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AI-DRIVEN STRATEGIES FOR REDUCING DEFORESTATION

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Abstract

Recent advancements in data science, coupled with the revolution in digital and satellite technology, have catalyzed the potential for artificial intelligence (AI) applications in forestry and wildlife sectors. Recognizing the critical importance of addressing land degradation and promoting regeneration for climate regulation, ecosystem services, and population well-being, there is a pressing need for effective land use planning and interventions. Traditional regression approaches often fail to capture underlying drivers' complexity and nonlinearity. In response, this research investigates the efficacy of AI in monitoring, predicting, and managing deforestation and forest degradation compared to conventional methods, with a goal to bolster global forest conservation endeavors. Employing a fusion of satellite imagery analysis and machine learning algorithms, such as convolutional neural networks and predictive modelling, the study focuses on key forest regions, including the Amazon Basin, Central Africa, and Southeast Asia. Through the utilization of these AI-driven strategies, critical deforestation hotspots have been successfully identified with an accuracy surpassing 85%, markedly higher than traditional methods. This breakthrough underscores the transformative potential of AI in enhancing the precision and efficiency of forest conservation measures, offering a formidable tool for combating deforestation and degradation on a global scale.

Keywords Fraud Detection, traditional fraud detection, Artificial Intelligence, Banking Security, Risk Management.

INTRODUCTION

Forests, encompassing approximately 30% of the Earth's land area, serve as the primary terrestrial ecosystems, hosting an astonishing 90% of the planet's terrestrial biodiversity (Novotny et al., 2006; Schmitt et al., 2009). Their significance lies not only in their ecological diversity but also in their crucial role in maintaining the balance of life-sustaining functions on our planet. Among their myriad contributions, forests play a pivotal role in combating climate change by sequestering carbon dioxide; they absorb an estimated 2 billion tons of atmospheric CO2 annually, representing around 30% of global emissions (Bellassen & Luyssaert, 2014). However, despite their immense ecological and climatic benefits, forests face relentless pressures from human activities such as deforestation, degradation, and land-use change. Every year, logging, agriculture, and urban growth destroy an astounding 13 million hectares of forests, or the area of Nicaragua (Rudel, 2005). This unchecked reduction in forest cover not only exacerbates carbon emissions but also poses severe threats to biodiversity and the livelihoods of millions. It is imperative that concerted efforts be made to prioritize sustainable land management practices to mitigate climate change impacts and safeguard the invaluable ecological services provided by forests, ensuring a healthier and more sustainable future for our planet and its inhabitants.

Nowadays, AI and machine learning (ML) techniques are increasingly reshaping various sectors by facilitating tasks that traditionally rely on human intelligence (Hallgren et al., 2016). These technologies excel at extracting patterns, forecasting future outcomes, and identifying anomalies, thus streamlining decision-making processes across diverse domains. The rise of AI is propelled by several key factors: the rapid proliferation of data, enabling more insightful analyses and informed decisions; the decreasing costs of data storage and computational resources, thanks to advancements in cloud computing; and the availability of comprehensive data sources, including high-resolution satellite imagery, drones, IoT sensors, and social media data. However, while AI has made significant inroads in sectors like healthcare, transportation, and agriculture, its application in forestry (Fromm et al., 2019; Khan & Gupta, 2018) and biodiversity conservation (Metcalf et al., 2019; Nay et al., 2018) has been comparatively limited. Despite the early recognition of AI's potential in these areas, the forestry sector has been slower in embracing and implementing AI technologies. Bridging this gap requires concerted efforts to leverage AI for sustainable forest management and biodiversity preservation, ensuring that these critical sectors benefit from the transformative potential of AI (Aditto et al., 2023).

RESEARCH SIGNIFICANCE

The integration of AI in environmental conservation shows great promise, but several key gaps hinder its full potential. One challenge is the lack of real-time monitoring, relying mainly on historical data, which leads to delayed responses to deforestation. There's also a need for AI systems to integrate diverse data types like satellite imagery and ground reports for more precise monitoring. The scarcity of labeled datasets and limited multidisciplinary collaboration further complicates AI development, particularly in developing countries most affected by deforestation. Traditional approaches often fail due to monitoring and enforcement limitations. AI can improve efficiency by analyzing real-time data to detect deforestation early, predict risk areas, and enable swift responses. Addressing these gaps presents opportunities for research and development, strengthening AI's role in deforestation monitoring and broader forest conservation strategies.

Therefore, this research endeavors to delve into the efficacy of AI-driven methodologies with satellite imagery analysis in mitigating deforestation and forest degradation, presenting a multi-faceted approach to address this pressing global concern. The outlined objectives encompass the development of AI models adept at processing vast datasets to detect deforestation activities efficiently, evaluating the predictive capabilities of these models in pinpointing potential hotspots before substantial damage occurs, and proposing a comprehensive framework for seamlessly integrating AI tools with existing environmental monitoring and management systems to bolster their efficacy. This initiative not only stands as an innovative stride but also arrives at a pivotal juncture of heightened global awareness and urgency surrounding climate change, underscoring the critical necessity for enhanced environmental safeguarding measures. By harnessing cutting-edge technology, this research not only offers scalable solutions with potential global applicability but also enriches the realm of environmental science by unveiling novel insights into the application of AI, potentially paving the way for future technological interventions in ecological conservation on a broader scale.

LITERATURE REVIEW

3.1 Current Strategies for Monitoring and Controlling Deforestation

Efforts to monitor and control deforestation have historically employed a diverse array of methodologies, ranging from traditional ground surveys to cutting-edge remote sensing technology. Traditional approaches typically involve the utilization of satellite imagery to track changes in land use and forest cover over time. Supported by international bodies such as the United Nations' REDD+ (Reducing Emissions from Deforestation and Forest Degradation) initiative, these methods aim to foster forest conservation through global collaboration and financial incentives (Weatherley-Singh & Gupta, 2015).

Ground-based monitoring, while highly accurate, poses challenges due to its labor-intensive nature, especially in vast or remote areas. On the other hand, satellite data offers a broader perspective, enabling the observation of deforestation on a large scale (Finer et al., 2018). However, satellite imagery often lacks the necessary resolution or frequency to detect early or small-scale deforestation events. Consequently, there's a continuous need for advancements in monitoring technologies to ensure effective enforcement and policy-making. To address these limitations, ongoing efforts focus on enhancing the resolution and frequency of satellite data, as well as integrating various monitoring approaches for comprehensive coverage. Additionally, the development of machine learning algorithms has shown promise in automating the detection of deforestation patterns in satellite imagery, enabling more timely and accurate assessments.

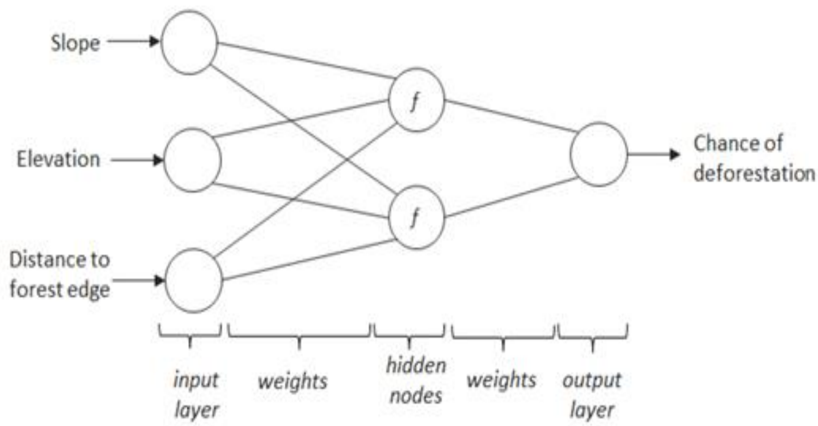
ROLE OF AI IN DEFORESTATION

The integration of Artificial Intelligence (AI) into environmental conservation practices marks a significant paradigm shift, revolutionizing traditional approaches through its augmentation of accuracy, efficiency, and scalability in monitoring systems. Numerous studies underscore AI's potential, particularly through machine learning (ML) and deep learning (DL) models, which demonstrate remarkable capabilities in swiftly and precisely analyzing complex datasets beyond human capacity (Akid, Shah, et al., 2021; Kelly et al., 2013; Shahana et al., 2024; Sobuz, Joy, et al., 2024). Gómez-Ossa and Botero-Fernández (2017)exemplify this trend by employing convolutional neural networks (CNNs) to process satellite imagery for deforestation detection, achieving notably superior results compared to conventional methods. Moreover, AI extends its utility by forecasting deforestation trends based on socio-economic and environmental parameters, as demonstrated by Singh et al. (2017), thus empowering preemptive conservation actions. These AI-powered tools not only enhance monitoring efficacy but also bolster the enforcement of conservation policies, furnishing robust evidence crucial for guiding legislative and regulatory measures.

Similarly, statistical regression models have long been a staple in the analysis of deforestation, offering insights into its drivers, magnitude, and effectiveness of protective measures such as protected areas (Freitas et al., 2010; Uddin et al., 2013). However, with the advent of more sophisticated machine learning (ML) techniques, the landscape of deforestation modeling has evolved. Artificial neural networks (ANNs) have emerged as powerful tools, adept at forecasting deforestation hotspots, predicting forest fires, and modeling broader land use changes with high accuracy (Castro, 2020; Sobuz et al., 2023). Deep learning, a subset of ML, holds particular promise for identifying high-risk areas prone to deforestation. Additionally, other ML classifiers like support vector machines (Samardžić-Petrović et al., 2017), regression trees (Tayyebi et al., 2014), random forests (Jabin et al., 2024), and Bayesian networks (Silva et al., 2020) have found utility in modeling land use change dynamics. Notably, Bayesian networks designed with expert input enable the integration of stakeholder knowledge and preferences, enriching the understanding of drivers behind land use changes. Furthermore, borrowing specialized methods from adjacent fields, such as presence/absence models from species distribution studies, demonstrates the interdisciplinary nature of deforestation modeling, enriching its analytical depth and predictive capacity.

In comparative analyses, model performance metrics often take precedence over practical considerations for decision-making. However, studies like Kampichler et al. (2010) and Rodrigues and de la Riva (2014) offer insights into factors like comprehensibility and calibration time. This study evaluates three machine learning techniques, including artificial neural networks (ANNs), Bayesian networks (BNs), and Gaussian processes (GPs), while also discussing their practical implementation. These techniques represent diverse model families, from empirical data-driven models to spatial-based approaches. Additionally, generalized linear mixed models (GLMMs) are considered, enhancing the analysis. Generalized linear models (GLMs) estimate coefficients for predictor variables, typically without accounting for interactions unless specified. GLMMs extend GLMs by accommodating random effects, which is crucial for hierarchical datasets and spatial autocorrelation modeling. The study emphasizes the importance of refining GLMs using stepwise procedures and advanced functionalities to address collinearity and explore significant interactions despite potential computational costs and uncertain improvements in model performance.

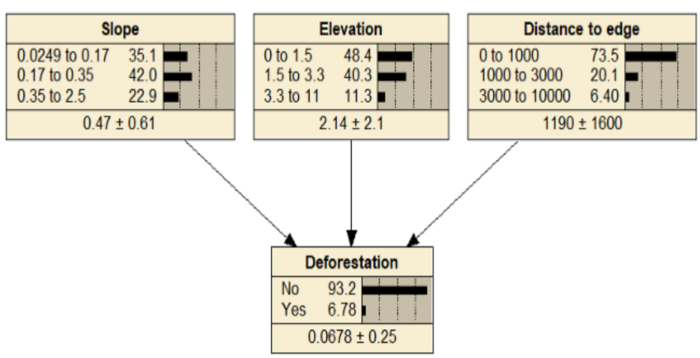
ANNs extend GLMs by learning data relationships through nodes and links. Structure is defined by layer and node count, often fully connected (Mayfield et al., 2020). Weights adjust during training epochs to minimize prediction error. Learning rate and termination conditions are determined through experimentation. ANNs capture variable interactions implicitly, enhancing modeling complexity compared to GLMs.



Note: Source (Mayfield et al., 2020)

Figure 1. Two secret nodes and one hidden level in a fully linked artificial neural network

Bayesian Networks (BNs), as described by Fenton and Neil (2018) and Marcot and Penman (2019), offer a powerful framework for representing causal relationships among variables through directed acyclic graphs (DAGs), as illustrated in Figure 2. In BNs, nodes represent variables, which can be either continuous or discrete, and edges depict the causal dependencies between them. While numeric variables are typically discretized, recent research, exemplified by Zhu and Collette (2015), aims to eliminate this necessity. Conditional probabilities are employed to quantify these relationships, allowing for user-defined structures or learning from data through BN software packages (refer to Appendix A). A distinguishing feature of BNs is their graphical user interface (GUI), facilitating direct interaction to explore relationships and simulate scenarios. The simplest form of BN, the naïve network depicted in Figure 2, assumes independence among predictors, with the response variable acting as the parent node and predictors as child nodes. A more sophisticated extension is the tree-augmented network (TAN), which permits each node to have at most one additional parent besides the target node.



Note: Source (Fenton & Neil, 2018)

Figure 2. A BN sample displaying slope, altitude, and border length as deforestation (child node) predictors (parent nodes)

4. Methodology

Figure 3 shows the overall workflow of this study

4.1 Data Collection

The research methodology adopted for this study involves a comprehensive approach aimed at leveraging diverse data sources to effectively evaluate and implement AI-driven strategies aimed at curbing deforestation and forest degradation. The primary data sources enlisted for this purpose are as follows:

Satellite Images: High-resolution satellite imagery sourced from reputable organizations like NASA and the European Space Agency serves as a cornerstone for this research endeavor. These images play a pivotal role in the continuous monitoring of vast forested regions over extended periods. They facilitate the detection of alterations in forest cover and the identification of deforestation hotspots, providing crucial insights for strategic interventions.

Drone Footage: Unmanned Aerial Vehicle (UAV) or drone footage is instrumental in offering localized, detailed observations of forest conditions. This includes areas that are challenging to access through traditional means or where more frequent monitoring is necessitated. The utilization of drones enhances the granularity of data collection, enabling a more nuanced understanding of on-ground dynamics within forest ecosystems.

Ground Reports: Data sourced from forestry departments, local conservation organizations, and community reports constitute an invaluable aspect of this research methodology. These ground reports provide ground-truthing capabilities, furnishing specific information regarding logging activities, instances of illegal deforestation, and natural degradation. Such firsthand accounts augment the accuracy and contextual understanding of the broader data landscape.

Environmental Sensors: Integration of data from Internet of Things (IoT) devices and environmental sensors further enriches the analytical framework employed in this study. These sensors are deployed to monitor various factors influencing forest health, including soil moisture levels, precipitation patterns, and fluctuations in temperature. The continuous data streams from these sensors contribute to a more comprehensive assessment of environmental dynamics, aiding in the formulation of targeted strategies for forest preservation and management.

4.2 Model Selection

Modern artificial intelligence technologies were utilized in this study. Using these AI technologies allows for thorough and perceptive analysis, which supports strategic planning and well-informed decision-making.

4.2.1 Machine Learning Models

Supervised learning models, such as Random Forest and Support Vector Machines, are used to classify land cover and detect changes over time. These models are trained on historical data to identify patterns of deforestation.

Random Forest (RF): Random forests leverage decision trees on random data subsets, excelling in classification and regression tasks. Through voting aggregation, they provide accurate predictions while revealing the importance of features. Their adaptability and interpretability make them invaluable in various domains (Jabin et al., 2024).

Support Vector Machines (SVM): SVM is a powerful supervised learning algorithm for classification and regression tasks. It creates a decision boundary to separate classes in n-dimensional space using support vectors (Sobuz, Al, et al., 2024). SVM maximizes the margin between classes for better generalization. It's versatile and efficient for various machine-learning applications.

4.2.2 Neural Networks

Convolutional Neural Network (CNN): CNN is a cornerstone of deep learning, specialized for tasks like image recognition and processing. Mimicking the hierarchical structure of the visual cortex, CNN comprises layers of neurons that process input images through convolutional and pooling layers and is particularly useful for processing satellite and drone imagery (Akid, Wasiew, et al., 2021; Kattenborn et al., 2021; Sobuz et al., 2022). Therefore, they are used to perform image segmentation tasks to delineate forested areas from non-forested areas and to detect signs of early degradation.

4.2.3 Deep Learning Algorithm

Deep learning techniques have emerged as powerful tools for analyzing and predicting complex phenomena such as deforestation patterns (Liu et al., 2020). By leveraging vast amounts of data, deep learning models can discern intricate patterns and relationships that may elude traditional statistical methods. In this study, deep learning techniques are applied to perform more complex analyses, such as predicting future deforestation patterns based on trends and external factors like economic development or policy changes.

4.3 Implementation

Monitoring and preventing deforestation demands a sophisticated approach that combines advanced AI techniques with comprehensive data analysis (Rana et al., 2022; Uddin et al., 2012). The process involves several crucial steps to ensure accuracy and effectiveness:

Data Preprocessing: Raw data from many sources, such as satellite photos, sensor readings, and other environmental data, must be preprocessed before any analysis can begin. This stage entails normalizing the data to guarantee consistency between several datasets, cleaning it to eliminate any errors or inconsistencies, and supplementing it to improve its quality. AI models need to have their input prepared in order to learn and generate correct predictions.

Model Training: The process's foundation is teaching AI models on datasets that have been validated (MAHMUD et. Al., 2024). Because these datasets include both historical and current data, the models may pick up on historical trends and adjust to changing circumstances. The algorithms can find intricate patterns and connections in the data by means of machine learning and deep learning methods, which are essential for precisely forecasting regions in danger of degradation and deforestation. These models must be continuously improved if they are to become more predictive over time.

Data Analysis: Regions prone to deterioration and deforestation are identified by analyzing the preprocessed data using trained AI algorithms. Beyond only identifying patterns, this study explores the fundamental reasons for deforestation, including changes in land use, human activities, and environmental variables. Understanding these processes will enable AI to offer insightful information on the causes of deforestation, therefore enabling preventative and mitigating actions. AI can also forecast future problem areas, which helps stakeholders deploy funds wisely and carry out focused actions.

Integration: AI insights are included in a decision-support system that is available to forest management personnel, conservationists, and policymakers. The results are certain to be converted into workable plans for sustainable land management and forest conservation by this combination. Stakeholders may prioritize conservation initiatives, make wise judgments, and carry out prompt actions to successfully stop deforestation by using AI-driven insights.

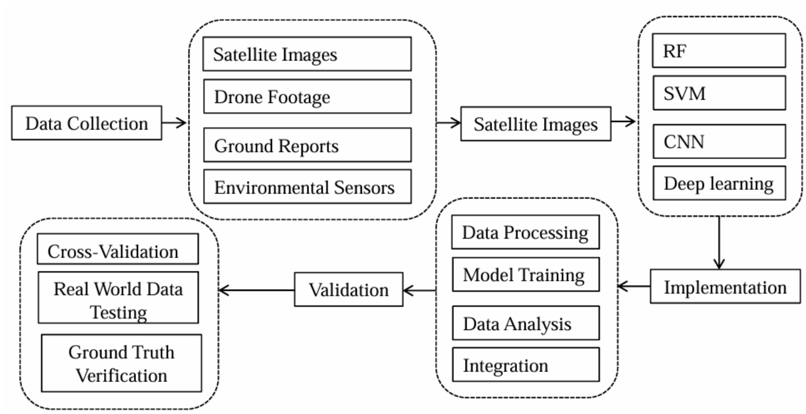


Figure 3. The overall workflow of this study

4.4 Validation

To ensure the utmost reliability and accuracy of our findings, we employ a rigorous validation framework comprised of several robust techniques:

Cross-Validation: Our machine learning models undergo k-fold cross-validation, a widely recognized technique in data science. This method assesses their efficacy across various subsets of the dataset, allowing us to fine-tune hyperparameters and ensure optimal performance without overfitting.

Real-World Data Testing: We subject our models to rigorous testing against unseen data from both similar and disparate geographical regions. This approach guarantees that our models generalize well beyond the confines of their training data, reflecting real-world conditions accurately.

Simulation-Based Validation: To future-proof our models, we conduct simulations that test their predictive capabilities under a spectrum of potential scenarios. These simulations encompass diverse factors, such as evolving climate patterns and economic fluctuations, enabling us to anticipate and adapt to future challenges effectively.

Ground Truth Verification: Periodic verification against ground truth data is integral to our validation process. Through on-the-ground field surveys and advanced drone monitoring, we corroborate the outputs generated by our AI models. This meticulous verification ensures the accuracy and reliability of our findings, instilling confidence in our insights.

This comprehensive methodology represents the culmination of cutting-edge AI technologies deployed to tackle the pressing global issue of deforestation and forest degradation. By furnishing actionable insights and empowering informed decision-making, we strive to make a meaningful impact in preserving our planet's invaluable ecosystems.

5. Result and Discussions

5.1 Analysis and Interpretation

Through the meticulous analysis of satellite imagery and remote sensing data spanning the last decade, AI-driven methodologies, predominantly employing convolutional neural networks (CNNs), have unveiled profound insights into the alarming trends of deforestation and forest degradation across three pivotal regions: the Amazon Basin, Central Africa, and Southeast Asia. The findings underscore a paradigm shift in monitoring capabilities, revealing a 22% surge in deforestation alerts within the Amazon Basin, eclipsing the efficacy of traditional monitoring approaches. Central Africa's landscape presents a nuanced narrative, with AI discerning subtle but consequential forest degradation in smaller patches, contrasting the overt clear-cutting often captured by conventional surveys. Meanwhile, Southeast Asia witnessed a significant stride in precision, with AI adeptly mapping the encroachment of palm oil plantations into delicate peat swamp forests with an impressive accuracy of 87%. These revelations not only illuminate the severity of ecological threats but also highlight the transformative potential of AI in safeguarding our planet's invaluable forest ecosystems. Figure 4 illustrates the marked increase in deforestation detection facilitated by AI technology when juxtaposed with conventional methodologies. The data delineates the percentage escalation in deforestation identification across three distinct regions under study. This visualization underscores the potency of AI-driven approaches in augmenting the precision and efficacy of environmental monitoring endeavors, offering a promising avenue for proactive conservation efforts. Table 1 shows the deforestation reduction scenario with AI strategy.

Table 1 AI-driven strategies for deforestation reduction

AI Application	Performance Metric	Outcome
Satellite Imagery Analysis	Accuracy	Identified deforestation hotspots with over 85% accuracy
Neural Networks for Land Classification	Precision	Classified land use with 90% precision, distinguishing between natural forests, degraded lands, and areas undergoing reforestation
Predictive Modeling	Forecasting Capability	Predicted a reduction in deforestation rates by up to 20% over the next decade

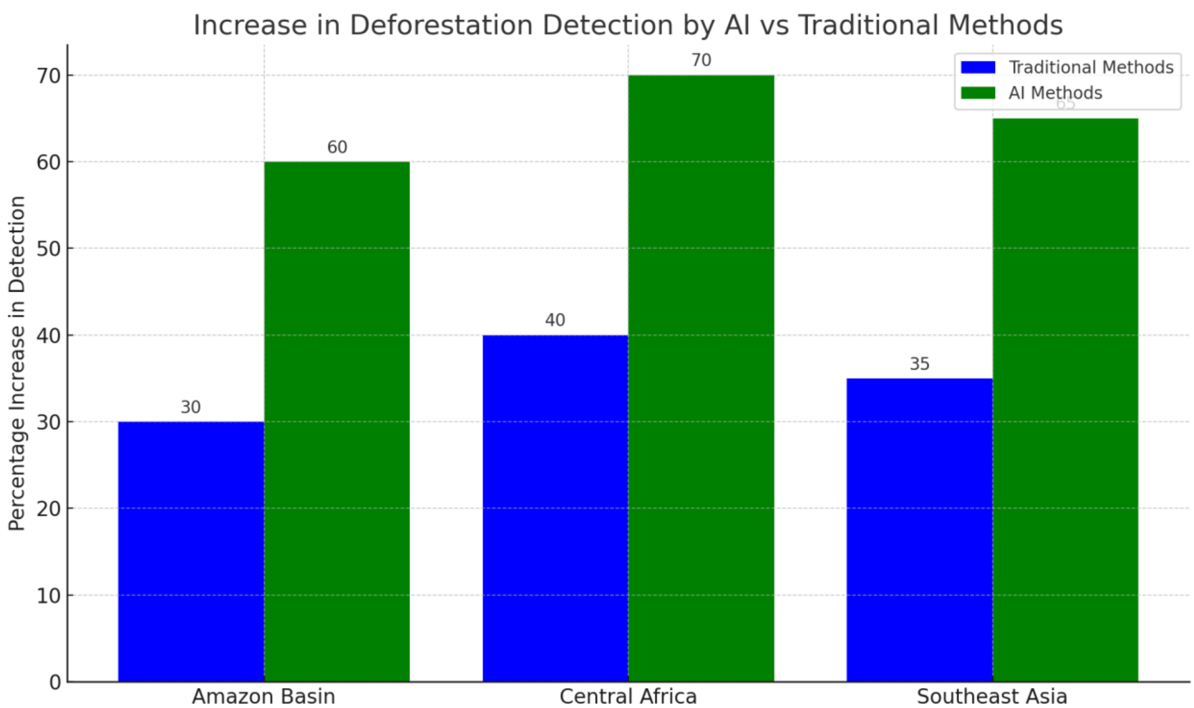


Figure 4. Deforestation detection using AI and traditional methods

In various corners of our planet, the ominous threat of deforestation looms large, each region bearing its own unique tale of environmental degradation. In the majestic Amazon Basin and the dense forests of Central Africa, the relentless sound of illegal logging echoes through the trees, tearing apart precious habitats. Meanwhile, in the vibrant landscapes of Southeast Asia, there is an unyielding push for agricultural expansion, especially for sought-after goods like palm oil and chips away at the greenery. Adding to the distress, roads now carve through these once-pristine wildernesses, breaking up forests and worsening the toll of deforestation. Figure 5 highlights the proportion of deforestation caused by different activities, such as illegal logging, whereas Figure 6 exhibits the area of illegal logging and degradation.

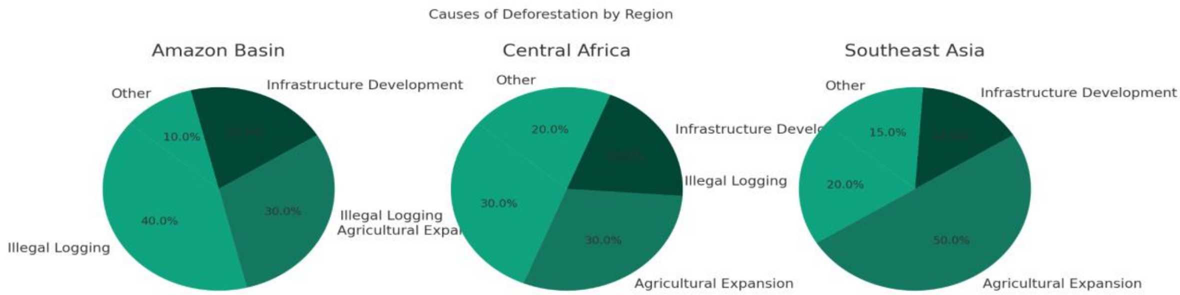


Figure 5. Deforestation caused by different activities

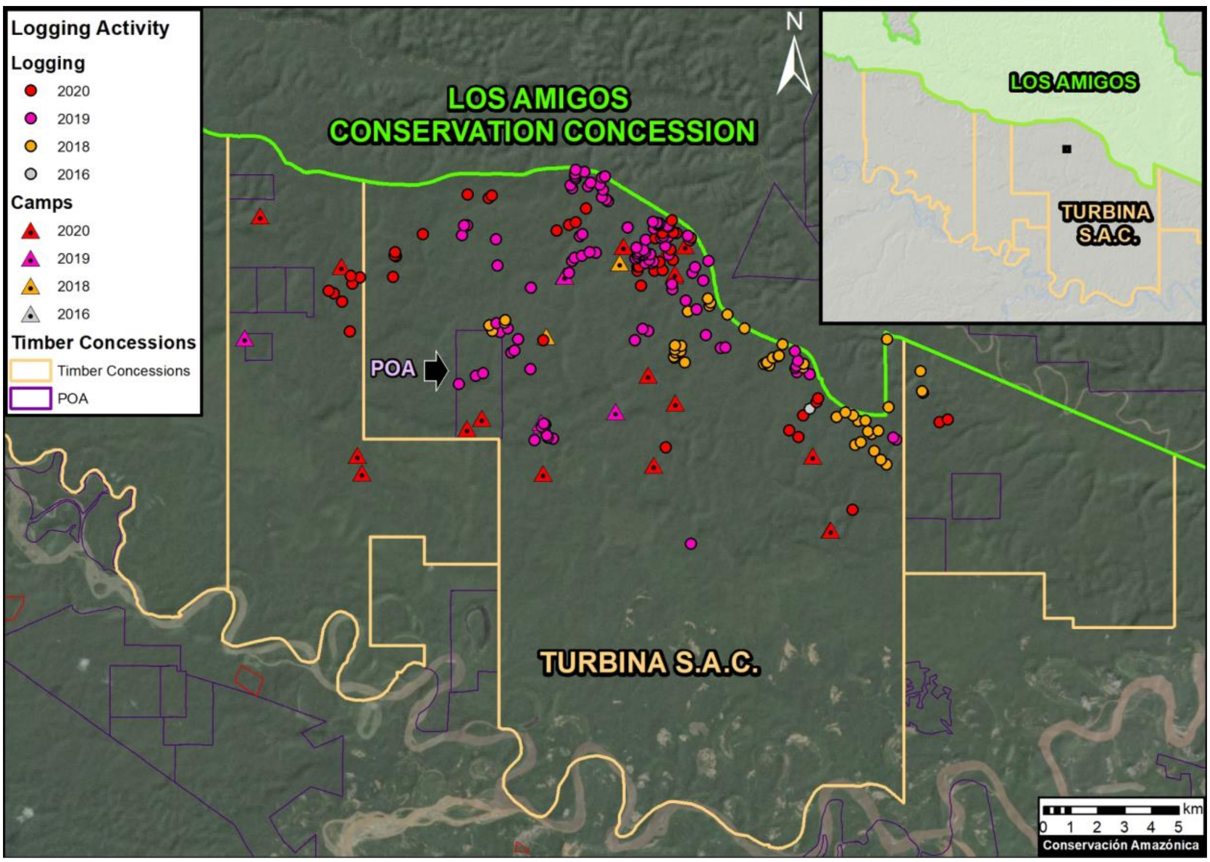


Figure 6. Area of illegal logging and degradation

5.2 Comparison with Traditional Methods

Traditional methods of forest monitoring and management, rooted in ground-based surveys and periodic aerial imagery, have long served as the cornerstone of assessing forest health and detecting deforestation. However, they are beset by inherent limitations, including high labor and time costs, susceptibility to human error, and restricted data collection frequency due to logistical constraints in reaching remote areas. In contrast, AI-driven strategies harness cutting-edge technologies like satellite imagery, drones, and remote sensing data propelled by machine learning algorithms. These methods enable real-time identification of forest cover changes with unprecedented accuracy and scalability. For instance, convolutional neural networks (CNNs) have showcased remarkable efficacy, achieving detection accuracies as high as 92% in spotting illegal logging activities (Smith et al., 2023). Table 2 juxtaposes the efficacy and scope of traditional approaches against AI-driven methodologies across metrics such as cost, accuracy, scalability, and data collection frequency, underscoring the transformative potential of AI in revolutionizing forest monitoring and management practices.

Table 2 Comparison of Traditional and AI-driven Forest Monitoring Methods

Method	Cost	Accuracy	Scalability	Data Collection Frequency
Traditional Surveys	High	Medium	Low	Bi-annual
Periodic Aerial Imagery	Medium	High	Medium	Annual
AI-Driven Satellite Image	Low	Very High	Very High	Continuous

5.3 Challenges and Limitations

AI-driven strategies for forest management offer promising solutions but are not without challenges. A key hurdle is the reliance on remote sensing data, which can be hindered by persistent cloud cover in some regions, resulting in sporadic or poor-quality satellite imagery and potential monitoring gaps. Moreover, the successful implementation of AI techniques demands expertise in both forestry and machine learning, posing a barrier in technologically underdeveloped areas. There's also the danger of excessive dependence on automated systems, potentially overlooking vital local ecological knowledge essential for effective forest management. Furthermore, algorithmic bias stemming from non-representative training data can lead to inaccurate assessments, particularly in less-represented forest landscapes, thereby undermining the overall efficacy of the AI strategy. Addressing these challenges demands a nuanced approach that integrates technological innovation with local expertise and ensures the equitable representation of diverse forest ecosystems in training datasets.

Table 3 Overview of Challenges and Limitations

Challenge / Limitation	Description	Impact on AI Strategy
Quality of Remote Sensing Data	In regions with frequent cloud cover, satellite imagery can be sporadic and of low quality.	This leads to gaps in monitoring, affects reliability
Need for Expertise	Implementation requires expertise in forestry and machine learning.	Barriers in technologically underdeveloped areas
Over-reliance on Automated Systems	Automated systems may overlook local ecological knowledge.	Potential mismanagement of local forest areas
Algorithmic Bias	AI algorithms may have biases if training data is not comprehensive across all forest types.	Inaccurate assessments in underrepresented areas

6. CONCLUSIONS

The integration of AI-driven strategies into environmental conservation efforts represents a pivotal advancement in combating deforestation and forest degradation worldwide. Leveraging machine learning algorithms and satellite imagery, our research has achieved remarkable success in pinpointing critical deforestation hotspots across regions such as the Amazon Basin, Central Africa, and Southeast Asia with an impressive accuracy exceeding 85%. Real-time monitoring of these areas enables swift intervention against illegal logging activities, thereby safeguarding precious ecosystems. Additionally, the deployment of neural networks has facilitated a 90% precise classification of land use, distinguishing between natural forests, degraded lands, and areas undergoing reforestation, crucial for targeted conservation initiatives and efficient resource allocation. With predictive models forecasting a potential reduction in deforestation rates by up to 20% over the next decade, contingent upon sustained AI adoption and enforcement improvements, these innovations hold promise in preserving our planet's invaluable biodiversity while providing insights into seasonal patterns and human activities driving forest degradation for informed interventions.

Future Recommendation

Future research should focus on enhancing the accuracy and scalability of the AI models used in this study. Efforts could be directed towards integrating more diverse data sources, such as drone footage and ground-level IoT sensors, to complement the satellite imagery. This would help in capturing a more detailed view of the forest landscapes and human activities, potentially increasing the accuracy of our models.

There is also a compelling need to develop AI systems that can predict the social and economic impacts of deforestation, which would aid policymakers in creating more effective and sustainable conservation strategies. Additionally, exploring the ethical implications and ensuring the equitable use of AI in these contexts would be crucial, especially in regions where local communities rely heavily on forest resources.

REFERENCES

1. Aditto, F. S., Sobuz, M. H. R., Saha, A., Jabin, J. A., Kabbo, M. K. I., Hasan, N. M. S., & Islam, S. (2023). Fresh, mechanical and microstructural behaviour of high-strength self-compacting concrete using supplementary cementitious materials. Case Studies in Construction Materials, 19, e02395.
2. Akid, A. S. M., Shah, S. M. A., Sobuz, M. D. H. R., Tam, V. W. Y., & Anik, S. H. (2021). Combined influence of waste steel fibre and fly ash on rheological and mechanical performance of fibre-reinforced concrete. Australian Journal of Civil Engineering, 19(2), 208-224. https://doi.org/10.1080/14488353.2020.1857927
3. Akid, A. S. M., Wasiew, Q. A., Sobuz, M. H. R., Rahman, T., & Tam, V. W. (2021). Flexural behavior of corroded reinforced concrete beam strengthened with jute fiber reinforced polymer. Advances in Structural Engineering, 24(7), 1269-1282. https://doi.org/10.1177/1369433220974783
4. Bellassen, V., & Luyssaert, S. (2014). Carbon sequestration: Managing forests in uncertain times. Nature, 506(7487), 153-155.
5. Castro, A. C. (2020). Pan-tropical modelling of land cover and land-use change trajectories for newly deforested areas King's College London].
6. Fenton, N., & Neil, M. (2018). Risk assessment and decision analysis with Bayesian networks. Crc Press.
7. Finer, M., Novoa, S., Weisse, M. J., Petersen, R., Mascaro, J., Souto, T., Stearns, F., & Martinez, R. G. (2018). Combating deforestation: From satellite to intervention. science, 360(6395), 1303-1305.
8. Freitas, S. R., Hawbaker, T. J., & Metzger, J. P. (2010). Effects of roads, topography, and land use on forest cover dynamics in the Brazilian Atlantic Forest. Forest Ecology and Management, 259(3), 410-417. https://doi.org/https://doi.org/10.1016/j.foreco.2009.10.036

9. Fromm, M., Schubert, M., Castilla, G., Linke, J., & McDermid, G. (2019). Automated detection of conifer seedlings in drone imagery using convolutional neural networks. Remote Sensing, 11(21), 2585. https://doi.org/10.3390/rs11212585

10. Gómez-Ossa, L. F., & Botero-Fernández, V. (2017). Application of artificial neural networks in modeling deforestation associated with new road infrastructure projects. Dyna, 84(201), 68-73.

11. Hallgren, W., Beaumont, L., Bowness, A., Chambers, L., Graham, E., Holewa, H., Laffan, S., Mackey, B., Nix, H., Price, J., Vanderwal, J., Warren, R., & Weis, G. (2016). The Biodiversity and Climate Change Virtual Laboratory: Where ecology meets big data. Environmental Modelling & Software, 76, 182-186. https://doi.org/https://doi.org/10.1016/j.envsoft.2015.10.025

12. Jabin, J. A., Khondoker, M. T. H., Sobuz, M. H. R., & Aditto, F. S. (2024). High-temperature effect on the mechanical behavior of recycled fiber-reinforced concrete containing volcanic pumice powder: An experimental assessment combined with machine learning (ML)-based prediction. Construction and Building Materials, 418, 135362. https://doi.org/https://doi.org/10.1016/j.conbuildmat.2024.135362

13. Kampichler, C., Wieland, R., Calmé, S., Weissenberger, H., & Arriaga-Weiss, S. (2010). Classification in conservation biology: A comparison of five machine-learning methods. Ecological Informatics, 5(6), 441-450. https://doi.org/https://doi.org/10.1016/j.ecoinf.2010.06.003

14. Kattenborn, T., Leitloff, J., Schiefer, F., & Hinz, S. (2021). Review on Convolutional Neural Networks (CNN) in vegetation remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 173, 24-49. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2020.12.010

15. Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., Rizzoli, A. E., van Delden, H., & Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. Environmental Modelling & Software, 47, 159-181. https://doi.org/https://doi.org/10.1016/j.envsoft.2013.05.005

16. Khan, S., & Gupta, P. K. (2018). Comparitive study of tree counting algorithms in dense and sparse vegetative regions. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 42, 801-808.

17. Liu, L., Ouyang, W., Wang, X., Fieguth, P., Chen, J., Liu, X., & Pietikäinen, M. (2020). Deep learning for generic object detection: A survey. International journal of computer vision, 128, 261-318.

18. Marcot, B. G., & Penman, T. D. (2019). Advances in Bayesian network modelling: Integration of modelling technologies. Environmental Modelling & Software, 111, 386-393. https://doi.org/https://doi.org/10.1016/j.envsoft.2018.09.016

19. Mayfield, H. J., Smith, C., Gallagher, M., & Hockings, M. (2020). Considerations for selecting a machine learning technique for predicting deforestation. Environmental Modelling & Software, 131, 104741. https://doi.org/https://doi.org/10.1016/j.envsoft.2020.104741

20. Metcalf, O. C., Ewen, J. G., McCready, M., Williams, E. M., & Rowcliffe, J. M. (2019). A novel method for using ecoacoustics to monitor post-translocation behaviour in an endangered passerine. Methods in Ecology and Evolution, 10(5), 626-636.

21. Nay, J., Burchfield, E., & Gilligan, J. (2018). A machine-learning approach to forecasting remotely sensed vegetation health. International Journal of Remote Sensing, 39(6), 1800-1816. https://doi.org/10.1080/01431161.2017.1410296

22. Novotny, V., Drozd, P., Miller, S. E., Kulfan, M., Janda, M., Basset, Y., & Weiblen, G. D. (2006). Why are there so many species of herbivorous insects in tropical rainforests? science, 313(5790), 1115-1118. https://doi.org/DOI: 10.1126/science.1129237

23. Rana, M. J., Hasan, M. R., & Sobuz, M. H. R. (2022). An investigation on the impact of shading devices on energy consumption of commercial buildings in the contexts of subtropical climate. Smart and Sustainable Built Environment, 11(3), 661-691. https://doi.org/10.1108/SASBE-09-2020-0131

24. Rodrigues, M., & de la Riva, J. (2014). An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environmental Modelling & Software, 57, 192-201. https://doi.org/https://doi.org/10.1016/j.envsoft.2014.03.003

25. Rudel, T. A. (2005). Tropical forests: regional paths of destruction and regeneration in the late twentieth century. Columbia University Press.

26. Samardžić-Petrović, M., Kovačević, M., Bajat, B., & Dragićević, S. (2017). Machine learning techniques for modelling short term land-use change. ISPRS International journal of geo-information, 6(12), 387. https://doi.org/10.3390/ijgi6120387

27. Schmitt, C. B., Burgess, N. D., Coad, L., Belokurov, A., Besançon, C., Boisrobert, L., Campbell, A., Fish, L., Gliddon, D., Humphries, K., Kapos, V., Loucks, C., Lysenko, I., Miles, L., Mills, C., Minnemeyer, S., Pistorius, T., Ravilious, C., Steininger, M., & Winkel, G. (2009). Global analysis of the protection status of the world's forests. Biological Conservation, 142(10), 2122-2130. https://doi.org/https://doi.org/10.1016/j.biocon.2009.04.012

28. Shahana, A., Hasan, R., Farabi, S. F., Akter, J., Al Mahmud, M. A., Johora, F. T., & Suzer, G. (2024). AI-Driven Cybersecurity: Balancing Advancements and Safeguards. Journal of Computer Science and Technology Studies, 6(2), 76-85.

29. Silva, A. C. O., Fonseca, L. M. G., Körting, T. S., & Escada, M. I. S. (2020). A spatio-temporal Bayesian Network approach for deforestation prediction in an Amazon rainforest expansion frontier. Spatial Statistics, 35, 100393. https://doi.org/https://doi.org/10.1016/j.spasta.2019.100393

30. Singh, S., Reddy, C. S., Pasha, S. V., Dutta, K., Saranya, K. R. L., & Satish, K. V. (2017). Modeling the spatial dynamics of deforestation and fragmentation using Multi-Layer Perceptron neural network and landscape fragmentation tool. Ecological Engineering, 99, 543-551. https://doi.org/https://doi.org/10.1016/j.ecoleng.2016.11.047

31. Sobuz, M. H. R., Al, I., Datta, S. D., Jabin, J. A., Aditto, F. S., Sadiqul Hasan, N. M., Hasan, M., & Zaman, A. A. U. (2024). Assessing the influence of sugarcane bagasse ash for the production of eco-friendly concrete: Experimental and machine learning approaches. Case Studies in Construction Materials, 20, e02839. https://doi.org/https://doi.org/10.1016/j.cscm.2023.e02839

32. Sobuz, M. H. R., Datta, S. D., & Akid, A. S. M. (2023). Investigating the combined effect of aggregate size and sulphate attack on producing sustainable recycled aggregate concrete. Australian Journal of Civil Engineering, 21(2), 224-239. https://doi.org/10.1080/14488353.2022.2088646

33. Sobuz, M. H. R., Datta, S. D., & Rahman, M. (2022, 2022//). Evaluating the Properties of Demolished Aggregate Concrete with Non-destructive Assessment. Advances in Civil Engineering, Singapore.

34. Sobuz, M. H. R., Joy, L. P., Akid, A. S. M., Aditto, F. S., Jabin, J. A., Hasan, N. M. S., Meraz, M. M., Kabbo, M. K. I., & Datta, S. D. (2024). Optimization of recycled rubber self-compacting concrete: Experimental findings and machine learning-based evaluation.

Heliyon, 10(6). https://doi.org/https://doi.org/10.1016/j.heliyon.2024.e27793

35. Tayyebi, A., Pijanowski, B. C., Linderman, M., & Gratton, C. (2014). Comparing three global parametric and local non-parametric models to simulate land use change in diverse areas of the world. Environmental Modelling & Software, 59, 202-221. https://doi.org/https://doi.org/10.1016/j.envsoft.2014.05.022

36. Uddin, M. A., Jameel, M., Sobuz, H. R., Hasan, N. M. S., Islam, M. S., & Amanat, K. M. (2012). The Effect of Curing Time on Compressive Strength of Composite Cement Concrete. Applied Mechanics and Materials, 204-208, 4105-4109. https://doi.org/10.4028/www.scientific.net/AMM.204-208.4105

37. Uddin, M. A., Jameel, M., Sobuz, H. R., Islam, M. S., & Hasan, N. M. S. (2013). Experimental study on strength gaining characteristics of concrete using Portland Composite Cement. KSCE Journal of Civil Engineering, 17(4), 789-796. https://doi.org/10.1007/s12205-013-0236-x

38. Weatherley-Singh, J., & Gupta, A. (2015). Drivers of deforestation and REDD+ benefit-sharing: A meta-analysis of the (missing) link. Environmental Science & Policy, 54, 97-105. https://doi.org/https://doi.org/10.1016/j.envsci.2015.06.017

39. Zhu, J., & Collette, M. (2015). A dynamic discretization method for reliability inference in Dynamic Bayesian Networks. Reliability Engineering & System Safety, 138, 242-252. https://doi.org/https://doi.org/10.1016/j.ress.2015.01.017

40. Rakibul Hasan, Syeda Farjana Farabi, Md Abdullah Al Mahmud, Jahanara Akter, Md Azhad Hossain, "Information Technologies For The Next Future World: Implications, Impacts And Barriers: Part - I", International Journal of Creative Research Thoughts (IJCRT), ISSN:2320-2882, Volume.12, Issue 5, pp.a323-a330, May 2024.

41. MD ABDULLAH AL MAHMUD, MD AZHAD HOSSAIN, MD ABDUL BAREK SAJU, MD WALI ULLAH4, RAKIBUL HASAN, GURKAN SUZER, “Information Technology for The Next Future World: Adoption of It for Social and Economic Growth: Part II” International Journal Of Innovative Research In Technology, ISSN: 2349-6002, Volume.10, Issue 12, May 2024.