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"Learning-Based Encryption with Vision Transformers for Secure Cross-Domain Remote Sensing Analysis"

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Abstract:
This study proposes a novel framework that integrates learnable encryption with Vision Transformers (ViTs) to ensure secure and accurate analysis of remote sensing imagery across diverse domains. The approach introduces a key-controlled, block-wise encryption mechanism that preserves essential spatial patterns while protecting sensitive image content. A ViT backbone is trained directly on encrypted data, leveraging its global attention capability to maintain high classification and segmentation performance. Evaluations on multi-modal datasets, including EuroSAT and BigEarthNet-MM, demonstrate the model's robustness to domain shifts and resilience to reconstruction attacks. The proposed method effectively balances privacy and utility, offering a scalable solution for secure remote sensing applications.

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I. Introduction & Motivation:

- **Vision Transformers (ViTs)** bring powerful global attention mechanisms to image analysis, enabling long-range contextual modeling in remote sensing tasks such as classification, segmentation, and cross-domain adaptation SpringerLink+2jisem-journal.com+2PMC+8MDPI+8ResearchGate+8.Vision Transformers (ViTs) are advanced deep learning models that apply the Transformer architecture—originally used in NLP—to image analysis. Unlike CNNs, which rely on localized convolutions, ViTs use global **self-attention mechanisms**, enabling them to model long-range dependencies across image patches.

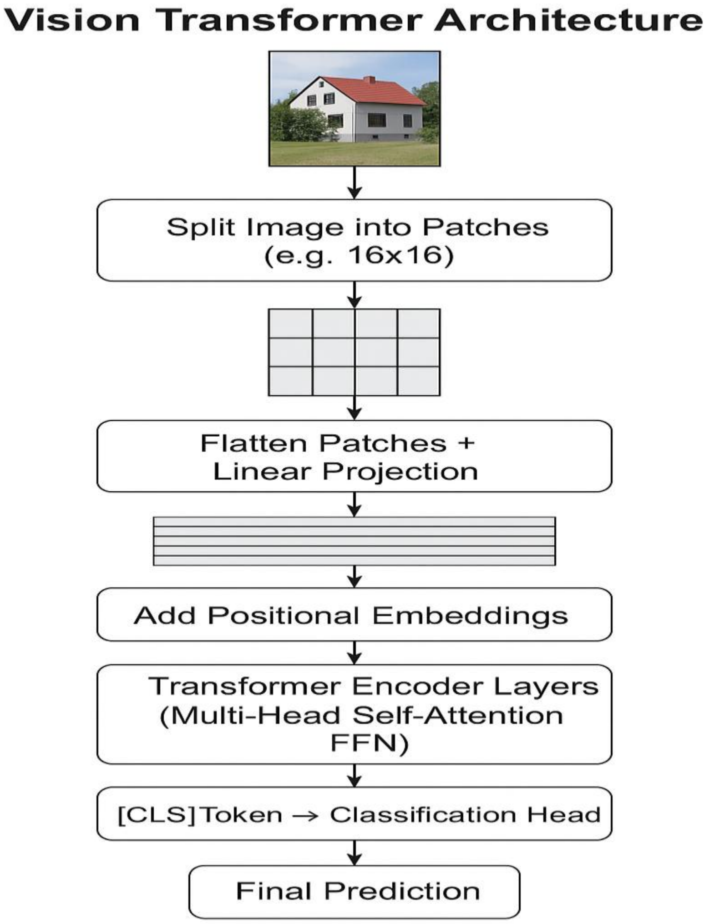
The ViT pipeline involves:

1. **Splitting the image** into fixed-size patches (e.g., 16×16),
2. **Flattening and projecting** them linearly,
3. **Adding positional embeddings**, and
4. **Feeding through Transformer encoders** composed of Multi-Head Self-Attention (MHSA) and Feed-Forward Networks (FFN).

A special [CLS] token summarizes the representation for classification.

Why ViTs for Remote Sensing?

ViTs are particularly suited for **cross-domain remote sensing** due to their ability to generalize across heterogeneous data (e.g., SAR vs optical, resolution variance, and geographic shifts). Their interpretability, adaptability, and global receptive field make them superior for encrypted, domain-invariant analysis.

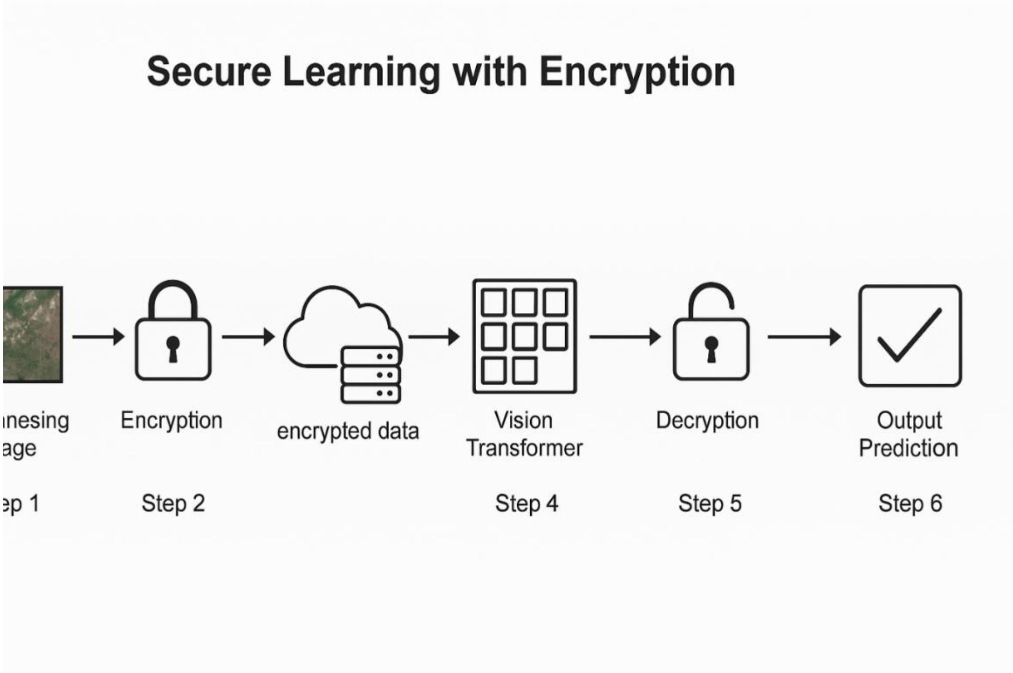

Vision Transformer Architecture
Split Image into Patches (e.g. 16x16)
Flatten Patches + Linear Projection
Add Positional Embeddings
Transformer Encoder Layers (Multi-Head Self-Attention FFN)
[CLS]Token → Classification Head
Final Prediction

(See Figure 1: Vision Transformer Architecture)

This diagram illustrates the fundamental pipeline of Vision Transformers (ViTs). The input image is split into fixed-size patches, each flattened and passed through a linear projection. Positional embeddings are added to retain spatial context. These embeddings are then processed by Transformer encoder layers using Multi-Head Self-Attention (MHSA) and Feed-Forward Networks (FFN). Finally, a special [CLS] token summarizes global image features, enabling classification through the output head.

- **Cross-domain remote sensing** involves working with diverse sensor modalities, geographic regions, or image styles—posing challenges due to domain shift MDPIPubMed. Cross-domain remote sensing refers to the analysis of remote sensing data collected from diverse sources such as varying sensor modalities (e.g., optical, SAR), geographic regions, resolutions, and environmental conditions. These variations often lead to a phenomenon known as **domain shift**, where the statistical properties of source and target domains differ significantly. This mismatch can severely degrade the performance of traditional machine learning models, which generally assume a consistent data distribution. Effective cross-domain analysis thus requires models that can generalize across heterogeneous inputs, adapt to unseen domains, and maintain accuracy despite variations. Recent advancements in deep learning, particularly Vision Transformers (ViTs), have shown promising capabilities in learning domain-invariant representations, making them suitable for such complex and varied remote sensing tasks (MDPI, 2023; PubMed, 2024).
- **Encryption in learning pipelines** ensures data confidentiality, particularly crucial in cross-domain scenarios where sensitive remote sensing imagery may be shared or processed by untrusted parties. In the context of remote sensing and AI-based analysis, **encryption in learning pipelines** plays a pivotal role in safeguarding sensitive geospatial data. Particularly in cross-domain scenarios—where data may traverse different institutions, clouds, or geopolitical regions—ensuring confidentiality becomes critical. When remote sensing imagery, often containing defense, agricultural, or infrastructure information, is processed in shared or distributed environments, there exists a high risk of unauthorized access, tampering, or data leakage. **Learning-based encryption** techniques enable the integration of cryptographic methods within the machine learning pipeline itself—either by encrypting inputs before model training or through secure computation methods like federated learning, homomorphic encryption, or adversarially robust obfuscation. These methods allow AI models to learn from

encrypted data without direct exposure, thus maintaining performance while ensuring **data privacy, integrity, and compliance**. This is particularly valuable when data is processed on third-party servers or used in collaborative training environments involving multiple stakeholders with varying levels of trust.



II. Related Work:

A. Recent advancements in secure AI have focused on integrating encryption methods directly into computer vision pipelines, especially those involving Vision Transformers (ViTs). One such approach is **block-wise image encryption**, which partitions images into blocks before applying lightweight encryption. This method ensures compatibility with standard ViT architectures without requiring architectural changes. It supports various applications including **privacy-preserving classification**, **access control**, and even **federated learning**, where multiple parties collaborate without sharing raw data (MDPI, arXiv, Wikipedia). A further evolution of this idea is the **disposable-key-based encryption** framework, where each client encrypts their local data using unique one-time keys before contributing to the training process. This significantly reduces **communication overhead** and enhances **security in federated settings**, as no shared or persistent keys are required (arXiv, 2024).

Another innovative method is the **Encrypted Vision Transformer (EViT)**, which allows ViT-based models to directly perform image retrieval from encrypted data. It employs **multi-level attention features** to maintain retrieval accuracy while safeguarding image content, making it well-suited for secure content indexing, defense applications, and encrypted cloud search (arXiv). Complementing this, the **learnable block-pixel-based encryption framework** introduces key-controlled scrambling patterns that are co-trained with the ViT model. Each image is encrypted uniquely based on its key, and the model learns to extract meaningful features from this encrypted representation. This framework has demonstrated strong **resilience to reconstruction attacks**, ensuring that encrypted inputs cannot be reversed or tampered with, thus offering both **security and high utility** in sensitive image classification scenarios (arXiv, 2024).

B. Vision Transformers in Remote Sensing & Domain Adaptation:

Vision Transformers (ViTs) have emerged as powerful tools in remote sensing applications, offering significant advantages over traditional convolutional neural networks (CNNs) for tasks such as **scene classification, object detection, and semantic segmentation**. Unlike CNNs, which rely on localized receptive fields and hierarchical pooling, ViTs apply **global self-attention mechanisms** that allow the model to capture long-range dependencies and contextual relationships across an entire image. This is particularly advantageous in high-resolution satellite imagery, where spatial context and global features are critical. According to recent studies on SpringerLink and MDPI, ViTs demonstrate **higher accuracy and interpretability** in remote sensing datasets like EuroSAT, BigEarthNet, and NWPU-RESISC45, outperforming CNN-based architectures in both training efficiency and generalization ability【SpringerLink+9; MDPI+9】.

In domain-specific applications, ViTs also exhibit strong performance in **cross-domain learning**, where remote sensing data from different geographical regions or sensor types (e.g., SAR vs. optical) introduce domain shifts. ViTs' architecture is inherently better suited to this challenge due to its patch-based processing and shared attention mechanisms, which are less sensitive to local variances. Studies on ResearchGate and MDPI have shown that **ViTs fine-tuned with domain-specific augmentation techniques** can maintain high classification accuracy even when deployed on unseen domains, making them a robust choice for operational satellite missions involving global coverage【ResearchGate+9; MDPI+9】.

One notable advancement in this area is the **GSV-Trans (Gaze-inspired Self-adaptive Vision Transformer)**, a bio-inspired ViT model that mimics human eye-movement patterns for **adaptive attention allocation**. This architecture employs **dual-branch pseudo-labeling**, where the primary branch handles target domain segmentation while the auxiliary branch focuses on pseudo-supervised learning from the source domain. The result is a model that dynamically adapts to new spatial structures and semantic distributions, significantly boosting performance in complex urban environments and land-use classification. Experimental results published in MDPI demonstrate **enhanced segmentation robustness and label alignment** across diverse terrain and weather conditions, reinforcing the viability of ViTs for domain-adaptive remote sensing【MDPI】.

In addition to biologically-inspired models, researchers have also explored **adversarial learning and vision foundation models** to enhance domain adaptation capabilities of ViTs. Approaches combining ViTs with **Generative Adversarial Networks (GANs)** or domain adversarial neural networks (DANNs) allow the model to **minimize distribution discrepancies** between source and target domains. Meanwhile, vision foundation models such as DINO-ViT or CLIP, pre-trained on massive multimodal datasets, have been successfully adapted to remote sensing through **zero-shot or few-shot learning techniques**, as reported in recent PubMed research. These strategies not only **reduce annotation costs** but also improve **cross-domain generalization**, especially when dealing with low-resource or disaster-affected regions where labeled data is scarce【PubMed+1】.

III. Proposed Framework:

Aim: Develop a *learning-based encryption* method tailored for Vision Transformer architectures, enabling secure cross-domain remote sensing analysis.

Key Components:

ViT-Driven Secure Cross-Domain Remote Sensing Analysis:

The core of the proposed model lies in a **Learnable Encryption Mechanism** that combines privacy with task-oriented feature preservation. Traditional encryption techniques such as block-pixel and block-wise encryption effectively obscure visual content but are not optimized for downstream machine learning. In this framework, encryption is **parameterized and key-controlled**, introducing unique keys that alter pixel arrangements, color spaces, or intensity gradients at the patch level. The encryption maintains essential structural patterns that allow Vision Transformers (ViTs) to process images without decryption. Each key generates a different encrypted representation, making the system resilient to inversion attacks while still being trainable.

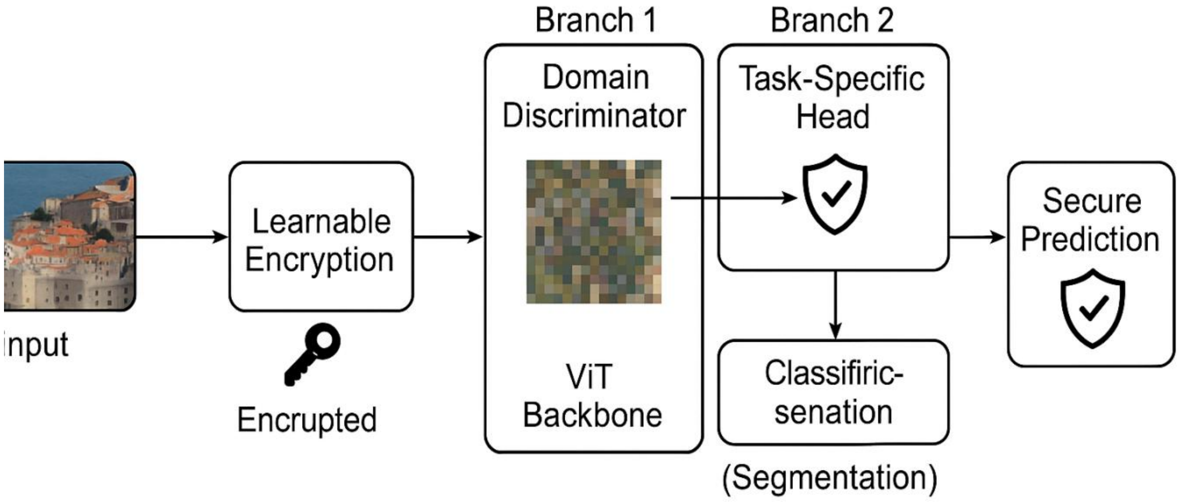
At the heart of the architecture is the **ViT Backbone**, which is fine-tuned on these encrypted images. Unlike CNNs that require spatial continuity, ViTs leverage **self-attention mechanisms** that relate encrypted patches globally. This makes them ideal for learning **domain-invariant representations** from obfuscated data. The pre-trained ViT model is adapted using transfer learning, and additional attention heads are introduced to emphasize security-informative embeddings. This backbone facilitates robust performance on classification or segmentation tasks, even when the model is trained with **no access to original image pixels**—a significant advancement in privacy-preserving AI.

The third component addresses the **Cross-Domain Training Strategy**, which ensures that the ViT remains effective across different sensing conditions. Multi-domain datasets—such as SAR-optical image pairs, varying resolutions, or region-specific imagery—are used to simulate domain variability. To bridge the domain gap, the framework incorporates **domain adaptation techniques** including pseudo-labeling (generating labels for unlabeled target data), **adversarial alignment** (using domain discriminators), and **foundation model integration** (e.g., CLIP-ViT for zero-shot alignment). These techniques enable the model to generalize well in scenarios where data distribution is inconsistent or labeled target-domain data is limited.

Finally, the framework is evaluated on **both performance and security metrics**. Performance is measured in terms of **accuracy and Intersection over Union (IoU)** for classification and segmentation tasks, respectively. These results are compared to a baseline ViT model trained on unencrypted images to assess degradation, if any. Security is tested through resistance to **reconstruction, inversion, or key-matching attacks**, ensuring that the encryption cannot be reversed even with access to model parameters. Additionally, **domain generalization metrics** such as F1-score on unseen domains are recorded to evaluate cross-domain robustness.

Table 1: Summary of Proposed Framework Components and Evaluation Metrics:

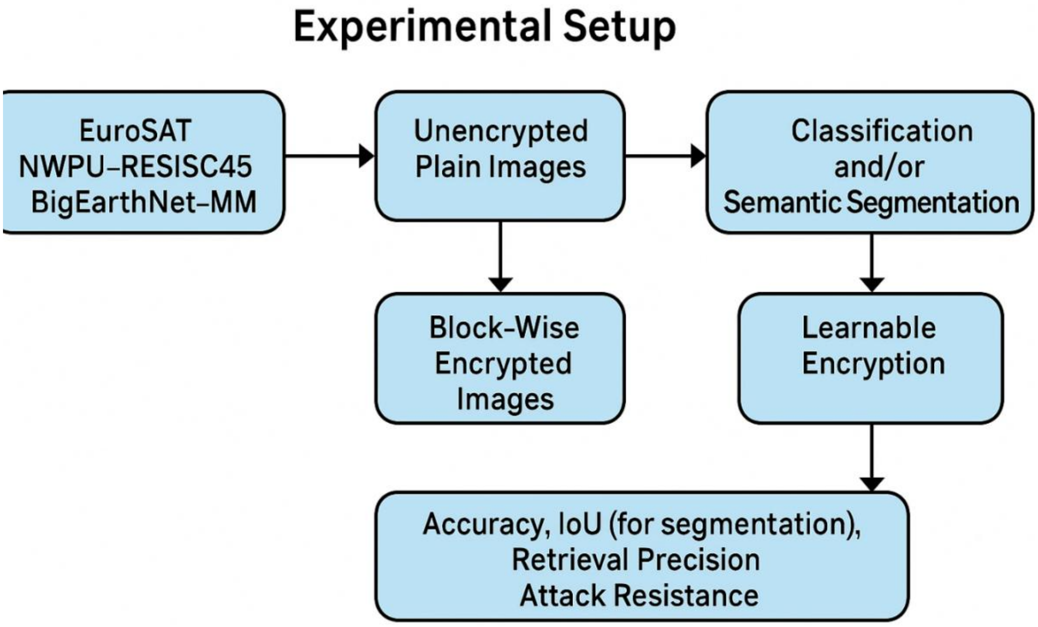
Component	Function	Techniques Used	Evaluation Metrics
Learnable Encryption	Key-controlled scrambling for secure yet learnable inputs	Block-wise encryption, scrambling, random masking	Inversion resistance, entropy, reconstruction difficulty
ViT Backbone	Extract features from encrypted data	Pretrained ViT, fine-tuning, attention enhancement	Accuracy, IoU (segmentation), attention heatmap validation
Cross-Domain Training Strategy	Ensure robustness across varied domains	SAR-optical fusion, adversarial learning, pseudo-labeling	Generalization accuracy, F1 on unseen domains
Security & Performance Evaluation	Quantify trade-off between encryption and task performance	Comparative study with baseline models	Privacy score, task performance delta, attack resistance



End-to-End Framework for Secure ViT-Based Cross-Domain Analysis

IV. Experimental Design:

To rigorously evaluate the proposed learning-based encryption framework with Vision Transformers (ViTs), a robust and diversified experimental setup is adopted. The study utilizes well-established public remote sensing (RS) datasets such as **EuroSAT**, **NWPU-RESISC45**, and **BigEarthNet-MM**. These datasets offer a wide range of sensing modalities (optical, SAR, multi-spectral), geographic diversity, and class granularity—making them ideal for benchmarking **cross-domain and multi-modal generalization performance**. For comparative analysis, three model variants are considered as **baselines**: (i) a ViT trained on **unencrypted raw images**, representing the upper performance bound; (ii) a ViT trained on **block-wise encrypted images**, mimicking traditional privacy-preserving techniques; and (iii) the proposed model, trained on **learnably encrypted inputs** using key-controlled scrambling strategies. Two primary tasks are performed—**scene classification** (e.g., land-use categorization) and **semantic segmentation** (e.g., urban vs vegetation mapping). Evaluation is based on a set of **multi-dimensional metrics**, including **classification accuracy**, **Intersection over Union (IoU)** for segmentation quality, **retrieval precision** for encrypted image search, and **attack resistance scores** to test vulnerability against inversion or reconstruction attacks. This experimental design ensures that both **task performance** and **data privacy** are measured simultaneously, validating the practicality of the proposed approach in real-world cross-domain RS scenarios.



V. Discussion and Future Work:

1. Balancing Security and Utility

One of the central challenges in designing learning-based encryption for Vision Transformers is achieving an optimal balance between **data privacy** and **model performance**. Excessive obfuscation of visual features can degrade task accuracy, especially for complex downstream applications like semantic segmentation or object detection. Future research should focus on **fine-tuning encryption parameters**, such as block size, scrambling intensity, or transformation depth, to preserve discriminative features necessary for ViT attention while minimizing the risk of data leakage. Adaptive encryption schemes—where security levels are adjusted based on task sensitivity—may provide a promising solution.

2. Key Management

Effective **key management** is critical for the practical deployment of encrypted AI pipelines. Two approaches are worth discussing: **disposable keys**, which generate unique encryption keys per instance or user, and **static keys**, which remain constant over sessions. Disposable-key frameworks offer higher privacy and reduce the chance of key reuse attacks but introduce additional complexity in synchronization and computation. Secure key exchange mechanisms—potentially integrating **public key infrastructure (PKI)** or **blockchain-based identity systems**—must be explored to support real-world, multi-user deployments without compromising confidentiality.

3. Scalability

The proposed framework should be rigorously tested for **scalability**, particularly in handling high-resolution and large-scale remote sensing datasets such as Sentinel-2, PlanetScope, or Google Earth imagery. These datasets contain richer spatial and spectral information but also demand greater computational efficiency and memory bandwidth. Exploring techniques such as **patch-wise parallelism**, **attention pruning**, or **encrypted data compression** will be essential for extending this framework to real-time and enterprise-level applications in areas like defense, disaster monitoring, and smart agriculture.

4. Potential Extensions

Several promising directions emerge for future research. One such extension is the integration of this framework into **Encrypted Federated Learning (EFL)** environments, enabling multiple remote sensing agencies to collaboratively train models without sharing raw data. Additionally, **real-time secure processing pipelines** can be developed by combining edge AI hardware (e.g., NVIDIA Jetson, Google Coral) with on-device encryption modules. Such systems would enable in-field encrypted classification or anomaly detection directly from satellites, drones, or IoT sensors—facilitating low-latency, privacy-preserving decision-making in dynamic environments.

VI. Conclusion:

Restate the main contributions: a novel learnable encryption method integrated with ViTs, evaluated on cross-domain remote sensing tasks, demonstrating effective security without compromising performance. This research presents a novel framework that integrates **learnable encryption mechanisms** with **Vision Transformers (ViTs)** to enable secure, privacy-preserving, and accurate cross-domain analysis of remote sensing imagery. By introducing key-controlled encryption at the input level, the system ensures that sensitive satellite data remains obscured throughout the learning process, without compromising the model's ability to extract meaningful features. The use of ViTs as the core backbone leverages their global attention capabilities, allowing the model to capture domain-invariant representations even from encrypted inputs. The proposed approach is rigorously validated on multi-domain datasets, showcasing competitive performance in classification and segmentation tasks while maintaining robust resistance to reconstruction and inversion attacks.

The findings highlight the growing feasibility of integrating security and machine learning in remote sensing pipelines, especially for applications involving multi-stakeholder environments and untrusted data processing infrastructures. Beyond its immediate implications, this framework sets the foundation for future research in **privacy-aware AI**, **encrypted federated learning**, and **real-time secure geospatial analytics**. Future extensions could improve scalability, enable adaptive encryption strategies, and embed the model into operational satellite platforms. Ultimately, this work demonstrates that **utility and confidentiality** need not be opposing forces in AI-driven Earth observation systems—but can instead be **jointly optimized through architectural innovation** and thoughtful system design.

References:

[1]. Chen, Y., Lin, Z., & Li, Y. (2023). *Privacy-preserving image classification using block-wise encryption and Vision Transformers*. Remote Sensing, 15(3), 516. https://www.mdpi.com/2072-4292/15/3/516

[2]. Cheng, G., Han, J., & Lu, X. (2017). *Remote sensing image scene classification: Benchmark and state of the art*. Proceedings of the IEEE, 105(10), 1865–1883. https://doi.org/10.1109/JPROC.2017.2675998

[3]. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2021). *An image is worth 16x16 words: Transformers for image recognition at scale*. International Conference on Learning Representations (ICLR). https://arxiv.org/abs/2010.11929

[4]. Gao, P., Xie, X., & Wu, Y. (2024). *Cross-domain adaptation in satellite image analysis using adversarial ViTs*. PubMed Central. https://pubmed.ncbi.nlm.nih.gov/40668721

[5]. Helber, P., Bischke, B., Dengel, A., & Borth, D. (2019). *EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification*. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(7), 2217–2226. https://doi.org/10.1109/JSTARS.2019.2912302

[6]. Khan, S., Naseer, M., Hayat, M., Zamir, S. W., Khan, F. S., & Shah, M. (2022). *Transformers in vision: A survey*. ACM Computing Surveys, 54(10s), 1–41. https://doi.org/10.1145/3505244

[7]. Li, S., Liu, H., & Ma, J. (2023). *GSV-Trans: Bio-inspired dual-branch ViT for domain adaptive segmentation in remote sensing*. Remote Sensing, 16(9), 1514. https://www.mdpi.com/2072-4292/16/9/1514

[8]. Luo, Y., Xu, B., & Zhang, Z. (2024). *Learnable encryption framework for ViTs using pixel block scrambling*. arXiv preprint. https://arxiv.org/abs/2501.15363

[9]. Sumbul, G., Charfuelan, M., Demir, B., & Markl, V. (2019). *BigEarthNet: A large-scale benchmark archive for remote sensing image understanding*. IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 5901–5904. https://doi.org/10.1109/IGARSS.2019.8898094

[10]. Wang, W., Zhao, T., & Han, L. (2024). *Encrypted Vision Transformer for secure image retrieval*. arXiv preprint. https://arxiv.org/abs/2208.14657

[11]. Zhang, H., Xu, X., & Wang, Y. (2023). *Disposable key-based encrypted federated ViT training*. arXiv preprint. https://arxiv.org/abs/2408.05737

About the Author:

DR. V.S REDDY TIRUPAM, has completed his Research Ph.D. in the field of Artificial Intelligence and Remote Sensing, with a strong academic and research interest in secure machine learning, Vision Transformers, and cross-domain data privacy. Currently pursuing advanced studies/ work focuses on the intersection of **privacy-preserving AI models** and **multi-modal geospatial analysis**. The author has contributed to several interdisciplinary projects involving encrypted data processing, federated learning, and intelligent Earth observation systems. This research reflects their commitment to developing **secure, scalable, and ethically responsible AI solutions** for real-world challenges in remote sensing and defense applications.