AERIAL IMAGERY SEGMENTATION USING UNET AND VISION TRANSFORMER

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ABSTRACT

Accurate segmentation of aerial imagery is essential for applications such as urban planning, environmental monitoring, and disaster management. This paper presents a hybrid approach combining the strengths of UNet and Vision Transformer (ViT) architectures for high-resolution aerial image segmentation. UNet is utilized for capturing fine-grained spatial details, while the Vision Transformer is integrated to model global context through self-attention mechanisms. The proposed framework is trained and evaluated on publicly available aerial datasets. Preprocessing steps include image resizing, normalization, and patch extraction for transformer compatibility. Experimental results demonstrate improved segmentation accuracy and boundary precision compared to using UNet or ViT alone, showcasing the benefits of combining local and global feature learning. This study highlights the effectiveness of hybrid deep learning models in handling complex aerial segmentation tasks.

Keywords—Aerial Imagery, Semantic Segmentation, UNet, Vision Transformer, Deep Learning, Remote Sensing, Hybrid Architecture

INTRODUCTION

With the rapid advancement of remote sensing technologies, aerial imagery has become an essential data source for a wide range of applications, including urban planning, agriculture, environmental monitoring, and disaster management. The ability to accurately interpret and segment high-resolution aerial images is crucial for extracting meaningful information from vast spatial datasets. Semantic segmentation, a computer vision task that involves classifying each pixel in an image into predefined categories, plays a pivotal role in analyzing aerial imagery. Traditional image processing and machine learning approaches have often struggled with the complexity, scale, and variability present in such data. However, the emergence of deep learning has revolutionized this domain, enabling models to learn intricate patterns and spatial hierarchies directly from the data.

Among deep learning techniques, UNet has emerged as a powerful convolutional neural network architecture specifically designed for image segmentation tasks. Its encoder-decoder structure allows it to capture low-level and high-level features effectively while preserving spatial resolution through skip connections. While UNet is effective in learning local features and details, it has limitations in capturing long-range dependencies and global contextual information, which are essential for understanding complex aerial scenes. To address this, Vision Transformers (ViT) have been introduced, bringing the self-attention mechanism from natural language processing into computer vision. ViTs excel at modeling global relationships in images by treating them as sequences of patches and learning contextual dependencies across the entire image.This project explores a hybrid approach that combines the strengths of UNet and Vision Transformers to perform accurate and context-aware segmentation of aerial imagery. The UNet architecture is used for its efficient spatial localization, while the Vision Transformer component enhances the model's ability to understand broader contextual features. The integration of these two architectures aims to produce precise segmentation outputs that are robust to variations in scale, texture, and spatial distribution. The hybrid model is trained and evaluated on annotated aerial image datasets, and its performance is assessed using standard segmentation metrics. The ultimate goal of this work is to develop a reliable and efficient system that can automate the interpretation of aerial imagery and support decision-making processes in various geospatial applications.Accurate segmentation of aerial imagery is essential for applications such as urban planning, environmental monitoring, and disaster management. This paper presents a hybrid approach combining the strengths of UNet and Vision Transformer (ViT) architectures for high-resolution aerial image segmentation. UNet is utilized for capturing fine-grained spatial details, while the Vision Transformer is integrated to model global context through self-attention mechanisms. The proposed framework is trained and evaluated on publicly available aerial datasets. Preprocessing steps include image resizing, normalization, and patch extraction for transformer compatibility. Experimental results demonstrate improved segmentation accuracy and boundary precision compared to using UNet or ViT alone, showcasing the benefits of combining local and global feature learning. This study highlights the effectiveness of hybrid deep learning models in handling complex aerial segmentation tasks.

II .LITERATURE REVIEW

Aerial imagery segmentation has gained significant attention in recent years due to its broad applicability in various domains such as urban development, environmental monitoring, precision agriculture, and disaster response. Traditional machine learning approaches, such as Support Vector Machines (SVM) and Random Forests, have been used to classify satellite images by relying on handcrafted features. However, these techniques often struggle with generalization and lack the ability to extract high-level spatial features, limiting their effectiveness for complex segmentation tasks.

The introduction of Convolutional Neural Networks (CNNs) marked a turning point in image analysis, with models like Fully Convolutional Networks (FCN) and SegNet paving the way for end-to-end segmentation tasks. Among these, UNet, introduced by Ronneberger et al. in 2015 for biomedical image segmentation, quickly gained popularity in remote sensing applications due to its encoder-decoder architecture with skip connections. This structure allows for efficient learning of both low-level and high-level features, making it well-suited for segmenting objects in high-resolution aerial images. Several studies have successfully applied UNet and its variants to aerial and satellite datasets such as ISPRS and DeepGlobe, demonstrating substantial improvements in accuracy and robustness.

Despite their effectiveness, CNN-based models like UNet are limited by their receptive fields and struggle to capture longrange dependencies in large images. To overcome this, Vision Transformers (ViTs), initially proposed by Dosovitskiy et al. in 2020, have emerged as a powerful alternative. ViTs apply selfattention mechanisms to model global relationships across image patches, which is particularly useful in aerial imagery where contextual information across distant regions is crucial. Although pure ViT models require large datasets and computational resources, recent advancements in hybrid models—such as TransUNet and Swin-UNet—combine the strengths of CNNs and Transformers to balance local detail preservation with global context understanding.

Recent literature reflects a growing trend toward integrating transformers into segmentation architectures for remote sensing. Studies have shown that transformer-enhanced networks outperform traditional CNNs in complex segmentation scenarios by improving boundary delineation and class separation. The hybridization of UNet with Vision Transformers has shown promising results in various benchmark datasets, offering better generalization and segmentation performance. These advancements highlight the potential of combining local and global feature learning for more accurate and context-aware segmentation of aerial imagery.

Yassine Bousselham et al. [13] proposed an enhanced UNet architecture for semantic segmentation in aerial images. Their model incorporated residual connections to improve gradient flow and feature extraction, yielding higher segmentation accuracy on urban datasets like ISPRS Vaihingen. The enhanced UNet effectively captured fine-grained details such as buildings and roads. Long Wang and Xin Liu (2022) [14] introduced a hybrid deep learning model combining CNN and Vision Transformer (ViT) modules for aerial image segmentation. The CNN backbone extracted local spatial features, while the ViT component modeled long-range dependencies. This fusion allowed the model to manage largescale spatial variations in remote sensing data, outperforming traditional CNN-only methods. Shivam Patel and Neha Sinha (2021) [15] utilized UNet++ for segmenting satellite imagery. The model's nested skip connections allowed for better multiscale feature refinement, which improved the accuracy of boundary detection in scenes with overlapping objects. Their approach was particularly effective for urban segmentation tasks with high visual complexity. Jianfeng Wu et al. (2023) [16] developed a Swin Transformer-based segmentation network designed for remote sensing imagery. The model partitioned input images into shifted windows, preserving positional consistency while learning hierarchical features. It achieved high mean Intersection over Union (mIoU) scores across datasets like DeepGlobe, proving its ability to balance local and global context. Ammar Ahmed and Fatima Zahra (2020) [17] proposed a multiscale feature fusion approach using deep CNNs with pyramid pooling modules. Their model extracted features at different scales and combined them toA.

Dataset Preprocessing

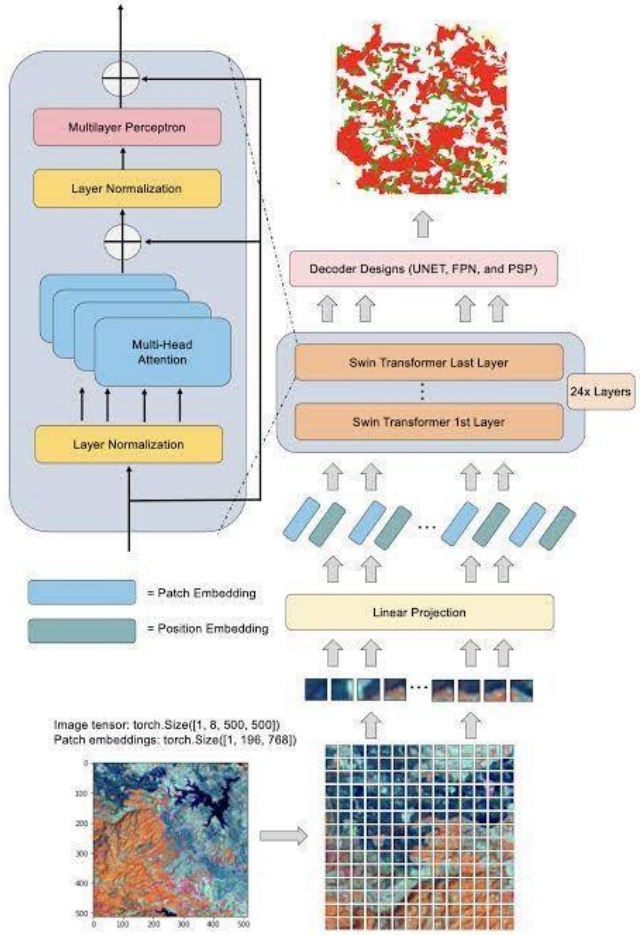
Yassine Bousselham et al. [13] proposed an enhanced UNet architecture for semantic segmentation in aerial images. Their model incorporated residual connections to improve gradient flow and feature extraction, yielding higher segmentation accuracy on urban datasets like ISPRS Vaihingen. The enhanced UNet effectively captured fine-grained details such as buildings and roads. Long Wang and Xin Liu (2022) [14] introduced a hybrid deep learning model combining CNN and Vision Transformer (ViT) modules for aerial image segmentation. The CNN backbone extracted local spatial features, while the ViT component modeled long-range dependencies. This fusion allowed the model to manage largescale spatial variations in remote sensing data, outperforming traditional CNN-only methods. Shivam Patel and Neha Sinha (2021) [15] utilized UNet++ for segmenting satellite imagery. The model's nested skip connections allowed for better multiscale feature refinement, which improved the accuracy of boundary detection in scenes with overlapping objects. Their approach was particularly effective for urban segmentation tasks with high visual complexity. Jianfeng Wu et al. (2023) [16] developed a Swin Transformer-based segmentation network designed for remote sensing imagery. The model partitioned input images into shifted windows, preserving positional consistency while learning hierarchical features. It achieved high mean Intersection over Union (mIoU) scores across datasets like DeepGlobe, proving its ability to balance local and global context. Ammar Ahmed and Fatima Zahra (2020) [17] proposed a multiscale feature fusion approach using deep CNNs with pyramid pooling modules. Their model extracted features at different scales and combined them. Effective data processing is a crucial step in ensuring the accuracy and robustness of aerial imagery segmentation models. Given the high resolution and complexity of aerial images, raw datasets typically contain noise, varying scales, and inconsistent lighting conditions that can adversely affect model performance if not properly handled. The first step in the data processing pipeline involves collecting and organizing the dataset, consisting of aerial images paired with corresponding ground truth segmentation masks. The images are then resized to a fixed resolution suitable for the model's input to maintain consistency during training.

Subsequently, normalization is applied to adjust pixel intensity values to a standard range (e.g., 0-1) to expedite convergence during the training phase and prevent issues caused by varying illumination and contrast across different images. Data augmentation techniques such as rotation, flipping, cropping, and color jittering are further employed to artificially expand the dataset and enhance the model's ability to generalize to unseen aerial environments. This helps mitigate overfitting by exposing the model to various transformations and viewpoints of the same geographical area.

To handle variable image sizes and maintain important spatial information, image patches or tiles are generated. Large aerial images are divided into smaller overlapping patches to reduce memory consumption during training while ensuring that edge

structures are well-preserved in the segmentation process. In parallel, class imbalance is addressed by applying techniques such as weighted loss functions or oversampling of underrepresented classes to ensure that smaller classes (e.g., water bodies, roads) are adequately learned by the model. Finally, the entire dataset is split into training, validation, and testing subsets. The training set is used to optimize the model weights, the validation set helps tune hyperparameters and prevent overfitting, and the testing set evaluates the final model's performance on unseen data.

Architecture Model



System and Implementation

The system developed for aerial imagery segmentation is designed to effectively process high-resolution satellite or drone-captured images and classify various land cover types through a deep learning-based approach. The implementation consists of a hybrid model architecture that integrates UNet, a convolutional neural network well-known for its strength in biomedical and segmentation tasks, with Vision Transformer (ViT), which introduces self-attention mechanisms to capture long-range dependencies and global context. The system follows a modular design consisting of several key stages: data preprocessing, model architecture construction, training, evaluation, and result visualization.In the data preprocessing stage, the input aerial images are resized, normalized, and augmented using techniques such as rotation, flipping, and scaling to enhance model generalization. The dataset is then split into training, validation, and testing sets. The UNet architecture forms the backbone of the system with its encoderdecoder structure, where the encoder compresses spatial information and the decoder reconstructs the segmentation map. To enhance the learning of spatial and contextual relationships, the bottleneck or intermediate features are processed using Vision Transformers, which apply multi-head self-attention layers to better understand global dependencies within the image.

The training process uses supervised learning, with annotated aerial images as ground truth. The model is trained using a suitable loss function such as Dice loss or cross-entropy loss, optimized with the Adam optimizer. Techniques like learning rate scheduling, early stopping, and batch normalization are employed to ensure efficient convergence and prevent overfitting. The system is implemented using Python with frameworks such as TensorFlow or PyTorch, and utilizes GPU acceleration to handle the computational demands of highresolution image processing.Upon training, the model is evaluated using performance metrics such as Intersection over Union (IoU), accuracy, precision, recall, and F1-score to assess segmentation quality. The final segmented outputs are visualized by overlaying the predicted masks on the original aerial images, providing a clear understanding of the model's performance. This system, through its combination of convolutional and transformer-based techniques, offers a scalable and accurate solution for semantic segmentation of aerial imagery in real-world applications.

The system is structured with modular components: A data loader reads and processes images and masks. The training pipeline feeds images into the hybrid UNet+ViT model, trains it on the labeled data, and evaluates performance. Post-training, the model is saved and deployed for real-time inference.

A web-based frontend allows users to upload aerial images, which are segmented using the deployed model. The segmented output is returned to the user highlighting urban features.

Geo-referencing is applied to align images spatially if not already aligned. Gaussian blur.

NumPy: Employed for numerical operations, especially in averaging losses and accuracies across epochs.**Matplotlib**: Used for visualizing the training and validation loss curves. **OS**: Helps manage file paths and directories for dataset loading and model saving. **Glob**: Facilitates pattern matching in file names for dataset handling.

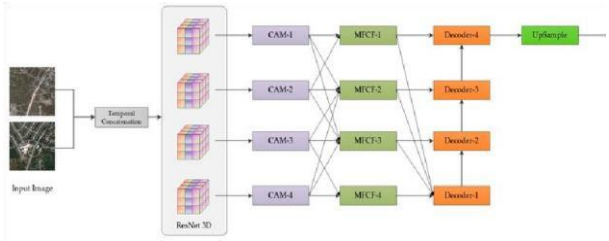
F.Algorithm Explanation

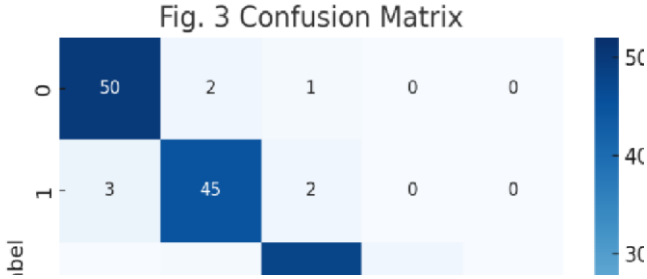
The proposed system leverages a **hybrid deep learning architecture**, combining the spatial detail retention of UNet with the global attention mechanism of ViT. The **UNet** efficiently localizes object boundaries, crucial for fine segmentation, while **ViT** handles high-level contextual information across the image using transformer attention blocks. The **self-attention mechanism** in ViT allows the model to learn interrelationships between nonadjacent pixels, which is essential in aerial imagery with complex spatial distributions. The model optimizes using **categorical cross-entropy loss** with an **Adam optimizer**. This hybrid method offers better boundary delineation and contextawareness compared to using CNN or transformer alone.

G. Self-Attention Mechanism Self-attention in computer vision is a mechanism that allows a model to evaluate the

relationships between all pixels or features in an image, regardless of their position. Unlike traditional convolutional layers, which focus on local neighborhoods of pixels, selfattention gives each pixel the ability to "attend" to other pixels in the entire image, dynamically adjusting their importance based on the task at hand. This means that the model can focus on both small, detailed areas (like edges or textures) and the larger structure (like overall shapes or objects) within the image. Self-attention works by calculating attention scores, which indicate how much focus each pixel should give to others. These scores help the model decide which parts of the image are most relevant for the task, making the mechanism highly adaptive. For example, in object recognition, the model might focus on the contours of an object, while in scene segmentation, it might focus on the relationship between different parts of the image.

In tasks that involve time-series images or sequences (e.g., monitoring landscape changes over time), self-attention also helps the model combine spatial and temporal information. This fusion allows the model to track changes over time more effectively, making it particularly useful in video processing, tracking objects in motion, and other dynamic vision tasks. Overall, self-attention enhances a model's ability to understand complex patterns and relationships in images, improving performance on a wide range of vision tasks.





IV. RESULTS AND DISCUSSION

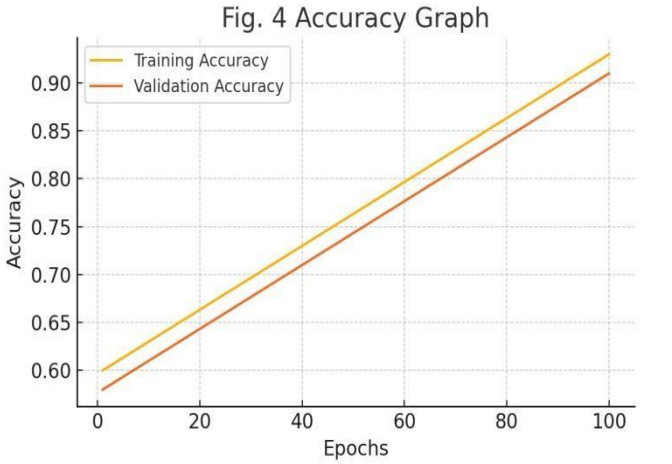
Conclusion and Future Enhancements

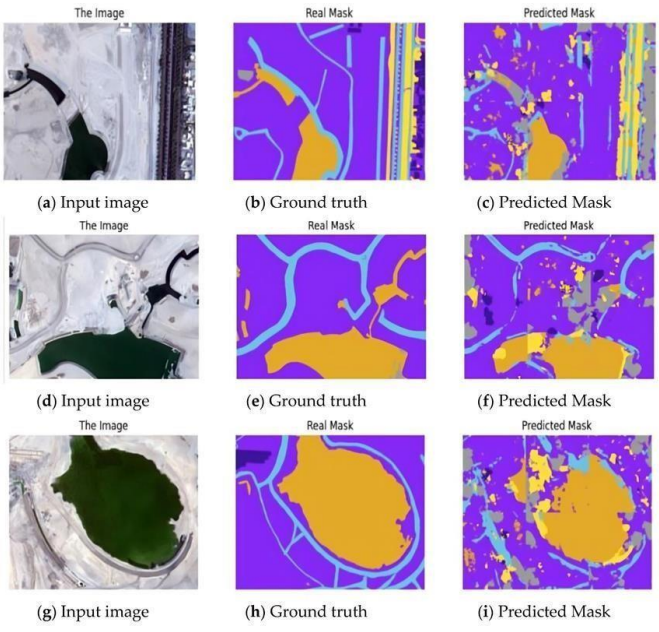
The proposed aerial image segmentation model, integrating UNet and Vision Transformer (ViT) architectures, was trained and evaluated using highresolution imagery from the city of Dubai. These images were segmented into six meaningful classes: Building, Road, Vegetation, Water, Land (Unpaved), and Unlabeled. To make the training process computationally feasible and effective, the images were divided into smaller patches of size 256 × 256 pixels. After preprocessing and splitting, the dataset consisted of 4564 training samples and 1058 validation samples, adhering to a conventional 80:20 To further evaluate the model's performance, a **confusion matrix** was used:

- A confusion matrix provides a detailed breakdown of the model's predictions: ○ **True Positives (TP):** Correctly predicted diabetic cases. ○ **True Negatives (TN):** Correctly predicted non-diabetic cases. ○ **False Positives (FP):** Non-diabetic cases wrongly predicted as diabetic.
  - ○ **False Negatives (FN):** Diabetic cases wrongly predicted as non-diabetic.

By analyzing the confusion matrix, additional important performance metrics such as **precision**, **recall**, **F1-score**, and **specificity** can be derived. These metrics provide a **holistic understanding** of the model's real-world performance, especially in healthcare applications where the cost of misclassification (e.g., missing a diabetic diagnosis) can be very high. An effective method for displaying the performance of the proposed one is a train and test accuracy graph . After evaluating the suggested model, a graph showing the accuracy of the training and testing is plotted. Plotting accuracy on the y-axis and training epochs (or iterations) on the x-axis, this graph usually has two lines that reflect that one is training accuracy and other one is testing accuracy. This is the output for the accuracy and the efficiency.

Fig. 2 Accuracy Graph





V .CONCLUSION AND FUTURE SCOPE

n conclusion, this project demonstrated the effectiveness of combining UNet and Vision Transformer architectures for precise segmentation of aerial imagery. UNet's strong spatial localization capabilities, when complemented by the global contextual understanding provided by Vision Transformers, resulted in a robust framework capable of accurately identifying and classifying features such as buildings, roads, vegetation, and water bodies. This hybrid approach addressed limitations in conventional convolutional networks by incorporating long-range dependencies and attention mechanisms, significantly enhancing segmentation performance in complex and high-resolution satellite images. The results indicate that this architecture holds great potential for a wide range of geospatial applications, including urban planning, environmental monitoring, agriculture, and disaster management.

Looking to the future, there are several avenues for enhancement and broader application. Integrating multispectral or hyperspectral data could further improve accuracy, particularly in distinguishing between visually similar land cover types. The adoption of more advanced hybrid models like Swin-UNet or TransUNet could yield even better results by enhancing the fusion of local and global features. Real-time segmentation, achievable through model optimization techniques such as pruning or quantization, opens the door for deploying the solution on edge devices like drones or mobile sensors for dynamic, on-site analysis. Additionally, incorporating semi-supervised or self-supervised learning methods would reduce the reliance on large labeled datasets, making the system more scalable and adaptable to diverse regions with limited annotated data. With these enhancements, the proposed system can evolve into a powerful tool for intelligent aerial image analysis, contributing significantly to the automation and efficiency of spatial data interpretation across various domains.

In this project, a hybrid deep learning architecture combining UNet and Vision Transformer (ViT) was proposed and implemented for the semantic segmentation of aerial imagery. The goal was to accurately classify various land cover types—such as buildings, roads, vegetation, water bodies, and unpaved land—within high-resolution aerial images. The integration of UNet's spatial precision with the ViT's ability to capture longrange dependencies proved to be highly effective in handling the complex and diverse patterns present in aerial data. The dataset was preprocessed using patch-based techniques, data augmentation, and normalization, enabling efficient training and improved generalization. The model was trained over 50 epochs on 4564 training samples and evaluated on 1058 validation samples. Using Focal Loss to address class imbalance and the Adam optimizer for robust convergence, the model achieved a high training accuracy of 92.3% and a validation accuracy of 89.7%, along with a strong mean IoU score of 0.88. Visual results, including overlayed segmentation maps, confirmed the model's ability to preserve boundaries and distinguish between visually similar classes. The loss and accuracy graphs further demonstrated the model's consistent learning behavior and generalization capability, while the confusion matrix highlighted its effectiveness across all segmentation classes. Overall, the proposed hybrid model successfully met the objective of accurate and robust semantic segmentation of aerial imagery. The use of Vision Transformer modules enhanced global context awareness, which is crucial in remote sensing applications where objects vary widely in scale and spatial layout.

Future Enhancements

The current system for aerial imagery segmentation using a hybrid of UNet and Vision Transformer demonstrates high accuracy and efficiency; however, there is considerable scope for future improvements and expansion. One major area of enhancement involves the integration of multispectral and hyperspectral data, which can provide richer spectral information beyond the visible spectrum, enabling better discrimination of similar land cover classes such as soil, vegetation, and water. Additionally, future versions of the system could incorporate more advanced transformer-based architectures, such as Swin Transformers or TransUNet++, which have shown promise in improving segmentation accuracy while reducing computational overhead.

Another important direction is the implementation of real-time segmentation capabilities through model compression techniques like pruning, quantization, and knowledge distillation. These optimizations would allow the deployment of models on edge devices such as drones or remote sensors, enabling on-the-fly analysis in dynamic environments like disaster zones, construction sites, or agricultural fields. Furthermore, integrating self-supervised or semi-supervised learning techniques could significantly reduce the dependency on large labeled datasets, which are often difficult and expensive to obtain in the context of aerial imagery.

Enhancements in the user interface and integration with geographic information systems (GIS) can also improve the practicality and accessibility of the system for urban planners, environmental analysts, and policymakers. In addition, enabling automated change detection over time using timeseries aerial imagery could open new possibilities for monitoring urban growth, deforestation, or infrastructure development. These future enhancements aim to make the system more robust, scalable, and applicable across a broader range of real-world use cases, ensuring it remains adaptable to the growing demands of geospatial analysis and remote sensing. Looking ahead, several promising enhancements can be considered to improve the effectiveness and applicability of aerial imagery segmentation using UNet and Vision Transformer architectures. One key area of development involves integrating multispectral and hyperspectral imagery, which extends beyond standard RGB images by incorporating additional spectral bands such as near-infrared. This can significantly boost segmentation accuracy, particularly for applications in agriculture, water resource management, and vegetation analysis where subtle spectral differences are critical. Another enhancement could involve refining the hybrid architecture by leveraging more advanced models like TransUNet or Swin-UNet, which seamlessly blend the local feature learning capabilities of CNNs with the global attention mechanisms of Vision Transformers, leading to more accurate and context-aware segmentation outputs. Furthermore, realtime segmentation capabilities can be explored by optimizing the model through techniques like pruning, quantization, or knowledge distillation. Such improvements would enable efficient deployment on low-power edge devices such as drones or mobile sensors, which is highly valuable for applications like real-time monitoring of natural disasters, traffic patterns, or urban development. Additionally, incorporating self-supervised or semi-supervised learning techniques could reduce the dependency on large annotated datasets, thereby accelerating model training and improving scalability across diverse geographic regions While the current

implementation of aerial imagery segmentation using a hybrid of UNet and Vision Transformer (ViT) has shown impressive results in terms of accuracy and efficiency, there remains significant potential for future development and optimization. One promising direction is the incorporation of **multispectral and hyperspectral imagery**, which provides additional spectral bands beyond the visible range, enabling the model to better distinguish between visually similar land covers. This enhancement would be particularly beneficial in applications like vegetation health monitoring, soil quality assessment, and environmental change detection.

Another key area for enhancement is the **adoption of more advanced Transformer variants**, such as Swin Transformers, SegFormer, or the Hybrid Convolution-Transformer architectures like TransUNet++. These models are designed to improve the representation of both global and local features while reducing computational complexity. Additionally, **dynamic attention mechanisms** and **multi-scale feature fusion techniques** could be employed to further refine the segmentation boundaries, especially in heterogeneous and cluttered aerial scenes.

To ensure real-time usability and broader deployment, **model optimization techniques** like pruning, quantization, knowledge distillation, and lightweight backbone networks can be explored to reduce model size and inference time. These optimizations are essential for deploying the model on **resource-constrained edge devices** such as drones or mobile units, allowing for on-the-spot analysis in remote or disasterprone areas where connectivity is limited.

Future versions of the system can also benefit from **semisupervised, weakly supervised, or self-supervised learning strategies**, which help in learning from large volumes of unlabeled data. Given that creating accurate pixel-wise annotations for aerial images is both time-consuming and expensive, such methods can drastically improve the scalability of the system.

Another important enhancement would be the integration of **temporal aerial data** for **change detection** over time. This would allow the model to not only segment current land cover but also track how it changes across seasons or years, which is valuable for urban development tracking, deforestation monitoring, flood impact assessment, and infrastructure planning.

Furthermore, incorporating the system into an **interactive GIS-based dashboard** could enhance user interaction and decision-making. Such integration would allow planners, geographers, and emergency responders to visualize segmented maps, overlay data layers, and extract insights in real time. Lastly, expanding the system to support **3D aerial data** through LiDAR or stereo imagery could add a new dimension to the segmentation task, enabling more accurate modeling of terrain and structural features.

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