

Deep Learning Approaches For Satellite Image Classification: A Review

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Abstract:

The classification of images has attracted significant attention due to its applications in several computer vision tasks, including satellite imaging, image analysis, surveillance, object recognition, and image retrieval. The primary objective of image classification is to provide class labels to images based on their content. The applications of imagery classification and analysis in remote sensing are significant since they are utilized in many sectors, including military and civilian areas. In satellite imagery, the challenge of image classification is heightened due to the rotation of objects inside a view and the typically varied background. This review paper discusses satellite image classification through various deep learning approaches, including its historical background and current approaches. It finds the most appropriate classification techniques for different types of satellite images and discusses the impact of preprocessing methods on classification accuracy. Moreover, a comparative analysis of several studies is given based on different parameters such as research objectives, used datasets, methods/algorithms, limitations, etc. Specific case studies that have significantly contributed to the understanding of satellite image classification are also discussed; further, an overview of challenges and future research directions in this field is also provided.

Keywords : GIS, Satellite Imagery, Artificial Intelligence, LULC

1. INTRODUCTION

In the last 100 years, remote sensing (RS) has been increasingly popular due to its essential function in several domains, including agricultural growth monitoring, land use and land cover change forecasting, and disaster analysis. At present, governments are making use of satellite imagery for a variety of purposes, including political decision-making, activities related to civil security, law enforcement, and systems for geographic information. The classification of satellite images is required for each of these applications to get useful information from them [1]. Through the process of satellite classification, images are classified into important categories based on their pixels. It is possible to achieve this objective by a variety of methodologies and procedures that are either supervised, unsupervised, or semi-supervised. According to the findings of several research, neural networks (NN) have the potential to observe the human knowledge acquisition process by associating visual pixels with suitable and meaningful labels. To increase classification accuracy and allow the smooth introduction of auxiliary data into the classification process, neural network-based algorithms are applied in the process of satellite image classification [1]. Satellite images acquired by remote sensing are one of the image varieties utilized for classification purposes. High-resolution satellite imagery has facilitated more effective applications by reducing the time required to address these concerns, eliminating the necessity for extensive and challenging field research. Images captured from extreme heights by remote sensing techniques reveal complicated and challenging backdrops. Moreover, the utilization of satellite imagery has gained significance to remain ahead of the escalating research and advancements in technology. It has become imperative to enhance research and advancement in this domain [2]. The Sentinel-2A/B satellites, which were just recently put into operation, are providing remote sensing imagery for a land cover classification case study in Beijing, China. These satellites have the highest chronological and geographic resolutions among satellites that are generally available to the public [3]. On the other hand, it is already generally accepted that the method of classification that is used can have a significant impact on the effectiveness of land use and cover mapping. Support Vector Machine (SVM), k-nearest Neighbors (KNN), Decision Tree (DT), Artificial Neural Networks (ANN), and Random Forest (RF) are some of the commonly used algorithms that help to improve the precision of land use and cover classification. This is due to the increasing computational power and advanced classification algorithms. In LCC, machine learning classifiers like as support vector machines (SVM), artificial neural networks (ANN), and radial basis functions (RF) can manage noisy and

imbalanced datasets while giving improved classification performance in comparison to previous parametric approaches. To get satisfactory classification outcomes using these machine learning approaches, the hyperparameters of the model need to be calibrated in a suitable manner. Traditional approaches frequently include the empirical establishment of hyperparameters or the manual adjustment of these parameters. As a consequence of this, the hyperparameters that are manually tuned are not sufficient for delivering accurate and reliable performance in land cover classification; hence, new techniques must be investigated. Before the implementation of a reliable and accurate classifier, it is necessary to build an automated and systematic technique for calculating the model hyperparameters [3]. This is because it is crucial to establish a process that is both automated and systematic. Numerical or threshold approaches primarily utilize visible and near-infrared bands to identify the existence of cyclones within clouds. Threshold techniques are commonly used because of their rapid computational efficiency. Nonetheless, requisite precision is essential, as these systems also produce considerable false positives. Threshold approaches are optimal for the classification of satellite cloud imagery. Numerous supervised and unsupervised methods are essential in cloud image classification. Modern deep learning techniques are frequently utilized in statistical approaches to identify cyclone activity, achieving excellent detection accuracy with little time complexity in the classification of satellite cloud imagery. Deep learning techniques are demonstrated to be resilient, producing optimal outcomes even with unstructured input. Furthermore, no foundational knowledge is necessary to create cutting-edge deep learning models [4]. This paper consists of the following sections. Section 1 is an Introduction. Section 2 discusses the Historical Background. Section 3 discusses current approaches to satellite image classification. Section 4 discusses about most effective classification techniques for different types of satellite images. Section 5 describes how preprocessing methods affect the accuracy of satellite image classification. Section 6 outlines a Comparative Analysis. Section 7 discusses how have specific case studies advanced our understanding of satellite image classification. Section 8 outlines challenges and future directions And the final section 9 is the Conclusion which concludes the paper.

Paper Contribution

This paper contributes to the literature survey and discussion of more than 25 papers. And also describes several approaches or techniques that have been utilized by several researchers.

- Current approaches to satellite image classification
- Most effective classification techniques for different types of satellite images
- Preprocessing methods affect the accuracy of satellite image classification
- Specific case studies advanced our understanding of satellite image classification
- Comparative analysis
- Challenges & future directions

2. Historical Background

In reality, one of the most crucial senses that facilitates learning, and discovery is the sense of sight. Consequently, the development of visual capabilities using machine learning has emerged as a crucial research domain for scholars. Due to the challenges associated with collecting and obtaining data for object detection and classification in images, classification might be seen as an issue concerning substantial data volumes [2]. Recently, machine learning techniques have been utilized to autonomously detect landslides. A variety of feature extraction and classification methodologies have been utilized on satellite imagery for the automated identification and predictions of landslides. Nevertheless, there has been limited study on fully automated detection with effective accuracy. The primary challenge in classifying and predicting landslides from satellite images is identifying a suitable database for training that produces highly accurate testing outcomes [5]. From the literature review, it is clear that the process of satellite image classification has developed from relatively simple to more complex models. In the early 1970s, classification was conducted via pixel-based techniques such as the K- means and maximum likelihood classifiers. In the decades that followed, improvements resulted in the use of refined methods like object-based image analysis and other high-level methods. By incorporating machine learning, especially Convolutionary Neural Networks (CNNs), the classification accuracy has been greatly improved touching a high of 95% in some cases [6] [7].

3. Current Approaches Of Satellite Image Classification

In Reference [8], In agriculture, forestry, geology, and natural resources, near-infrared images enhance classification. However, deep learning approaches that used both RGB and NIR images performed similarly to RGB images alone in classification. Because deep learning may not have properly included spectral data. Most deep learning methods mix all pixel values without band direction during convolution. This combination may lose information, especially in multi-band satellite images, where essential spectral data may be concealed. Thus, the model's accuracy and adaptability may suffer. This research introduces the separated-input-based U-Net (SiU-Net), an effective model. This model modifies the U-Net architecture by distinguishing between RGB and NIR images. Comparisons were made between the DeepLabV3+ and U-Net models to determine how effective SiU-Net is in classifying different types of land cover. The land cover dataset that we used consisted of 300 patches and was derived from the 2020 satellite. Sentinel-2 images, which included both RGB and NIR bands, were used to generate the patches. The resolution of each patch was 10 meters, and each patch was split into pieces that were 512 pixels wide and 512 pixels tall. Approximately sixty-four percent (192 patches) of the total 300 patches that did not overlap were chosen for training, sixteen percent (48 patches) were chosen for validation, and twenty percent (60 patches) were chosen for testing. The test findings were utilized in the conclusion of the final performance assessments. An F1 score of around 0.797 was produced by SiU-Net, which was higher than the scores of DeepLabV3+, which were roughly 0.541, and U-Net, which was 0.720. In addition, the F1 score of SiU-Net (0.589) was higher than that of DeepLabV3+ (0.051) and U-Net (0.455) while using limited training data. Furthermore, the SiU-Net model displayed a slower rate of performance degradation as a result of data imbalance. It would appear that the SiU-Net model is most appropriate for use in circumstances that involve training data that is both limited and inconsistent. In Reference [9], During this research, an FGMCN model and the SPP solution were developed, both of which have been validated independently. FGMCN and the competing algorithms were utilized to analyze the test sets consisting of the five images. The findings are reported as the average scores, and each approach is carried out five times using randomized training and test sets. This is done to limit the impacts of random clustering. It was determined that the discrete test samples prevented the planned SPP from being utilized at this point. All of the top scores are shown in bold numbers. Based on the OA, AA, and Kappa coefficients, it can be concluded that the newly developed FGMCN approach is superior to the methods that are currently common. It is ResNet-34 and ADMF that outperformed SSRN in terms of their results, which are terrible. Even though MSPSSRN, CANet, and SDF2N all demonstrate improved performance, the FGMCN method that was recommended consistently produces superior results. As a result of the highest number of classifications, the DEIMOS-2 classification faces the greatest challenges. The various classifications can be distinguished from one another by a significant class difference. In addition to our model, ResNet-34, CANet, and SDF2N are the only networks that can identify bridges. The utilization of fine-grained multiscale learning is primarily responsible for the greater stability that our technique exhibits in this particular environment. In addition, this demonstrates that grassland might be difficult for any algorithms to recognize due to the lack of labeled pixels and the fact that it is comparable to agricultural or forest regions. The confusion matrix demonstrates that grassland is frequently misclassified as agricultural land, which is an erroneous classification. The accuracy of other methods is around 45 percent. It has been demonstrated that the FGMCN algorithm that was suggested has the highest recall rate and F1 score. As stated in Reference [10], an Independently validated FGMCN model and SPP solution were developed in this research. The five image test sets were examined using FGMCN and competing methods. Each approach is repeated five times using randomized training and test sets to decrease random clustering, and the average scores are reported. Due to discrete test samples, the planned SPP was not used. Bold numbers denote top scores. OA, AA, and Kappa coefficients show that the novel FGMCN approach beats conventional methods. ResNet-34 and ADMF outperform SSRN. MSPSSRN, CANet, and SDF2N perform better, but FGMCN regularly outperforms all. The largest number of classes makes the DEIMOS-2 classification the hardest. The different groups varied greatly in class. Only ResNet-34, CANet, SDF2N, and our model identify bridges. Our technique is more stable due to fine-grained multiscale learning. Due to inadequately labeled pixels and their closeness to forest or agricultural landscapes, grassland might be difficult for any algorithms to recognize. The confusion matrix shows that

grassland is commonly misclassified as farmland. Other methods have 45% accuracy. The proposed FGMCN algorithm has the highest recall and F1 score. In Reference [11], Traditional remote sensing images and scene assessment used color and texture data. Mid-level remote sensing image classification methods include VLAD and orderless Bag-of-Features (BoF). Convolutional Neural Networks are increasingly used in remote sensing and classification of images. This research attempts to increase ResNet50 efficiency through network activities, network head generation, and hyperparameter optimization. Piecewise schedulers modify hyperparameter optimization using linear decay learning rates. SGDM optimizes hyperparameters utilizing weight and bias learning rate variables. Experiments and analyses utilize UCM, RSSCN, SIRI-WHU, Corel-1K, and Corel-1.5K. Research and competition results show that our image classification model is more efficient and effective than current research.

4. What Are The Most Effective Classification Techniques For Different Types Of Satellite Images?

The next few sections outline the best classification methods for various types of satellite imagery.

The purpose of this research is to demonstrate how the combination of FGMCN and SPP may enhance multispectral classification in high-resolution visualization. To enhance multiscale information imagery learning, the technique that has been described develops a multiscale residual network that is more exact. A comparison will be made between the suggested method and six other image classification algorithms via the use of five remote sensing images obtained from the GF-1, GF-2, DEIMOS-2, GeoEye-1, and Sentinel-2 satellites. Overall Accuracy (OA), Average Accuracy (AA), and Kappa coefficient are three metrics that demonstrate that the proposed approach provides a high level of classification accuracy for high-resolution multispectral imaging. The outcomes of the experiments demonstrate this. It is also possible for SPP to reduce the number of scattered pixel-wise classification results, which would improve both accuracy and appearance [9]. Even when CNN-based deep learning models are utilized, it is challenging to analyze and classify high-quality remote sensing images as they arrive from satellites. The purpose of this research was to analyze a novel vision transformer model that takes advantage of deep learning to enhance image classification. To extract multi-scale and multi-resolution geographical data from high-resolution remote sensing satellite imagery, the proposed approach makes use of a multi-head local self-attention mechanism. This mechanism provides both a local and global context. To tune the model, a linear decay learning rate scheduler was utilized. These remote sensing satellite image datasets were utilized to conduct experiments and conduct analysis: EuroSat, UCM, RSSCN, and SIRI-WHU. The results of the experiments demonstrate that the proposed approach is superior to those of common models when it comes to identifying small datasets that include complicated features [12]. The hyperspectral (HS) image postprocessing-based spectral-spatial classification (SSC) technique is presented in this article. The incorporation of spectral and spatial data into pixel-based classifiers is what makes this technique such an improvement. An efficient transformation of hyperspectral pictures is achieved by the utilization of principal component analysis, and the Naive Bayes classifier is utilized to compute the spectral-posterior probability. The generation of spatial-posterior probabilities allows for the utilization of an adaptive fast Fourier transform (AFFT) in conjunction with a probabilistic proximity function. To produce an accurate SSC map, the probabilities are utilized. Two approaches are proposed: the traditional NB-AFFT-SSC methodology and the iteration-wise variable sequencing-based (IVS-NB-AFFT-SSC) method, which classifies a class for each iteration. Both of these methods are utilized in the classification process. Two wrapper-based feature selection approaches are utilized to generate principal components (PCs) for every hyperspectral image class, which ultimately results in an improvement in classification accuracy. The effectiveness of the technique has been demonstrated by extensive testing on three real-world datasets known as Washington DC Mall, Salinas-A, and Botswana. The generalization of the technique is demonstrated by the utilization of wrappers such as support vector machines and K-nearest neighbors within the methodology. IVS enables users to zero down on a specific group of personal computers that are relevant to their field of interest, demonstrating that the proposed method is effective [13].

5. How Do Preprocessing Methods Affect The Accuracy Of Satellite Image Classification?

The preprocessing techniques have a significant impact on the classification performance of the satellite image by improving the image quality as well as the features of the image. Different methods, including Normalization, denoising, and edge preservation, are used for the enhancement of the performance of

the classification algorithm. The subsequent sections describe how these preprocessing methods affect the classification accuracy.

Key Pre-processing Techniques

- Normalization: It scales pixel values to the same range making the model converge faster and also providing accurate results [14].
- Denoising: Such methods as hybrid directional lifting filter out noise while retaining other features important for classification, successful in this aspect [15].
- Edge Preservation: The preservation of edges and contours helps make distinctions between different forms of land cover easier for the classifier to achieve [15].

Data Pre-processing Techniques

- Atmospheric Corrections: Researchers have established various methods of atmospheric correction including Sentinel-2 atmospheric correction and standardized surface reflectance giving a classification accuracy of more than 96% when applied to the Sentinel-2 data [16].
- Texture Analysis: The use of geostatistical texture analysis can significantly improve classification accuracy by up to 10% for agricultural data and indicates the relevance of spatial dependency of pixels in the classification process [17].
- Dimensionality Reduction: Algorithms such as PCA in the literature have demonstrated enhanced classification performance and added accuracy when incorporating deep learning [18].

Impact on Classification Algorithms

- Deep Learning Models: When combined with various preprocessing techniques and architectures of CNN such as VGG, and Resnet, has shown enhancements in the classification of numerous hierarchical satellite images, going as high as 99.99% [19] [20].
- Ensemble Learning: With the help of the hierarchical frameworks and by selecting the dependent features it is possible to increase the degree of classification accuracy and demonstrate the efficiency of the application of several preprocessing techniques [20].

While preprocessing methods generally enhance classification accuracy, there may be diminishing returns when overly complex techniques are applied, potentially complicating the model without significant gains in performance.

6. Comparative Analysis

Table 1 shows the comparison of all the methods / algorithms utilized in addressing the problem of satellite image classification.

Table 1. Comparative Analysis

Ref	Objective / Goal of Research	Dataset Utilized with Application	Methods / Algorithm Used with Accuracy	Limitations
[21]	This research presents an effective strategy using security-preserving deep learning (PPDL) approaches to address satellite image data privacy challenges while using public DL models.	French Satellite pour l'Observation de la Terre (SPOT) satellite. The dataset utilized in this research contains 37,774 Images.	This research proposes a Paillier system for partially homomorphic encryption, allowing secret information processing without exposing the underlying data. Our approach achieves reliable results for both customized CNNs and transfer learning methods. The results show that our CNN-based models preserve data privacy while retaining functionality. Our proposed encryption technique has favorable	Assessment of the results derived from the above-proposed technique will be attempted on different datasets. Furthermore, comparing the efficiency of the other approaches for PPDL: SS, SMPC, and DP with the proposed approach in the future will be important work. In addition, the comparative

			security properties, including correlation coefficient (-0.004), entropy (7.95), energy (0.01), contrast (10.57), number of pixel change rate (4.86), and unified average change intensity (33.66).	evaluation of building one combined PPDL model using several of the proposed techniques and investigating how the performance of the model in terms of privacy and classification accuracy will be continued.
[22]	This research compares the LULC classification performance of ArcGIS Pro with Google Earth Engine using Landsat, Sentinel, and Planet satellite datasets in a case study for Charlottetown, Canada.	This research utilized three datasets namely Landsat-8, Sentinel-2, and Planet.	Using both ArcGIS Pro and Google Earth Engine, the SVM classifier outperforms other classifiers. The SVM in ArcGIS Pro achieves 89% accuracy with Landsat, 91% with Sentinel, and 94% with Planet. In Google Earth Engine, the SVM achieves 87% accuracy with Landsat 8 and 92% with Sentinel 2. Additionally, change detection findings indicate that 13.80% and 14.10% of forest areas have become empty land and urban class, respectively, and 3.90 % have become urban areas from 2017 to 2021, indicating substantial urbanization.	The findings of this research will inform future research by determining the most effective classifier and platform for remotely sensed images.
[23]	This technique uses deep learning for recognizing changes and visual semantic embedding. Using this technology and an information retrieval framework, annotations are found for satellite images of forest changes.	This research utilized two datasets. Initially, Landsat scene 230_65 images were utilized for June 21, 2017, June 24, 2018, and July 13, 2019. This dataset focuses on a Brazilian Amazon area damaged by deforestation over the given period for detecting bi-temporal changes. Interested papers from the Web of Science from 2018	The creation of an automatic technique to classify satellite images of forests is described based on keyphrases from a determined corpus. The technique involves using visual semantic embeddings, keyphrases extraction, and information retrieval. They are tested on pairs of Amazon rainforest images as well as on research articles related to deforestation. Consequently, the results provide evidence of the	Future research might enhance visual semantic learning by pre-training networks for change detection. Future research should explore other keyword extraction approaches and select possible annotations based on meaning. While this approach is used for deforestation, it may be applied to other areas that require adding semantic information to image

		to 2019 have been collected using keywords including 'Amazon Brazil deforestation' from 2017-2020. The publications in this 'Amazon corpus' are 446 in total. Another set of articles that I was able to identify is the 'Forest corpus' which comprises 9722 papers from the Web of Science that contain the word deforest* and addresses global deforestation between 1975 and 2016 from a more general perspective. The corpora are annotated for candidate keywords that relate to the various image pairings. Also, the 'fastText custom' word embedding model is developed employing the 'Forest corpus'.	fact that keyphrases provide better semantic information without harm to the quality of the annotation in comparison with keywords. Moreover, it is further shown that both the recall scores of fastText models are substantially superior to BERT models especially while working with a vast number of candidates of annotations.	combinations such as medicine.
[24]	This research tries to differentiate between public and private classrooms in remote sensing images, despite major intra-class and modest inter-class inequalities.	This research used RSSCN7, AID, UCM, and NWPU-RESISC45 datasets for cross-domain scene classification in remote sensing images. This dataset was obtained from Google Earth.	The proposed solution is Sample-prototype optimal transport-based universal domain adaptation (SPOT), which has two sub-components. First, an imbalanced optimal transport method and a sample complement mechanism are employed to find shared and exclusive classes by using the entropy of the optimal transport assignment matrix. Second, to widen class distinction and make classes more similar, the optimal transport	A novel unbalanced optimum transport technique is proposed to overcome the constraint of conserving marginal distribution mass and obtain partial alignment effects.

			technique is used. Experimental results show that SPOT enhances classification accuracy and robustness in the universal domain adaptation for RS images thus solving the stated problems.	
[25]	This research seeks to balance computational cost and accuracy in transformer-based LULC analysis models. Using transfer learning and fine-tuning techniques, we maximize transformer-based model resource use.	EuroSAT and PatternNet Dataset	Transfer learning and fine-tuning are shown to considerably increase the efficiency and utility of transformer-based models in LULC classification, notably the Vision Transformer and Swin Transformer variants. This research demonstrates that these two techniques are particularly effective.	More studies will be made to include the practical uses of the research. The feasibility of the methodology will be investigated within the context of data size and computer vision problems. Further, to bring reliability and interpretability to the framework in research on Land Use and Land Cover (LULC), the possibility of employing more spectral bands of satellites will be investigated.
[26]	This research article introduces “the OPS-SAT case”, a unique data-centric competition addressing these challenges. The European Space Agency's OPS-SAT satellite showcases machine learning system architecture for space with limited labeled data and open-source software.	Created their own OPS-SAT case dataset and aimed to create numerous small and labeled 200 px ×200 px patches from the larger 1944 px × 2048 px OPS-SAT image.	According to the results of our EO application work, the simulation of OPS-SAT, which included its operational limits, was successful. Relevant data were gathered by immediately transferring the trained machine learning model to the satellite. This demonstrated that the most effective models from the competition phase are also effective in space.	We predict that future few-shot learning AI systems will gradually alter onboard deployment to match our proposed approach. Future advancements may involve using the satellite in an iterative development cycle. The advantages of rapid deployment are obvious: Shortening satellite data gathering time and decreasing labeling campaign expenses and complexity.

7. How Have Specific Case Studies Advanced Our Understanding Of Satellite Image Classification?

Several years of case studies that have examined different methodologies and technologies have contributed to the progress of satellite image classification. These studies point to the positive outcome

of extracting features using machine learning techniques, the significance of the quality of data, and the comparative results of classifiers when functioning in different contexts. The following presents specific case findings that form the basis for analyzing key insights.

Ops-Sat Case Study

- Over the past decade, the OPS-SAT initiative has solved the problem of the availability of a small number of labeled samples in machine learning through onboard calculation.
- A data-driven competition was staged showcasing those high levels of data augmentation that can generate result sets that are relevant within a short period hence enabling the development of satellite image classification systems [26].

Casablanca Case Study

- This study aimed to compare supervised and unsupervised learning methods that include Random Forest and Support Vector Machines using the Landsat 8 data.
- Some of the features like ADC, IR, and VFR had high classification accuracy of over 90 percent depending on select parameters of data adopted from the urban environment [27].

Almora Town Case Study

- Using the data acquired from the Landsat of 1999 and 2020, the use of classifiers such as Maximum Likelihood and Mahalanobis Distance were compared [28].
- One key message of the study was that the accuracy of a classifier has a major influence on the ability to identify changes in land use over time, and shows how various methods can be applied when studying geographical regions [28].

Transfer Learning And Cnns

- This research also focused on the possibility of enhancing the land-use categories recognition error rate using transfer learning and CNNs.
- The study employed the EuroSAT dataset which furnished a standard platform to compare the performances of various classification algorithms [29].

While the case studies in this research reveal considerable development within satellite image classification, some of the obvious remaining challenges lie with high-quality labeled datasets and complex models' computation requirements. Any solution to such problems will thus be very significant to further steps in the domain.

8. CHALLENGES & FUTURE REDIRECTIONS

Satellite image classification still faces a few challenges, since the data are complex and variable. Future directions that consider these challenges must come with the advancement of machine learning techniques to ensure increased accuracy and efficiency in satellite image analysis. A few of the key challenges and potential future directions are discussed below:

As shown below in Fig 1 represents and highlights key challenges which is faced by researchers and academicians in solving the problems of satellite image classification

CHALLENGES

- **Real-time remote sensing information:** Therefore, real-time data produced from satellite imagery is required for automatic detection of landslides. This involves the utilization of very efficient algorithms for the purpose of achieving quick analysis [5].
- **Restricted training dataset:** It is a significant challenge to acquire substantial datasets for the purpose of training a model using machine learning, which may result in the model's accuracy in landslides detection being compromised [5].
- **Environment Condition** - The reflection of landslides is dependable upon a number of environmental circumstances, such as the amount of rainfall, the nature of the soil, and where the land is located. The machine learning model requires a more comprehensive feature selection approach [5], which is necessary when all of these factors are taken into consideration.
- **Robust Internet Connection** - The challenges identified in this research include the necessity for a robust internet connection, the restricted access to high-resolution satellite data inside GEE, and the need for an efficient approach to gathering training and validation points, aside from manual collection [10].

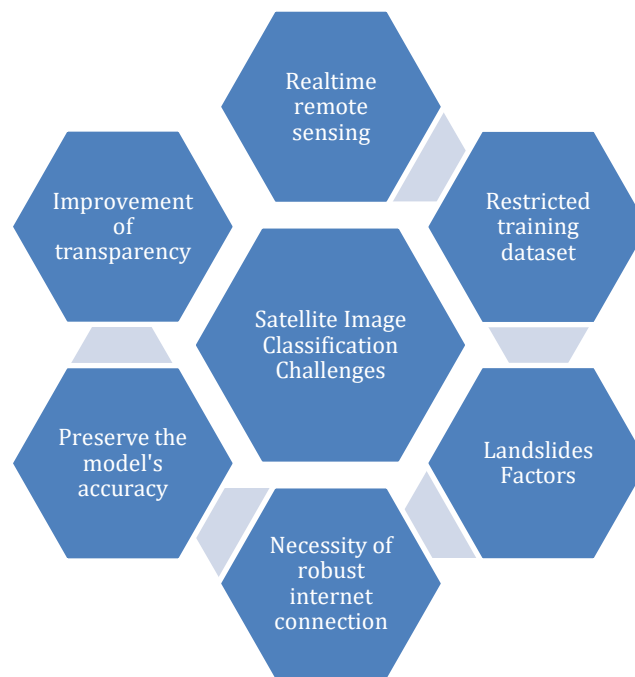


Fig 1. Various challenges for the classification of satellite images

- **Model's Accuracy** - To preserve the model's accuracy over time, consistent updates and retraining are essential owing to changes in the environment and land use dynamics. These adjustments can significantly affect the model's performance. Consequently, it is imperative to continuously enhance the model to accommodate these changes and maintain its efficiency [25].
- **Transformer based Model** - Knowing and interpreting the findings provided by transformer-based models might be challenging due to their complications. Enhancing the transparency and interpretability of these models is crucial for establishing stakeholder confidence and facilitating the efficient utilization of the insights generated. Consequently, this research incorporates Captum into our framework, which is model-agnostic and provides sophisticated interpretability approaches applicable to many models, including transformers. This connection improves the transparency and interpretability of the models, enabling stakeholders to trust and successfully utilize the insights offered [25].

FUTURE DIRECTIONS

- Future research includes development of an efficient image classification and segmentation methodology for identifying criminal activities from satellite imagery. Interpretation utilizing explainable artificial intelligence through the development of hybrid techniques in the analysis of satellite images found in fuzzy cognitive maps. Development of an end-to-end high-resolution application for detecting small and tiny elements in remote sensing images. Development of solutions based on large language models utilizing time series analysis of multi-source satellite images [2].
- Future research will investigate unsupervised algorithms and deep learning models that enhance the categorization of satellite images to improve the classification and detection of urban areas in the Casablanca region of Morocco [10].
- In the future, it is planned to evaluate an efficient ResNet50 with a small number of training samples. Most deep network models are trained on natural images, e.g., ImageNet; remote sensing images are quite different as they are taken by different distant sensors. Exploring transfer learning by combining natural images and remote sensing images is one possible direction for future work [11].

9. CONCLUSION & FUTURE WORK

Consequently, the review outlines the progress made toward advancing satellite image classification using deep learning techniques. It can be seen from previous and current methods of classification that the performance of the classification is dependent on the types of images and how these images have been preprocessed. Comparing the studied case, one can emphasize the variety of tasks and goals, datasets, as well as the strengths and weaknesses of the chosen algorithms. The case studies described here represent

daily practical solutions and achievements that expand the knowledge of the field. However, it is clear that current and future work still has some problems to solve especially in accuracy and speed of classifications. More research should be done to address these challenges while more ideas should be researched to improve the classification of satellite images.

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