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Business-Oriented Information System for Detecting Deforestation Points Using Satellite Data and Deep learning

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Abstract: This study aims to develop a business-oriented software, EcoWatchtower, for real-time monitoring of deforestation areas using satellite data and machine learning. The objective is to create a system capable of detecting deforestation activities by analyzing satellite images with a deep learning model.

The methodology is based on comparing captured images with reference models to identify anomalies. The results show that the system can automatically generate geolocated alerts, facilitating the rapid intervention of eco-guards, especially in areas where physical surveillance is limited. The main innovation of EcoWatchtower lies in its ability to provide proactive and automated monitoring, precisely marking GPS points of at-risk areas. This system overcomes the challenges of traditional methods by offering an intelligent and continuous solution for forest protection.

In conclusion, EcoWatchtower represents a significant advancement in the fight against deforestation, despite challenges related to data complexity and the continuous improvement of deep learning algorithms.

Keywords: Deforestation, Machine Learning, Business-Oriented Software, Real-Time Monitoring, Satellite Data

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1 Introduction

Tropical forests, essential for regulating the global climate and conserving biodiversity, are currently threatened by accelerated deforestation and degradation. This global phenomenon, driven by human activities such as agriculture, urbanization, and mining, has disastrous consequences for biodiversity, climate, and local communities (Cortez et al., 2009). The current pressure on these ecosystems has reached alarming levels, making the urgent need for innovative technological solutions for the protection and sustainable management of natural resources clear.

Current monitoring methods, based on manual observation and passive alert systems, show significant limitations in terms of accuracy, responsiveness, and coverage. These shortcomings justify the development of a business-oriented information system for detecting deforestation points using satellite data combined with machine learning. Unlike traditional approaches, this system can provide continuous, real-time monitoring by quickly identifying subtle changes in forest cover through the use of convolutional neural networks (CNN) for satellite image processing (Pacheco, 2022).

A key aspect of this system is its ability to act as an eco-guardian in areas where surveillance personnel are insufficient. In remote regions or those with limited network connectivity, the system can operate offline, with a decentralized database. When a threat is detected, alerts are sent via SMS to eco-guards present in the field, enabling increased responsiveness and more effective patrols. This functionality is particularly crucial in areas with limited network coverage, ensuring that vital information reaches the right people without delay, thus optimizing conservation efforts.

One of the main contributions of this research is addressing the challenges related to the analysis of massive spatial data and the modeling of deforestation risks. Although previous studies have explored the use of satellite data to monitor deforestation, existing systems often lack responsiveness and flexibility due to the complexity of the data and computational constraints. Our system, tested in the Tumba-Lediima Reserve in the Democratic Republic of Congo, stands out for its ability to adapt to different geographical contexts, making its results generalizable to other threatened environments.

In response to the gaps identified in the literature, we propose a solution that overcomes the limitations of current approaches by integrating predictive models based on machine learning, capable of processing complex and varied datasets. This innovation improves the accuracy and effectiveness of interventions while providing a robust foundation for large-scale tropical forest conservation.

The underlying hypotheses of this study are based on the idea that the application of machine learning, combined with satellite data, would not only allow for faster and more accurate detection of deforestation areas but also better anticipation of future risks. This hypothesis is justified by the preliminary results obtained during the tests, which show a high sensitivity of the model to different environmental parameters. The key parameters selected for this study, such as the resolution of satellite images and learning algorithms, have been optimized to maximize detection accuracy, although other configurations have also been explored to refine the results.

By integrating features that compensate for the lack of eco-guards and connectivity issues, this study addresses a significant gap in the literature by offering a flexible and responsive system for deforestation monitoring, adapted to complex and varied environments.

2 Materials and Methods

2.1. Materials

We used a computer equipped with a 10th generation Intel Core i7 processor with 8 GB of RAM. In addition to the computer, several tools were employed, including PyCharm, an integrated development environment (IDE) specifically designed for Python, as well as Jupyter Notebook, another development environment dedicated to data analysis. For database management, PostgreSQL was used as the database management system (DBMS). Satellite images were acquired via EarthExplorer using data from the Landsat 8 satellite.

2.2. Methods

The main method of this research was observation, supplemented by a few other approaches, as mentioned below:

2.1.1. Development of the EcoWatchtower Software

The "EcoWatchtower" software was developed using Python, a programming language renowned for its flexibility and capabilities in the field of artificial intelligence. This software functions as a virtual ecological sentinel, continuously monitoring vast forested areas. A key aspect of this design is the integration of a deep learning model for the processing and analysis of satellite images. This model enables the identification and reporting of changes in forest cover in real-time, providing a swift and effective response to deforestation threats.

To ensure data security and integrity, we designed and implemented a relational database using PostgreSQL as the database management system (DBMS). We opted for UML (Unified Modeling Language) to model the structure and relationships between the various entities within the database. Class diagrams were essential in establishing links between multiple entities and ensuring the consistency of the data schema, while use case diagrams described the interactions between external actors and the information system.

PostgreSQL was selected for its robustness, high performance, and open-source status, making it a cost-effective and reliable solution for managing large volumes of data. Its widespread adoption in the industry and the presence of an active community were also determining factors, ensuring continuous technical support and access to resources to optimize the system's use in our project.

- **Use Case Diagram**

In this context, the use case diagram illustrates the roles of the Ecoguard and the Administrator interacting with the EcoWatchtower software. It shows how these roles access various features such as alert monitoring, user account management, and system configuration.

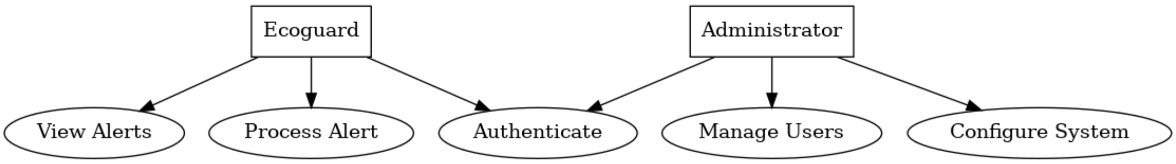


Figure 1: Use Case Diagram

- **Class Diagram**

For the EcoWatchtower software, the class diagram illustrates the structure of the various components within the system. It includes classes for data processing, satellite image analysis, user management, and alert generation. This diagram provides a clear understanding of how the software components interact and are organized, highlighting the relationships and dependencies between different parts of the system. Through this diagram, one can comprehend the overall architecture of the software, ensuring that all elements work together cohesively to achieve the intended functionality.

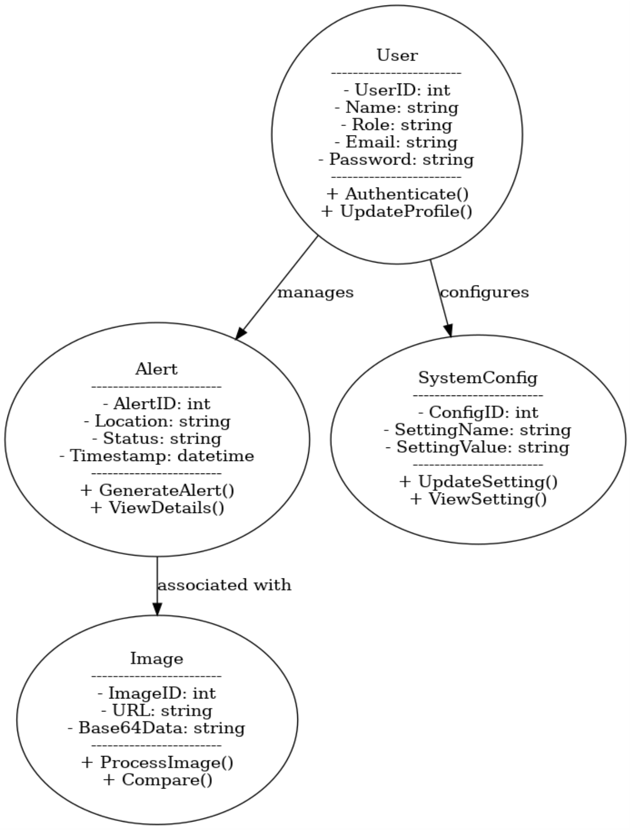


Figure 2: Class Diagram

- **Sequence Diagram**

The sequence diagram for EcoWatchtower details how the system processes a sequence of events, such as receiving satellite images, analyzing the data, generating an alert, and notifying the ecoguard. It allows for the visualization of the workflow for specific functionalities, showing the interactions between different components of the system over time. This diagram helps in understanding the step-by-step execution of processes within the software, ensuring that all actions are carried out in the correct order and efficiently.

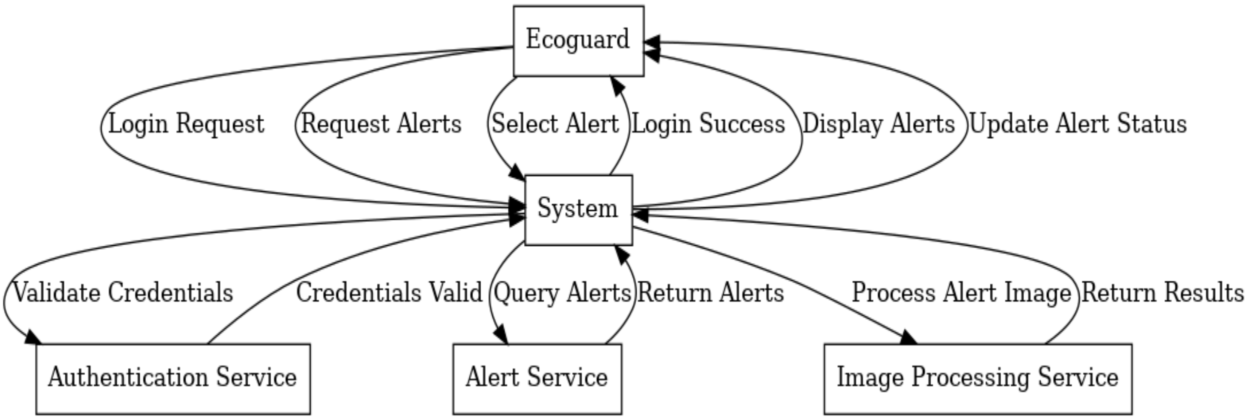


Figure 3: Sequence Diagram

- **Activity Diagram**

The activity diagram illustrates the step-by-step process of how the EcoWatchtower system manages deforestation detection, from the acquisition of satellite images to the generation of reports and alerting the ecoguard. This diagram maps out the workflow, showing the sequence of activities involved, decision points, and the flow of control between different steps in the process. It provides a clear overview of how tasks are organized and executed within the system, ensuring that all necessary actions are performed systematically and efficiently.

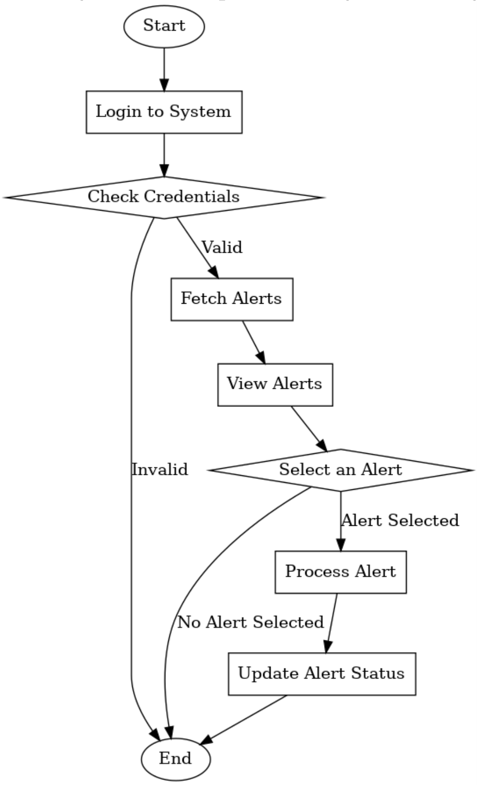


Figure 4: Activity Diagram

- **Turtle Diagram Analysis**

In addition to the various UML diagrams, we utilized an ERP (Enterprise Resource Planning) system with the Turtle Diagram. This diagram, applied to deforestation point detection in this study, highlights the essential elements of the process in question:

- **Inputs**: The primary inputs include satellite images acquired via platforms like EarthExplorer (specifically Landsat 8 images), as well as historical deforestation data and predictive models developed using deep learning algorithms. These data sources are critical for the system's proper functioning.

- **Who**: This involves the different stakeholders in the process: system developers responsible for designing and maintaining the tool, database administrators who manage and secure the data, and ecoguards who are the end-users tasked with monitoring forest areas. Each of these actors plays a crucial role in ensuring the system's effectiveness.

- **How** : This details the processing steps, from acquiring satellite images and analyzing them using tools like Envi and Terrset to applying deep learning models in development environments such as Jupyter and PyCharm. The secure storage of data in a centralized PostgreSQL database is also an essential step.

- **Means**: The ERP system ensures centralized management of information, using PostgreSQL for database management and communication tools (like SMS and email) to quickly transmit alerts to ecoguards. These tools guarantee the robustness and reliability of the detection process.

- **Outputs** : The process outputs include real-time deforestation alerts sent to ecoguards, detailed reports on forest conditions, and recommendations for preventing deforestation. These results enable rapid and effective intervention in the field.

- Performance Measures : These include the accuracy of detection, image processing time, ecoguard responsiveness, and user satisfaction levels. These indicators help evaluate the overall effectiveness of the system and guide continuous improvements. The centralization of data and speed of communication are crucial, particularly in areas with low network connectivity, to maximize ecoguard efficiency and proactively protect forests.

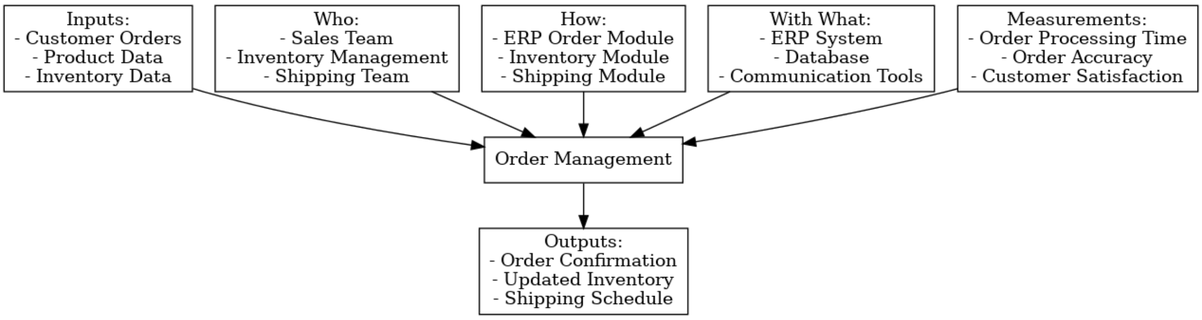


Figure 5: Turtle Diagram Analysis

2.1.2. Data Simulation Setup

A machine learning-based model was established, incorporating a dataset representing various deforestation scenarios. This model was integrated with a web application capable of comparing real-time captured images with simulated ones from the model, enabling the identification of areas affected by deforestation. The simulation was conducted in the Tumba-Lediima Reserve in the Democratic Republic of Congo, serving as a case study to test the effectiveness and accuracy of the EcoWatchtower system.

- **Data Modeling**

The initial phase of model design involved collecting and organizing an extensive set of satellite data, including images of forested areas at different stages of deforestation. These data were used to train the model, familiarizing it with the various visual patterns associated with deforestation. The choice of algorithms was guided by their ability to handle complex and heterogeneous data, which are characteristic of satellite images, while maintaining high prediction accuracy.

- **Model Training and Validation**

The model's training involved applying supervised learning techniques, where satellite images were manually labeled to indicate deforested areas and those still intact. This training phase is crucial as it allows the model to accurately distinguish the subtle signs of deforestation from new data sets. To ensure the model's robustness, a validation phase was conducted, testing the model on new data and adjusting its parameters to improve performance.

- **Integration into EcoWatchtower**

Once designed and validated, the model was integrated into the overall architecture of EcoWatchtower. This integration automated the deforestation point detection process. Each time a new satellite image is received, the model compares it to the reference database and generates an alert if similarities with deforestation cases are detected. This automation is essential for providing continuous and responsive monitoring, which is crucial in areas with limited human presence.

2.1.3. Workflow

The workflow summarizes the study's methodology, illustrating how each major phase in the development and implementation of the EcoWatchtower system is connected and progresses.

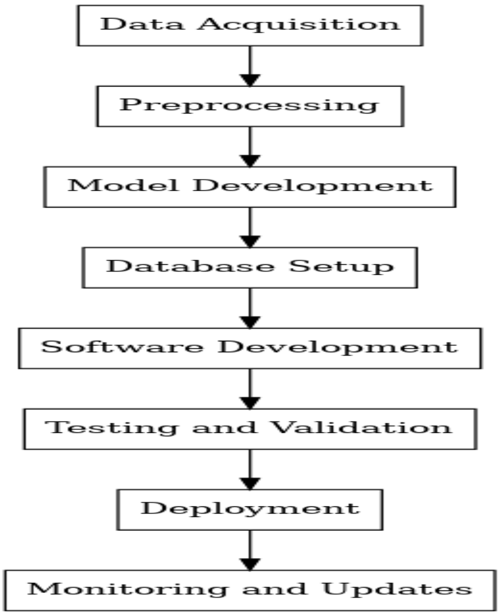


Figure 6: Workflow

3 Results

3.1. **Development of EcoWatchtower**

The development of EcoWatchtower marks a significant advancement in proactive forest management, particularly in areas threatened by deforestation. By integrating machine learning, this software functions as a digital sentinel, supplementing or even replacing the work of eco-guards in regions where human resources are limited. The system aims to enhance field teams' responsiveness by providing continuous, automated monitoring of forested areas using satellite data. EcoWatchtower's ability to generate real-time alerts and log GPS coordinates of affected areas enables rapid, targeted intervention, thereby reducing the response time to deforestation threats. This functionality is crucial for forest conservation, especially in remote or hard-to-reach regions, where early detection of environmental changes can be the deciding factor between conservation and the irreversible loss of natural resources.

3.2. Administrator Environment

EcoWatchtower's administrator environment provides centralized and secure system control. Creating a user account is a critical step in ensuring that only authorized individuals have access to the system, which is vital for protecting sensitive data. The administrator is responsible for registering users, and this process is reinforced by an email confirmation system, adding an extra layer of security. This feature is particularly important in the context of an environmental monitoring system, where data handling must be meticulously controlled to prevent any form of sabotage or error.

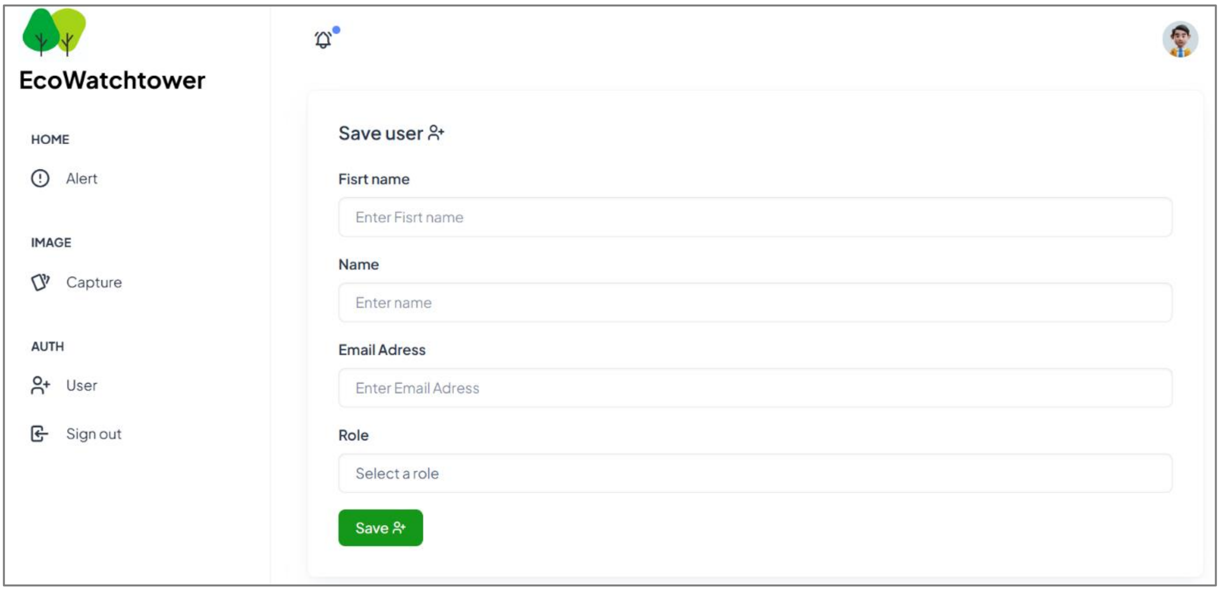
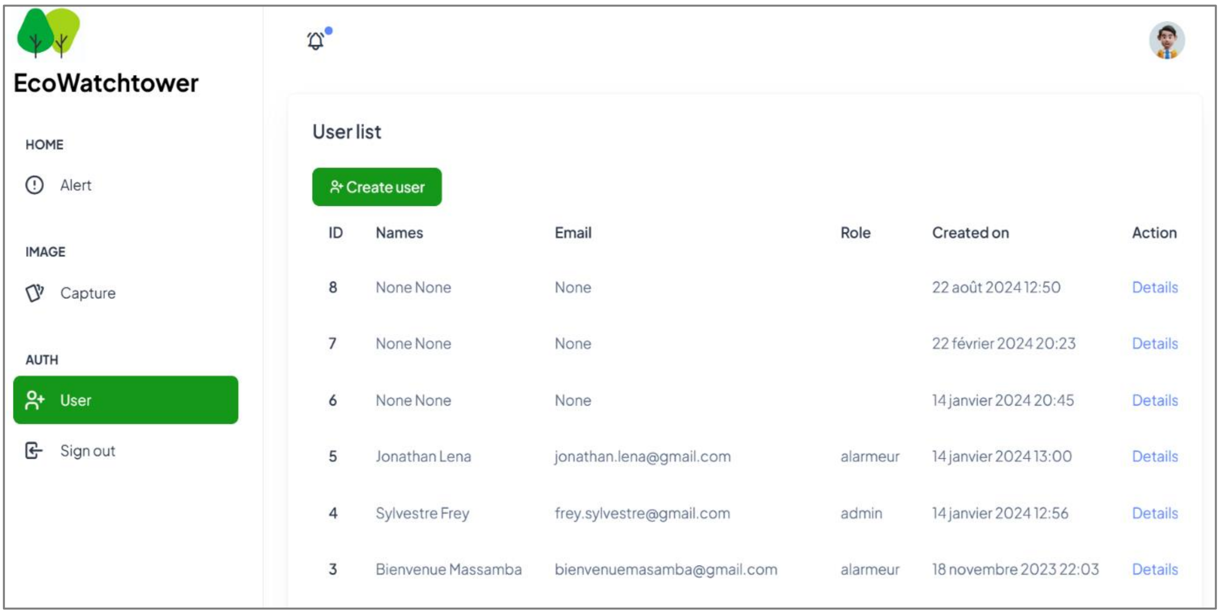


Figure 7: Administrator Environment

The user management feature allows the administrator to manage accounts in real-time, providing the necessary flexibility to quickly adapt the team according to operational needs. This ability to add, modify, or delete users ensures that the system remains agile and secure, particularly when personnel changes occur, such as departures or reassignments.



3.3. User Environment

The user environment of EcoWatchtower is designed to be intuitive and secure. User authentication serves as the first line of defense, ensuring that only authorized individuals can access the system. This feature not only safeguards the data but also maintains the integrity of the surveillance operations.

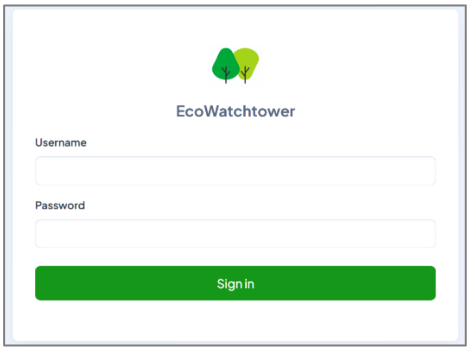
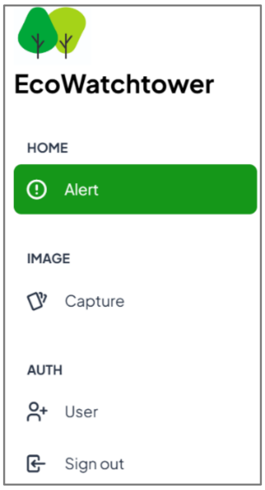
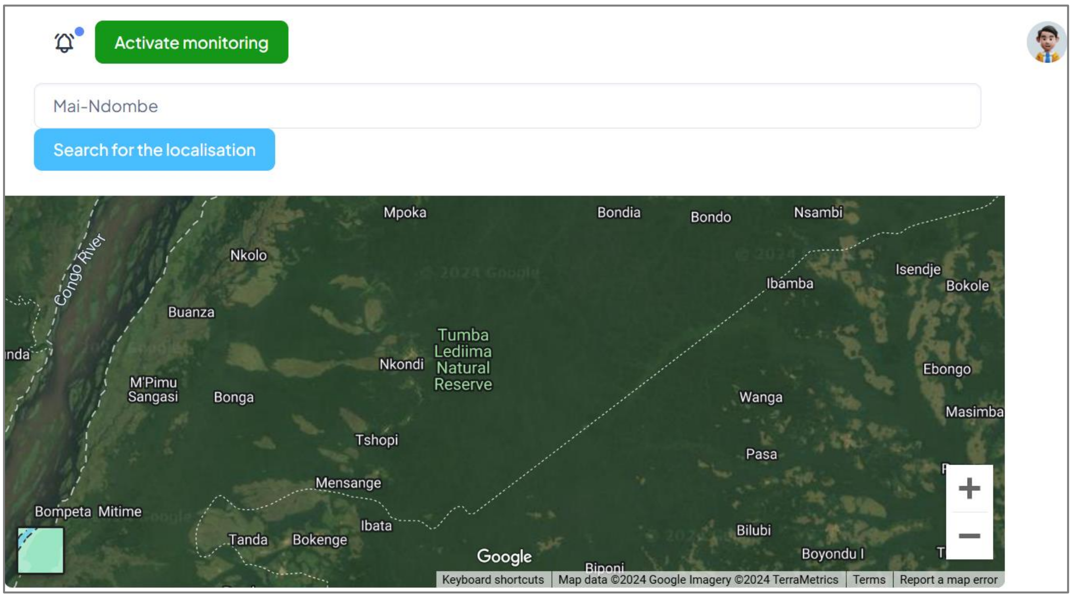


Figure 8: User Environment

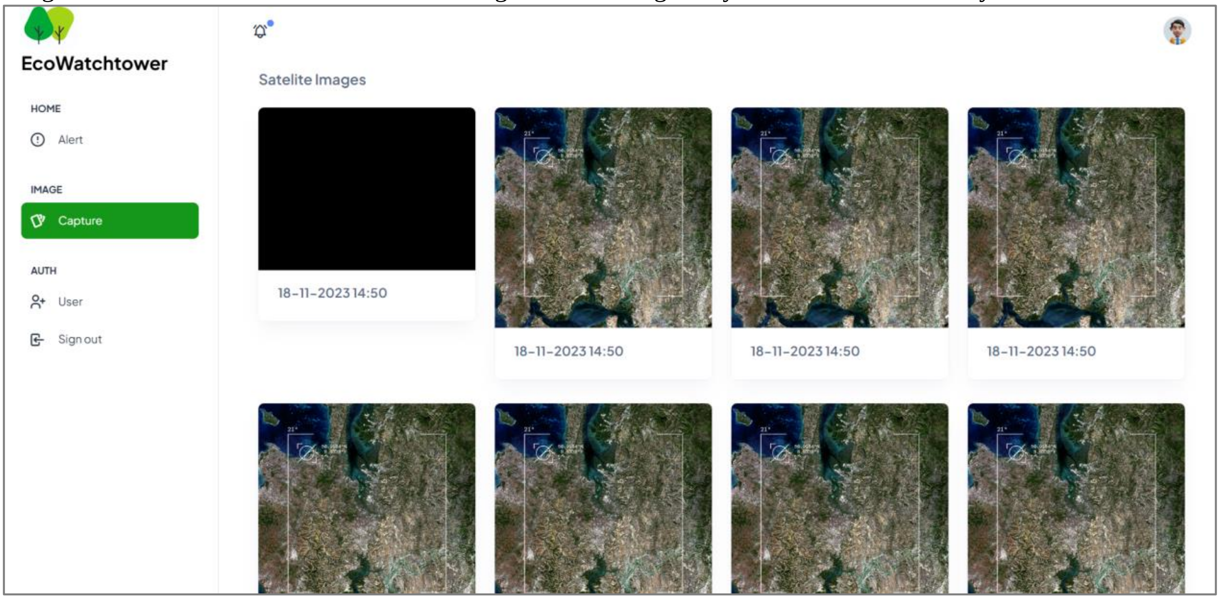
The application menu provides a clear and functional user interface, allowing eco-guards to quickly access essential features such as viewing alerts and accessing satellite images. This ease of use is crucial for eco-guards, who often need to respond swiftly to alerts in challenging field conditions.

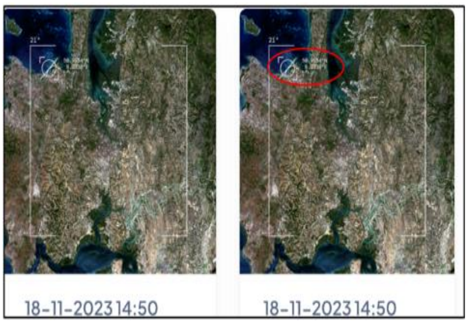


The Application-Satellite Images interface enables real-time monitoring of targeted areas. By activating the surveillance, users can view satellite images and record environmental changes. This feature is particularly useful for detecting early signs of deforestation, allowing for swift intervention before the damage becomes too severe.

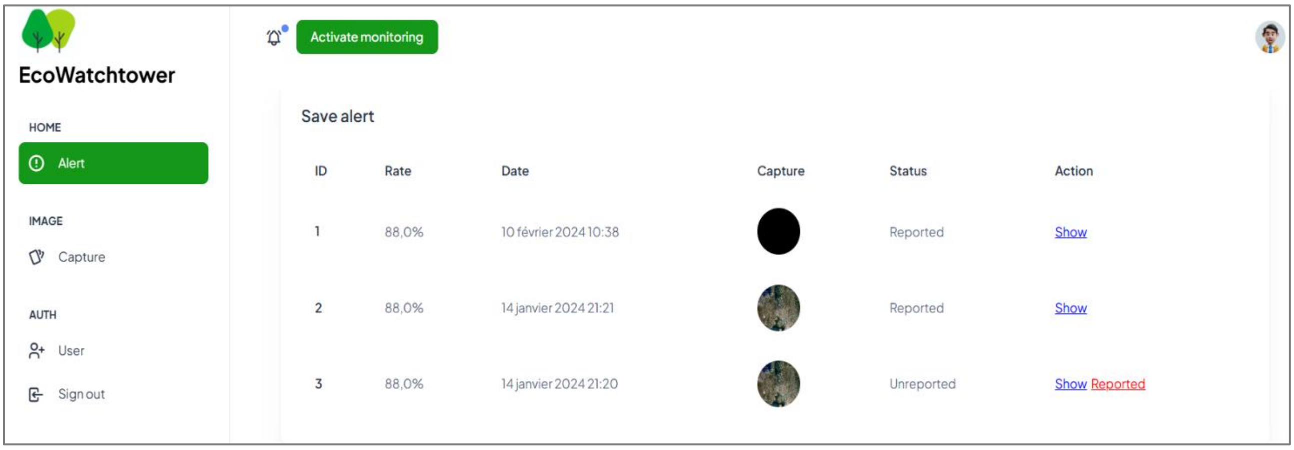


The Captures tab integrates a deep learning model that compares current satellite images with those from the simulated deforestation model. This comparison allows for the automatic detection of deforestation signs, thereby reducing reliance on continuous manual monitoring and enhancing the system's overall efficiency.





Finally, the alert list is a critical tool for managing interventions. Each alert generated by the system includes precise GPS coordinates, enabling eco-guards to quickly locate the affected areas and carry out targeted interventions. This feature not only enhances responsiveness but also optimizes the allocation of human resources by avoiding unnecessary patrols in unaffected areas.



4 Comparative analysis with previous studies

The study conducted with EcoWatchtower, a system based on deep learning and remote sensing, stands out for several key aspects compared to similar systems studied previously. For example, Dumond et al. (2009) developed a business-oriented software named "Asphodèle," focused on tactical simulation, while Chevrou (1993) designed a surveillance system for forest fire defense, based on databases and geographic information systems (GIS). Although these systems have been effective in their respective domains, they present fundamental differences compared to EcoWatchtower, particularly in terms of objectives, technologies used, and applicability.

4.1. Comparison of Methods and Results

Unlike these systems, EcoWatchtower integrates deep learning not only to detect deforestation points but also to generate real-time alerts based on a comparative analysis of satellite images. The systems studied by Dumond and Chevrou lacked this real-time responsiveness, which is a significant improvement brought by EcoWatchtower.

Additionally, the clustering and association algorithms used in EcoWatchtower allow for more precise identification of environmental changes, compared to the more traditional approaches of previous studies. This precision is essential to ensure effective monitoring and to enable eco-guards to respond quickly to identified threats, an aspect that was not as well-developed in the previous systems.

4.2. Analysis of Results

The integration of these advanced technologies into EcoWatchtower has led to reduced data processing time and improved accuracy of generated alerts. While previous studies utilized more manual or semi-automated methods, our system fully automates the process, thereby minimizing human errors and delays. The results show that, compared to more traditional methods, EcoWatchtower is capable of detecting deforestation incidents with increased accuracy, making it a more reliable tool for environmental monitoring.

4.3. Contributions of the Study

Our study makes a significant contribution to the existing literature by proposing a system that not only combines the best practices of previous systems but also improves them through the integration of modern technologies like and big data. Furthermore, EcoWatchtower addresses some of the gaps in previous studies, such as the lack of real-time monitoring and the need for intensive human intervention. This system offers a more holistic and automated approach, capable of operating autonomously in remote forest environments.

4.4. Importance for Future Research

The improvement in precision and responsiveness in detecting deforestation, combined with the ability to operate in areas underserved by eco-guards, makes EcoWatchtower a model for future environmental monitoring systems. The results obtained here provide a solid foundation for the development of even more sophisticated systems, integrating technologies like artificial intelligence to enhance the protection of our forests.

5 CONCLUSION

The implementation of information systems dedicated to detecting deforestation, integrating satellite data and deep learning techniques, marks a major advancement in the protection of forests worldwide. These technologies offer precise and real-time monitoring capabilities, allowing for the rapid identification of threatened forest areas and the triggering of appropriate preventive measures. By targeting the most vulnerable regions, these systems help mitigate the destructive impact of deforestation on biodiversity, climate, and local communities.

However, despite these considerable advantages, challenges remain. The complexity of satellite data, which can be affected by various environmental factors such as cloud cover or seasonal variations, represents a significant technical obstacle. Additionally, while algorithms are effective, they require continuous improvement to adapt to the diversity of forest landscapes and evolving deforestation practices.

It is essential to recognize that technology alone cannot solve the global deforestation problem. Sustained investment in research and development is necessary to overcome current limitations and maximize the effectiveness of these tools. Interdisciplinary collaborations between engineers, ecologists, policymakers, and local actors are also crucial to ensure that these systems are adapted to specific contexts and can be integrated into broader conservation strategies. By investing in these efforts, we can hope not only to curb deforestation but also to promote sustainable forest management on a global scale, thereby contributing to environmental preservation for future generations.

6 BIBLIOGRAPHY

[1] Altarez, D., Richard, A., Armando, M., & Tek, M. (2023). Deep learning U-Net classification of Sentinel-1 and 2 fusions effectively demarcates tropical montane forest's deforestation. Remote Sensing Applications: Society and Environment, 29,100887. https://www.sciencedirect.com/science/article/pii/S2352938523000315

[2] Bilel, M. (2016). L'apprentissage automatique et la révolution des données: défis et applications. https://scholar.google.com/

[3] Bourennane, W. (2013). Étude et conception d'un système de télésurveillance et de détection de situations critiques par suivi actimétrique des personnes à risques en milieu indoor et outdoor. https://www.theses.fr/](https://www.theses.fr/

[4] Branthôme, M. (2021). Apprentissage de la programmation informatique à la transition collège-lycée. STICEF (Sciences et Technologies de l'Information et de la Communication pour l'Éducation et la Formation), 28(3), 1-35. http://sticef.univ-lemans.fr/num/vol2021/03-branthome/sticef_2021_ns_branthome_03p.pdf

[5] Chevrou, D. (1993). Système de défense des forêts contre les incendies et analyse stratégique de l'espace. https://scholar.google.com/

[6] Cortez, R., Pérez, G., Martinez, J., & Ramirez, L. (2009). L'impact des activités humaines sur la biodiversité dans les forêts tropicales. https://scholar.google.com/

[7] Dumond, M., Bernard, C., Lavallée, P., & Dupuis, S. (2009). Asphodèle : Un logiciel orienté métier pour la simulation tactique. https://scholar.google.com/

[8] FAO. (2023). Des forêts saines et productives sont essentielles afin de réaliser les objectifs liés au développement, au climat, à la terre et à la biodiversité. https://www.fao.org/

[9] FAOSTAT. (2019). Statistiques mondiales des forêts. https://www.fao.org/faostat/

[10] Ines, L., & Briche, A. (2023). Détection et estimation de changement pour le suivi et surveillance du couvert forestier par les images Landsat de la Wilaya de Bordj Bou Arreridj. https://www.theses.fr/

[11] Istrate, D., Vacher, M., Serignat, J. F., Besacier, L., & Castelli, E. (2006). Système de télésurveillance sonore pour la détection de situations de détresse. https://www.sciencedirect.com/science/article/pii/S1297956206000083

[12] Komal, K., Priya, R., Krishna, K. S., & Rupali, K. (2024). Déforestation detection using CNN - A review. https://scholar.google.com/

[13] Mohammed, B., Kamel, B., & Abdelouahab, M. (2017). Deep Learning for Tomato Diseases: Classification and Symptoms Visualization. https://scholar.google.com/

[14] Pacheco-Pascagaza, A. M., Gou, Y., Louis, V., Roberts, J., Rodríguez-Veiga, P., Bispo, P. C., Espírito-Santo, F., Robb, C., Upton, C., Galindo, G., Cabrera, E., Indira Paola Pachón Cendales, Castillo-Santiago, M., Oswaldo, C. N., Carmen, M., Marco, I., & Balzter, H. (2022). Near Real-Time Change Detection System Using Sentinel-2 and Machine Learning: A Test for Mexican and Colombian Forests. https://www.frontiersin.org/articles/10.3389/frsen.2022.707

[15] Pacheco, A. (2022). Utilisation des réseaux neuronaux convolutionnels pour le traitement des images satellitaires. https://scholar.google.com/

[16] Potapov, P., Matthew, C., Amy, P., Andres, H., Alexandra, T., Svetlana, Z., & Viviana, T. (2022). The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results. https://www.frontiersin.org/articles/10.3389/frsen.2022.707

[17] Ramcharan, B. G. (2023). The International Law and Practice of Early-Warning and Preventive Diplomacy: The Emerging Global Watch. https://brill.com/view/title/613

[18] Zouinar, M. (2020). Évolutions de l'Intelligence Artificielle: quels enjeux pour l'activité humaine et la relation Humain-Machine au travail? Activités, 17(1), avril. http://www.activites.org/v17n1/v17n1.pdf