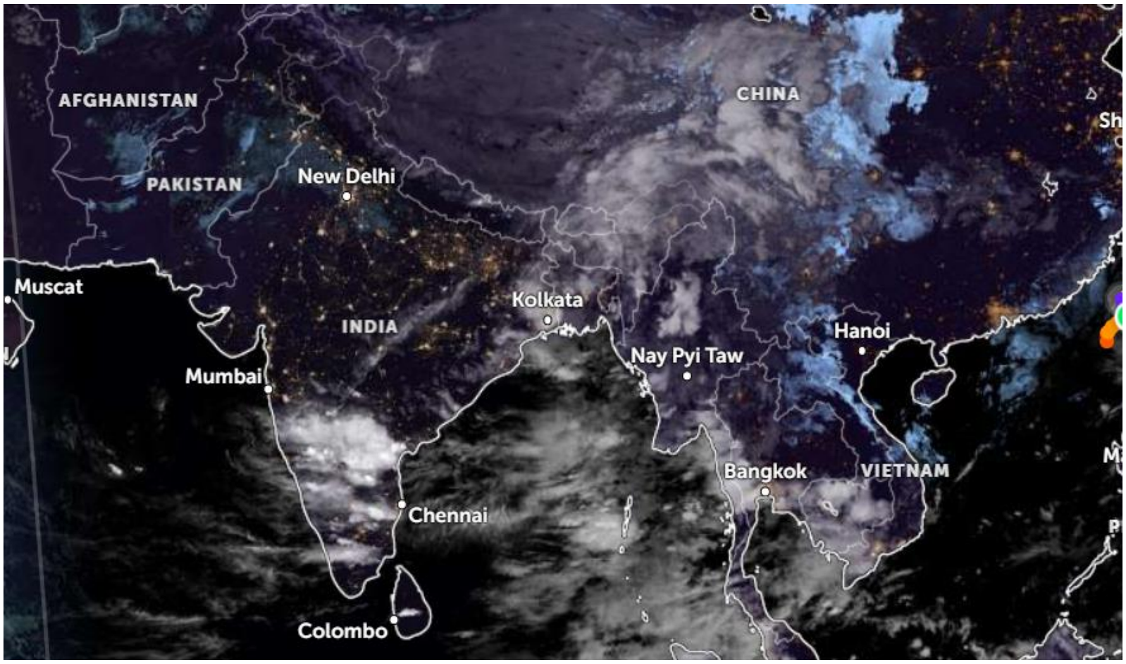

Fig. 1 Live satellite image for weather tracking

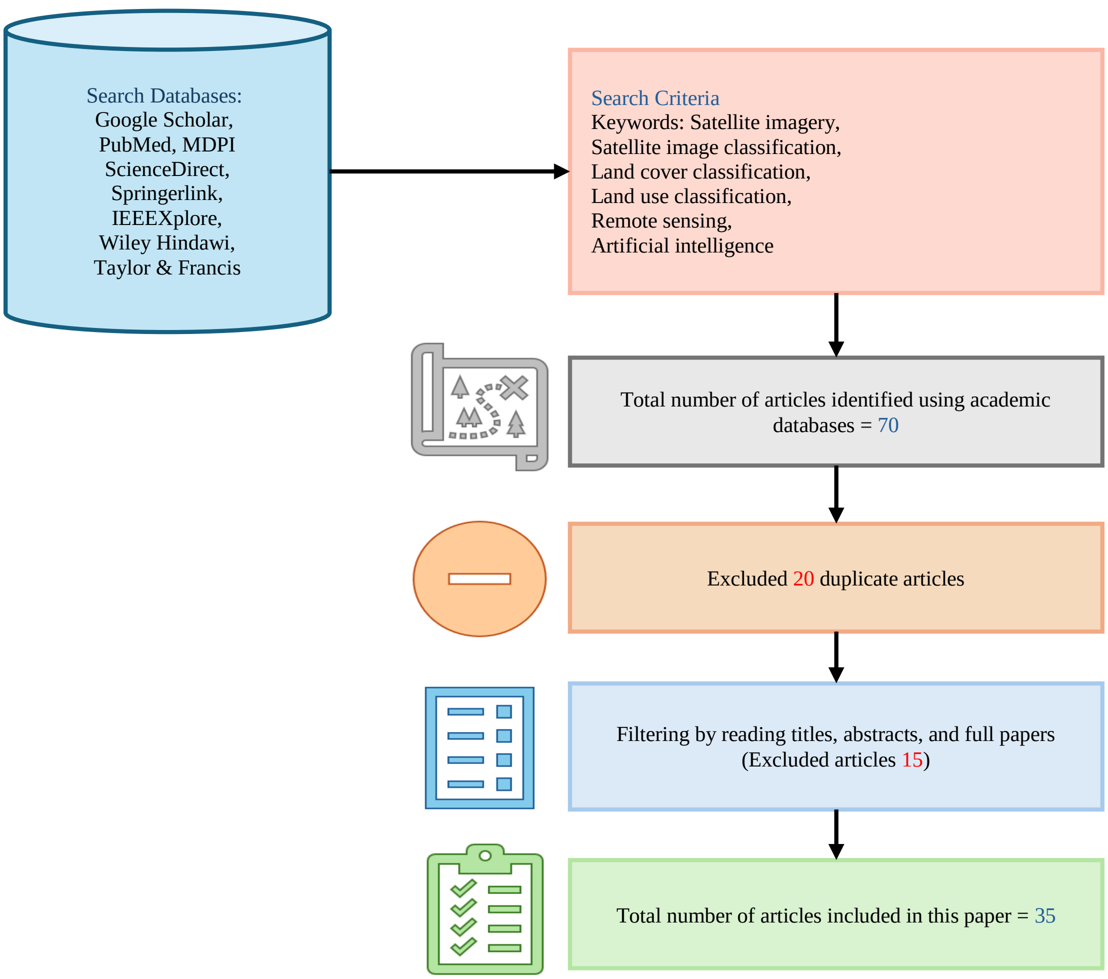

Fig. 2 Process for selection of articles

After selecting the required articles to analyse existing methods for satellite image classification, this article consists of the following sections. Section 1 is an Introduction, followed by Section 2, which discusses Deep learning techniques in satellite image classification. Section 3 explores Advances in multispectral and hyperspectral image classification. Section 4 explores AI-driven satellite image classification: integration of machine learning and remote sensing. Section 5 discusses Transfer learning in satellite image classification: challenges and opportunities. Section 6 Comparative analysis of existing Deep learning methods. Section 7 outlines Challenges and future directions. Section 8 is the Conclusion, which concludes the work. Figure 3 shows the paper organization flow of the entire manuscript.

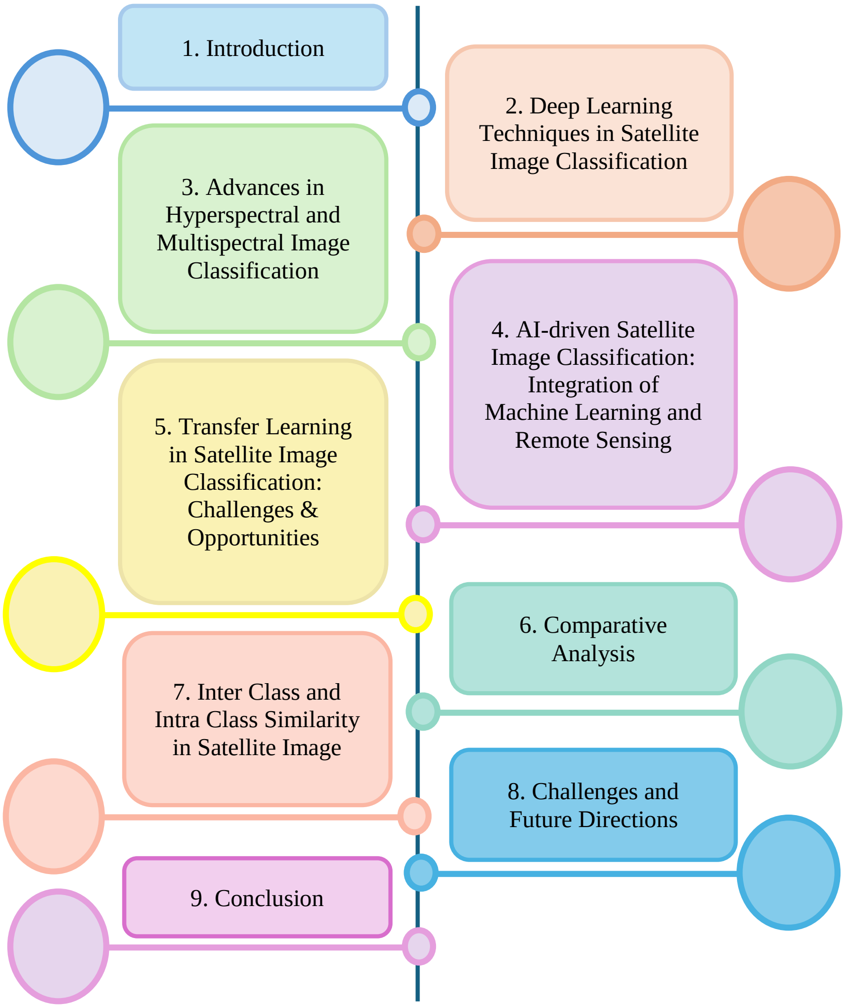

Fig. 3 Paper organization

1.1. Paper Contribution

- The state-of-the-art trends in satellite image classification using deep learning methods
- New developments in multispectral and hyperspectral automatic image classification
- AI-driven satellite image classification: the coupling of artificial intelligence and RE
- Transfer learning in satellite image classification: challenges and opportunities & Comparative Analysis

Further, the paper expands on the presented challenges and further research directions and finishes with a summary of the paper.

1.2. Problem Statement

The classification of satellite imagery has long been a central challenge in remote sensing, particularly when dealing with heterogeneous and high-resolution data.

Existing methods, including traditional classifiers and more recent deep learning and object-based image analysis techniques, often perform well only on specific datasets or narrowly defined image types. This task-specific design, together with strong variability in spectral and spatial characteristics, leads to inconsistent and often inadequate performance when classifying complex land cover patterns in diverse environments.

1.3. Research Gaps

These persistent limitations reveal a clear research gap: current satellite image classification approaches lack robust generalization across varying spatial resolutions, spectral configurations, and land cover classes. In particular, there is insufficient understanding of how to effectively integrate deep learning, multispectral, and hyperspectral information, and transfer learning strategies into a unified framework that can handle spectral–spatial variability while maintaining high accuracy.

Furthermore, existing studies rarely provide a comprehensive comparative perspective that jointly examines methodological advances, practical constraints, and future research directions in satellite image classification. Addressing this gap motivates the present work, which systematically reviews recent techniques and evaluates how emerging AI-driven strategies can be leveraged to improve the reliability and scalability of satellite image classification systems.

2. Deep Learning Techniques in Satellite Image Classification

According to Reference [6], various deep learning algorithms can improve satellite image classification effectiveness. It is possible to acquire accurate classification results by combining a number of different Convolutional Neural Networks (CNNs) with segmentation methods that are suitable for the application. Nevertheless, these models depend on the context and cannot be generalized due to this fact. The purpose of this research is to offer a new and better deep-learning model for the classification of satellite images based on regions in real-time. This is done in order to improve the model's performance in a variety of circumstances by training it using images of different types of crops, water, urban, and terrain. Time-based methods are utilized in the process of collecting all imagery information by Google Earth Engine. Images are first classified according to the type of crop and the harvest season, and then all images are provided to a CNN model that has been trained to differentiate between these characteristics.

The preliminary classification is accomplished by this model by the utilization of a variety of methods, such as VGGNet 19, Google Net, and ResNet V2. The final image is generated with the application of a thresholding method layer for post-processing, which is performed after classification. This data can be utilized by researchers to apply the proposed model in part(s) or as a whole for applications that are particular to satellite image processing.

In Reference [7], the proposed method is analyzed in this research in comparison to several other deep learning models to determine how effective it is in the classification of urban villages. To accomplish the satellite branches and the street-view branches, respectively, the Trans-MDCNN and MVRAN that were suggested were employed. In its place, well-known deep learning models have been utilized, and to maintain a level of fairness, the training set and the test set have been maintained in their original state.

Both conventional CNN models, such as VGG, ResNet, DenseNet, and EfficientNet, as well as the Vision Transformer (ViT), which is frequently utilized, were taken into consideration for the purpose of providing an analysis. With an average OA gain of 3.4%, the Trans-MDCNN model that has been developed beats other models that are already in use. Furthermore, multiscale inflated convolutional blocks are proposed in order to learn about the local characteristics of urban villages on several levels.

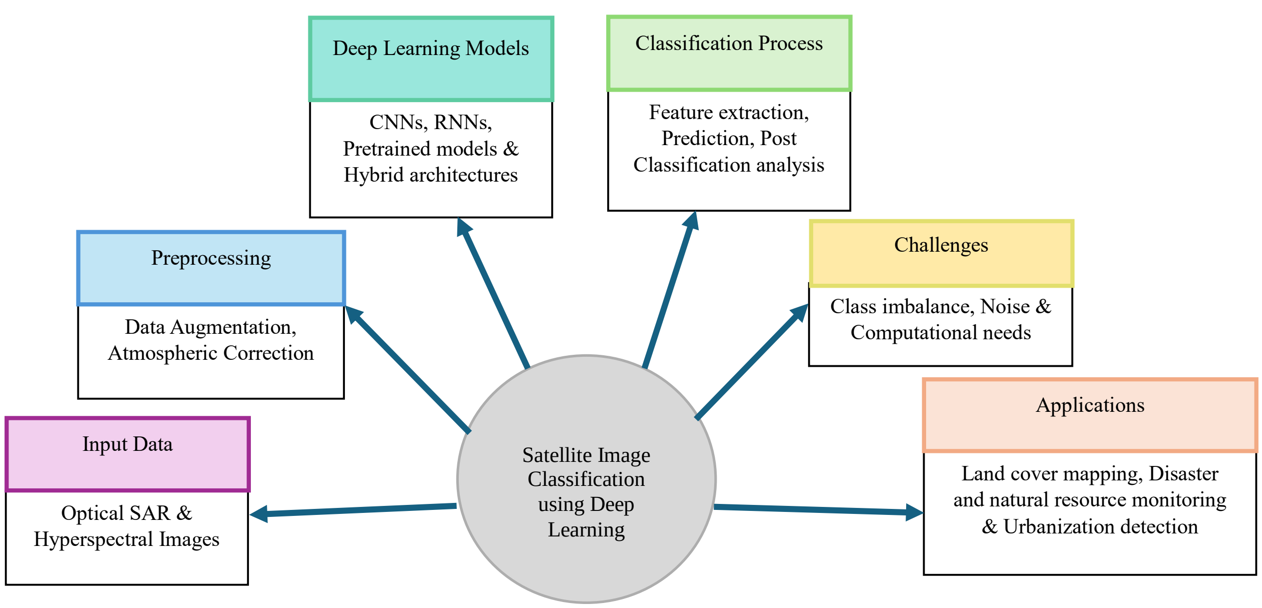

Fig. 4 Satellite image classification using deep learning process

This is due to the fact that the combination of CNN and Transformer offers a number of advantages. The next step is for the Transformer to acquire global features by learning residual connections. Through the use of satellite pictures, the Trans-MDCNN is able to successfully extract both local and global characteristics, which results in excellent inter-class separability. Additionally, other models should be used in place of the deep learning model that is used in the street-view branch of the EfficientNet. With an average OA increase of 6.28%, EfficientNet outscored VGG, ResNet, and ViT in this research because of its superior performance. The neural network that comes with EfficientNet strikes a compromise between breadth, depth, and resolution, which results in strong learning of the properties of urban villages based on street-view illustrations.

In Reference [8], Automatic landslide detection and classification using satellite images are crucial. Classification methods include standard machine learning and Deep Learning model-based techniques. To extract and choose features, machine learning utilizes an explicit technique, while deep learning uses an implicit approach for classification.

The deep learning model uses hidden network layers to extract and choose characteristics without supervision, resulting in more accurate outputs. Previous research suggests that utilizing satellite images for autonomous landslide detection and classification requires improving trainable parameters during training. The optimization technique in deep learning enhances model efficiency, accuracy, and learning speed during training.

The proposed work utilizes the Bijie dataset, which includes 770 landslide and 2000 non-landslide satellite images. The dataset is produced by preprocessing images. Image enhancement improves the database sample size. The images are all the same size and format. The dataset is separated into two categories: landslide and non-landslide. About 70% of the data is utilized for training and 30% for testing the model. To maintain uniqueness, images from the training dataset are excluded from the testing set. The train-test ratio affects the model's learning rate, which is the predicted error response while updating weights. Several hyperparameters that have to be considered in the training procedure of the network are the batch size, learning rate, momentum, and epoch. An attention technique on the feature map based on a proposed model with a backbone convolutional network taken from ResNet101 is applied.

According to the Reference [1, 9], using pretrained models, this research develops effective methods for the classification of satellite images with AlexNet, VGG19, GoogleNet, and Resnet50 for the extraction of features. Additionally, the research generates efficient strategies for the classification of satellite images. A more positive result is obtained by the Resnet50 model when compared to the results obtained by earlier models on three different datasets, namely SAT4 (95.8%), SAT6 (94.1%), and UC (98%) Merced Land.

3. Advances in Multispectral and Hyperspectral Image Classification

The research presents an automated method for the classification of multispectral satellite images. The method was developed after an extensive investigation [10]. For this classification, image fusion is necessary but not required. The technique that is being discussed begins with the acquisition of a multispectral satellite picture, which is followed by the use of the Brovey transform method to merge three RGB bands. A panchromatic band with a spatial resolution of 30 meters and 15 meters, respectively, is also incorporated into this method appropriately. Following this, the technique of PCA is applied to the merged images to minimize the size of the images.

Following that, a Convolutional Neural Network was utilized for classification. It has been determined that the proposed approach is compatible with FCM, GIFP-FCM, and FKLICM in terms of classification outputs. Images collected from the Landsat 8 OLI multispectral satellite have been processed using this technology. A total of five different groups has been assigned to the images to facilitate the detection of various forms of land cover. Through the computation of the kappa coefficient and several other accuracy metrics, the proposed approach is evaluated to determine its effectiveness. The findings obtained demonstrate that the proposed approach produces results with a high degree of accuracy. It has been demonstrated through a comparative analysis of the findings with the other approaches that are considered to be state-of-the-art; therefore, it is possible to make efficient use of the proposed approach to solve the challenges associated with land cover classification.

In Reference [8, 11], several researchers remove noise from multispectral images, and a multi-valued anisotropic diffusion approach was utilized to collect edge information and derive local minima for seed points. Two datasets, QuickBird image and GeoEye-1, were used for experiments. The proposed approach was compared to three algorithms: standard region growth, toboggan watershed, and mean shift. With a threshold value of 0.5 and mean square spectral error, the proposed approach achieved the highest accuracy (91.15%) and kappa coefficient (96.70%). Some researchers also proposed an approach for classifying Multispectral (MS) images that uses nonparametric supervised classification. Various class statistic distributions were used to create a digital vector. In the MS image, a high posterior probability was calculated only when an unknown pixel's digital number matched a training class pixel. Given the statistical properties of the DN vector, each class vector must follow a Gaussian mixed distribution.

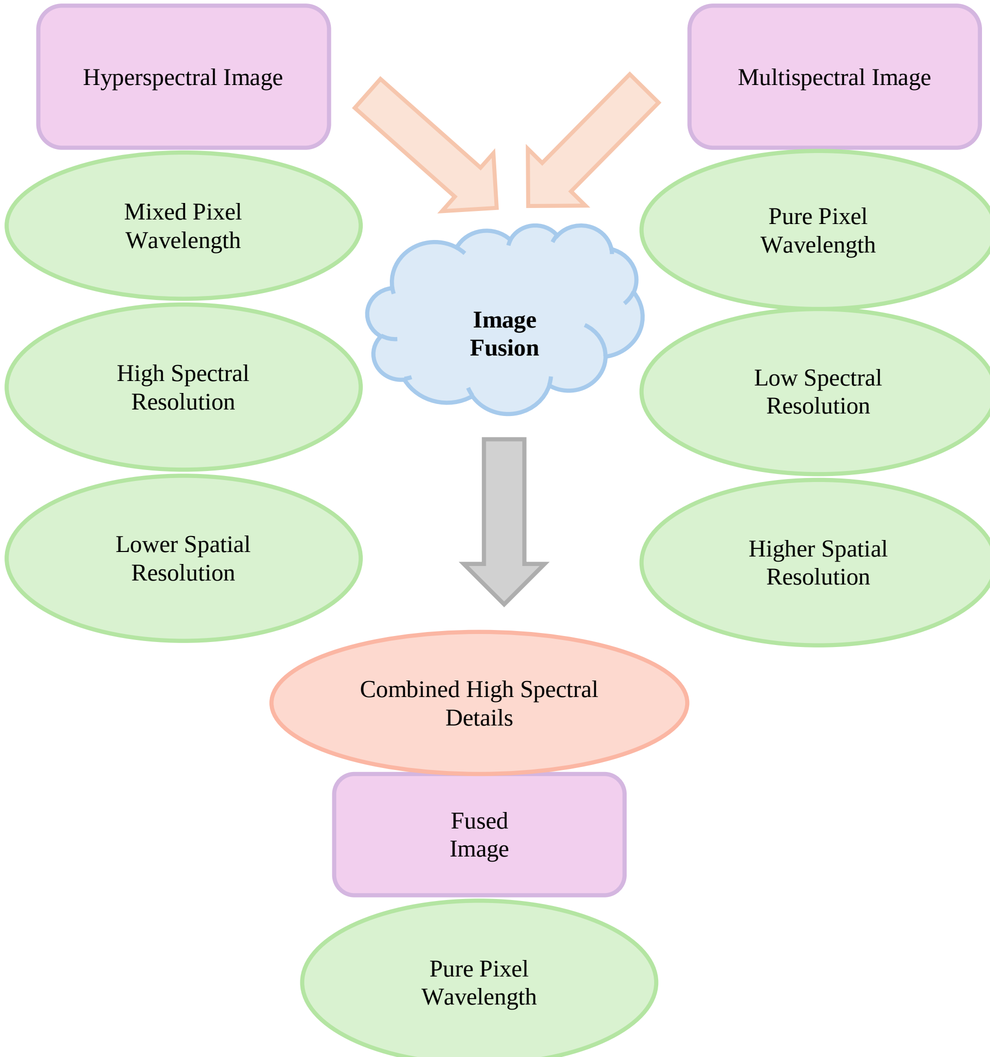

Fig. 5 Working of image fusion in multispectral and hyperspectral images (image source taken from [13])

In Reference [2, 12], A high-accuracy wavelet transform-based multispectral image classification system has been created. An RF-based classifier was utilized to classify land images in multi-data fusion with complicated backdrops. Real-world applications demand additional algorithm parameter settings. Traditional methods cannot utilize the additional information offered by distant sensing images. Deep learning can now classify distant sensing images utilizing high-resolution data and computer technological advancements. Deep learning is described by CNN, DBN, and AE models.

4. AI-Driven Satellite Image Classification: Integration of Machine Learning and Remote Sensing

Even though at a rate that has never been seen before, current techniques of AI and ML are growing and causing old terrestrial technology to become obsolete. However, the application of these techniques on board satellites appears to be trailing behind. When seen from this perspective, one of the most critical issues is the demand for high-quality annotated data to train such systems. Due to the necessity of this criterion, the process of designing solutions based on machine learning is not only costly but also time-consuming and inefficient. An example of the OPS-SAT, which is a novel data-centric competition to overcome the problems that have been discussed, is provided in this paper. It is possible to show the development of machine learning systems for space by utilizing the enormous processing capabilities of the OPS-SAT satellite, which is managed by the European Space Agency (ESA). The use of a relatively small quantity of labeled data and the utilization of open-source software that is widely utilized and accessible to the general public are how this is done [14].

According to researchers [15], when it comes to the collection of data in a variety of aspects of life, whether it be scientific, economic, or political, remote sensing is an extremely important tool.

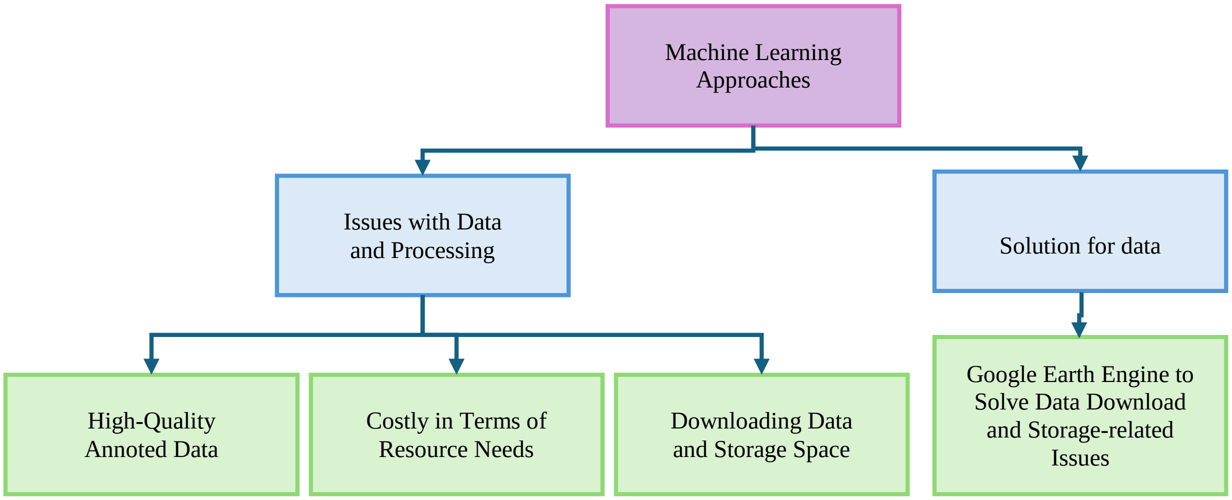

Fig. 6 Issues and solutions related to machine learning approach

Nowadays, there is a significant demand for precise information on land cover. It is becoming increasingly popular for researchers to undertake research that involves the utilization of satellite images and remote sensing techniques for planning and development. The goal of this research is to discover practical answers to the many challenges that are harming the Earth. The recovery, processing, and interpretation of these massive volumes of satellite images present several significant issues. The classification of satellite imagery is a subject that is both widely discussed and extremely complicated. In classification studies conducted in the last decade, the entire focus was on the three machine learning algorithms known as RF, CART, and SVM. These algorithms have been utilized in cities or countries other than Morocco, which has resulted in a significant shortage of knowledge regarding land use in Morocco. Using the Google Earth Engine, it is possible to bypass this problem by implementing six different algorithms and comparing them on a variety of evaluation criteria. So, the problem of downloading data and storage space came to be avoided using the Google Earth Engine.

A natural calamity or a disaster caused by humans that results in the loss of life is called a landslide. The building cannot be stopped, and the natural factors that cause landslides cannot be regulated. This is because the country is still in the process of developing. In light of this, an early warning system has the potential to save lives from such risks. It is possible to engage in pre-processing of satellite image databases to extract the features that will be used to train the model for the identification of landslides using artificial intelligence. When it comes to utilizing a wide range of data sources and providing assistance for geographical information analysis to reduce the risk of calamities, artificial intelligence and machine learning are essential in the digital era. Examples of neural networks that have achieved an accuracy of more than 90 percent in their analysis include recurrent and convolutional neural networks [8, 11].

5. AI-Driven Satellite Image Classification: Integration of Transfer Learning and Remote Sensing

Parallel plots display transfer learning fine-tuning experiment results. Results from these experiments were lower than those from previous research using pre-training on ImageNet. Despite extensive hyperparameter research, the pre-training strategy on ImageNet consistently produced better results. Transfer learning might result in lower outcomes than pre-training due to many variables.

Because of differences in content, distribution, and complexity, the source datasets that are utilized for transfer learning are not the same as the target set. There is a possibility that ineffective adaptation will occur during transfer learning if the qualities that were learned do not correspond to the problem area.

Additionally, it is possible that the hyperparameters that were chosen, such as the frozen layer count and the learning rate, were not appropriate for the dataset that was being targeted. Negative transfer is the term used to describe the phenomenon of transfer learning that takes place and results in bad performance. The performance of models and their adaptability to a variety of satellite missions can be improved by the use of transfer learning research on larger satellite image datasets. Future research can improve on-board AI systems by improving their ability to interpret and extract insights from satellite images, leading to improved satellite mission performance [16].

Traditional techniques for developing classification include features that are handcrafted and transfer learning. Low accuracy in highly populated metropolitan regions and restricted performance with high-resolution satellite images are common issues with these systems due to variations in building forms, orientation, and perspective.

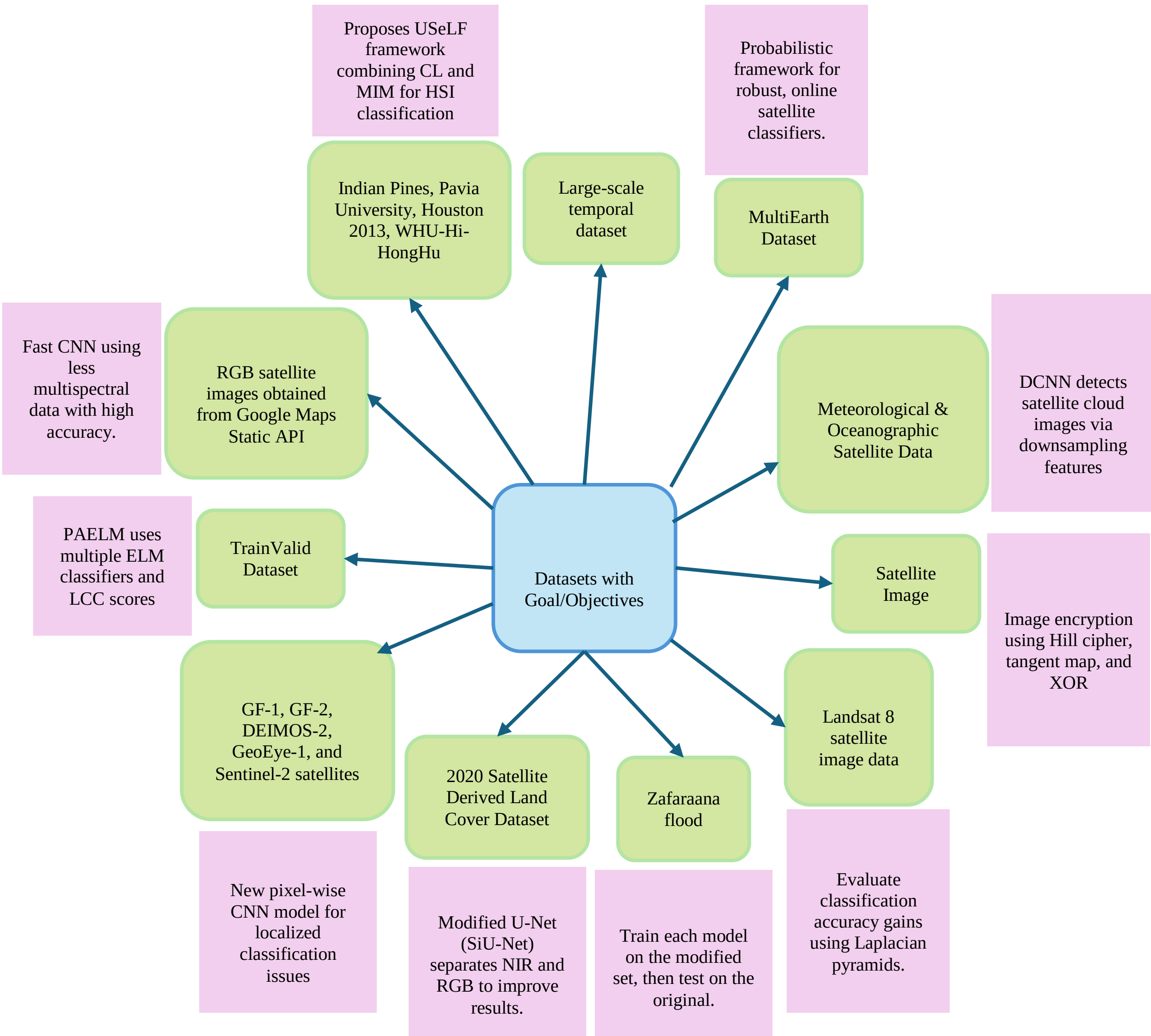

Fig. 7 Datasets and related objectives for satellite image classification

This paper develops a deep learning-driven method to perform segmentation of urban areas using U-Net and ResNet-34 for classification. SAS Planet has developed the dataset for the same with images of resolution 0.5 m. One-hot encoding is used for the classification of buildings. The encoded data is applied to the U-Net for training.

The proposed algorithm was tested on an Indian dataset, particularly on the urban areas of the Nashik region in the state of Maharashtra. The classification dataset achieved 60% accuracy, while the building detection achieved 85% accuracy. Bi-temporal images are used to compute change detection. The informed maps from GIS show changes in buildings, using various colors to differentiate new, existing, and demolished structures [17].

This article explores transfer learning in satellite image quality assessment, which strengthens a model's adaptability to new tasks by using previously gained information. Transfer learning is a useful technique for satellite image processing due to restricted dataset availability. The article presents a YOLOv5-based transfer learning system for satellite image quality assessment. Initial training uses a large dataset of natural images to build a generic convolutional neural network model. The early layers of the model remain fixed while subsequent layers are trained to respond to satellite image data. Further model performance improvement is achieved by fine-tuning. Satellite image damage assessment accuracy is good with this method. Unlike standard deep learning approaches, the proposed approach uses pre-trained models' experience to reduce data reliance. Additionally, its generalization capabilities are strong across multiple tasks and datasets, showing transfer learning potential across domains [18].

6. Comparative Analysis of Existing Literature

As per recent research of the current decade, several datasets are utilized for a range of applications along with the advanced algorithms of deep learning. Figure 7 discusses diverse datasets with targeted applications. Each dataset is applied to advance deep learning models, enabling them to achieve the target aim and objective. However, there are still a few limitations and challenges with data and applied methods, which are discussed in Table 1.

Table 1. Literature review analysis for existing methods

Ref	Dataset with Utilized Application	Methods / Algorithm Used with Accuracy	Limitations
[6, 20]	Large-scale temporal dataset using Google Earth Engine, real-time satellite images.	The proposed model achieves 98.9% crop type recognition, 95.4% land type identification, and 96.5% water and urban cover area classification accuracy.	Future research can enhance performance by applying approaches such as Q-Learning, reinforcement learning, and RNNs to reduce additional information and improve accuracy and performance.
[21]	MultiEarth Dataset, Water Mapping & Deforestation in the Amazon	In water mapping, RBC improves balanced classification accuracy by 26.95% for SIC, 13.81% for LR, and 12.4% for GMM. The accuracy of deforestation identification improved by 15.25% for SIC, 14.17% for GMM, and 14.7% for LR. By using recursion, RBC improves the accuracy of state-of-the-art deep learning models, such as DeepWaterMap (9.62%) and WatNet (11.03%), without extra training data.	Future research will address missing data from cloud cover and other disturbances in satellite imaging, as well as ways for automatically analyzing class change probabilities.
[22]	Meteorological & Oceanographic Satellite Data Archival Centre, a Vast satellite meteorological application	A Python-based deep convolutional network was developed using the Keras API and TensorFlow as the front and back ends.	Future research might explore CNN-based approaches that operate directly on satellite photos without affecting image properties or processing performance.
[23]	Satellite Image Encryption	Encryption technology can be made more secure by the integration of AI algorithms. The impact of AI on diabetic retinopathy diagnosis, cancer detection, and bio-mathematical problems has hinted at the potential of adaptive encryption methodology.	Encryption technology can be made more secure by the integration of AI algorithms. The impact of AI on diabetic retinopathy diagnosis, cancer detection, and bio-mathematical problems has hinted at the potential of adaptive encryption methodology.
[24]	Landsat 8 satellite image data, Remote Sensing application	The research purpose is to present fascinating details about utilizing the Laplacian pyramid in remote sensing classification.	The research purpose is to present fascinating details about utilizing the Laplacian pyramid in remote sensing classification.
[25]	Zafaraana flood, European Space Agency Sentinel Application Platform	Researchers will test and confirm the approach in numerous locations, focusing on the south valley. This will only improve the Red Sea coastline satellite image classification.	Researchers will test and confirm the approach in numerous locations, focusing on the south valley. This will only improve the Red Sea coastline satellite image classification.
[26]	RGB satellite images obtained from Google Maps Static API, Accurate and efficient	Misclassifications occur between visually similar classes; the model captures only the dominant class in mixed LULC images, is limited to RGB data, and may	Misclassifications occur between visually similar classes; the model captures only the dominant class in mixed LULC images, is limited to

	LULC classification for use as a web-based classification service	require fine-tuning for other geographic regions.	RGB data, and may require fine-tuning for other geographic regions.
[27]	2020 Satellite Derived Land Cover Dataset, Land Cover Classification	To improve land cover classification using multispectral satellite data, future research should quantify the number of encoders based on spectral band correlation coefficients.	To improve land cover classification using multispectral satellite data, future research should quantify the number of encoders based on spectral band correlation coefficients.
[28]	GF-1, GF-2, DEIMOS-2, GeoEye-1, and Sentinel-2 satellites, Geological Application	SPP may significantly minimize speckles in pixel-wise classification results, enhancing the accuracy and visual appeal of the proposed technique.	SPP may significantly minimize speckles in pixel-wise classification results, enhancing the accuracy and visual appeal of the proposed technique.
[29]	TrainValid Dataset, Regional scale application	However, future work should focus on reducing PAELM's operating time and enhancing its flexibility through optimization. Although ELM was a suitable base classifier for developing PAELM, it is recommended to use other classifiers or a different number of classifiers in the ensemble system to improve performance.	However, future work should focus on reducing PAELM's operating time and enhancing its flexibility through optimization. Although ELM was a suitable base classifier for developing PAELM, it is recommended to use other classifiers or a different number of classifiers in the ensemble system to improve performance.
[36]	Indian Pines, Pavia University, Houston 2013, WHU-Hi-HongHu	Hyperspectral image land-cover classification in agricultural and urban scenes using self-supervised pre-training with downstream supervised classification.	Unified Self-Supervised Learning Framework (USeLF) combining contrastive learning and masked image modeling for pre-training, followed by supervised fine-tuning; achieves higher OA/AA/Kappa than prior SSL methods (e.g., SSLSM, 2CSL, SS-MTr) and supervised SpectralFormer on all four datasets.

7. Inter-Class and Intra-class Similarity in Satellite Image

This subsection covers the inter-class and intra-class diversity present in the satellite images. The inter-class diversity implies that some objects detected by the machines possess similarities with one another when captured from the satellites. The example is shown below in Figure 6.

There are various types of roads taken by the satellites, which look very much alike, although they are very different from one another. For a machine to detect and differentiate between these categories, it is an overhead.

Similarly, the concept of intra-class defines the similarity of the structural and monumental premises in the images captured by the satellites and their difficulties in recognizing them through various artificial intelligence models. These two properties of similarity play a major role in the identification of the challenges while distinguishing and differentiating several types of satellite images using artificial intelligence.

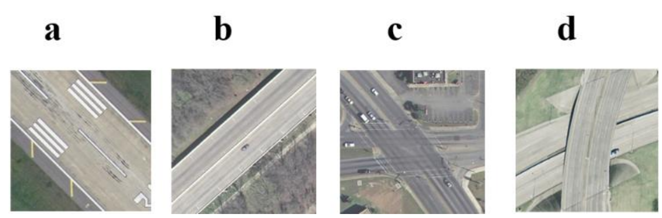

Fig. 8 Inter-Class Diversity: types of roadways, (a)Runway, (b)Freeway, (c)Intersection, and (d)Overpass [33].

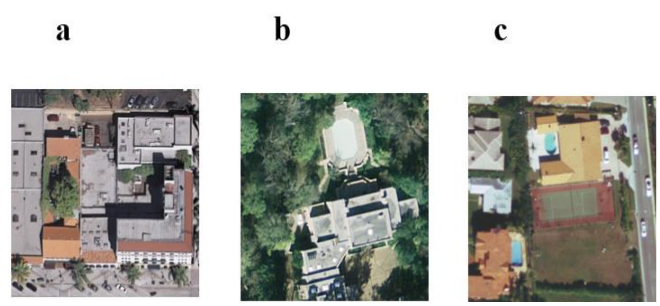

Fig. 9 Intra-Class Diversity: Places, (a)Building, (b)Sparse-Residential, anb (c)Tennis Court [33].

8. Challenges and Future Redirections

Satellite image classification faces several challenges, including the quality of high-resolution images, the need for better algorithms, and the integration of unreliability in predictions.

- This research aims to enhance region detection in satellite images to overcome the mentioned challenges. To discover regions in satellite images in real-time, the detection algorithm faces significant challenges in detection speed. YOLO neural networks have been shown to improve detection time by merging object classification and localization into a single regression task. The latest version of YOLOv5 has the finest object detection performance in natural images. YOLOv5 uses a path aggregation network (PANet) and upgraded CSPDarknet53 as its neck and backbone, respectively [1].
- Automated landslide detection requires real-time remote sensing data from satellite images and rapid algorithms for processing [8].
- Obtaining large-scale data sets for training a machine learning algorithm might be challenging, limiting the model's capacity to accurately detect landslides [8].
- To automatically detect and classify landslides, extract important features from the database to correctly differentiate between landslide and non-landslide images [8].
- Landslides are influenced by various environmental factors, including rainfall, soil type, and topography. Considering these features requires a more precise feature selection approach for machine learning models [8].
- Large volumes of satellite images provide significant challenges for recovery, management, and interpretation [15].
- Classifying buildings with complicated forms leads to decreased model performance due to non-rectangular or unusual geometries [17].
- In densely populated metropolitan regions, building density, complicated spatial arrangements, and overlapping structures may prevent correct classification, restricting model generalization. These challenges will be tackled in future work [17].
- This work addresses the constraints of limited datasets in post-disaster configurations by freezing early layers and fine-tuning subsequent layers [18].
- Preventing unauthorized access to satellite images is a significant challenge in real-world applications. Researchers must continuously create algorithms to protect satellite data from cyber intrusions as risks from bad individuals evolve [23].
- Limited dataset diversity, class imbalance, noisy satellite imagery, CNN overfitting, PSO parameter tuning complexity, and high computational demands hinder robust deployment [30].
- Despite advances in deep learning, present models fail to evaluate and enhance semantic segmentation strategies for remote sensing data [32].

8.1. Future Directions

- Deep Learning Models: CNNs and vision transformers may be improved to enhance classification accuracy and efficiency [19, 31].
- Increasing the degree of similarity between classes and within classes in satellite imagery requires the use of sophisticated approaches in the areas of feature representation and similarity evaluation. To overcome the challenges that are presented by high-dimensional data, the incorporation of innovative loss functions and distance metrics has the potential to considerably enhance the performance of content-based image retrieval (CBIR) systems [34].
- Utilizing balanced deep linear discriminant analysis can maximize interclass variance over intraclass variance, which ultimately results in improved feature representation [35].

9. Conclusion

There is a total of 35 publications that have been referred to in this review research. These papers were obtained from various research databases as well as indexing engines such as Google Scholar, Scopus, and Web of Science. In this review paper, the state-of-the-art techniques in satellite image classification are discussed.

These techniques include the incorporation of deep learning techniques associated with it, advancements in multispectral and hyperspectral image classification, artificial intelligence-driven satellite image classification that incorporates machine learning and remote sensing, and transfer learning techniques. After an in-depth review of satellite image classification, this article concluded that although researchers have made significant efforts, there are still a great deal of challenges to overcome in this research, and further efforts will be necessary in the work that will be done in the future.

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