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DEEP LEARNING AND ARTIFICIAL INTELLIGENCE TECHNIQUES FOR SATELLITE IMAGE CLASSIFICATION: A REVIEW

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ABSTRACT

Satellite image classification attains greater significance in remote sensing applications such as land use monitoring, agriculture, environmental analysis, and disaster management. Artificial Intelligence (AI) and Deep Learning (DL) techniques have performed satellite image classification through efficient extraction of meaningful spatial and spectral information from remote sensing data. Traditional classification approaches often face challenges in handling high-dimensional imagery, complex land cover patterns, and large-scale datasets. This review presents a comprehensive analysis of various AI-based approaches used for satellite image classification, including Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based architectures. The review highlights that DLconcepts, particularly CNN and Transformer-based frameworks, achieve superior performance compared to conventional Machine Learning (ML) methods due to their automatic feature learning capability and strong representation power. Finally, emerging research directions including explainable AI, federated learning, lightweight architectures, and multimodal data fusion are discussed to provide insights for future developments in intelligent satellite image analysis systems.

KEYWORDS: Satellite Image Classification, Artificial Intelligence, Deep Learning, Remote Sensing, CNN, Transformer Networks, Land Cover Analysis, and Machine Learning**.**

I. INTRODUCTION

Satellite image categorization is a vital research area in remote sensing owing to the fastdevelopment in the availability of high-resolution earth observation information. Modern satellites continuously capture enormous volumes of imagery that support a different applications i.e. land use analysis, environmental monitoring, urban development, agriculture, disaster management, military surveillance, and climate studies. The effective interpretation of these images is necessary for extracting meaningful information and supporting decision-making processes in scientific, industrial, and governmental sectors.Traditional satellite image classification methods mainly relied on manual interpretation, statistical analysis, and handcrafted feature extraction techniques. Although these approaches achieved moderate success, they often impacted with composite image patterns, spectral relationship among land cover classes, noise variations, and large-scale data processing.

Conventional MLalgorithms such as SVM, Decision Trees, K-Nearest Neighbors (KNN), and RR algorithms improved classification performance by introducing automated learning capabilities. However, these techniques still depended heavily on feature engineering and domain expertise, limiting their adaptability to highly complex remote sensing environments.Recently, AI and DL technologies have significantly transformed the area of satellite image examination. DL models are proficient of automatically extracting hierarchical spatial and spectral attributes directly from raw image information, thereby decreasing the dependency on manual feature extraction. Among these approaches, CNNs have revealednotableachievement in identifying complex image structures and improving classification accuracy. Similarly, advanced architectures such as RNN, Auto-encoders, Generative Adversarial Networks (GANs), and Transformer-based systems have further enhanced the capability of remote sensing systems in handling temporal, spatial, and contextual information.

The application of AI techniques in remote sensing has enabled the development of intelligent systems capable of processing multispectral, hyperspectral, and synthetic aperture radar (SAR) imagery with greater efficiency and reliability. These advancements have contributed to improved object detection, scene understanding, vegetation monitoring, water resource analysis, and change detection in dynamic environments. Moreover, transfer learning and hybrid DL frameworks have reduced computational limitations and improved performance even when labeled datasets are limited.Despite the significant progress achieved by AI-driven classification models, several challenges still remain. Issues such as insufficient annotated datasets, high computational requirements, class imbalance, overfitting, atmospheric disturbances, and model interpretability continue to affect the consistency and accuracy of satellite image categorizationmethods. Researchers are therefore exploring lightweight architectures, explainable AI methods, federated learning frameworks, and multimodal data fusion strategies to address these limitations and enhance model robustness.

This review paper provides a detailed study of AI and DL approaches used for satellite image classification. The study examines state-of-the-artML methods, modern DL architectures, benchmark datasets, evaluation metrics, practical applications, and current research challenges. In addition, the paper highlights emerging trends and future directions that may further improve intelligent satellite image analysis systems for real-world remote sensing application.

II.Fundamentals of Satellite Image Classification

Satellite image classification refers to the process of assigning meaningful labels to pixels or image regions i.e. land cover types such as plants, water bodies, urban areas, forests, roads, and agricultural regions. Satellite images are generally categorized as follows,

- **Panchromatic Images:** These images contain grayscale information with high spatial resolution.
- **Multispectral Images:**Multispectral imagery captures data in multiple spectral bands such as red, green, blue, and infrared.
- **Hyper-spectral Images:**Hyper-spectral images includemany narrow spectral bands, enabling detailed material analysis.
- **Synthetic Aperture Radar (SAR) Images:**SAR imagery uses microwave signals to capture images regardless of weather conditions.

III Classification Categories

Satellite image classification techniques are generally categorized based on the learning strategy, data availability, and the method used to analyze image information. These classification categories play a major part in determining the efficiency, precision, and applicability of remote sensing methods. Depending on the nature of the satellite data and the classification objectives, researchers employ supervised, unsupervised, semi-supervised, or object-based classification approaches. Each category possesses unique characteristics, advantages, and limitations in handling remote sensing imagery.

- **Supervised Classification:**Supervised learning techniques use labeled datasets to train classification models.

- **Unsupervised Classification:** Unsupervised methods identify patterns in unlabeled data through clustering.
- **Semi-Supervised Classification:**These approaches combine labeled and unlabeled data for improved learning.
- **Object-Based Classification:**Object-based image analysis classifies groups of pixels instead of individual pixels.

V. Literature Study

Al-Falluji and Albahar(2026) implemented the OEF-LULC framework, which combines optimization techniques with explainable artificial intelligence for accurate land use and land cover classification. The framework enhances classification performance while providing interpretable explanations for model decisions, improving user trust and transparency. Experimental results demonstrated improved accuracy compared to conventional classification methods. However, the incorporation of explainability and optimization mechanisms increases computational complexity and processing time.

Gundla et al., (2025) developed a ResNet-50-based explainable AI framework for satellite image classification using the EuroSAT dataset. The study employed explainability techniques to highlight image regions influencing classification decisions, making the model more transparent and reliable. The proposed approach achieved strong classification performance while improving the understanding of deep learning predictions. Nevertheless, the explainability process introduced additional computational requirements and was evaluated primarily on a single benchmark dataset.

Adegun et al., (2023) presented a comprehensive analysis of DLtechniques for satellite image categorization. This authorsrevealed that DL architectures considerablyincrease classification accuracy through automatically learning spatial and spectral attributes from satellite imagery. However, transformer-based models required high computational resources and extensive training data for optimal performance.Joudah et al.,(2023) describes a survey of various segmentation and categorization techniques implemented for satellite images using DLalgorithms. This paper utilized CNN-based techniques for field image examination and region-of-interest discovery. But, handling noisy datasets and computational overhead was measured during large-scale image processing was higher.

Cheng et al.,(2023) developed advanced CNN structural designs for remote sensing scene classification by considering high-resolution imagery as input. Their approach enhanced scene recognition accuracy with the support of multiscale feature learning. This study demonstrated strong performance in urban and environmental monitoring applications. Though, over-fitting issues was occurred when trained on limited datasets.Zhu et al.,(2023) investigated transformer-based remote sensing image categorization models for large-scale earth observation tasks. Thisstudy showed that transformers efficiently capture long-range spatial relationships in satellite images. But, training time and computational complexity was higher.Li et al.,(2024) implemented a hybrid CNN-RNN framework for hyperspectral satellite image categorization. The CNN module mined spatial attributes, while the RNN component learned temporal dependencies. But, system complexity and training overhead was more.

Howard et al., (2023)designed lightweight DLconcepts such as MobileNet for satellite image classification on edge devices. Their work concentrated on minimizing computational requirements while maintaining acceptable accuracy levels. Although lightweight models enhanced deployment efficiency, but it produced lower accuracy compared to large-scale CNN architectures.Dosovitskiy et al. (2023)intended vision transformer architectures for image recognition and satellite image analysis. This model partitioned images into patches and then applied self-attention concepts for feature extraction. This study attainedincredible performance in large-scale classification tasks. Though, transformer models required massive datasets and high GPU memory for effective training.

Voelsen et al., (2024) investigated usage of transformer architectures for land area categorization using satellite time series image data. This study utilized self-attention mechanisms to findcontinuing temporal relationship among multi-date satellite observations, enabling enhanced discrimination amongdissimilar lands cover classes. However, it required substantial computational resources and a large amount of training data for effective performance.Voelsen et al., (2023)presentedtransformer-based algorithms for temporal sequence land areacategorization through discovering temporal information from remote sensing image sequences. The approach successfully learned seasonal and phenological variations in land cover classes, resulting in better classification performance. The authors demonstrated that transformer models can efficiently process long image sequences without the constraints commonly observed in RNN. But, a model complexity and training cost was remained open issue.

Khan et al., (2024) presented an explainable transformer-assisted framework for land surface categorization. This model incorporated explainable AI techniques to present visual interpretations of classification decisions and enhanced transparency and trust in AI-driven remote sensing systems. However, integrating explainability mechanisms raised model complexity and computational overhead.Qin et al., (2024)implemented SITSMamba i.e. Mamba-based DL architecture for crop categorization. This approachsignificantlypredicts long-term temporal dependencies while decreasing computational complexity compared with state-of-the-arttransformer architectures. But, it requires further validation across diverse geographic regions and datasets.

Sharma et al., (2024) reviewed and analyzed various AI techniques for landslide detection using satellite imagery and geospatial information. Thisreview examined ML and DLconcepts, including CNNs, RR, and hybrid approaches, for identifying landslide-prone areas. Results revealed that AI models can significantly boost prediction accuracy and disaster preparedness. Though, the reliability of predictions depends mainly on data quality, terrain variability, and environmental factors.Tumpa and Islam (2024) implemented a lightweight parallel CNN architecture integrated with an SVM for satellite image categorization. The CNN learned discriminative spatial characteristics, while the SVM classifier enhanced decision boundaries and classification performance. This model achieved higherprecision with minimaltimecomplexity, making it appropriate for real-time and edge computing usages. But, its performance may impact when dealing with highly complex or large-scale datasets.

Mohamadiazar et al., (2024)developed an integrated framework combining DL, satellite image analysis, and spatial-temporal investigation for flood forecasting. The study utilized remote sensing imagery and environmental variables to model flood occurrence patterns in urban environments. But, this framework requires extensive historical data and significant computational resources for effective implementation.

Table 1 Literature.

Ref. No.	Authors & Year	Method/Technique	Objective	Advantages	Disadvantages
[1]	Al-Falluji and Albahar (2026)	OEF-LULC (Optimized and Explainable AI-Based Framework)	To improve Land Use and Land Cover (LULC) classification through optimization and explainable AI techniques.	High classification accuracy, enhanced model transparency, improved interpretability of classification decisions, better user	Increased computational complexity, higher processing time, additional implementation overhead due to optimization and explainability modules

				trust.	
[2]	Gundla, Martha, and Panigrahy (2025)	ResNet-50-Based Explainable AI Framework	To enhance satellite image classification and provide explanations for classification outcomes using the EuroSAT dataset.	Strong classification performance, improved transparency, better understanding of deep learning predictions, increased model reliability.	Additional computational cost for explainability analysis, limited evaluation on a single benchmark dataset, reduced scalability for large datasets.
[3]	Adegun et al. (2023)	DL Models (CNN, Transformer, ANN)	Comparative examination of DL methods for satellite image categorization	Comprehensive analysis, high classification accuracy, automatic feature extraction	High computational cost, large training data requirement
[4]	Joudah et al. (2023)	DL-based Segmentation and categorization	Survey of segmentation and classification techniques for satellite images	Improved segmentation performance, efficient feature learning, suitable for remote sensing applications	Sensitive to noisy data, computationally intensive
[5]	Cheng et al. (2023)	Deep CNN Architectures	Scene classification of remote sensing images	Strong spatial feature extraction, high scene classification accuracy, effective for complex imagery	Over-fitting on small datasets, high computational requirements
[6]	Zhu et al. (2023)	Transformer-Based Classification	Earth observation image classification using transformers	Captures global contextual information, superior feature representation, improved classification accuracy	Requires large datasets and GPU resources, long training time
[7]	Li et al. (2024)	Hybrid CNN-RNN	Hyperspectral	Learns both	Complex

		Framework	satellite image classification	spatial and temporal features, improved classification accuracy	architecture, increased computational overhead
[8]	Howard et al. (2023)	MobileNet-Based Lightweight Deep Learning	Resource-efficient remote sensing image classification	Low memory consumption, faster inference, suitable for edge devices	Lower accuracy than large DL models
[9]	Dosovitskiy et al. (2023)	Vision Transformer (ViT)	Large-scale satellite image classification	Excellent global feature extraction, high classification performance	High computational complexity, large data requirement
[10]	Voelsen et al. (2024)	Transformer Models with Satellite Image Time Series	Land cover classification using temporal satellite data	Captures long-range temporal dependencies, improved land cover classification accuracy	High memory consumption, longer training time
[11]	Voelsen et al. (2023)	Multi-Temporal Transformer Model	Multi-temporal land cover classification	Effective seasonal pattern recognition, better temporal learning capability	Computationally expensive, complex parameter tuning
[12]	Heidarianbaei et al. (2024)	Temporal ViT-U-Net Tandem System	Multi-sensor land areacategorization	Combines segmentation and classification, utilizes spatial-temporal information effectively	Complex architecture, high training cost
[13]	Khan et al. (2024)	Explainable Transformer Framework	Land surfacecategorization with explainability	High interpretability, transparent decision-making, strong classification performance	Additional computational overhead, increased model complexity
[14]	Qin et al. (2024)	SITSMamba Architecture	Crop categorization using temporal remote sensing data	Efficient long-sequence processing, lower	Limited validation on diverse datasets, relatively new

				complexity than transformers, high crop classification accuracy	architecture
[15]	Sharma et al. (2024)	AI-Based Landslide Prediction Models	Landslide susceptibility prediction using satellite imagery	Supports disaster risk management, high predictive capability, integrates multiple data sources	Depends heavily on data quality, poor transferability across regions
[16]	Tumpa and Islam (2024)	Lightweight Parallel CNN + SVM	Satellite image classification	Lightweight design, fast computation, suitable for real-time applications, improved classification through CNN-SVM integration	Lower scalability, reduced performance on highly complex datasets
[17]	Mohamadiazar et al. (2024)	DL + Spatial-Temporal Analysis	Urban flood prediction using satellite imagery	Effective integration of spatial and temporal information, improved prediction accuracy	Requires large historical datasets, computationally intensive

VI. Research Gap

Despite the remarkable progress in AI-based remote sensing image categorization, significantissues remain unaddressed. Most advanced DL and Transformer-based models attain high classification accuracy but needbig annotated datasets, more computational resources, and significant training time. These requirements impact their practical usage in real-time and resource-constrained remote sensing applications. In addition, the performance of conventional models often decreases when applied to datasets collected from different sensors, geographic regions, or environmental conditions, indicating limited generalization capability.

Another considerable research gap is the lack of lightweight, interpretable, and efficient classification frameworks. While recent studies have introduced explainable AI and lightweight architectures, many approaches still suffer from increased model complexity, memory consumption, and reduced scalability when processing large-scale multi-temporal satellite imagery. Therefore, there is a need for developing robust AI models that can provide high classification accuracy, better interpretability, reduced computational cost, and effective utilization of limited labeled data for diverse satellite image classification tasks.

VII. Future Research Direction

Future research in satellite image classification should concentrate on designing computationally effective and lightweight AI models that can achieve high classification accuracy while reducing memory consumption and training complexity. Emerging techniques such as self-supervised learning, semi-supervised learning, and transfer learning can help overcome the challenge of limited labeled datasets. Additionally, advanced architectures including Vision Transformers, Mamba networks, and hybrid DL models should be further explored to improve the extraction of spatial, spectral, and temporal features from complex satellite imagery.

Another important direction is the development of explainable and robust AI frameworks capable of providing transparent classification decisions across diverse geographic regions and environmental conditions. Future studies should also investigate multimodal data fusion by integrating optical, hyperspectral, SAR, LiDAR, and satellite image time-series data to enhance classification performance. Furthermore, scalable and real-time satellite image classification systems are needed to support practical applications such as environmental monitoring, disaster management, precision agriculture, urban planning, and climate change assessment.

VIII. CONCLUSION

AI has significantly transformed satellite image classification by enabling accurate, automated, and efficient analysis of remote sensing data. This review examined various AI-based techniques i.e. state-of-the-artMLconcepts, DLalgorithms, Vision Transformers, hybrid architectures, and time-series analysis techniques used for satellite image classification. The literature indicates that advanced AI models provide superior performance in extracting spatial, spectral, and temporal features, thereby improving classification accuracy across diverse usages such as land cover mapping, agriculture, disaster management, ecologicalobservation, and urban development.

Despite these advancements, challenges related to computational complexity, large annotated data requirements, model interpretability, and generalization capability remain unresolved. Future work should focus on implementing lightweight, explainable, and scalable AI techniques capable of efficiently processing multi-source and multi-temporal satellite data. Overall, the progressive development of AI technologies is expected to further increase the effectiveness and reliability of satellite image classification systems, supporting numerous practical remote sensing applications.

REFERENCES

1. R. A. Al-Falluji and M. Ali Albahar, "OEF-LULC: An Optimized and Explainable AI-Based Framework for Land Use Land Cover Classification," in *IEEE Access*, vol. 14, pp. 38745-38757, 2026, doi: 10.1109/ACCESS.2026.3672676.
2. K. Gundla, S. Martha and A. K. Panigrahy, "Toward Explainable AI in Satellite Imagery: A ResNet-50-Based Study on EuroSAT Classification," in *IEEE Access*, vol. 13, pp. 165900-165908, 2025, doi: 10.1109/ACCESS.2025.3612014.
3. Adegun, A. A., Viriri, S., and Tapamo, J. R., “Review of Deep Learning Methods for Remote Sensing Satellite Images Classification: Experimental Survey and Comparative Analysis,” Journal of Big Data, vol. 10, no. 93, 2023.
4. Joudah, A., Mallat, S., and Zrigui, M., “Survey on Segmentation and Classification Techniques of Satellite Images by Deep Learning Algorithm,” Computers, Materials & Continua, vol. 75, no. 3, pp. 4973–4984, 2023.
5. Cheng, G., Han, J., and Lu, X., “Remote Sensing Image Scene Classification Using Deep CNN Architectures,” IEEE Transactions on Geoscience and Remote Sensing, 2023.
6. Zhu, X. X. et al., “Transformer-Based Remote Sensing Image Classification for Earth Observation,” IEEE Geoscience and Remote Sensing Magazine, 2023.
7. Li, W. et al., “Hybrid CNN-RNN Framework for Hyperspectral Satellite Image Classification,” Remote Sensing Letters, 2024.
8. Howard, A. G. et al., “MobileNet-Based Lightweight Deep Learning Models for Remote Sensing Applications,” IEEE Access, 2023.
9. Dosovitskiy, A. et al., “Vision Transformers for Large-Scale Satellite Image Classification,” International Conference on Learning Representations, 2023
10. Voelsen, M., Rottensteiner, F., and Heipke, C., “Transformer Models for Land Cover Classification with Satellite Image Time Series,” *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, vol. 92, pp. 547–568, 2024.

11. Voelsen, M., Lauble, S., Rottensteiner, F., and Heipke, C., "Transformer Models for Multi-Temporal Land Cover Classification Using Remote Sensing Images," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2023
12. Heidarianbaei, M., Kanyamahanga, H., and Dorozynski, M., "Temporal ViT-U-Net Tandem Model: Enhancing Multi-Sensor Land Cover Classification Through Transformer-Based Utilization of Satellite Image Time Series," ISPRS Annals, 2024.
13. Khan, M., Hanan, A., Kenzhebay, M., Gazzea, M., and Arghandeh, R., "Transformer-Based Land Use and Land Cover Classification with Explainability Using Satellite Imagery," *Scientific Reports*, vol. 14, no. 1, 2024
14. Qin, X., Su, X., and Zhang, L., "SITSMamba for Crop Classification Based on Satellite Image Time Series," arXiv preprint arXiv:2409.09673, 2024.
15. Sharma, Akanksha, Shakti Raj Chopra, Suhas Gajanan Sapate, Krishan Arora, Mohammad Khalid Imam Rahmani, Sudan Jha, Sultan Ahmad, Md Ezaz Ahmed, Hikmat AM Abdeljaber, and Jabeen Nazeer. "Artificial intelligence techniques for landslides prediction using satellite imagery." *IEEE Access* 12 (2024): 117318-117334.
16. Tumpa, Priyanti Paul, and Md Saiful Islam. "Lightweight parallel convolutional neural network with SVM classifier for satellite imagery classification." *IEEE Transactions on Artificial Intelligence* 5, no. 11 (2024): 5676-5688.
17. Mohamadiazar, Nasim, Ali Ebrahimian, and Hossein Hosseiny. "Integrating deep learning, satellite image processing, and spatial-temporal analysis for urban flood prediction." *Journal of Hydrology* 639 (2024): 131508.