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Deep Learning Applied to Deforestation Detection in Brazilian Biomes :

An Approach Based on Convolutional Neural Networks, Vision Transformers and Attention
Mechanisms

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Giovana Augusta Benvenuto

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Tese, apresentada à Universidade Estadual Paulista (UNESP), Instituto de Biociências, Letras e Ciências Exatas, São José do Rio Preto, para obtenção do título de Doutora em Ciência da Computação.

Área de Concentração: Computação Aplicada

Orientador: Profº Dr. Wallace Correa de Oliveira Casaca

Coorientador: Profº Dr. Rogério Galante Negri

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IMPACTO POTENCIAL DESTA PESQUISA

A pesquisa desenvolvida neste trabalho apresenta impacto científico e tecnológico, ao propor novos modelos de aprendizado profundo para a segmentação de áreas de desmatamento. Os modelos desenvolvidos foram aplicados a biomas nacionais e demonstraram vantagens para aplicações em tempo real, alcançando resultados competitivos com menor demanda de recursos computacionais. Dessa forma, as abordagens propostas podem contribuir para o monitoramento de áreas de interesse de maneira viável e com menor custo computacional, apoiando iniciativas de acompanhamento e gestão ambiental.

POTENTIAL IMPACT OF THIS RESEARCH

The research developed in this work presents both scientific and technological impact by proposing new deep learning models for the segmentation of deforested areas. The developed models were applied to national biomes and demonstrated advantages for real-time applications, achieving competitive results while requiring lower computational resources. Thus, the proposed approaches can contribute to the monitoring of areas of interest in a feasible and cost-effective manner, supporting environmental monitoring and management initiatives.

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Dedico este trabalho à minha família

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“...mas aquele que perseverar até o fim, será salvo.”

São Mateus 10, 22

RESUMO

O Brasil abriga dois dos biomas mais biodiversos do planeta: a Amazônia e a Mata Atlântica. Apesar de sua importância ecológica e climática, essas regiões têm sido severamente impactadas nas últimas décadas pelo avanço do desmatamento, majoritariamente associado à ação humana. Nesse contexto, o uso de tecnologias de Sensoriamento Remoto (SR) aliado a métodos avançados de Inteligência Artificial (IA) tem se mostrado uma estratégia promissora para ampliar a capacidade de monitoramento ambiental em larga escala. Esta tese investiga o uso de técnicas de Aprendizado Profundo para a segmentação automática de áreas desmatadas nesses biomas. Para isso, propõe-se uma arquitetura híbrida que combina redes neurais convolucionais com módulos baseados em *transformers* e mecanismos de atenção, explorando simultaneamente características espaciais e temporais extraídas de imagens de satélite multiespectrais. A metodologia considera dados bi-temporais, permitindo capturar mudanças na cobertura vegetal e aprimorar a identificação de padrões associados ao desmatamento. Os modelos propostos foram avaliados por meio de uma extensa bateria experimental, sendo comparados a treze modelos consolidados da literatura em diferentes cenários experimentais. Os resultados demonstram que as abordagens desenvolvidas alcançam desempenho competitivo, apresentando o melhor equilíbrio entre acurácia de segmentação e eficiência computacional. Além das contribuições científicas, esta pesquisa também visa fomentar o desenvolvimento de soluções tecnológicas aplicáveis ao monitoramento ambiental, contribuindo para o avanço do uso de IA em aplicações de SR no Brasil.

Palavras-Chave: visão computacional; inteligência artificial; aprendizagem profunda; sensoriamento remoto; desmatamento.

ABSTRACT

Brazil hosts two of the most biodiverse biomes on the planet: the Amazon and the Atlantic Forest. Despite their ecological and climatic importance, these regions have been severely impacted in recent decades by the advance of deforestation, largely associated with human activities. In this context, the use of Remote Sensing (RS) technologies combined with advanced Artificial Intelligence (AI) methods has emerged as a promising strategy to expand large-scale environmental monitoring capabilities. This doctoral thesis investigates the use of Deep Learning techniques for the automatic detection and segmentation of deforested areas in these biomes. To this end, a hybrid architecture is proposed that combines Convolutional Neural Networks with transformer-based modules and attention mechanisms, simultaneously exploring spatial and temporal features extracted from multispectral satellite imagery. The methodology considers bi-temporal data, enabling the capture of changes in vegetation cover and improving the identification of patterns associated with deforestation. The proposed model was evaluated through an extensive experimental framework and compared with thirteen well-established models from the literature across different experimental scenarios. The results demonstrate that the proposed approach achieves competitive performance, presenting the best trade-off between segmentation accuracy and computational efficiency. In addition to its scientific contributions, this research also aims to foster the development of technological solutions applicable to environmental monitoring, contributing to the advancement of AI-based RS applications in Brazil.

Keywords: computational vision; artificial intelligence; deep learning; remote sensing; deforestation.

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LIST OF ACRONYMS

AI Artificial Intelligence.

C2f Cross-Stage Partial Network Fusion.

C3k2 Cross Stage Partial with kernel size 2.

CE Cross-Entropy.

CNN Convolutional Neural Network.

DL Deep Learning.

DNN Deep Neural Networks.

EF Early Fusion.

FCN Fully Convolutional Networks.

FFNs Feed-Forward Networks.

FLOPs Floating Point Operations.

FN True Negatives.

FP False Positives.

FPS Frames Per Second.

GEE Google Earth Engine.

GELAN Generalized Efficient Layer Aggregation Network.

GT Ground-Truth.

IoU Intersection over Union.

LF Late Fusion.

LSTM Long Short-Term Memory.

mAP mean Average Precision.

MHSA Multi-Head Self-Attention.

ML Machine Learning.

MLP Multilayer Perceptron.

MPA Mean Pixel Accuracy.

MSI Multispectral Instrument.

NIR Near-Infrared.

NLP Natural Language Processing.

OLI Operational Land Imager.

PA Pixel Accuracy.

PGI Programmable Gradient Information.

PRODES Programa de Monitoramento da Floresta Amazônica Brasileira por Satélite.

ReLU Rectified Linear Unit.

RS Remote Sensing.

SGD Stochastic Gradient Descent.

SiLU Sigmoid Linear Unit.

SN Siamese Network.

SPPF Spatial Pyramid Pooling Fast.

SWIR Shortwave Infrared.

TIRS Thermal Infrared Sensor.

TN False Negatives.

TP True Positives.

UAV Unmanned Aerial Vehicles.

ViT Vision Transformers.

WCE Weighted Cross-Entropy.

YOLO You Only Look Once.

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1 INTRODUCTION

Brazilian territory, the fifth largest in the world, encompasses vast regions characterized by diverse climatic and geological conditions. These areas are classified into six major biomes, Amazon, Atlantic Forest, Cerrado, Caatinga, Pampa, and Pantanal, each exhibiting remarkable diversity in vegetation and wildlife (Ellwanger; Nobre; Chies, 2023). This biological richness plays a fundamental role in shaping Brazil's natural heritage and cultural diversity.

Although the country is home to an extraordinary abundance of living organisms and a wide range of ecosystems, Brazilian biomes have experienced recurrent environmental crises over the past decades. These include the expansion of deforestation and wildfires which, among several factors, are largely driven by anthropogenic activities (Nobre et al., 2016; Pivello et al., 2021). Indeed, the impacts of deforestation and wildfires cause irreversible damage not only to Brazil's environment but also indirectly affect other countries worldwide, as well as the global economy itself.

For instance, to better contextualize the magnitude of the problem, data released by the Federal Government Portal (Secretaria de Comunicação Social – SECOM, 2025) indicate a 32.4 % reduction in deforested areas in Brazil between 2023 and 2024. The total area cleared in the Amazon biome remained substantial, reaching 377 708 ha, equivalent to approximately 528 000 soccer fields. The Atlantic Forest, in the meantime, recorded 13 472 ha of deforestation. Although this area is significantly smaller, it was the only biome to show an increase in deforestation compared to the previous years.

In light of the intensification of these critical events and considering global initiatives aimed at forest preservation, such as the United Nations Sustainable Development Goal 15 (SDG 15), one of the objectives established by the United Nations in the 2030 Agenda for Sustainable Development (Nações Unidas Brasil, 2025), as well as the 30th United Nations Climate Change Conference (COP30) (Presidência da República, Casa Civil, 2025) in 2025, it becomes evident that there is an urgent need to develop technological tools, as well as prevention and mitigation strategies, capable of supporting the characterization, detection and monitoring of risk areas and environmental incidents across Brazilian biomes.

Through continuous monitoring of the country's diverse ecosystems, it becomes possible to track the emergence and expansion of deforested areas, revealing potential illegal activities within protected regions. In this context, quick assessment of the case enables timely alerts to public authorities and other responsible agencies, allowing measures to be implemented to mitigate damage, protect lives, and mobilize health and inspection teams in the field (Luemba; Kunzayila; Casaca, 2021).

To ensure the continuous monitoring of biomes, one of the key technologies that enables the multitemporal analysis of vast vegetated areas is Remote Sensing (RS) (Ban, 2016). Data acquired through different Earth observation sensors are generally georeferenced, when com-

combined with appropriate computational techniques, allow for the identification of phenomena ranging from geophysical variables to environmental changes. These include mass movement rates (Negri et al., 2021), vegetation cover changes (Sapucci et al., 2021), land use and land cover dynamics (Negri; Silva; Casaca, 2018), landscape dynamics (Gino et al., 2023), flooded-area mapping (Negri et al., 2025), among others.

Once acquired, RS data can be combined and analyzed to, for example, characterize vegetation disturbance patterns (Rodrigues et al., 2024) or detect deforestation hotspots within biome areas. However, due to the nature of these images, which typically exhibit high dimensionality and complex patterns that are difficult to categorize, the adoption of advanced computational approaches becomes necessary. In this context, robust Pattern Recognition and Computer Vision techniques play a crucial role, being fundamental for the effective processing and interpretation of such data in environmental monitoring applications (Basso et al., 2021).

Given the challenges associated with processing large collections of RS imagery, including the joint manipulation of spatial, temporal, and spectral information with high levels of precision and detail (Yuan et al., 2020), Deep Learning (DL) models have gained increasing prominence in this field. This trend is largely supported by the massive volume of data generated by modern sensors, as well as by the flexibility of multilayer architectures employed in DL. Such architectures are capable of accurately approximating the complex nonlinear relationships among environmental, geometric, and temporal parameters, thereby enabling more robust modeling of intricate Earth observation phenomena (LeCun; Bengio; Hinton, 2015; Yuan et al., 2020).

Two DL architectures have been particularly prominent in this context: Convolutional Neural Network (CNN) and Transformer-based models (LeCun; Bengio; Hinton, 2015; Oubadriss; Laassiri; Makrani, 2024). CNNs have been widely adopted in RS applications, especially for semantic segmentation and change detection tasks, due to their ability to learn hierarchical spatial features from large volumes of annotated imagery (Yuan et al., 2020). More recently, the Transformer architecture, originally proposed for natural language processing tasks (Vaswani et al., 2017), has shown a remarkable ability to capture global contextual relationships within data and has been adapted to Computer Vision through the development of Vision Transformers (ViT) (Dosovitskiy et al., 2021). Despite the growing attention these models have received, their use in applications such as deforestation monitoring remains relatively limited (Benvenuto et al., 2025).

Considering the aforementioned challenges, this doctoral research aimed to explore and develop new methodologies based on the DL paradigm for multitemporal deforestation pattern detection, performing semantic segmentation, in biomes such as the Amazon Rainforest and the Atlantic Forest. Here, special attention was given to modeling temporal dependencies in RS data so that deforestation signals could be captured consistently over time, even in the presence of noise, cloud contamination and acquisition gaps. Beyond accurately identifying targets with temporal consistency, that is, preserving the historical coherence of the scene across frames captured at different time points, the proposed methodologies were designed to enable automatic

target classification. As a result, the developed approaches constitute supervised methods capable of delivering accurate and temporally coherent deforestation mapping.

From a more technical perspective, we developed hybrid models that combine the well-established performance of CNNs with spatial attention mechanisms, and later with the representation and learning capabilities of ViT architectures. Indeed, our proposed designs are further enhanced by attention mechanisms and a composite loss function to effectively address the problem. More specifically, the first model adapts layers derived from the eighth version of the You Only Look Once (YOLO) architecture to the backbone of the network, while the second integrates these layers with a ViT module, followed by a convolutional upscaling strategy. For both, Spatial Attention mechanisms are applied at two distinct stages of the network, and skip connections are established between the downsampling and upsampling paths to preserve multiscale feature information. Finally, the learning scheme is guided by a composite loss function that combines Focal Loss and Dice Loss. This formulation is particularly suitable for handling class imbalance and contributes to improved model refinement and segmentation accuracy.

The proposed models were evaluated on three datasets: two single-temporal datasets from the Amazon Rainforest and the Atlantic Forest, and a third bi-temporal dataset from the city of Altamira, located in the Amazon biome. The third dataset is also an original product of this research, designed to represent real-world scenarios with imbalanced data and to incorporate temporal aspects, thereby enriching the evaluation set. The experimental setup involved a comparative analysis with a total of thirteen methods, considering qualitative, quantitative, and efficiency perspectives. Among the variations of the proposed architectures, the lightest version of the ViT-based model stood out, providing the best trade-off between segmentation accuracy and computational efficiency. These results indicate that the proposed approaches are suitable for application in real-world deforestation scenarios, as they achieve high accuracy even when trained on limited datasets. Their lightweight architectures enable fast training and inference, and they can be applied both to detect deforestation in a single period and to assess increases in deforestation over time. This supports continuous observation and monitoring of conservation areas, while enabling the early detection of deforestation at both small and large scales.

1.1 JUSTIFICATION AND OBJECTIVES

Over the past few years, DL has become a key resource for mapping deforested areas and other landscape disturbances. In this context, progress has been driven mainly by increasingly sophisticated CNN architectures and by the refinement of classic Machine Learning (ML) strategies for large-scale RS data.

Although recent literature reports techniques with relative effectiveness in specific supervised contexts, there are still numerous gaps. In particular, many approaches do not explore bi-temporal inputs, with results restricted to a single image, fail to discuss the computational cost associated

with the proposed models, and do not test them in different domains, varying regions and vegetation (Benvenuto et al., 2025). Furthermore, although many studies have adopted DL algorithms to address different RS applications in recent years, newer techniques coupled with these networks, such as attention mechanisms and transformer-based modules, remain relatively underexplored. In this sense, the application of DL to these problems is still at the frontier of knowledge.

The need to develop innovative technological solutions that combine accuracy, efficiency, and automation for the classification and monitoring of environmental incidents in protected forest areas in Brazil is another central motivation for this research. Such solutions may create tangible opportunities for integration between academia and industry.

Therefore, in light of the previously discussed aspects, the identified motivations and the gaps observed in the literature, the main objective of this PhD research is to design and evaluate new DL-based methodologies for the multitemporal semantic segmentation of deforestation patterns in Brazilian biomes, with emphasis on the Amazon Rainforest and the Atlantic Forest. To accomplish this, the following specific objectives were established:

- a) The investigation of classical and recent DL algorithms and techniques in the context of RS for deforestation detection and segmentation, analyzing their contributions and limitations.
- b) The implementation, enhancement, and evaluation of different DL strategies and network architectures for the application addressed in this study.
- c) The combination of DL-based algorithmic solutions in order to build more robust and accurate model for segment deforested areas.
- d) The analysis of distinct data collections, including temporal series of multispectral images, as well as the investigation of preprocessing strategies required for their effective use within the implemented Artificial Intelligence (AI) computational frameworks.
- e) The exploration and optimization of the training procedures for the developed models in order to improve their overall performance.
- f) Lastly, an experimental evaluation of the impact of the developed computational model in practical RS applications, with a particular focus on the Brazilian forest biomes of the Amazon and the Atlantic Forest.

1.2 CONTRIBUTIONS

Considering the objectives established throughout this PhD thesis, the main contributions of this research can be summarized as follows:

- Addressing the first objective of this research, i.e., an extensive literature review was conducted to explore algorithms relevant to the problem under investigation. A critical

analysis of the selected studies was also performed, while identifying representative models to be used as baselines in the comparative analysis.

- Embracing objectives b) and c), this work proposes two DL models. The first incorporates and adapts layers from a network widely known for real-time object detection, YOLOv8, integrating them into its encoder. The second replaces part of the YOLO architecture with a ViT module. Both models employ a U-shaped decoder guided by a spatial attention mechanism and skip connections. The proposed models are trained using a composite loss function that combines Dice Loss and Focal Loss. This combination encourages the models to achieve a high overlap with the reference data while reducing the impact of class imbalance.
- Considering objective d), a custom dataset was developed using images acquired by the Landsat-8 satellite with the support of the Google Earth Engine (GEE) platform, comprising bi-temporal data for monitoring the expansion of deforested areas. Within this objective, we also propose a preprocessing strategy for bi-temporal images, in which a fusion procedure based on logical operations is applied to generate maps that highlight areas of interest.
- Based on objective e), we conducted a comprehensive ablation and optimization study of the modules composing the proposed model, focusing in the ViT approach, aiming to evaluate the effectiveness of the adopted combinations and to establish a robust, consistent, and competitive architecture across different scenarios.
- Finally, according to the last objective, the proposed approaches was evaluated in three different scenarios and compared with well-established models from the literature. The results demonstrate its effectiveness across distinct experimental settings, outperforming competing approaches in terms of both accuracy and efficiency, while providing the best trade-off between segmentation quality and computational cost.

In summary, this research addresses the challenge of accurately and efficiently detecting deforestation using RS data and DL techniques, including the synergic combination of CNNs and ViTs. By combining convolutional architectures with transformer-based modules and attention mechanisms, the proposed approach seeks to improve the representation of spatial patterns associated with forest degradation while maintaining computational efficiency. Through extensive experimentation and comparative analyses, this work aims to contribute to the development of more robust and practical tools for environmental monitoring in Brazilian forest biomes.

In addition to these scientific and technological contributions, this doctoral research also resulted in a set of peer-reviewed publications, both directly related to the thesis and in broader, but complementary, topics.

The main publications directly related to this thesis are:

- (Benvenuto et al., 2025) "Precision Meets Speed: An Attention Encoder–Decoder Network for Deforestation Segmentation", *IEEE Geoscience and Remote Sensing Letters - Topic: 38th Conference on Graphics, Patterns and Images (SIBGRAPI 2025)* (**Qualis/CAPES: A1, Google h5-index:86**).
- (Benvenuto et al., 2025) "Assessing the Performance of Deep Learning Networks for Real-Time Deforestation Segmentation in the Amazon and Atlantic Biomes", *Apresentado em 52º Seminário Integrado de Software e Hardware (SEMISH), 2025* (**Qualis/CAPES: A4**)

Other publications produced during the PhD period, include:

- (Benvenuto; Colnago; Casaca, 2022) "Unsupervised Deep Learning Network for Deformable Fundus Image Registration", *47th IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP, 2022* (**Google h5-index: 137**).
- (Benvenuto et al., 2022) "A Fully Unsupervised Deep Learning Framework for Non-Rigid Fundus Image Registration", *Bioengineering*, 2022. (**Google h5-index: 71**).
- (Benvenuto; Casaca, 2023) "Retinal Images Registration via Unsupervised Deep Learning", *Workshop de Teses e Dissertações - 36th Conference on Graphics, Patterns and Images (SIBGRAPI), 2023*. (**Qualis/CAPES: A3**).
- (Colnago et al., 2022) "Risk Factors Associated with Mortality in Hospitalized Patients with COVID-19 during the Omicron Wave in Brazil", *Bioengineering*, 2022. (**Google h5-index: 71**)
- (Benvenuto et al., 2024) "GECET: Garotas nas Engenharias, Ciências Exatas e Tecnologias: Projeto de Extensão voltado para a participação feminina nas áreas STEM" *Anais Estendidos do XXX Simpósio Brasileiro de Sistemas Multimídia e Web*, 2024. (**Qualis/CAPES: A3**).

1.3 TEXT ORGANIZATION

This manuscript is organized as follows. Chapter 2 presents the theoretical foundation of the study, introducing general concepts of RS, the fundamentals of DL, with emphasis on CNNs and Transformers, and the problem of semantic segmentation. Chapter 3 reviews related works that employ different DL strategies for detecting deforestation areas across various types of imagery, along with a comparative analysis of these approaches. Chapter 4 describes the proposed methodologies, highlighting its main components and the strategy adopted to address the targeted problem, as well as the evaluation frameworks. Chapter 5 presents the experimental development and discusses the results obtained from the multiple trained configurations. Finally, Chapter 6 summarizes the main findings of this study.

6 CONCLUSION

In this doctoral thesis, we addressed the problem of deforestation area segmentation, focusing on the Brazilian biomes of the Amazon and the Atlantic Forest. The literature review revealed that, although many studies have benefited from DL techniques, important gaps still remain, particularly regarding the use of single-temporal and bi-temporal inputs, as well as the evaluation of methods across different geographic regions and application scenarios. Furthermore, only a limited number of works systematically investigate the impact of computational complexity on model performance, especially in terms of scalability and practical deployment.

Therefore, this research contributes to scientific advancement by proposing two novel architectures. The first combines the efficiency of YOLOv8 with spatial attention mechanisms, while the second builds upon these initial findings and integrates them with the strong representation capability of ViT. Furthermore, the models are enhanced by an attention-based decoder employing spatial attention mechanisms, as well as a composite loss function that integrates the class-balancing properties of Focal Loss with the region-overlap optimization of Dice Loss.

Another important contribution of this work is the construction and organization of a dedicated dataset composed of bi-temporal image pairs from the Amazon region, specifically from the municipality of Altamira, using Landsat-8 satellite imagery acquired between 2016 and 2017. Furthermore, a temporal fusion strategy was proposed to enhance relevant changes between the image pairs through the application of logical operations, enabling the generation of maps that better highlight deforestation patterns. The dataset and the first developed model are publicly available on GitHub¹.

In addition, we introduced a new bi-temporal fusion strategy specifically designed to effectively handle pairs of multitemporal images. The proposed method undergone a comprehensive comparative evaluation across three distinct datasets and was benchmarked against thirteen well-established architectures from the literature, taking into account the particular characteristics of each model and dataset. A systematic ablation study was also conducted to identify the most effective configuration of the second proposed architecture, ensuring a well-founded and optimized final design.

Based on the conducted experiments, we conclude that the proposed models outperformed the state of the art, particularly in its ViT 128-variant configuration. This version, being the lightest, employs smaller patch dimensions in the Transformer module, resulting in a more efficient yet highly effective architecture. The comparative experiments demonstrated that the proposed method achieved improvements both quantitatively and qualitatively, showing strong adherence to ground truth boundaries and consistently attaining higher average accuracy values, especially in terms of F1-Score. Across all three evaluated datasets, the model delivered competitive or

¹ <https://github.com/GiBenvenuto/Precision-Meets-Speed-Attention-Encoder-Decoder-Network-for-Deforestation-Segmentation>

superior performance.

For Datasets 1 and 2, it outperformed classical architectures such as U-Net and ResUnet, as well as Transformer-based models like TransU-Net++ and attention-enhanced approaches such as Attention U-Net. For Dataset 3, the proposed method surpassed different YOLO variations and traditional architectures specifically designed for image pair analysis, such as Siamese-based networks. These results reinforce the robustness, adaptability, and effectiveness of the proposed hybrid framework across distinct scenarios and data characteristics.

Additionally, to achieving the highest accuracy results, the proposed 128 model stands out particularly in terms of computational efficiency, demonstrating remarkably fast performance. Even with the inclusion of Transformer modules, the architecture maintains a well-balanced number of parameters and GFLOPs. The lightest configuration requires less than 13 minutes for training, and, even more notably, achieves inference times ranging from 0.0034 to 0.0054 seconds, depending on the dataset. This represents a highly favorable trade-off between accuracy and efficiency, especially considering that competing methods with comparable accuracy often require training and inference times up to ten times longer.

The growing demand for sustainable and efficient models promotes the relevance of this work. In this context, the proposed methodologies contributes to the scientific community by demonstrating the effectiveness of hybrid architectures, specifically, the integration of highly optimized CNNs for real-time applications with Transformer-based modules. The results show that it is possible to achieve high accuracy while maintaining a balanced computational cost and reduced execution time, making such models suitable for real-world environmental monitoring tasks.

As highlighted previously, the proposed models achieved strong performance even when trained on limited datasets and without the use of data augmentation techniques. The hybrid ViT 128 model also demonstrated satisfactory results under domain shift conditions, reinforcing its generalization capability. In this way, the proposed solutions presents strong potential for operational and scalable deployment. Both can be applied in parallel processing frameworks to efficiently cover large territorial areas, enabling fast identification of deforestation hotspots and supporting timely decision-making processes.

The proposed models are based on a supervised learning approach and, as such, presents the inherent limitation of requiring labeled data for training. Although robust results even with limited data availability, the quality of the annotations directly influences the results. In particular, poorly constructed or imprecise GT data can induce the network to learn incorrect patterns, ultimately leading to prediction errors and penalizing overall performance. Therefore, careful dataset curation and high-quality reference labeling remain critical factors for achieving optimal results.

As future work, multiple improvements can be explored. One possible direction is to expand the experimental evaluation by testing the models on additional datasets and exploring different input compositions, particularly considering alternative spectral band combinations provided by

satellite sensors. Or even to extended to related tasks, such as the detection of fire hotspots or active fire events, which share visual and contextual similarities with deforestation patterns.

Another promising avenue involves optimizing the network to further reduce its computational cost, including structural adjustments aimed at decreasing the number of required operations. In parallel, investigating self-supervised or semi-supervised learning strategies could help reduce the dependence on labeled data, thereby addressing the current limitations of the proposed approaches.

Finally, integrating the proposed approaches into operational systems represents a pivotal step toward practical deployment, enabling the effective use of the developed methodologies in real-world environmental monitoring applications.

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