REVIEW ARTICLE

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN FORESTRY

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ABSTRACT:

Forests are critical to global ecological balance, providing essential ecosystem services, regulating climate, and supporting biodiversity. Managing and protecting these vast ecosystems is a complex task requiring extensive data collection, processing, and analysis. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools to enhance forestry practices. From forest health monitoring and wildfire prediction to species identification and carbon sequestration modelling, AI and ML offer innovative solutions to the multifaceted challenges in forestry. This review provides an in-depth examination of AI and ML applications in forestry, emphasizing recent advancements, methodologies, and future directions.

KEYWORDS: *Artificial Intelligence, Machine Learning, Modelling, Forest*

INTRODUCTION:

Forests cover approximately 31% of the Earth's land area and play a vital role in maintaining ecological balance. Forests act as carbon sinks, help in water conservation, protect biodiversity, and mitigate climate change. However, forests face numerous challenges such as deforestation, habitat degradation, forest fires, and climate change-induced shifts. To address these issues, traditional forestry methods, while effective, are increasingly supplemented with advanced technologies like AI and ML, enabling more precise and proactive management practices. AI and ML have revolutionized various sectors, and forestry is no exception. These technologies can analyze vast datasets, extract patterns, and predict future outcomes. The objective of this review is to provide an overview of AI and ML applications in forestry, focusing on their use in forest monitoring, forest health assessment, wildlife conservation, and climate-related predictions.

There is a pressing need for advanced materials in various areas such as technology, transportation, infrastructure, energy, and healthcare. Yet, conventional methods of finding and investigating novel materials face constraints because of the intricate nature of chemical compositions, structures and desired characteristics. Additionally, innovative materials should not just allow for new uses, but also incorporate eco-friendly methods for their production, utilization, and disposal. In order to address technological and environmental challenges, alloys are becoming more complex in terms of their composition, synthesis, processing, and recycling due to the increasing need for diverse material properties (Mishra et al., 2024).

Digital evolution is a transformative force reshaping every aspect of computer science and information technology. By enhancing computing power, advancing algorithms, improving data analytics, and fostering better connectivity and cyber security, digital evolution drives technological advancements that boost productivity, innovation, and societal well being. Embracing and guiding digital evolution will be crucial for maximizing its benefits and addressing its challenges. The advancement in computing power has been a cornerstone of the digital revolution, driving progress across all areas of computer science and information technology. From the invention of the transistor to the dawn of quantum computing, each leap in computational capability has unlocked new possibilities and transformed the way we live and work. As we continue to push the boundaries of what is possible, addressing the associated challenges and ethical considerations will be essential to harness the full potential of these advancements for the benefit of society (Mishra and Agarwal, 2024).

Forest ecosystem plays a very important role in the global carbon cycle. It stores about 80% of all above ground and 40% of all below ground terrestrial organic carbon. During productive season, carbon dioxide from the atmosphere is taken up by vegetation stored as plant biomass. For this reason, the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol recognized the role of forests in carbon sequestration. Specially, the Kyoto Protocol pointed out forests as potential carbon storage. Disturbances in the forest due to natural and human influences lead to more carbon release into the atmosphere than the amount used by vegetation during photosynthesis. Sustainable management strategies are, therefore, necessary to make the forest a carbon sink rather than source. However, the state of tropical forests continues to deteriorate. Land conversion is the main reason for93.4% of the annual net forest loss, while conversion to plantation forest explains the remaining 6.6%. Land conversion resulted from forest mismanagement, such as illegal forest practices and lack of sound policies and regulations for sustainable forestry. It has been suggested that the concentration of green house gases like carbon dioxide in the atmosphere can be controlled by planting suitable tree species having higher growth rate and carbon sequestration potential on wastelands and degraded lands. This will definitely minimize climate change-global warming and save our environment Rouchoudhury and Mishra, 2024).

Forest Monitoring and Management

Forest monitoring and management are vital for maintaining the health and sustainability of forest ecosystems. As forests face increasing threats from deforestation, climate change, and human activities, the need for effective monitoring techniques has become more pressing. Traditional methods of forest monitoring, which often rely on field surveys and manual data collection, are time-consuming, costly, and limited in scope. The integration of artificial intelligence (AI) and machine learning (ML) offers a transformative approach to forest monitoring, enabling efficient data processing, real-time decision-making, and more comprehensive ecosystem assessments. By leveraging advanced AI and ML models, forestry professionals can analyze vast datasets from remote sensing technologies such as satellite imagery, LiDAR (Light Detection and Ranging), and UAV (Unmanned Aerial Vehicles), making forest monitoring more efficient, accurate, and scalable. This section explores the key applications of AI and ML in forest monitoring and management, with a focus on remote sensing data processing, forest inventory, and biomass estimation. Sustainable forest land management is a multifaceted discipline that demands a holistic and scientifically rigorous approach. By integrating ecological principles, technological advancements, and community engagement, we can strive toward a future where forests continue to thrive, providing essential services for both nature and humanity (Mishra and Agarwal, 2024).

Remote Sensing Data Processing

Remote sensing technologies, such as satellite imagery, LiDAR (Light Detection and Ranging), and UAV (Unmanned Aerial Vehicle) imaging, are widely used in forestry to monitor forest structure, biomass, and changes in land cover. However, the massive amount of data generated from these systems poses a significant challenge in processing and analysis. AI and ML techniques, particularly deep learning algorithms, have shown remarkable success in automating remote sensing data interpretation. Convolutional neural networks (CNNs), for instance, are extensively used for image classification, object detection, and segmentation tasks. These algorithms help in identifying deforestation hotspots, monitoring reforestation efforts, and assessing forest health at large scales with high accuracy. In a study by Zhu et al. (2020), a deep learning model was developed to classify tree species from high-resolution remote sensing images. The model achieved an accuracy of over 90% in distinguishing between different tree species, significantly enhancing the accuracy of species distribution mapping.

Satellite and Aerial Imagery Analysis

Remote sensing technologies have revolutionized forest monitoring by enabling large-scale data collection over vast and often inaccessible areas. Satellite imagery from sources like NASA’s Landsat, ESA's Sentinel satellites, and commercial providers is commonly used to monitor forest cover, detect deforestation, assess forest health, and evaluate land-use changes. The vast quantities of remote sensing data collected through these methods require advanced analysis techniques to extract meaningful insights. AI and ML techniques, particularly deep learning models like Convolutional Neural Networks (CNNs), play a critical role in automating image classification, segmentation, and feature extraction. CNNs can identify specific patterns, such as tree species, canopy cover, and signs of forest degradation, with high precision. In [Zhu et al. (2020)], a CNN-based model was used to classify tree species from high-resolution satellite images. The model achieved over 90% accuracy in distinguishing between species such as oak, pine, and eucalyptus, highlighting the potential of deep learning for enhancing forest classification accuracy. This approach enables the identification of specific tree species over large areas, supporting biodiversity assessments and resource management.

LiDAR Data for Forest Structure Analysis

LiDAR, which uses laser pulses to measure the distance between the sensor and the Earth's surface, provides detailed information about forest structure, including canopy height, tree density, and biomass. LiDAR is especially valuable for estimating forest biomass and carbon storage, which are critical for climate change mitigation. AI and ML models, such as Random Forests, Gradient Boosting Machines, and Support Vector Machines (SVMs), have been applied to LiDAR data to predict forest metrics like tree height, canopy volume, and biomass. These algorithms process the 3D point cloud data generated by LiDAR sensors to create detailed maps of forest structure. In a study by [Belgiu & Drăguț (2016)], a random forest model was applied to LiDAR data for biomass estimation in temperate forests. The AI-driven model provided higher resolution and more accurate estimates of above-ground biomass compared to traditional inventory methods, reducing error margins by 30%. This capability enables forest managers to monitor carbon stocks and assess the impact of forest management practices.

Unmanned Aerial Vehicles (UAVs) and Drone Imagery

UAVs or drones are increasingly used for forest monitoring because they provide high-resolution, real-time data over specific areas of interest. Drones equipped with multispectral or hyperspectral cameras can capture images at multiple wavelengths, which is useful for detecting subtle changes in vegetation health and species composition. AI and ML models process drone imagery to detect features such as tree crown delineation, gaps in forest cover, and signs of disease or stress. UAV-based monitoring is particularly beneficial for detecting forest changes at smaller scales, such as in urban forests or conservation areas, where high-resolution data is essential for decision-making. In [Li et al. (2021)], a UAV equipped with a high-resolution camera captured images of a pine forest affected by beetle infestation. A deep learning algorithm (CNN) was used to analyze the imagery and detect signs of beetle damage, achieving a detection accuracy of 88%. This method outperformed traditional ground-based surveys, allowing for earlier detection and intervention.

Forest Inventory and Biomass Estimation

Traditional forest inventories require field measurements, which are labor-intensive and time-consuming. AI and ML techniques can assist in automating forest inventories by analyzing remotely sensed data to estimate tree height, canopy cover, and biomass. Random forest algorithms, regression trees, and support vector machines (SVMs) are commonly applied to estimate biomass from LiDAR and satellite data. For example, using AI-based models, biomass estimates can be produced with higher spatial resolution and reduced uncertainty compared to traditional models. An AI-driven approach by [Belgiu and Drăguţ (2016)] used random forests for biomass estimation in temperate forests, reducing the prediction error by 30% compared to non-ML methods.

Automating Forest Inventory with AI

Forest inventories, which involve the systematic collection of data on tree species, height, diameter, and volume, are essential for forest management and conservation. Traditional forest inventories require extensive fieldwork, which is labor-intensive and costly, particularly for large or remote areas. AI and ML have the potential to automate and optimize forest inventories by analyzing remote sensing data. Machine learning models, such as decision trees, regression models, and neural networks, are used to estimate tree attributes from remotely sensed data. For example, these models can predict tree height and diameter by analyzing LiDAR or UAV data, providing faster and more accurate inventory results than manual methods. In a study on tropical forests, an AI-based approach using random forests was developed to estimate tree height and basal area from UAV imagery. The model demonstrated an 85% accuracy rate, significantly reducing the time and labor required for field data collection.

Biomass and Carbon Stock Estimation

Biomass estimation is critical for understanding the carbon sequestration potential of forests, which is a key component of climate change mitigation strategies. Estimating above-ground biomass requires accurate measurement of forest structure, including tree height, canopy cover, and trunk diameter. AI and ML algorithms are increasingly used to estimate biomass from remote sensing data. By combining LiDAR and satellite imagery, machine learning models can predict biomass with greater accuracy than traditional models. These predictions are essential for understanding the carbon dynamics of forests and for reporting on carbon storage for initiatives like REDD+ (Reducing Emissions from Deforestation and Forest

Degradation). A biomass estimation model developed using a combination of LiDAR and optical satellite data achieved a 20% improvement in accuracy compared to traditional biomass estimation methods. This AI-driven model allowed for precise biomass mapping across forested landscapes, helping inform carbon accounting and forest management decisions.

Forest Change Detection and Deforestation Monitoring

Deforestation and Land-Use Change Detection

Deforestation is a major threat to forest ecosystems, contributing to biodiversity loss, greenhouse gas emissions, and soil degradation. Monitoring deforestation in real-time is crucial for implementing effective conservation strategies. AI and ML techniques, particularly in combination with satellite data, can detect land-use changes and deforestation at a much faster rate than human analysis. AI-based models process temporal sequences of satellite images to identify changes in forest cover, allowing for the detection of illegal logging activities or land conversion for agriculture. These models can also quantify the rate of deforestation and forecast future trends, providing essential data for policy-making. The Global Forest Watch platform, which uses AI and machine learning to analyze satellite imagery, provides near real-time alerts on forest cover changes worldwide. This system enables governments, NGOs, and local communities to monitor deforestation and take action against illegal logging activities.

Forest Regeneration and Reforestation Monitoring

AI and ML are also used to monitor forest regeneration and reforestation efforts. These technologies can track the growth of young forests and evaluate the success of reforestation projects by analyzing satellite or UAV data. Machine learning models assess tree density, canopy closure, and species composition to determine the health and progress of regenerating forests. By providing precise and timely data, AI-driven monitoring tools support the management of reforestation initiatives, ensuring that restoration goals are met and maintained.

Forest Health and Disease Monitoring

Pest and Disease Detection

Forest pests and diseases can severely damage forest ecosystems, causing loss of biodiversity and reducing the economic value of forests. Early detection and intervention are critical to mitigating the impact of these threats. Machine learning models, especially those based on image recognition and pattern recognition, are used to detect signs of pest infestations and disease outbreaks. For instance, deep learning-based image classification algorithms can be employed to analyze aerial imagery of forests to detect tree discoloration or defoliation, which are early indicators of disease or pest infestation. A study by [Li et al. (2021)] demonstrated the use of a CNN model to detect pine beetle infestations using UAV images. The model achieved a detection accuracy of 88%, allowing for earlier identification of infested areas compared to traditional methods.

Stress Detection in Trees

Trees face numerous stressors, both biotic (e.g., pests, diseases) and abiotic (e.g., drought, nutrient deficiency, pollution). These stressors can significantly reduce tree health, affect forest ecosystems, and lead to large-scale forest die-offs if not managed properly. Early detection of stress is crucial for forest management as it allows for timely interventions and helps prevent further damage. Traditional stress detection methods, which rely on visual inspection or laboratory analysis, are often time-consuming, labor-intensive, and less effective at large scales. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as key technologies for automating and enhancing stress detection in trees. By leveraging data from remote sensing technologies such as satellite imagery, hyperspectral imaging, and unmanned aerial vehicles (UAVs), AI and ML can identify early signs of tree stress, offering more efficient and precise management solutions.

Types of Stress in Trees

Tree stress can be categorized into biotic and abiotic factors, both of which can cause significant physiological changes in trees.

Biotic stressors

These include pests, pathogens, and invasive species that directly attack trees. For example, bark beetle infestations, fungal diseases, or parasitic plants can lead to leaf discoloration, defoliation, and ultimately tree death.

Abiotic stressors

These include non-living factors such as drought, nutrient deficiency, soil compaction, air pollution, and extreme temperatures. Drought stress, for instance, can cause leaf wilting, reduced growth and a decline in photosynthetic activity.

Early detection of these stressors is essential for forest managers to mitigate their effects before they escalate into severe health issues for trees and forests.

Remote Sensing for Stress Detection

Hyper spectral and Multi spectral Imaging

Hyper spectral imaging captures light reflected from vegetation across a wide range of wavelengths, often beyond the visible spectrum. By analysing these reflectance patterns, AI and ML algorithms can detect subtle physiological changes in trees that indicate stress before they are visible to the naked eye. Multi spectral imaging, while offering fewer wavelength bands than hyper spectral imaging, also provides valuable data on vegetation health. Stressed trees exhibit altered reflectance patterns in specific spectral bands, particularly in the near-infrared (NIR) and shortwave infrared (SWIR) regions, due to changes in leaf structure, water content, and chlorophyll levels. AI and ML models analyse these patterns to detect stress and identify the underlying cause (e.g., water deficiency, pest infestation, or nutrient limitation). A study by Yuan et al. (2019) used hyper spectral data and a support vector machine (SVM) model to detect drought stress in coniferous trees. The model successfully differentiated between healthy and drought-stressed trees with 92% accuracy by analysing changes in NIR and SWIR reflectance. Such early detection allows forest managers to implement water conservation strategies before irreversible damage occurs.

Thermal Imaging

Thermal imaging is another remote sensing tool used to detect abiotic stress, particularly drought. Water-stressed trees tend to have reduced transpiration, which leads to elevated leaf temperatures. By measuring canopy temperature with thermal cameras mounted on UAVs or satellites, AI-driven models can detect areas of heat stress, signalling the presence of water deficiencies. Machine learning algorithms, such as random forests and neural networks, are employed to process thermal data and correlate temperature anomalies with drought stress. These models help forest managers identify areas in need of irrigation or other interventions, preventing widespread tree mortality during periods of drought. In a drought-prone region of California, researchers used a combination of thermal imaging and deep learning models to monitor water stress in oak trees. The AI-based model detected early signs of drought stress several weeks before visual symptoms appeared, enabling better water resource management in the area.

AI and Machine Learning in Stress Detection

AI Models for Stress Detection

AI and ML algorithms excel at analysing large, complex datasets to detect patterns that are often imperceptible to human observers. Several machine learning techniques are used for tree stress detection, including:

Support Vector Machines (SVMs)

Effective for classifying stressed and healthy trees based on hyper spectral and multi spectral data. SVMs can create a hyper plane that separates different stress conditions based on their spectral signatures.

Random Forests

Frequently used for analysing remote sensing data to predict stress levels. Random forests combine multiple decision trees to improve prediction accuracy by reducing overfitting and generalizing well to new data.

Neural Networks

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), are applied to image data for detecting stress-related features such as leaf discoloration, canopy thinning, or structural damage. In [Li et al. (2021)], a CNN-based model was developed to detect stress in citrus trees caused by a fungal disease. The model analysed UAV-captured imagery and identified stressed trees with 87% accuracy. This method provided an efficient, non-invasive approach to monitoring disease outbreaks in orchards and forests.

Predictive Modelling for Stress Conditions

Predictive models are essential for anticipating the onset of tree stress based on environmental factors such as soil moisture, temperature, and atmospheric conditions. These models integrate weather data with remote sensing observations to forecast the likelihood of stress-related events, such as droughts or pest outbreaks. For instance, AI-driven models that incorporate climate data can predict when and where drought stress will occur, enabling forest managers to take pre-emptive action. Similarly, predictive models based on pest population dynamics and temperature trends can forecast the likelihood of insect infestations, allowing for targeted pest control measures. Researchers (Rädler et al., 2020) combined soil moisture data with satellite-derived vegetation indices to predict drought stress in Mediterranean forests. A machine learning model was used to forecast drought intensity and timing, achieving an 80% accuracy rate. This information helped forest managers optimize irrigation and reduce the impact of water shortages.

Applications in Disease and Pest Detection

Pest Infestation Detection

Biotic stress from pests can cause significant damage to forests, leading to defoliation, reduced growth, and tree mortality. AI-based models, particularly those employing image recognition techniques, are effective in detecting pest infestations in trees. Early detection of bark beetle infestations is critical to preventing widespread tree mortality in coniferous forests. Machine learning models analyse UAV or satellite images to detect discoloration, crown thinning, or bark changes that are indicative of beetle activity. In addition to image analysis, acoustic sensors and AI-driven sound classification models are used to detect the presence of pests by analysing sounds produced by insect larvae or adult beetles. An AI-based system using CNNs was developed to detect pine beetle infestations in coniferous forests based on multi-spectral UAV imagery (López et al., 2018). The system identified infested areas with 90% accuracy, allowing forest managers to quickly isolate and treat affected regions.

Disease Monitoring

Fungal and bacterial diseases are major biotic stressors in forests, and detecting them early is crucial to preventing outbreaks. AI and ML models can process visual and spectral data to identify disease symptoms such as leaf spots, blight, or cankers. Machine learning models can also be trained to analyse patterns in disease spread, allowing for better prediction of future outbreaks. A study by Xie et al. (2020) developed an SVM-based model to detect powdery mildew in oak trees using hyperspectral data. The model achieved an accuracy rate of 85%, providing a fast and non-invasive method for disease detection. By identifying early signs of infection, this model allows for more targeted and efficient disease management strategies.

In addition to detecting pests and diseases, AI models are also used to monitor the physiological stress of trees due to factors like drought, nutrient deficiency, or pollution. Hyper spectral imaging combined with machine learning can help in assessing tree health by analysing leaf reflectance patterns, which are altered under stress conditions.

Wildfire Prediction and Management

Wildfire Risk Mapping

Wildfires are increasingly becoming a major threat to forest ecosystems, particularly in regions prone to prolonged droughts and extreme temperatures. AI and ML can aid in predicting wildfire risk by analysing variables such as vegetation type, moisture levels, temperature, and wind patterns. These models help in creating risk maps, which are essential for resource allocation and preparedness. ML algorithms, such as decision trees and neural networks, have been used to predict wildfire occurrence by processing historical fire data and environmental conditions. AI-based risk models can accurately forecast fire-prone areas, allowing for timely interventions. Lahaye et al. (2018) used a combination of SVM and neural networks to create wildfire risk models for Mediterranean forests. Their models achieved a precision of over 85%, outperforming traditional statistical models.

Fire Spread Prediction

AI can also be employed to predict the spread of ongoing wildfires. By incorporating real-time data on wind speed, humidity, fuel type, and fire location, ML models can simulate the progression of wildfires and help authorities plan containment strategies.

Biodiversity and Wildlife Conservation

Species Identification and Habitat Modelling

Machine learning algorithms are transforming biodiversity studies by facilitating species identification and habitat suitability modelling. AI-driven image recognition systems can identify plant and animal species from camera trap photos or UAV imagery. These systems are particularly useful for monitoring rare or elusive species in dense forest ecosystems. Habitat modelling, which predicts suitable habitats for species based on environmental parameters, is another area where AI excels. Neural networks and ensemble learning methods are used to analyse environmental variables and predict species distribution patterns. In a study by Mac Aodha et al. (2019), a deep learning algorithm was applied to camera trap images to identify animal species in tropical forests. The model achieved an accuracy of 93%, drastically reducing the time required for manual identification.

Poaching Detection

AI is being used to combat illegal logging and poaching in protected areas. Acoustic sensors and AI-based sound classification models can detect the presence of chainsaws or gunshots in real-time, allowing for swift intervention by forest rangers.

Carbon Sequestration and Climate Change Modelling

Carbon Stock Estimation

Forests are essential carbon sinks, and understanding their role in carbon sequestration is critical for climate change mitigation. AI-driven models are used to estimate carbon stocks and predict future carbon sequestration potential. These models combine remote sensing data with forest inventory information to provide accurate carbon estimates at both local and global scales.

Climate Impact Predictions

AI is also applied to predict the effects of climate change on forests. By analyzing large datasets on temperature, precipitation, and other climatic factors, machine learning models can predict how forests will respond to future climate scenarios. These predictions are crucial for developing adaptive forest management strategies.

Challenges and Future Directions

Data Availability and Quality

One of the key challenges in AI-driven forest monitoring is the availability and quality of data. Remote sensing datasets often vary in resolution, temporal frequency, and accessibility. In many regions, high-resolution data is either unavailable or prohibitively expensive, limiting the application of AI models.

Integration of Multisource Data

The integration of multiple data sources, such as satellite imagery, LiDAR, UAV data, and ground-based measurements, is essential for accurate forest monitoring. However, harmonizing these diverse datasets poses technical challenges, particularly in terms of data resolution, format, and temporal synchronization.

Data availability and quality

High-quality, large-scale datasets are essential for training accurate AI models. In many regions, data collection is still a bottleneck.

Model interpretability

Many AI models, particularly deep learning models, function as black boxes, making it difficult for forest managers to understand the reasoning behind predictions.

Ethical concerns

The use of AI in biodiversity conservation, such as poaching detection, raises ethical concerns related to privacy and surveillance.

Future Directions

Integration with IoT

The Internet of Things (IoT) can enhance forest monitoring by deploying sensor networks that collect real-time data on temperature, humidity, and soil moisture. AI models can process this data to improve fire risk assessments, pest monitoring, and forest health evaluations.

Block chain for Transparency

Block chain technology could be used in combination with AI for tracking timber harvesting, ensuring that logging practices are sustainable and legal. This integration would enhance transparency in forest management.

CONCLUSION:

AI and machine learning are revolutionizing forestry by providing powerful tools for forest monitoring, health assessment, wildfire prediction, biodiversity conservation, and climate modelling. While challenges remain, the continued advancement of AI technologies promises to significantly improve forest management and conservation efforts, contributing to the sustainability of these critical ecosystems. AI and ML are transforming forest monitoring and management, offering powerful tools to analyse large-scale remote sensing data, automate forest inventories, and detect changes in forest structure and health. While challenges remain, such as data availability and model interpretability, the continued development of AI-driven forest monitoring systems will significantly enhance the ability to manage forests sustainable, ensuring their conservation for future generations. AI and machine learning have emerged as powerful tools for detecting stress in trees, providing early warning systems for drought, disease, and pest infestations. By analysing remote sensing data, such as hyper spectral and thermal imagery, AI-driven models can identify subtle physiological changes in trees before they manifest as visible symptoms. Despite challenges related to data availability and model interpretability, AI's potential to enhance forest management practices is immense**.** As these technologies continue to evolve, they will play a key role in ensuring the health and sustainability of forests in the face of environmental change.

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