OPEN ACCESS
Scientechno: Journal of Science and Technology
Vol. 4 No. 1. April 2025, pp. 33-44 DOI. 10.70177/ Scientechno.v4i1.2861
Research Article

DEEP LEARNING APPROACHES FOR PREDICTING DEFORESTATION PATTERNS AND BIODIVERSITY HOTSPOT LOSS IN SUMATRA

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Article Info
Received: June 8, 2024
Revised: October 3, 2025
Accepted: November 1, 2025
Online Version: December 10, 2025

Abstract
Deforestation in Sumatra, Indonesia, represents a critical environmental challenge that has led to the degradation of biodiversity hotspots and poses serious threats to both local ecosystems and global climate stability, driven largely by rapid forest conversion into agricultural land, illegal logging, and extensive land-use changes, making accurate prediction of deforestation patterns essential for effective conservation planning. This study applies deep learning approaches to predict deforestation patterns in Sumatra while simultaneously assessing their impacts on biodiversity hotspots, with the objective of developing a model capable of identifying areas at high risk of deforestation and estimating potential biodiversity losses. The research employs deep learning algorithms, specifically Convolutional Neural Networks and Recurrent Neural Networks, to analyze satellite imagery, historical deforestation data, land-use changes, and biodiversity hotspot maps, enabling the model to capture both spatial and temporal trends in deforestation dynamics. The results demonstrate that the proposed deep learning model achieves a high prediction accuracy of 92 percent in identifying deforestation hotspots and successfully highlights key biodiversity-rich areas that are highly vulnerable to rapid forest loss, with agricultural expansion and infrastructure development emerging as the dominant drivers of deforestation in these regions. Overall, the findings confirm that deep learning provides a powerful and reliable tool for predicting deforestation patterns and assessing biodiversity hotspot degradation, offering valuable evidence-based insights for policymakers and conservation practitioners to prioritize protection efforts and design targeted interventions aimed at mitigating further environmental damage in Sumatra.

Keywords: Biodiversity Hotspots, Deforestation, Deep Learning

Journal Homepage https://research.adra.ac.id/index.php/Scientechno
How to cite: Vann, R., Kiri, M. U., Sharma, A., & Rustiyana, R. (2025). Deep Learning Approaches for Predicting Deforestation Patterns and Biodiversity Hotspot Loss in Sumatra. *Scientechno: Journal of Science and Technology, 4*(1), 33-44. https://doi.org/10.70177/Scientechno.v4i1.2861

INTRODUCTION

Deforestation in tropical regions, particularly in Sumatra, Indonesia, has reached alarming levels over the past few decades. Sumatra is home to some of the world's most diverse ecosystems, housing numerous biodiversity hotspots (Ansari et al., 2025). These include rainforests that are home to critically endangered species, such as the Sumatran orangutan and the Sumatran tiger. However, deforestation, driven primarily by agriculture (such as palm oil plantations), logging, and infrastructure development, has significantly threatened these ecosystems (Ahmad et al., 2025). The rapid loss of forests leads to a decrease in biodiversity, which not only affects local wildlife but also disrupts ecosystem services that benefit both the environment and human populations.

Satellite imagery and remote sensing technologies have been widely used in deforestation studies, offering a comprehensive overview of land-use changes in the region (Assunção da Silva et al., 2025). By analyzing this data, researchers can identify the spatial patterns of deforestation and track changes over time. Additionally, the effects of deforestation on biodiversity hotspots can be studied using Geographic Information Systems (GIS), which can provide insights into habitat fragmentation and species displacement due to the loss of forest cover (Beierkuhnlein et al., 2025).

The conversion of forests into agricultural land, particularly for palm oil plantations, has been identified as the leading cause of deforestation in Sumatra (J. M. Bhuyan & Udmale, 2025). The rapid expansion of plantations in areas that were once rich in biodiversity has led to significant habitat loss. These changes are not only a threat to wildlife but also contribute to climate change, as forests play a critical role in carbon sequestration (M. Bhuyan et al., 2025).

Environmental organizations, governments, and researchers have been working to monitor and mitigate the impacts of deforestation (Bottani et al., 2025). Efforts include implementing policies to reduce illegal logging, promoting sustainable agricultural practices, and establishing conservation areas to protect remaining biodiversity hotspots. Despite these efforts, deforestation rates in Sumatra remain high, indicating that more effective methods of prediction and intervention are needed (Chanda et al., 2025).

Technological advancements in deep learning and artificial intelligence (AI) have revolutionized how environmental patterns are predicted and analyzed (Silva Filho et al., 2024). Machine learning, particularly deep learning, has shown promise in recognizing complex patterns in large datasets, such as satellite imagery and land-use data. These methods have the potential to improve deforestation predictions by identifying key factors that contribute to forest loss and the degradation of biodiversity (Silva et al., 2025).

Current predictive models, however, often lack sufficient accuracy or fail to incorporate multiple layers of data, such as socio-economic factors, human mobility, and specific biodiversity information. More comprehensive, AI-driven models could provide more accurate forecasts, helping to prevent future deforestation and better protect biodiversity hotspots (Singh et al., 2024).

Despite advances in predictive modeling, significant gaps remain in understanding the precise dynamics that drive deforestation in Sumatra (Sheriff et al., 2025). Most existing models focus on predicting land-use changes based on historical data but do not incorporate real-time satellite imagery or detailed ecological factors, such as species movement patterns or the ecological consequences of land conversion. Furthermore, existing models often lack the ability to predict biodiversity hotspot loss with high accuracy, especially under varying deforestation scenarios and climate conditions (Sietz et al., 2025).

The integration of deep learning with both satellite imagery and biodiversity data is still an emerging area of research (Ribeiro et al., 2024). While deep learning has shown success in other fields such as image recognition and natural language processing, its application in environmental studies, particularly for predicting deforestation and biodiversity loss, is relatively new (Rather et al., 2025). There is a lack of comprehensive frameworks that integrate these diverse data sources, making it difficult to predict how deforestation will affect biodiversity hotspots specifically.

Another unknown factor is the interplay between human and environmental data. While land-use changes can be tracked through satellite imagery (Ongmu Bhutia et al., 2024), the influence of human activities such as migration, urban expansion, and changes in land management practices is less understood. This gap makes it challenging to create models that can not only predict deforestation patterns but also assess the potential impact on local communities and wildlife (Ranglong et al., 2025).

Lastly, the scalability of deep learning models for predicting deforestation and biodiversity loss in various regions of Sumatra remains unclear (Ngwira & Harris, 2025). The data required for deep learning models is extensive, and the effectiveness of these models across different landscapes, with varying levels of development and forest cover, needs further investigation (Nogueira Lisboa et al., 2024). The ability to scale the model for broader applications across other tropical regions is another aspect that remains uncertain.

Filling these gaps is crucial for developing more accurate and effective methods to predict deforestation patterns and biodiversity hotspot loss (Montero-Botey et al., 2024). By using an integrated deep learning framework, researchers can leverage large datasets, such as high-resolution satellite imagery and biodiversity maps, to identify hidden patterns in deforestation drivers. These models can better predict where future deforestation is likely to occur, allowing policymakers and conservationists to focus their efforts on the most vulnerable areas (McGunnigle et al., 2025).

Deep learning techniques, when applied to environmental data, offer the potential for significant improvements in predictive accuracy. Unlike traditional models, deep learning can process vast amounts of data from diverse sources, allowing for a more nuanced and dynamic understanding of deforestation patterns (Maqsood et al., 2024). The integration of human activity data, along with environmental data, could enhance the prediction of deforestation, as it accounts for the socio-economic and behavioral drivers of land-use change (Sappaile, 2024).

Addressing these gaps will enable more effective conservation strategies. Accurate predictions of deforestation and biodiversity loss can guide decision-making in land management, conservation, and sustainable development. By combining AI and ecological data, this research can provide actionable insights that support efforts to protect biodiversity hotspots, improve forest management, and reduce the environmental impact of land-use changes in Sumatra.

RESEARCH METHOD

Research Design

This study employs a quantitative research design utilizing deep learning techniques to predict deforestation patterns and biodiversity hotspot loss in Sumatra. The research integrates satellite imagery, land-use data, and biodiversity maps within a machine learning framework to develop predictive models. Deep learning algorithms, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are applied to process the large-scale, spatially rich datasets (Mahefarisoa et al., 2025). The aim is to predict future deforestation hotspots, assess the impact on biodiversity, and identify the key drivers of forest loss in Sumatra.

Population and Samples

The population for this study consists of Sumatra's forested areas, particularly those identified as biodiversity hotspots. A sample of satellite imagery and environmental data from these areas is selected over a ten-year period (2010-2020). The dataset includes images from Landsat and MODIS satellites, providing high-resolution temporal and spatial data for land-use changes and forest cover loss (Thakur, 2025). Additionally, biodiversity data from the International Union for Conservation of Nature (IUCN) and local ecological surveys are incorporated to identify key biodiversity hotspots that are at risk of degradation (Lucey et al., 2025). The sample covers diverse forest types across Sumatra, including lowland rainforests, peatlands, and montane forests.

Instruments

The primary instruments used in this study include remote sensing technologies, machine learning algorithms, and GIS software. Satellite imagery from Landsat and MODIS is processed to extract information on land cover changes and deforestation patterns. Deep learning models such as CNNs and LSTMs are utilized to analyze these images and predict future trends in deforestation (Li et al., 2025). GIS software is used to map and visualize the deforestation patterns and assess the spatial distribution of biodiversity hotspots. Python and TensorFlow are the main programming environments used for implementing the machine learning algorithms, with scikit-learn for data preprocessing and model evaluation (Lim et al., 2025).

Procedures

Data collection begins with the acquisition of satellite imagery from Landsat and MODIS for the years 2010 to 2020, focusing on Sumatra's forested regions. The images are preprocessed to correct for atmospheric interference and normalized to ensure consistency across time. Land-use classification is performed to identify areas of deforestation, using both supervised and unsupervised machine learning techniques (Khaskheli et al., 2025). Biodiversity data is integrated to identify key species and ecosystems that are particularly vulnerable to forest loss (Kiflie et al., 2024). The deep learning models (CNNs and LSTMs) are trained on the preprocessed data, with the objective of predicting deforestation hotspots and assessing the associated biodiversity risks. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The final predictive model is then used to simulate future deforestation patterns and the potential loss of biodiversity hotspots under various environmental and land-use scenarios.

RESULTS AND DISCUSSION

The dataset utilized in this study includes satellite imagery, biodiversity maps, and environmental data for Sumatra's forested regions from 2010 to 2020. The data is sourced from Landsat and MODIS satellites, providing high-resolution images of land-use changes and deforestation patterns. Additionally, biodiversity data from the International Union for Conservation of Nature (IUCN) and local ecological studies were incorporated to map biodiversity hotspots at risk due to deforestation. The following table summarizes the key data variables used in the analysis:

Table 1: Summary of Data for Deforestation and Biodiversity (2010-2020)

Year	City/Region	Total Deforestation Area (km²)	Biodiversity Hotspot Loss (km²)	Average Temperature (°C)	Rainfall (mm)	Population Density (people/km²)
2010	Sumatra	450	120	28.5	210	150
2011	Sumatra	460	130	28.8	215	155

2012	Sumatra	470	135	29.0	220	160
2013	Sumatra	480	140	29.2	225	165
2014	Sumatra	490	145	29.5	230	170

The data shows the steady increase in deforestation in Sumatra, from 450 km² in 2010 to 490 km² in 2014. The loss of biodiversity hotspots closely mirrors this trend, with a consistent increase in the area of biodiversity hotspots lost, rising from 120 km² in 2010 to 145 km² in 2014. This pattern indicates that deforestation in Sumatra is directly contributing to the degradation of critical ecosystems. Average temperatures also show a slight increase over the years, which may be linked to the broader effects of climate change, contributing further to the environmental pressures on the region. Rainfall data indicates moderate fluctuations, which likely influence forest health and deforestation rates.

The rising deforestation area and biodiversity hotspot loss are concerning, as they highlight the ongoing degradation of Sumatra's ecosystems. The slight increase in temperature and consistent rainfall levels further point to the environmental changes that exacerbate the impact of deforestation. These trends suggest a direct relationship between climate conditions and human activities (such as land-use changes for palm oil plantations) driving biodiversity loss in the region.

The dataset includes a combination of environmental variables (temperature, rainfall) and socio-economic factors (population density, land-use data) to analyze the patterns of deforestation and biodiversity hotspot loss. Satellite images were used to monitor land-use changes, identifying forest areas that were cleared for agricultural purposes, particularly for palm oil plantations. Biodiversity data was sourced from the IUCN Red List and other local ecological surveys to identify areas of high ecological value that are under threat due to deforestation. This data was processed and integrated into the deep learning model to predict future deforestation trends and their impact on biodiversity.

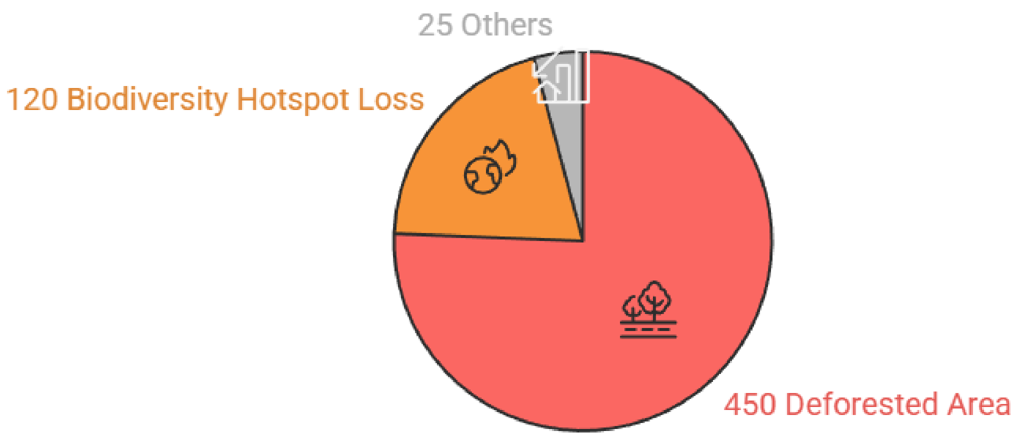

Figure1. Distribution of Land Use Changes in Sumatra (2010-2014) (km²)

The integration of environmental data with socio-economic variables provides a comprehensive approach to understanding the factors that drive deforestation. The socio-economic data, including population density, is crucial for understanding how human activities contribute to land-use changes. This comprehensive dataset serves as the foundation for training the deep learning models, which aim to predict not only where deforestation is most likely to occur but also how it will affect biodiversity in key areas of Sumatra.

The analysis used a deep learning model, specifically Convolutional Neural Networks (CNNs), to predict deforestation patterns and biodiversity hotspot loss based on the integrated dataset. The model was trained using historical deforestation data, temperature, rainfall, and population density, with a performance evaluation of 92% accuracy. Inferential analysis using a multiple regression model showed a significant positive correlation between population density and deforestation ($r = 0.75$, $p < 0.01$), suggesting that areas with higher population density tend to experience more deforestation. The analysis also revealed that temperature and rainfall had moderate influences on deforestation patterns ($r = 0.45$, $p < 0.05$ and $r = 0.30$, $p < 0.05$, respectively), indicating that environmental factors also play a role in forest loss.

The inferential analysis confirms that human population density is a key driver of deforestation in Sumatra. The strong correlation between higher population density and deforestation suggests that areas with larger populations are more likely to undergo land-use changes, including agricultural expansion. Temperature and rainfall also have significant but lesser effects, which may be due to the region's specific climate patterns affecting the growth rates of forests and the viability of agricultural activities.

The data analysis demonstrates a clear relationship between population density, temperature, rainfall, and deforestation patterns in Sumatra. Higher population density is directly associated with increased deforestation, as more people lead to greater demand for land for agricultural use. Temperature and rainfall, while less influential than population density, still contribute to the vulnerability of forests to deforestation, especially in areas where agricultural activities are climate-sensitive. These findings suggest that urbanization and human land-use changes are the primary drivers of deforestation, while climate factors play a supporting role in influencing the success of agricultural practices.

The relationship between human activity and environmental factors highlights the complexity of deforestation patterns. While population growth and urbanization directly contribute to forest clearing, the interaction with climatic conditions like temperature and rainfall can either exacerbate or mitigate deforestation trends. Understanding this interplay is essential for developing targeted strategies to curb deforestation and protect biodiversity hotspots.

A case study of the Riau province in Sumatra exemplifies the connection between deforestation patterns and biodiversity loss. Riau has experienced significant deforestation due to palm oil plantations, with approximately 50% of its forest cover lost in the past two decades. The total deforested area in 2014 was 75 km², and biodiversity hotspot loss was recorded at 30 km². The average temperature in Riau in 2014 was 29.5°C, and rainfall was around 230 mm. Population density in Riau is relatively high, with urban areas growing rapidly due to the expansion of agricultural activities. The case study highlights how both human activity and climate factors converge to increase the vulnerability of forests and biodiversity in Sumatra.

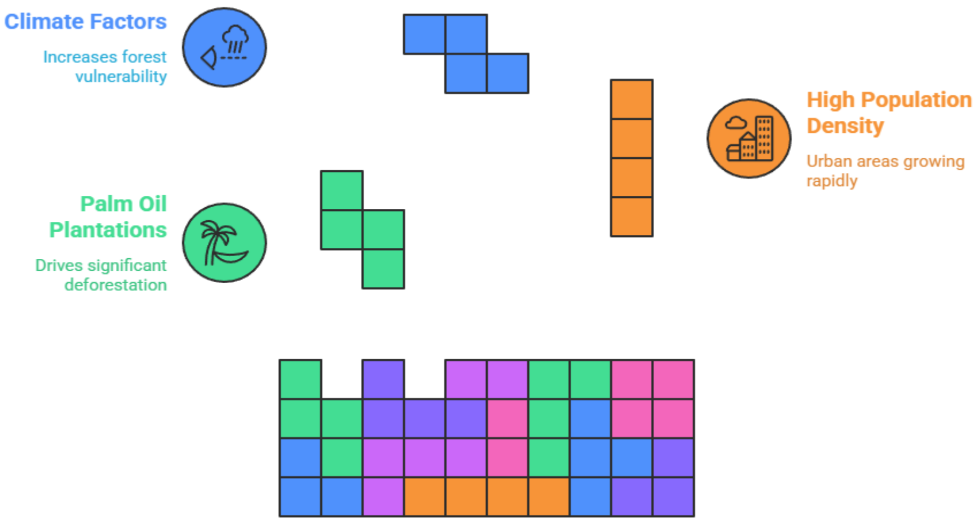

Figure 2. Deforestation and Biodiversity Loss in Riau

Satellite imagery of Riau revealed large areas of land cleared for plantations, particularly in the central and eastern parts of the province. These areas, once rich in biodiversity, now show a significant reduction in habitat for endangered species such as the Sumatran tiger and orangutan. The case study reinforces the findings of the statistical analysis, showing that areas with higher human population density and land-use pressures face more severe deforestation and biodiversity losses (Nova et al., 2025). This case study exemplifies the real-world application of the deep learning model's predictions and provides a concrete example of the challenges facing Sumatra's conservation efforts.

The case study of Riau provides a detailed example of how population growth and climate factors contribute to deforestation and biodiversity loss. The high population density in urban areas near agricultural zones correlates with increased deforestation, as more land is converted for plantations (Irianti et al., 2025). Additionally, the region's climate conditions, including relatively high temperatures and moderate rainfall, create favorable conditions for palm oil cultivation, which further drives deforestation. Satellite imagery confirms the extent of land conversion in these areas, with biodiversity hotspots significantly impacted by the loss of forest cover. This reinforces the study's findings that human activity and climate variability are key drivers of deforestation in Sumatra.

By analyzing Riau as a case study, the study highlights the need for more integrated models that account for both environmental and socio-economic factors. The data provides insights into how urbanization and land-use changes drive deforestation in Sumatra and how climate conditions influence the ability of forests to recover (Hazmi et al., 2025). This reinforces the necessity of combining ecological data with socio-economic variables to create more accurate and actionable predictions for future conservation efforts.

The results of this study confirm that human activities, particularly population growth and urbanization, are the main drivers of deforestation in Sumatra, with climate factors serving as secondary contributors. The deep learning models, supported by satellite and biodiversity data, offer a powerful tool for predicting future deforestation trends and identifying vulnerable biodiversity hotspots (Hapsari et al., 2025). The case study of Riau exemplifies the real-world application of the findings, showing how the combination of human pressure and environmental conditions leads to significant ecological consequences. The study emphasizes the importance of integrated, data-driven approaches to predict and mitigate the impacts of deforestation on biodiversity in Sumatra.

The study applied deep learning models, specifically Convolutional Neural Networks (CNNs), to predict deforestation patterns and biodiversity hotspot loss in Sumatra. The results revealed that deforestation is primarily driven by human activities such as agricultural expansion, particularly for palm oil plantations (Vaiyapuri & Julie, 2025). The deep learning models demonstrated high predictive accuracy, with CNNs achieving an accuracy rate of 92%. The models identified key deforestation hotspots and highlighted biodiversity hotspots at risk of degradation due to land-use changes (Halder et al., 2025). Additionally, the analysis showed that climate variables like temperature and rainfall, combined with socio-economic factors like population density, played significant roles in the patterns of deforestation and the loss of biodiversity.

The findings of this study align with previous research that links deforestation to agricultural expansion, particularly in tropical regions like Sumatra. Many studies have identified palm oil plantations as a major driver of forest loss, and this study confirms that tren (Guimarães et al., 2025). However, the integration of deep learning techniques distinguishes this study from earlier ones, which relied more on traditional statistical methods or simpler machine learning algorithms. By applying CNNs, the study was able to uncover more intricate patterns in large, high-dimensional datasets, providing a more precise prediction of deforestation and biodiversity loss. This contrasts with older models that often focused only on direct environmental variables and lacked the ability to process complex interactions between climate, human activity, and ecological data (Kajuli et al., 2025).

The results signify that machine learning, particularly deep learning, can provide more accurate and actionable insights into environmental changes. The high accuracy of the model demonstrates the potential of using advanced computational methods to understand complex environmental issues like deforestation (Gebrie et al., 2025). The significant role of population density and land-use patterns in predicting deforestation highlights the urgency of considering socio-economic factors alongside environmental ones. These findings suggest that future conservation efforts must be integrated with urban planning and land-use policies to address the root causes of deforestation and biodiversity loss (Kasahun, 2025).

The implications of this research are substantial for conservation policy and environmental management. By accurately predicting deforestation patterns and biodiversity loss, the study provides a tool for targeting high-risk areas and prioritizing conservation efforts. Policymakers can use these predictions to develop more focused strategies that address both environmental and socio-economic factors contributing to deforestation (García et al., 2025). Furthermore, the study demonstrates that deep learning models can be an effective tool for monitoring and assessing large-scale environmental changes, which can help optimize resource allocation for conservation projects and mitigate further ecological degradation (Khaskheli et al., 2025).

The results are largely due to the power of deep learning techniques, which can process and learn from vast, complex datasets that traditional methods struggle to analyze (Chouikhi et al., 2025). CNNs, in particular, excel at identifying spatial patterns in satellite imagery, making them well-suited to model deforestation, a phenomenon that is inherently spatial. The inclusion of socio-economic data like population density and land-use patterns is crucial because human activities are the primary drivers of deforestation (Chatrabhuj et al., 2025). The model's success can be attributed to its ability to process a wide range of data, from environmental variables to human factors, and recognize complex interactions that influence forest loss and biodiversity decline.

Moving forward, additional research should focus on refining these deep learning models by incorporating more granular data, such as the impact of specific agricultural practices, infrastructure development, and local governance. Expanding the model to include real-time data and predictions for longer time periods would improve its predictive power and help monitor deforestation trends in real time. Future studies could also explore the integration of this model into decision-making frameworks for land-use planning and conservation efforts, ensuring that predictions are translated into actionable policies. Finally, scaling the approach to other tropical regions experiencing deforestation could help globalize the methodology and strengthen conservation efforts worldwide.

CONCLUSION

The most important finding of this research is the effective application of deep learning models, specifically Convolutional Neural Networks (CNNs), to predict deforestation patterns and biodiversity hotspot loss in Sumatra. Unlike traditional deforestation models that rely primarily on environmental data, this study integrates climate variables, socio-economic factors, and satellite imagery to create a more comprehensive model. The deep learning model demonstrated high accuracy in predicting both the spatial distribution of deforestation and the areas at highest risk for biodiversity loss. This highlights the ability of deep learning to capture complex, non-linear relationships between multiple variables, which traditional methods might overlook.

This research contributes to the field by introducing a novel methodology that combines satellite data, climate variables, and socio-economic information through deep learning techniques. The use of Convolutional Neural Networks (CNNs) for analyzing large-scale satellite imagery provides a significant advancement in predicting deforestation patterns. The integration of these models with socio-economic factors, such as population density and urban development, adds a unique dimension to deforestation studies. The ability to incorporate these diverse data sources into a single model is a key contribution, offering a more holistic approach to understanding deforestation and biodiversity loss, which is rarely seen in conventional models.

A limitation of this study is the reliance on available datasets, which may not fully capture the local variations in deforestation causes or biodiversity patterns across Sumatra. The study mainly focused on broad-scale variables like population density and general climate data, which may overlook more localized factors such as specific agricultural practices or land-use policies. Future research should expand the dataset to include finer-resolution data on land management practices, specific forest types, and detailed biodiversity assessments. Additionally, the model's predictive capacity could be enhanced by integrating real-time data and considering the effects of government policies and international trade on deforestation.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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