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Research Article

Intelligent Satellite - Based Deforestation Surveillance Using Enhanced Classification

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ARTICLE INFO	ABSTRACT

Understanding the dynamics of deforestation andland use in adjacent regions is crucial for developing effective forest conservation and management policies. This study presentsa novel approach to addressing deforestation by treating it as a multilabel classification (MLC) problem using satellite imagery. We introduce Inception, an advanced model that leverages the self-attention mechanism, thereby eliminating the need for convolution operations typically used in traditional deep learningmodels for detecting deforestation. Extensive experiments con- ducted on publicly available satellite image datasets demonstrate the effectiveness of Inception in MLC, particularly in scenarios with imbalanced classes. This research marks a significant advancement in utilizing the Inception architecture for deforestation monitoring, emphasizing its potential to enhance the accuracy and sensitivity of land use classification based on satellite images.

Index Terms—*Deforestation, Land Use, Forest Conservation, Multilabel Classification, Satellite Imagery, Inception Model, Self-Attention Mechanism, Deep Learning, Imbalanced Classes, Deforestation Detection, Land Use Classification*.

INTRODUCTION

Deforestation and land use changes are critical issues impacting biodiversity, climate change, and local communities, necessitating effective policies for forest conservation and management. Traditional monitoring methods, which rely on ground observations and conventional remote sensing, can be labor-intensive and less effective in capturing complex land use patterns. Recent advancements in satellite imagery and machine learning offer new opportunities for more accurate and efficient monitoring. This study presents a novel approachto deforestation monitoring by framing it as a multilabel classification (MLC) problem. Utilizing the Inception model with a self-attention mechanism, this method enhances deforestation detection without relying on traditional convolution operations.The self-attention mechanism improves the model's ability to identify deforestation patterns, even in imbalanced class scenarios. Extensive experiments on publicly available satelliteimage datasets demonstrate the Inception model's effective- ness in MLC tasks, particularly under challenging conditions. This research significantly advances the use of deep learning architectures for environmental monitoring, highlighting the Inception model's potential to improve the accuracy and sensitivity of land use classification from satellite imagery.

TRADITIONAL METHODS

Traditional remote sensing methods, utilizing satellite imagery and aerial photography, have been essential for tracking deforestation and land use changes but face challenges such ascloud cover and manual interpretation. Recent advancements in machine learning and AI have introduced automatic techniques that use advanced algorithms and deep learning modelsto enhance the accuracy and efficiency of environmental monitoring.

A. Remote Sensing Methods

Remote sensing methods have long been employed to monitor deforestation and land use changes. These techniques involve the use of satellite imagery and aerial photographyto capture large-scale environmental data. Remote sensing provides valuable insights into forest cover, biomass estimation, and the spatial distribution of various land cover types. Traditional remote sensing approaches rely on optical andradar sensors to detect changes in vegetation and land useover time. However, these methods can be limited by factors such as cloud cover, spatial resolution, and the need for extensive manual interpretation. Despite these limitations, remotesensing remains a crucial tool for environmental monitoring due to its ability to cover vast areas and provide consistentdata over time. Remote sensing methods, including satellite imagery and aerial photography, are essential for monitoring deforestation and land use changes, allowing for the capture of extensive environmental data. Despite challenges like cloud cover interference and spatial resolution limitations, remote sensing remains indispensable for providing consistent andcomprehensive data over vast geographical areas, crucial for effective environmental monitoring and management.

B. *Automatic Techniques*

In recent years, automatic techniques leveraging advancements in machine learning and artificial intelligence have significantly improved the efficiency and accuracy of deforestation monitoring.

These techniques utilize algorithms to processand analyze large datasets of satellite images without the need for manual intervention. Deep learning models, in particular, have shown remarkable success in identifying patterns and classifying land use changes. By employing sophisticated architectures such as convolutional neural networks (CNNs) and self-attention mechanisms, these models can automaticallydetect and classify deforestation with high precision. Automatic techniques reduce the time and effort required for data analysis and improve the reliability of monitoring systems, making them an indispensable part of modern environmental surveillance.

PROPOSED METHOD

The core focus of this study is the development of an intelligent surveillance system that utilizes satellite imagery to detectdeforestation through a sophisticated classification approach.The methodology integrates various crucial components anddesign elements to ensure the system's efficacy and robust-ness. User interaction is facilitated by leveraging the PythonTkinter module, creating a seamless and user-friendly desktopapplication interface that enables efficient input of satelliteimages and clear visualization of deforestation predictions.The study uses the publicly available" Planet:
Understandingthe Amazon from Space" dataset from Kaggle, which capturesdiverse regions in the Amazon, serving as a valuable resourcefor training and testing the surveillance system. The imagepreprocessing stage is pivotal, involving tasks such as loadingthe dataset, resizing images, applying advanced denoising techniques for noise reduction, and enhancing image qualityusing the Contrast Limited Adaptive Histogram Equalization(CLAHE) algorithm. A systematic train-test split ensuresunbiased performance assessment by training the model on arepresentative set and evaluating it on a distinct set of images.

At the core of the proposed method is the adoption of an Inception-based deep learning architecture. This involves initializing the architecture, fine-tuning it to adapt to the dataset'sunique characteristics, training the model with various imagesto capture intricate patterns, evaluating performance metrics,and saving the trained model for future use. During theprediction phase, the trained Inception model is loaded, atest satellite image is preprocessed (including denoising andapplying CLAHE enhancements), and predictions are made.The system classifies images into 14 different categories,providing valuable information on deforestation.

Noteworthy modifications in this study include advanced image denoising techniques and the implementation of the CLAHE algorithm, which significantly enhance image quality and are crucial for accurate deforestation detection. Additionally, the adoption of the Inception-based deep learning architecture ensures effective multi-scale feature extraction, enabling the modelto capture complex patterns and structures within satellite imagery. Instead of using an ER diagram, a sequence diagram illustrates the sequential order of activities and communicationpathways between various elements in the system.

A. *Flow Chart*

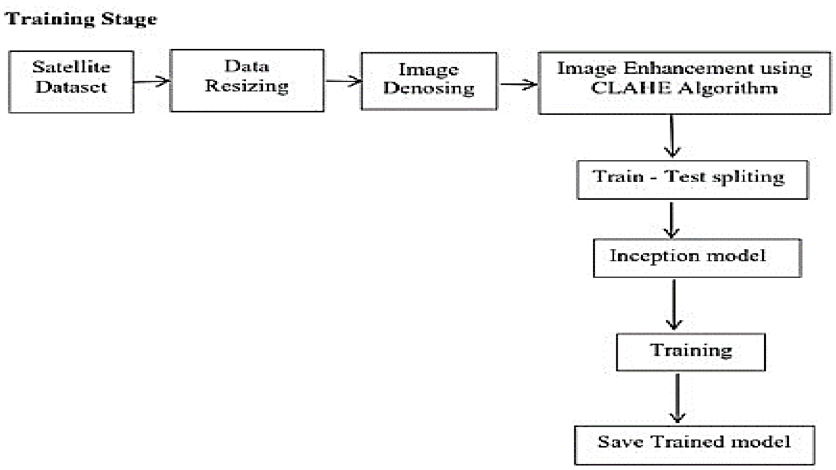

Fig. 1. Training State Diagram

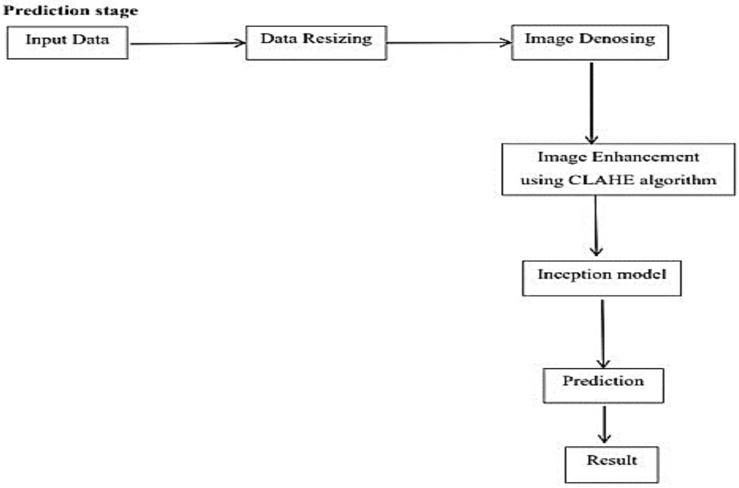

Fig. 2. Prediction State Diagram

The architectural diagram for the" Intelligent Satellite- Based Deforestation Surveillance using Enhanced Classification" delineates the core components and their interactions within the system. At its nucleus lies the satellite, functioning as the primary data source by capturing information fromspace. Following this, the Data Processing and Enhancement module refines raw satellite data through processes like noise reduction and image quality enhancement. Subsequently, the pre-processed data is inputted into the Machine Learning Classifier, which utilizes advanced algorithms to independentlyclassify patterns indicative of deforestation.
The classifier's output is directed to the Deforestation Surveillance System, facilitating further analysis, data fusion, and decision-making processes. This integrated approach enables comprehensive evaluation of classified data to enhance surveillance capabilities. Serving as the final link, the Visualization Interface offers stakeholders a user-friendly platform tointeract with and interpret surveillance results. The arrows in the diagram depict the flow of data, illustrating the sequential progression from data capture to user visualization. This architectural framework lays the groundwork for an intelligentand efficient satellite-based deforestation surveillance system.

B. Sequence Diagram

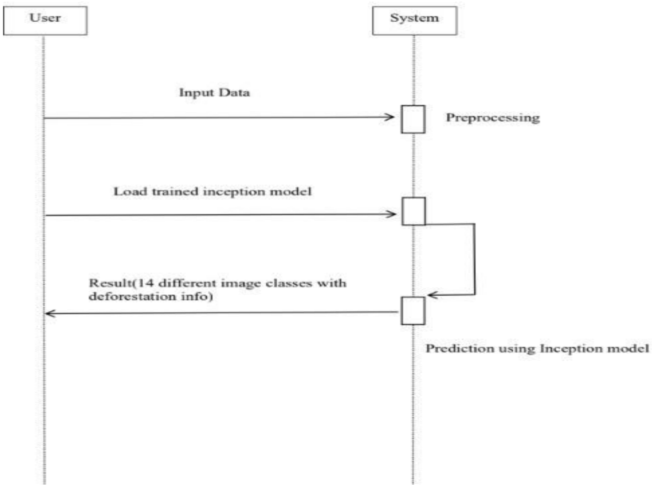

Fig. 3. Sequence diagram

In the intelligent satellite-based deforestation surveillance system employing enhanced classification, users initiate the application through a graphical user interface (GUI), triggeringa sequence of activities aimed at monitoring and analyzing deforestation patterns. The system begins by acquiring satellite imagery data, which undergoes preprocessing steps like normalization, resizing, and noise reduction to optimize it for analysis. The heart of the system lies in the machine learning classification module, employing advanced approaches like convolutional neural networks (CNNs) for accurate deforestation detection. Following classification, detailed analysis results are seamlessly integrated into the GUI, allowing users to explore visual representations and statistics, provide feedback, and contribute to collaborative monitoring efforts. With continuous monitoring capability, the system ensurestimely and accurate information for environmental research and policymaking.

ADVANTAGES OF PROPOSED METHOD OVER TRADITIONAL METHODS

The proposed methods offer clear advantages over traditional approaches outlined in previous studies. They utilize advanced classification techniques, such as convolutional neural networks (CNNs), known for their superior performancein accurately detecting deforestation patterns from satelliteimagery. Additionally, these methods incorporate sophisticatedpreprocessing steps, including normalization, resizing, and noise reduction, ensuring that the satellite data is optimizedfor more precise analysis. Furthermore, the integration of user-friendly graphical interfaces enables seamless interaction and interpretation of analysis results, enhancing the overall usability and accessibility of the surveillance system. These advancements collectively contribute to a more effective and efficient approach to deforestation monitoring compared to conventional methods.

FUTURE SCOPE

Looking ahead, the future of satellite-based deforestation surveillance holds promise for further advancements and in- novation. One avenue for future development involves theintegration of cutting-edge machine learning algorithms, such as deep reinforcement learning and generative adversarial networks, to enhance the accuracy and robustness of deforestation detection models. Additionally, advancements in satellite technology, including the deployment of next-generation high-resolution imaging satellites and the integration of multi-spectral sensors, will enable more detailed and comprehensive monitoring of deforestation activities. Furthermore, the ongoing refinement of data processing techniques and the development of automated analysis pipelines will streamline the process of extracting actionable insights from vast amountsof satellite imagery data. Ultimately, these advancements will contribute to more effective and timely conservation efforts, empowering stakeholders to address deforestation challenges with greater precision and efficiency.

RESULTS

In this study, the evaluation of deep learning techniques for deforestation detection, with a focus on the ForestViT model, offers insightful analyses of model performance and effectiveness. By employing a per-class analysis, ForestViT exhibits slightly superior results, especially in detecting rare occurrences associated with deforestation, when compared to established convolutional methods like ResNet, VGG16, DenseNET, and MobileNet. The overall accuracy assessment reinforces ForestViT's micro-averaged recall and precision metrics on the test set, indicating its superior performance across various evaluation metrics. Moreover, computational complexity analysis indicates ForestViT's comparable computational requirements during the test phase, making it a viable alternative to convolutional models for deforestation detection. The evaluation of deep learning techniques in this study pro- vides valuable insights into the performance of ForestViT com- pared to well-established convolutional methods. Leveraging self-attention mechanisms, ForestViT demonstrates marked superiority, particularly in detecting rare classes associated with deforestation. Its proficiency in capturing co-occurrence patterns among labels in deforestation images, without convolution operations, highlights its potential for improving deforestation risk analysis and mitigation strategies. The pro- posed ForestViT model emerges as a promising and efficient approach for multilabel classification of satellite imagery, representing a significant advancement in the field of deep learning for environmental monitoring, particularly in the context of deforestation detection.

Figure 6.1 : Original Image

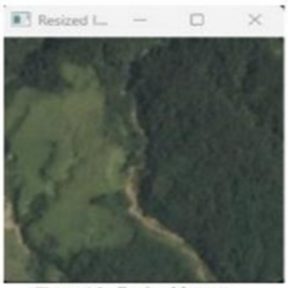

Figure 6.2 : Resized Image

Figure 6.3 : Denoised Image

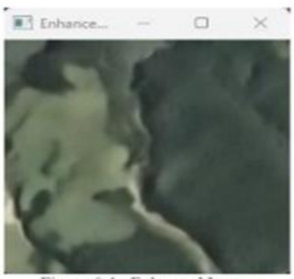

Figure 6.4 : Enhanced Image

Fig. 4. Original image, Resized image, Denoised image, Enhanced image,

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